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Nexus between innovations, environmental challenges and labor mobility

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Nexus between innovations, environmental challenges and labor mobility

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Infrastructure development, human development index, and CO_2 emissions in China: A quantile regression approach

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This study investigates the relationships between infrastructure development, human development index (HDI), and CO_2 emissions in China. Infrastructure has played an essential role in achieving social and economic developmental goals in China, but environmental pollution has significantly increased in the country in the last two decades. Our analysis uses time series data from 1990 to 2021 and quantile regressions, and we find that infrastructure has positive and statistically significant relationships with HDI, CO_2 emissions, and GDP in all quantiles. Recent infrastructure upgrades improve living standards and increase HDI but damage the environment, and infrastructure is the main source of CO_2 emissions in the country. Therefore, the government should invest in sustainable infrastructure to mitigate CO_2 emissions. The government may consider infrastructure options such as low carbon transportation, including railway infrastructure, urban metros, and light rail.

KEYWORDS

infrastructure, human development index, CO2 emissions, China, quantile regression

1 Introduction

China has implemented various economic reforms in recent decades that have significantly increased GDP, whereas CO_2 emissions and global warming potentially increase during the transition period (Wang et al., 2022). Economic growth has improved living standards, literacy rates, and health quality, but environmental concerns are a key issue in the country's economy. The sustained economic growth from the last two decades has also helped to improve China's human development index (HDI) from 0.41 in 1978 to 0.75 in 2017 (UNDP, 2017). This is a tremendous improvement in HDI and made China the first country to move from low HDI in 1990 to high HDI. According to (UNDP, 2017), China's improvement in HDI can be attributed to the rural development and improving rural lives during the industrialization and transition period. The Chinese government has implemented various reforms to achieve balanced human development in rural and urban populations.

Theoretically infrastructure affect the CO_2 emissions from the following aspects; firstly upgradation of infrastructure makes easier the transportation of commodities; thus, it increases the CO_2 emissions due the large transportation activities. The improvement of infrastructure raises industrial production due to easy access to market, the raise in industrial production leads to increase in CO_2 emissions. Thirdly the infrastructure increase facilitates the social and economic development and increase the income of the people, the raise in income leads to increase the energy consumption. Infrastructure development in China has proceeded rapidly, especially transport infrastructure, rising at an annual rate of 7.3% over the last three decades (Wang et al., 2022). Infrastructure are basic business channels, including school systems, sewage, water, communication systems, and transportation, but infrastructure development and expansion cause ecological damage (Shan et al., 2021). For instance, during infrastructure construction, smoke, wastewater, industrial emissions, and CO_2 are released, which harm the environment (Akbar et al., 2021). Transport infrastructure leads to CO_2 emissions in China and facilitate the social development (Xu et al., 2022; Zhou et al., 2022). Furthermore, natural resources tend to be consumed in large quantities during infrastructure construction and operation. Despite these challenges, improvements in infrastructure are associated with HDI improvements. For instance, according Meng et al. (2019), China has extensively reformed its health care system over the past 10 years. These reforms have focused on improving primary care, expanding and improving social health insurance coverage, ensuring everyone has access to basic public health services, and reforming public hospitals. In addition, China has made remarkable reforms in the internationalization of education and huge numbers of international students travel to China to study (Economy, 2018), these international students contribute to the scientific and research activities in the country. The expansion of international students in China expected to positively affect the scientific productivity (Yin & Zong, 2022).

Investment in infrastructure development promotes HDI by creating growth channels and improving productivity and incomes (Razmi et al., 2012; Horvat et al., 2021). Electricity and transport infrastructure are the main channels that facilitate production processes. The improvement in HDI includes increases in *per capita* income, and infrastructure development is the main source of these increases. However, infrastructure development and industrialization also result in higher rates of CO_2 emissions. Therefore, HDI and infrastructure improve in parallel with CO_2 emissions in the country. Furthermore, the literature suggests that the long-term impact of infrastructure development is greater than its short-term impact. For instance, Kusharjanto and Kim (2011) suggested that in the short-term, a 1% increase in the share of households with access to electricity will lead to a 0.052% increase in adult literacy, but in the long-term will cause a 0.12% increase in adult literacy.

Although the positive impact of infrastructure on HDI may be achieved over the long term, its impact on carbon emissions is instant. This is particularly important for transport infrastructure, which produces large amounts of CO_2 emissions. China's low-carbon emission goals are yielding some success, but effort is needed to accomplish desired welfare levels (Shan et al., 2021). Currently, China is the world's largest energy consumer and makes significant contributions to CO_2 emissions, but environmental protection law and reforms helps to mitigate its CO_2 emissions (Zhang, 2000; Abbas et al., 2021). Despite these laws and reforms, the growth rate of CO_2 emissions remains a major challenge for the Chinese government. In the 10 years from 2009 to 2019, Chinese CO_2 emissions increased by 1.5 times (Zhao et al., 2022). With development at a transitional stage, high energy consumption and infrastructure lead to high CO_2 emissions (Zeeshan et al., 2022a; Zeeshan et al., 2022b), but improvements in infrastructure also stimulate improvements in HDI (Acheampong et al., 2022). Therefore, this study investigates the relationships between infrastructure development, HDI, and CO_2 emissions in China.

Infrastructure has been investigated either with HDI or CO_2 emissions, to best of our knowledge infrastructure, CO_2 emissions and HDI has not been analyzed in single study. Besides, infrastructure has dual impact on the economy; on one had it facilitate the social development and improve HDI, which on other hand it contributes to the CO_2 emissions. Thus, this study covers both negative and positive aspects using the case of China. Infrastructure development has given keen attention from last few decades in China economy, which expected to improve the HDI and effect the CO_2 emissions in country. Therefore, this study main objective to analyze Infrastructure, HDI and CO_2 emissions in China. The contributions of this study are threefold. First, previous literature such as Wang et al. (2022) has linked infrastructure, economic development, and industrial pollution. However, the relationship between infrastructure and HDI has not been examined. This study examines the relationships between HDI, CO_2 emissions, and infrastructure. Second, we use the context of China's transitioning economy to provide insights into how infrastructure development can affect HDI and carbon emissions in transitional economies. Third, we use quantile regressions to provide more robust findings to support policy recommendations. The remainder of this paper is structured as follows. Section 2 reviews literature related to this study. Section 3 presents information about China's infrastructure development, HDI, and emissions. Section 4 explains our research methodology. Section 5 provides the results and discusses the findings. Section 6 summarizes the research findings and provides recommendations and directions for future research.

2 Literature review

This section comprehensively analyses previous research related to HDI, CO_2 emissions, and infrastructure. Sapkota (2014) performed cross-country research investigating how infrastructure access affects human development. His research used three basic infrastructure types—roads, clean water sources, and access to electricity—general moment methods, and panel data for the period 1995–2010. The findings revealed a significant positive relationship between infrastructure development and HDI. Furthermore, water and electricity had significant positive relationships with health and education indexes. Mohanty et al. (2016) explored the relationship between infrastructure development and HDI in India using 30 districts of the Odisha region. Infrastructure was represented by access to water, schools, banking, village electricity, postal services, and telecommunications. Their study reported that access to these types of infrastructure positively affected human development, and recommended that local governments should improve rural infrastructure. Nchofoung et al. (2022) investigated infrastructure development using linear and non-linear impacts on general human development in African countries. Their findings suggest that all infrastructure development indexes except ICT positively affect HDI, whereas ICT development negatively affects HDI. Furthermore, there is a positive relationship between HDI and the sanitation, water, and electricity index.

Chawla et al. (2022) investigated the impact of infrastructure development on HDI. Living standards, knowledge, and healthy living were used to measure HDI and social opportunities were conceptualized as social infrastructure. Panel data were used to explore the relationships between variables. The findings indicate that in most countries' social infrastructure, disparity is a major issue. Inequity in education and health was found a positive effect in the regions, whereas regions with less social infrastructure had greater social disparities. They recommended implementing equity policies in infrastructure development. Djokoto (2022) investigated the nexus between investment and HDI in 137 countries for the period 1990–2019. His findings suggest that infrastructure development is one of the main factors that promotes HDI. Specifically, there was a 60% correlation between infrastructure investment and HDI.

Dzator et al. (2021) investigated the implications of infrastructure development for carbon emissions in OECD countries, examining the period 1960–2018 and using variables including energy consumption, urbanization, and trade openness. They reported that rail transport increases CO_2 emissions, whereas air transport does not influence CO_2 emissions. Higher energy consumption and population size greatly increased CO_2 emissions. Thus, regions with larger populations may set up railway transport and adapt to consumption of renewable energy, which may reduce CO_2 emissions in the region. Additionally, foreign trade and financial development also increase regional CO_2 emissions. Cantos Sanchez and Gumbau Albert (2015) also examine OECD countries. Specifically, their research concentrated on the environmental impacts of transport infrastructure, and used general translogarithmic methods of moments to analyze data. They found that the output-elasticity of aggregate transport infrastructure is negative, whereas elasticity is positive. Therefore, the region is experiencing both an increase in HDI and a rise in environmental pollution.

Sharif and Tauqir (2021) investigated the relationship between infrastructure development and carbon emissions in Pakistan for the period 1972–2017. They used ordinary least squares (OLS) and fully modified OLS methods for analysis. Their findings suggest positive relationships between infrastructure development and HDI and carbon emissions in Pakistan. Furthermore, their findings indicate that infrastructure development increased human development at the cost of environmental pollution, and the authors recommended investing in green vehicles to reduce emissions in the country. Lyu et al. (2022) explored the relationship infrastructure and pollution in Chinese cities. They used panel data for the period 2011–2017 and employed robustness tests to validate their baseline findings, and found that infrastructure greatly reduced CO_2 emissions. Muller et al. (2013) explored the nexus between human development and climate change by using infrastructure development and CO_2 emissions. Their research compared the carbon footprints of developed and developing countries, and found that developed countries had carbon footprints five times higher than developing countries. Their research suggests that reductions in emissions can be attributed to three factors: innovation in green technologies, agglomeration of producer service industries, and adoption of industrial structure. Furthermore, the research suggests that Chinese cities with higher technological development have greatly reduced CO_2 emissions. The authors recommended promoting low-carbon and green development to mitigate global warming. Yin and Jin (2021) investigated the relationship between economic development and carbon emissions by comparing China and the US. They found that countries with high HDI and energy consumption have higher CO_2 emissions. They also acknowledged that countries like China and the US had made remarkable developments in trying to mitigate CO_2 emissions. Rahman et al. (2021) uses a cross-sectionally dependent panel to analyze effects of human capital, exports, economic growth, and energy consumption on CO_2 emissions. Their findings suggest a long run association between human capital, exports, economic growth, energy consumption and CO_2 emissions. Hussain et al. (2022) reinvestigate natural resources, economic policies, urbanization, and environmental Kuznets curve, they reported EKC hypothesis do no exists in G7 countries. Tan et al. (2022) found that negative association between CO_2 emissions and disclosures. Mohmmed et al. (2019) reported that among the other factors GDP is one main reasonable factor for the CO_2 emissions in the top 10 countries. Bashir et al. (2022a) found institutional quality and economic growth and financial developed reduces the CO_2 emissions. Bashir et al. (2022b) found that natural resources consumption leads to environmental degradation. Sadiq et al. (2022) reported that nuclear energy can contribute to HDI. Bashir (2022) found the existence of pollution haven hypothesis in most of the countries. Xia et al. (2022) that globalization and economic development increase the CO_2 emissions.

The past studies analyze the infrastructure with CO_2 emissions such as Dzator et al. (2021); Akbar et al. (2021); Xu et al. (2022); Emodi et al. (2022) and Churchill et al. (2021) investigated the relationship and they found a positive relationship between CO_2 emissions and infrastructure upgradation. Other studies such Nchofoung et al. (2022); Chawla et al. (2022); Mohanty et al. (2016) and Sapkota (2014) analyzed the infrastructure and infrastructure and HDI and found a positive relationship between HDI and infrastructure. However, both HDI and CO_2 emissions with infrastructure using the case of China has not been examined. The research provides value addition to the existing literature by adding both HDI, Co2 emission with infrastructure in single study. And quantile regression will also provide robust estimation and better statistical inferences and policy recommendations.

3 HDI, CO_2 emissions, and infrastructure trends in China

Figure 1 shows HDI and CO_2 emissions trends from 1990 to 2021. The percentage of total greenhouse gas emissions was relatively low in 1991, but gradually increased until 1996, then levelled off from 1997 to 2000. The trends in greenhouse gas emissions between 1991 and 2000 can be explained by reduced industrial and infrastructure developments in that period. Most sources of greenhouse gases are upgrading of infrastructure, operation of industrial machinery, and energy consumption. There is a sharp increase in the percentage change in greenhouse gases between 2002 and 2012, which shows that China underwent tremendous changes in industrialisation, exploitation of natural resources, and development of infrastructure during this period. Furthermore, China joined the WTO in 2002, opening its economy for trade with the rest of the world (Ullah et al., 2019).

Overall, there is a sharp rising trend in greenhouse gases emissions in China in the previous two decades. However, China has committed to reducing its greenhouse gas emissions by the year 2060. Currently, China operates over 1,058 coal plants, more than half of the world's total. China's heavy reliance on coal power is a challenge but the country is gradually implementing production of clean energy. According to world development indicators (WDI), from 1991 to 1995 there was a slight rise in CO_2 emissions in China. This suggests

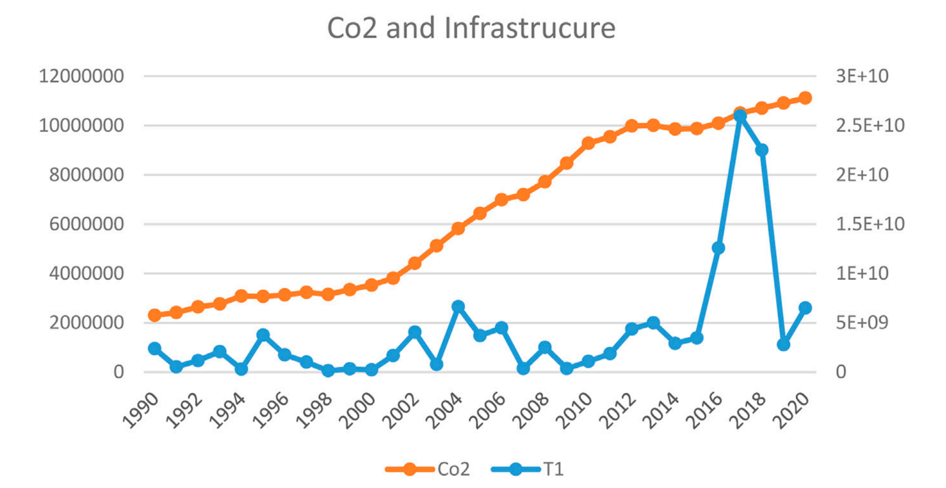

FIGURE 1
CO_2 emissions and Infrastructure.

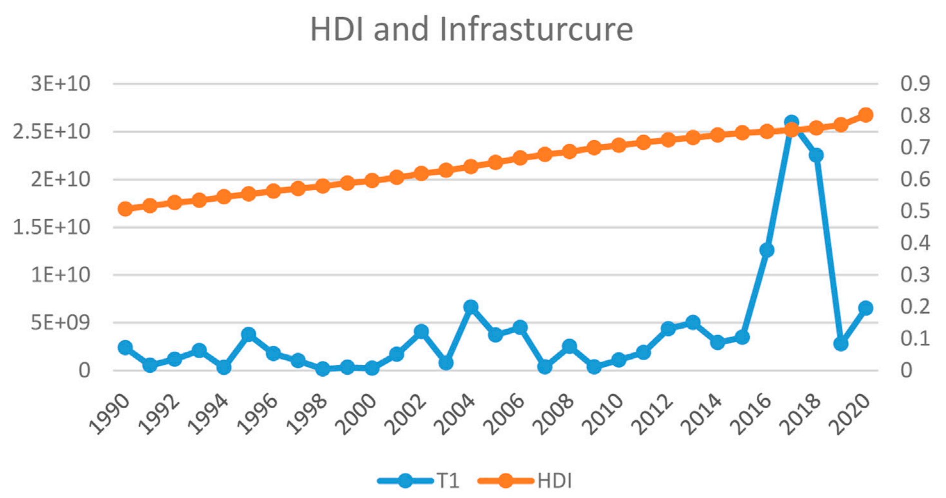

FIGURE 2
Hdi and infrastructure.

that in this period China was at an early stage of industrialization and CO_2 emissions are slightly lower in this period. From 1997 to 2000, CO_2 emissions *per capita* remained stable. From 2001 to 2014, CO_2 emissions *per capita* increased significantly. China's *per capita* GDP and trade increased significantly after joining the WTO in 2002, and in this period both income levels and per-capita emissions increased. Thus, the affordability of products and *per capita* emissions from the burning of fossil fuels are the main sources of CO_2 emissions in this period.

The increase in emissions can also be explained by population size. In 2022, China's population was 1.4 billion, which explains the country's high CO_2 emissions. Countries with larger population size are expected to have larger CO_2 emissions. For example, India has the second largest population and is the third largest CO_2 emitter in the world. Chinese energy mainly comes from fossil fuels, and industrial development in the last two decades has increased consumption of fossil fuels in industrial production, increasing CO_2 emissions in the country. CO_2 emissions from electricity and heat generation increased slightly from 1970 to 1980, indicating that the country was gradually making reforms and opening up to foreign investment. This investment increased demand for electricity, which explains the spike between 1977 and 1980. There was also a considerable increase in CO_2 emissions between 1984 and 2003 due to increased demand for electricity from the industrial and domestic sectors. Energy demand has also been increasing since 2002 due to expansion of trade and industrial production. According to Ling et al. (2021) China's electricity supply mostly comes from thermal generation, which provides more than 70% of all the electricity generated in the country. Over 60% of electricity from thermal generation comes from coal. However, the country is

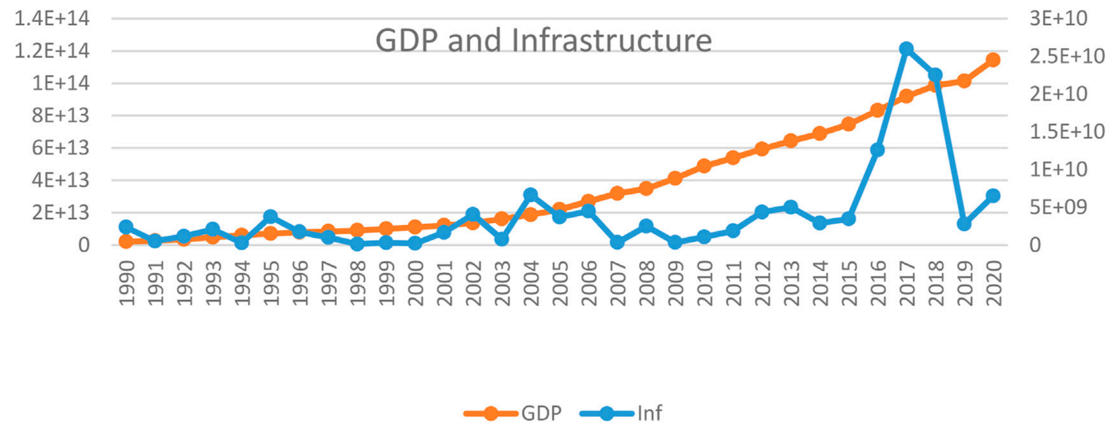

FIGURE 3
Gdp and infrastructure.

introducing laws and reforms to promote adoption of non-fossil-fuel energy sources (Yang & Lin, 2016).

Figure 2 presents trends in HDI and infrastructure. HDI has a deviation trend from 1990 to 2016. However, between 2016 and 2019 HDI is higher, which may reflect improvements in education, *per capita* GDP, and public health (Ullah et al., 2020). Furthermore, other measures such as clean drinking water and access to the electricity are also responsible for improvements in HDI in the region. According to WDI statistics, the proportion of people in urban populations who had access to at least basic drinking water services reached 100% in 2014. This can be attributed to the increasing urban population and government infrastructure improvements that made drinking water widely available. Access to at least basic drinking water services in the rural population has also been increasing gradually. This rising trend reflects the government's effort to balance infrastructure development in both urban and rural areas. Overall, there is a rising trend in both urban and rural populations' access to drinking water. In the year 2000, 80% of the Chinese population had access to drinking water; by 2020 this figure had increased to 94%. Access to electricity has also improved in recent decades; according to WDI statistics, the percentage of China's rural population with access to the electricity increased from 95% to 99% between 2000 and 2009, and reached 100% in 2012, and has since remained at this level. This indicates that the country has invested extensively in making urban areas fully operational by providing access to energy.

Improvements in sanitation are another important factor in the country's increasing HDI. WDI statistics suggest an overall rising trend in the percentage of people using either basic or safely managed sanitation services. It is suggested that the percentage of the rural population using safely managed sanitation services rose from 4% to 47% between 2000 and 2020. In the same period, the percentage of the urban population using safely managed sanitation services rose from 27% to 87%, and the percentage of the total population using safely managed sanitation services rose from 13% to 69%. This indicates that at least 45% of people in the early 2000's had access to at least basic sanitation services. By 2020, 85% of people both in rural and urban areas were using at least basic sanitation services.

Figure 3 depicts the association between GDP and HDI in China from 1990 to 2021. GDP increases steadily, indicating that infrastructure upgrades increase income, and hence GDP. WDI statistics report that net adjusted national income also increased steadily from 1970 to 1980. As mentioned earlier, these years were characterised by poor economic performance and policies that caused income levels to be low. However, after 2002, income levels increase substantially, reflecting industrialization and increasing trade activities. This can be considered a boom period in the Chinese economy.

4 Model and methodology

4.1 Model

This paper uses the following model for analysis

$$HDI, CO_2, GDP, G = f\,(Inf) \tag{1}$$

where *HDI* is the human development index, CO_2 is carbon dioxide emissions, *GDP* is gross domestic product, and *G* is government spending and *Inf* represents the infrastructure. In our model use infrastructure (Inf) as independent variable while, HDI, CO_2 emissions are the independent variables. G and GDP is used as control variable in the model the main targeted variables are Co2 emissions and HDI. According to the theory the model suggest that infrastructure determines the explanatory variables such as HDI, CO_2 emissions GDP and G. Theoretically the expected coefficient sign of HDI with other variables such as HDI, CO_2 emissions and GDP is positive.

4.2 Methodology

This study uses quantile regression for empirical analysis. Quantile regression is applied for this study because infrastructure developed in China has been carried out in different period. This method will differentiate the impact of infrastructure on CO_2 emission and HDI in different quantile. Besides the significance of coefficient in each quantile provide better statistical inferences and policy recommendation. Quantile regression helps to determine relationships between independent variables and dependent variables based on median values of residuals (Hoang et al., 2019). This method is preferred over OLS regression because it has high resistance to influence by outlying observations and is not based on assumptions about the target variable's distribution. Also, quantile regression is preferred over the OLS method because it uses different estimation weights such as symmetric weights for the median, whereas OLS estimates the conditional mean function (Furno and Vistocco, 2008). Quantile regression also helps in meeting conditions that linear regression cannot meet, such as normality, independence, homoscedasticity, and linearity. Quantile regression is used in a broad range of research, including financial economics, healthcare, and ecology (Huang et al., 2017). In our setting, quantile regression can be used to empirically examine the extent to which various factors such as HDI, CO_2 emissions, GDP, and government spending. In quantile regressions, a conditioned quantile is used to generalize unconditional quantiles. The OLS framework minimizes the sum of squared residuals as follows:

$$\min_{\{\beta_j\}_{j=0}^{k}} \sum_i \left(v_i - \sum_{j=0}^{k} \beta_j x_{j,i} \right)^2 \tag{2}$$

where v_i represents the largest variables for data set i and predictor variable j, and β_j represents parameters of estimation for the regression model. Because the aim of the quantile regression is to minimize the weighted sum of absolute deviations (Zietz et al., 2008), we can achieve the function:

$$\min_{\{b_j\}_{j=0}^{k}} \sum_i \left| v_i - \sum_{j=0}^{k} b_j x_{j,i} \right| h_i \tag{3}$$

In the above equation, p_i is defined as $p_i = 2q$ and shows the weights. For the case where the residual is strictly positive for observation i, p_i is defined as:

$$p_i = 2 - 2q$$

In the situation where observation i is zero or negative, the quantile variable q has a value between 0 and 1, which provides the predicted value in the equation. Following Gould (1998), bootstrapping is the method used to estimate standard errors in the quantile regression coefficients. The standard error estimation method is comparatively more volatile to heteroscedasticity, which is more stable in quantile regressions (Rogers, 1994). This paper uses quantile regression for two main reasons. First, this technique can provide more accurate estimations, which may help in determining the relationships between HDI, CO_2 emissions, GDP, and G. Second, this technique provides estimations of stability and relationships between regression coefficients on the target variable at different points; in our case, for HDI and CO_2 emissions. This study uses data extracted from World Bank Development indicators, which are available online, and HDI data from https://countryeconomy.com/.

TABLE 1 Descriptive statistics.

	CO_2	G	GDP	HDI	INF
Mean	7053457	15.49763	6.2239	0.6694	2190569
Median	7189817	15.74849	4.6130	0.6780	2374270
Maximum	11192409	17.63135	1.9540	0.8182	2968946
Minimum	3021242	13.13564	6.7703	0.5411	1250450
Std. Dev	2989032	1.130671	5.2703	0.0754	618207.5
Skewness	−0.125982	−0.297579	0.6108	−0.0931	−0.333549
Kurtosis	1.393126	2.301046	2.0448	1.7426	1.534380
Jarque-Bera	11.90489	3.792371	10.8211	7.2706	11.66878
Probability	0.002599	0.150140	0.0044	0.0263	0.002925
Sum	7.623939	1673.744	6.72021	72.2960	2.37012
Sum Sq. Dev	9.560376	136.7906	2.97021	0.609145	4.09021

5 Results and discussion

This section provides our results and discussion. We use the effect of infrastructure (INF) on the factors such as CO_2 emissions and HDI, and control for GDP and government spending (G). Table 1 presents descriptive statistics for the variables included in the model. GDP has high mean value, whereas CO_2 and infrastructure have subsequent high value. GDP has the highest variation among model variables, followed by CO_2 emissions and infrastructure.

Table 2 presents the results of our quantile regressions. We use infrastructure as the independent variable and take HDI and CO_2 emissions as dependent variables. GDP and G are control variables. The quantile regressions suggest that HDI is positively and statistically significantly associated with infrastructure in all quantiles, which indicates that infrastructure increases HDI in all quantiles. This implies that HDI can be enhanced by developing infrastructure. These findings are consistent with those of Sapkota (2014), Mohanty et al. (2016), and Nchofoung et al. (2022), who found a positive and statistically significant relationship between infrastructure and HDI. Infrastructure types such as access to hospitals and health help to improve public health and standards of living. In addition, access to water, schools, banking, village electricity, postal services, and telecommunications are essential in promoting and facilitating businesses and employment opportunities. Therefore, infrastructure acts as channel through which individuals can earn an income, improve their livelihoods, set up income generating activities, improve their health, and gain skills and education. Investments should therefore be made to develop new infrastructure and improve existing infrastructure.

The second model shows the relationship between CO_2 emissions and infrastructure; our results suggest that infrastructure level is statistically significantly associated with CO_2 emission levels for all quantiles. This implies that infrastructure upgrading leads to higher levels of energy consumption, which increases CO_2 emissions. This result is supported by previous researchers who have also found a positive relationship between infrastructure and CO_2 emissions (Dzator et al., 2021). Construction and operation of infrastructure such as transport systems, buildings, and plants increase CO_2

TABLE 2 Quantile regression results.

Dependent variable					
		HDI	CO2	GDP	G
Independent Variable	Quantile	Coefficient	Coefficient	Coefficient	Coefficient
Inf	0.100	1.0001 (0.0000)	3.8950 (0.0000)	3874447. (0.0000)	1.09021 (0.0000)
	0.200	1.0002 (0.0000)	3.90953 (0.0000)	4219649. (0.0000)	1.1135 (0.0000)
	0.300	9.43201 (0.0000)	3.923139 (0.0000)	3837541. (0.0000)	1.13532 (0.0000)
	0.400	9.47029 (0.0000)	3.956296 (0.0000)	4398242. (0.0000)	1.18929 (0.0000)
	0.500	9.63029 (0.0000)	4.268306 (0.0000)	5332674. (0.0000)	6.60292 (0.0866)
	0.600	1.12029 (0.0000)	4.685580 (0.0000)	7418318. (0.0000)	5.98039 (0.0732)
	0.700	1.20029 (0.0000)	4.913026 (0.0000)	8328711. (0.0000)	2.28029 (0.3494)
	0.800	1.30029 (0.0000)	5.202157 (0.0000)	9019529. (0.0000)	1.85938 (0.3809)
	0.900	1.46029 (0.0000)	5.597264 (0.0000)	9378368. (0.0000)	2.50793 (0.1997)

TABLE 3 Diagnostic test.

Quantile slope equality test				
Dependent variable				
Independent Variable	HDI	Co2	GDP	G
	Coefficient	Coefficient	Coefficient	Coefficient
	25.49642 (0.0000)	32.72275 (0.0000)	57.01067 (0.0000)	15.73248 (0.0000)
Symmetric Quantiles Test				
	13.77296 (0.0000)	3.054296 (0.2172)	4.222157 (0.1211)	0.194210 (0.9075)
Coefficient Stability Test—Wald Test				
	272.5212 (0.0000)	540.8883 (0.0000)	72.51726 (0.0000)	2.991122 (0.0837)

emissions, and development of infrastructure and transitional phases increase consumption of energy. China has invested heavily in infrastructure, and a large percentage of this infrastructure is run using non-renewable sources of energy, so the impact on CO_2 emissions is immense. Furthermore, with increasing population and access, infrastructure drives CO_2 emissions *per capita* in the country.

Our third model tests the relationship between GDP and infrastructure; for all quantiles, infrastructure is positively and statistically significantly associated with GDP, suggesting that infrastructure development improves GDP. Infrastructure is crucial in fostering economic development and prosperity. Infrastructure upgrades for transitional economies such as China help to increase economic growth and production and enable the country to utilize both its human and capital resources. These findings are supported by previous studies such as Chawla et al. (2022), and because the calculation of HDI incorporates a GDP measure, the findings suggest one mechanism by which infrastructure development promotes HDI.

The relationship between government spending (G) and infrastructure is presented in final model. Quantiles 1 to 4 show a positive relationship between these variables. However, quantiles 5 to 9 have no significant association. This means that increase in infrastructure stimulate the government spending only for lower quantiles of infrastructure. Infrastructure projects usually take a long time to complete, which means they create relatively long-term job opportunities. The association between government spending and infrastructure may also be bidirectional, whereby government spending may drive upgrading of infrastructure (Tam, 1999). Furthermore, infrastructure increase employment levels, raises people's income levels, and stimulates economic activity in the country.

Table 3 reports diagnostic tests for the quantile regression, including slope equality tests for median regressions for the different models. The findings are tested using Chi-square statistics and restrictions are imposed on the lower and upper quantiles. The Chi-square values are significant at the 5% level across the different models; we conclude from these statistics that

TABLE 4 Pairwise granger causality tests.

Null hypothesis	F-Statistic	Prob
G does not Granger Cause CO2	2.76088	0.0991
CO_2 does not Granger Cause G	1.66004	0.2000
GDP does not Granger Cause CO2	39.4241	5.0122
CO_2 does not Granger Cause GDP	0.27159	0.6032
HDI does not Granger Cause CO2	8.31263	0.0046
CO_2 does not Granger Cause HDI	8.01617	0.0054
INF does not Granger Cause CO2	54.1884	4.9291
CO_2 does not Granger Cause INF	6.12960	0.0149
GDP does not Granger Cause G	4.44871	0.0369
G does not Granger Cause GDP	0.27090	0.6037
HDI does not Granger Cause G	0.90907	0.3422
G does not Granger Cause HDI	1.65379	0.2008
INF does not Granger Cause G	0.06411	0.8006
G does not Granger Cause INF	1.11449	0.2936
HDI does not Granger Cause GDP	6.9044	0.0161
GDP does not Granger Cause HDI	1.96616	0.1634
INF does not Granger Cause GDP	2.85134	0.0943
GDP does not Granger Cause INF	11.4008	0.0010
INF does not Granger Cause HDI	4.29712	0.0406
HDI does not Granger Cause INF	1.99238	0.1611

the coefficients differ across quantiles and conditional quantiles are not identical. The coefficient stability test is based on the Wald test and suggests that in almost all models, probability values are statistically significant, implying that variable coefficients are stable. Granger Causality tests is applied for robustness estimation, which main validates or support the bassline findings. Table 4 represents Granger Causality tests which indicate the casual relationships between variables. GDP drives CO_2 emissions, which implies that increases in economic activity cause increased CO_2 emissions in China. There is bidirectional causality between HDI and CO_2 emissions, indicating that HDI increase CO_2 emissions and CO_2 emissions increase HDI. This means infrastructure improvements boost economic activity and lead to higher CO_2 emissions. There is unidirectional causality between HDI and GDP, and the results suggest that infrastructure upgrading increases GDP.

Overall, the results suggest that infrastructure upgrading increases HDI and CO_2 emissions in China. With population growth in both developed and developing countries, the demand for high-quality infrastructure is increasing, and such infrastructure narrows income disparities, creates new employment, increases business opportunities, and sustains economic growth. In addition to developing infrastructure, countries with sustainable economic growth goal may seek to transition from fossil fuel energy to renewable energy, to achieve economic growth and a clean environment. Therefore, future infrastructure developments should address financial, climate, and inclusive challenges. Governments should also consider technological upgrades to existing infrastructure to enable more efficient use. This can help increase economic productivity, thus increasing HDI and GDP, and reducing emissions. The results of this study are in line with other studies such as Xu et al. (2022), Zhou et al. (2022), Emodi et al. (2022), Chawla et al. (2022), Yin and Jin (2021) and reported a positive relationship between HDI, CO_2 emissions and infrastructure.

6 Conclusion

The modernization and development of China's economy is based on upgrading the country's infrastructure. China's economic growth is rapid, but environmental challenges are one of the main concerns to both academia and government. Therefore, this study explores the relationships between infrastructure, HDI, and CO_2 emissions in China. We use time series data from 1990 to 2021 and a quantile regression method. Our findings reveal that infrastructure positively influences CO_2 emissions, but also improves HDI in China. Infrastructure also has positive implications for GDP and government spending.

Based on these findings, we suggest the following policy recommendations. First, the government should plan to establish low carbon infrastructure to reduce environmental pollution in the country. Therefore, infrastructure is needed to transition from consumption of fossil fuels to renewable energy. This could help to both provide the energy needed for infrastructure processes and achieve environmental sustainability. Indeed, these efforts will eventually lead China to become a zero-emissions country by 2050. Second, the government should invest in research and development (R&D) and in particular should direct reasonable expenditure towards infrastructure R&D, innovation, and new technologies that could help achieve low carbon emissions. Third, the government may choose other options in infrastructure development and establish low carbon transportation systems, such as railway infrastructure and urban transport projects including metros and light rail, and renewable energy projects such as hydro-power, wind, and solar generation. This sustainable infrastructure could help China to achieve both higher HDI and environmental sustainability goals.

This study has some limitations. First, the study only considers China, so our findings may not be generalisable to other countries. Future studies should examine other countries to test the relationships between infrastructure and HDI and CO_2. The second limitation is the nature of the data used. Whereas we use annual time-series data, future research may use household data. The third limitation is that we include transportation investment by government and public investment in infrastructure; future research may use another proxy for infrastructure to analyse the relationship between HDI and CO_2 emissions. Fourthly we applied quantile regression, the future studies may use some additional sophisticated techniques if short run and long run effect is desirable; some advance techniques such as quantile ARDL can applied which will provide both short run and long estimation. Fifthly future studies may use the regional or provisional effect in China and CO_2 emission and HDI effect in China. Sixthly the future research may add technological innovation in model which may provide most clear implications infrastructure for HDI and CO_2 emissions.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://databank.worldbank.org/country/CHN/556d8fa6/Popular_countries.

Author contributions

YL: Conceptualization, writing of main draft PeP: Funding and review the main draft PaP: Data collection, review of the main draft FU: Data analysis SN: Review the final draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The analyzing the role of electric vehicles in urban logistics: A case of China

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In recent years, the rapid development of electric vehicles has gained widespread attention, and has especially brought new vitality to the fast-growing logistics service industry. Electric vehicles in urban logistics are not only ideal transportation tools but also do not affect the environment. This study thus implements the economic valuation of electric vehicles in urban logistics from the viewpoints of both manufacturers and business users through the investigation of pricing mechanism and discusses the potential for improving policy-making together with the real case in China. The net present value (NPV) approach is used to quantitatively analyze the investment decisions of urban logistics electric vehicles, with government regulation, incentive policy, and carbon emission trading taken into consideration. Our findings provide insights into the decision-making mechanism for commercializing electric vehicles in urban logistics that involves optimizing the government subsidy and transaction price between the manufacturers and business users. The results imply that with rationalized government policy incentives and coordinated transaction price, both manufacturers and business users are expected to achieve their break-even in limited time periods. The carbon cap placed on business users rather than manufacturers would be relatively more conducive to the marketization process.

KEYWORDS

urban logistics (UL), electric vehicle (EV), economic valuation, government policy, environment, carbon trading (CT)

1 Introduction

The consistent increase in energy price in international market and environmental concern leads to search alternate solution for transportation. Therefore, electrification of vehicles was essential for sustainable development of transportation. Moreover, urban transportation consumes a greater amount of fuel and energy than rural transportation due to the large number of vehicles used in urban areas (Liu et al., 2023). Therefore, it is necessary to empirically analyze the role of electric vehicles in urban transportation. Over the past decade, the development of new energy vehicles has attracted attention worldwide and has been promoted to realize an environment-friendly society and all-round sustainability. There has been a gradual acceptance of new energy vehicles such as electric passenger cars in the marketplace, which is promoted by local governments (Wan et al., 2015). Following this trend, electric vehicles in urban logistics have begun entering the market and becoming an important part of green transformation in the logistics industry (Quak et al., 2016; Strale, 2019). Electric vehicles in urban logistics are mainly used for relatively short-distance (intra-city) transportation service including branch line logistics transportation between outlets and distribution stations and the last kilometer of urban delivery logistics (Wang et al., 2019).

With the rapid development of e-commerce, the express delivery industry has been penetrating into a larger number of households, creating huge demand for urban logistics service carried out by logistics electric vehicles. To achieve carbon neutrality goals, the government is pushing for the development of electric vehicles in urban logistics through incentive policies, since electric vehicles have advantages of lower electricity usage cost and less emission over the conventional fuel vehicles (Jones et al., 2019; Dean et al., 2022). However, there is an issue to be concerned regarding whether logistics service providers would prefer to use electric vehicles and whether manufacturers would be willing to invest in producing them. These will depend on whether their cost disadvantages can be mediated by the market penetration induced by government incentive policies, on their social responsibility propelled by environmental concern on energy conservation and emission reduction, and also on the market trend of gradual phasing out of conventional vehicles in the logistics industry. In China, for instance, reality reflects that there is a trend for conventional fuel vehicles to be replaced by electric vehicles in urban logistics, promoted by some large e-commercial retailers and logistics service providers such as JD.COM, Gome, SUNING.COM, and SF Express, responding to the government's call on creating a green, low-carbon, and circular economy. The development of electric vehicles in the logistics industry is still in its initial stage. The realization of sustainable development requires the coordination of manufacturers and logistics service providers and the government's regulation and incentive policies.

During the development of electric vehicles in urban logistics, two parties are involved, the manufacturers as suppliers and urban logistics service providers as business users. In terms of business characteristics, the market development process of electric vehicles in urban logistics is rather different from that of electric passenger vehicles, since the former is for business firms that are profit driven and the latter is for household users that are driven by usage satisfaction. The business feature of the former is characterized by not only profit drive, but also both parties are expected to comply with environmental regulations. During the process of transforming conventional fuel vehicles into electric vehicles in urban logistics, manufacturers face the challenge of cost disadvantage due to market competition, which is concerned with the achievement of its green investment break-even in an acceptable payback period (Porter, 2008). Without the government incentive policy, the cost disadvantage may drive the sales price to increase, which in turn may affect the purchase cost of the logistics service providers as the business users and makes them less motivated. In this sense, government incentives, such as subsidies, play a role in facilitating the market penetration of electric vehicles in logistics service. The marketization of electric vehicles in urban logistics can only be realized and sustained when both parties reach their break-even in an acceptable payback period. It requires the manufacturers and business users to act as partners and share government subsidies through transaction price coordination between them. Following up with the growth of sales through market penetration, government subsidies for promoting electric vehicles in urban logistics should be gradually reduced and possibly even withdrawn within a few years as scheduled. Thus, the economic feasibility of electric vehicles in urban logistics needs to be examined under different scenarios for managerial implication. In this regard, there are some issues that need to be addressed, for instance, what characters, unlike those of electric passenger cars, influence the marketability of electric vehicles in urban logistics? How can both manufacturers and logistic service providers reach break-even within limited time periods through a coordination process of transaction price determination? How can their business behaviors be effectively guided through government regulations and policy incentives to comply with environment standards? In the existing literature, limited research is dedicated to the marketization of electric vehicles in urban logistics from the perspective of logistics service providers, for whom it is necessary to consider profitability and economic feasibility. Moreover, investigation on its mechanism has both research and practical implications under government policies and carbon-trading context. The research in these aspects reflects the important innovation points of this study. There are several ways in which this paper makes contributions to the literature. First, it focuses on the economic evaluation of electric vehicles in urban logistics, which has been neglected past studies. Second, we applied the net present value approach for economic evaluation, which could provide better estimation and evaluation of electric vehicles in urban logistics. Third, we use data from China, which is among the top users of the electric vehicle, and this research provides a better understanding of the role of electric vehicles in the urban logistics. The remaining paper is organized as follows. Section 2 presents the literature review. Section 3 presents the net present value (NPV) models of both manufacturers and business users by introducing electric vehicle in urban logistics, taking into account government regulation and incentive policy, then the game approach is utilized to study their coordination process in determining the optimal transaction price, and the scenarios under the enforcement of carbon trading is also considered. Section 4 presents a numerical analysis together with sensitivity analysis based on the real case in China to illustrate the model, and the results are discussed in Section 5. The paper ends with the conclusion.

2 Literature review

2.1 Electric vehicles in urban logistics

As the current global environmental situation is gradually becoming grim and the energy problem is gradually becoming prominent, all countries in the world are paying attention to the research of electric vehicles. The large-scale promotion of the use of electric vehicles has the functions of ensuring the energy security, improving the local environment, and promoting economic development (Ahman, 2006). Marmiroli et al. (2020) compared the environmental assessment of electric and conventional light-duty vehicles. The results showed that electric vehicles have advantages in urban environments due to the large amount of stopping and regenerative breaking that occurs during urban transportation. The trend of replacing conventional fuel power with new energy power in the future automobile industry is gradually clear (Specchia et al., 2005). However, the market share of electric vehicles for urban logistics is much lower than the potential in some countries (İmre et al., 2021). To estimate the potential and possible directions of electric vehicle adoption, several scholars used the Bass diffusion model (Park et al., 2011; Lee et al., 2019; Brdulak et al., 2021). The Bass model captures the growth trend of a new product's sales forecast. Yu et al. (2018) also used the diffusion model to assist the evaluation of policies' effectiveness in the adoption of electric vehicles in China. Li et al. (2020) examined electric vehicles in urban logistics distribution systems under a sharing economy. They found that in the first simulation, sharing distribution networks can reduce trip times and costs. The second simulation estimated different timepoints of electricity price, which indicates that low electricity prices reduce traffic congestion and cost. Furthermore, they suggested that an increase in carbon tax reduces the CO_2 emissions. Gao et al. (2022) evaluated inceptives for the adaptation electric vehicles in urban logistic, and they analyzed different factors including price, driving rate, and decision related to time window. This suggests that price and driving range of the electric vehicle motivate the consumer to adopt EV. Furthermore, wider time window also motives the consumer to adopt EV. Juvvala and Sarmah (2021) analyzed the policy electric vehicles in city logistics, and they used a real-life case study and use the MACO mathematical model test. The hypothesis found that the purchase subsidy and the zone entry fee play an important role in city logistics. Roumboutsos et al. (2014) found that electric vehicles help urban logistics significantly and improve urban terrific congestion, and they also suggested that electric vehicles reduce the pollution emissions. Based on a real-world application, Duarte et al. (2016) assessed the adequacy of electric vehicles for urban logistics in Lisbon. They compared the energy impacts of switching to electric mobility and found that the battery electric vehicles lead to low vehicle usage energy consumption. Quak et al. (2016) addressed recent advancements, challenges, and prospects for the large-scale use of electric freight vehicles in daily city logistics. Iwan et al. (2019) illustrated that electric vehicles are suitable for urban logistics by investigating the potentials of electric mobility in commercial transport in terms of travel patterns and daily mileage. Ehrler et al. (2021) analyzed a real-life case of electric vehicles for grocery logistics in Germany and argued the prerequisites and perspectives for a successful introduction of electric freight vehicles for urban logistics. Some scholars even look into the sharing economy to improve the routing model for urban logistics distribution using electric vehicles (Verena et al., 2019; Zuo et al., 2019).

2.2 Firms' environmental behaviors and government policies

Firms should take the liability to reduce environmental externalities *via* green technology investments. While complying with government regulations, Yalabik and Fairchild (2011) argued that government subsidies are more effective than penalties in encouraging firms' technology adoptions to become environment-friendly. Their findings suggest that the incentive policy is a stronger driving force for firms' environmental innovation than the penalty policy. By using a lifecycle approach, Ding et al. (2014) drew the impact of government policies on how to motivate firms to reduce their pollution externalities by producing environment-friendly products. Ding et al. (2016) explored a decision-making mechanism for an environmentally sustainable supply chain that is jointly constrained by environmental carrying capacities and carbon caps, and also takes government policy incentives into account. They addressed the impact of government policy incentives on value transition and profit allotment in different settings of the collaborative supply chain system.

The industrialization of electric vehicles in urban logistics needs the government to issue policies on supporting the construction of infrastructure and encouraging the research and development of key technologies. Governments in different countries have taken differential policies to support measures in the development of electric vehicles, including research and development, demonstration projects, and market support (Ahman, 2006; Lebeau et al., 2016). Mirhedayatian and Yan (2018) evaluated the impacts of supporting policies for electric vehicles on company and environment. Juvvala and Sarmah (2021) carried out a real-life case study showing that car purchase subsidies and zone entry fees are important considerations when promoting electric vehicles in urban logistics. Luo et al. (2014) analyzed how the government's subsidies for the purchase prices would affect the supply chain of new energy vehicles and proved that it is the most effective way to stimulate the sales of new energy vehicles.

2.3 Carbon trading

Carbon trading, as a market-based instrument, has been studied and used to optimize resource allocation and reduce carbon emissions. Most of the related research studies have been conducted at the macro level of country or industry, including carbon price, allocation approach of carbon emission rights, comparison of trading schemes in different countries, and the impact of emissions trading on economy and industries (Comodi et al., 2016; Kanamura, 2016; Bakhtyar et al., 2017; Zhang et al., 2017). Wang et al. (2019) proposed an ideal vehicle combination including electric vehicles and fuel vehicles to achieve low carbon emissions and distribution costs in the urban logistics network. There are only a few quantitative assessments of the impact of carbon trading and carbon emission constraint on energy-intensive firms, e.g., profits, cost transfers, innovation, and production planning (Gong and Zhou, 2013). To meet the regulatory requirements, Benjaafar et al. (2013) used relatively simple and extensive models to illustrate how to consider carbon emission in operational decisions with procurement, production, and inventory management. Toptal et al. (2014) studied the joint decision of manufacturing firms' production planning and green technology investment under the constraint of carbon cap-and-trade policy and compared the impact of different policies on manufacturing firms' optimal order quantity and green technology investment decision.

Existing studies of electric vehicles by and large have focused on the passenger vehicles with associated technologies, infrastructures, and government policies. The research on the marketization potential in urban electric logistics industry remains rare, combined with government policies and the carbon trading context. To fill this research gap, our study intends to explore the economic feasibility of electric vehicles in urban logistics by taking the view of both manufacturers and

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business users. The pricing model with an applicable government policy scheme is deduced to be compatible with the market development mechanism.

3 Modeling background and assumptions

3.1 Government policy for electric vehicles in urban logistics

It is the government's responsibility to internalize environmental externalities by motivating business organizations to reduce emissions through regulation and incentive policies. In the logistics service industry, it is shown as the gradual replacement of conventional fuel vehicles with electric vehicles promoted by government incentive policies, leading to the marketization of electric vehicles in urban logistics. China has become world's largest producer and seller of new energy vehicles, and world's largest market for electric vehicles developed with policy support. With the consideration of fast development of electric vehicles in the Chinese market, promoted by government policies, we will focus our study on the reality in China. In terms of government policies in China, the purchase tax of new energy vehicles was exempted in 2014, and various related policies were subsequently issued with a clear indication to support the application of electric vehicles in urban logistics. According to the statistics of China Association of Automobile Manufacturers (CAAM), electric vehicles in urban logistics began to sprout in 2014 and achieved a blowout from 2015 to 2017, encouraged by government policies. However, the government issued a policy for electric vehicles with subsidy scheme change from 2018. Compared with previous years, the subsidy dropped sharply. Financial subsidy was reduced by 40% and over 50% in 2018 and 2019, respectively, and announced to be withdrawn in 2023, which may significantly impact the marketization of electric vehicles in urban logistics. Withdrawing subsidies is expected and will come sooner or later. The relevant issue is how to arrange the process of reducing the government subsidy so that it will be compatible with the requirement for the marketization of electric vehicles in urban logistics, leading the industry into a rational development stage in which fair market competition is compatible with low carbon emission and the internalization of environmental externalities.

3.2 Participants in the business of electric vehicles in urban logistics

3.2.1 Manufacturer: Supplier of electric vehicles in urban logistics

Suppliers of electric vehicles in urban logistics, one of the subjects in this study, are characterized by technical imperfections and immaturity at the early stage of their development of electric vehicles in urban logistics, so their initial investments and uncertainties are usually high, most likely leading to high unit costs and negative profits. To enable the production of electric vehicles in urban logistics to compete with conventional fuel vehicles in a competitive market, manufacturers are motivated by government incentive policies on one hand and enforced by environment regulation on the other hand. Along with the sales growth of the electric vehicles, the manufacturers expect to break-even in certain periods.

3.2.2 Logistics service provider: Business user of electric vehicles in urban logistics

Although electric vehicles in urban logistics have the advantage of low emissions that conventional fuel vehicles cannot match, the relative high-purchase cost and imperfect charging facilities are obstacles to their use. On the other hand, electric vehicles in urban logistics enjoy preferential incentive policies and relatively lower driving cost under the government's promotion. Choosing between electric vehicles and conventional fuel vehicles in urban logistics has become a dilemma faced by the logistics service providers. As a business user, the usage cost of electric vehicles in urban logistics is an essential factor to consider. If its life cycle cost is lower than that of conventional logistics vehicle, electric vehicles in urban logistics will have economic advantage favored by business users. Otherwise, it will be difficult to compete in the market place.

3.3 Assumptions

Consider a supplier–buyer business relationship that involves business transactions of urban logistics vehicles between manufacturers and business users in the competitive market. For convenience, we consider all the manufacturers in the market of urban logistics vehicles as a whole, and all the business users as a whole. Manufacturing companies manufacture logistics vehicles on a made-to-order basis, and sell them directly to consumers. Similarly, logistics service providers purchase logistics vehicles for business operations. Due to the increase in the demand for logistics industry, electric vehicles are gradually replacing conventional fuel vehicles. The manufacturers are beginning to produce logistics electric vehicles to gradually replace the conventional fuel vehicles.

We assume that the production of electric logistics vehicles requires additional initial investment, resulting in a cost disadvantage compared with conventional fuel vehicles in the competitive market. To encourage the manufacturers and logistics service providers to improve their environmental performance by reducing environmental pollution, the government enforces regulation by imposing a penalty on manufacturing and using conventional fuel vehicles, and grants policy incentives to subsidize manufacturing and buying electric logistics vehicles. The government policy incentives will help reduce the cost disadvantage of the electric logistics vehicles in the marketplace.

We assume that in the competitive market, the purchase price of electric logistics vehicles for the business user is relatively similar to the market price, which may be lower than the manufacturer's production cost of the electric logistics vehicles. The manufacturer will be compensated by the government subsidy only when it sells an electric logistics vehicle and shares the subsidy with the business users by coordinating the transaction price through negotiation. The purchase price of conventional fuel vehicles is determined by the market price.

We further assume that the electric logistics vehicles gradually replace the conventional ones in the market place, which means that the logistics service providers use both electric vehicles and conventional fuel vehicles simultaneously with an increasing usage of the former and decreasing usage of the latter. The usage costs of electric vehicles in urban logistics mainly include vehicle purchase cost and vehicle operation cost (including electricity cost, maintenance cost, insurance cost, and other expenses). Purchase cost includes purchase tax expense. We assume that purchase tax is free for electric vehicles in urban logistics, but is charged at a portion of the purchase price for conventional fuel vehicles.

Carbon trading is used to set the cap for carbon emission and then create a carbon market where emitters can buy and sell emission credits. The cap can be either placed on the source side (manufacturers) or placed on the end side (business users). However, the cap is not allowed to set for both the source side and the end side at the same time for the same industry to avoid double counting. The carbon cap is set at a much lower level than the average level of carbon emissions in producing and using logistics vehicles. Hence, emitters need to buy carbon credits to comply with the carbon cap whenever their carbon emissions exceed the cap. When discussing the scenario under carbon trading context, for convenience, we assume that the carbon cap-and-trade policy is implemented at the same time when the electric logistics vehicles are produced and used.

Regarding government policies, there are three alternatives to be considered: 1) the current implemented scheme in which the government subsidy is proportional to the production cost of electric vehicles, which is based on the fact that the manufacturer's battery procurement cost is proportional to the production cost of electric vehicles; 2) the rationalized subsidy scheme in which the government subsidy is granted on the increment cost basis, which means the government subsidy only compensates for the additional costs incurred by the investment of electric vehicles compared with those of conventional fuel vehicles; and 3) the rationalized subsidy scheme together with the carbon cap enforced either on the manufacturers or business users. In the following section, these three schemes will be discussed.

4 Modeling the marketization of electric vehicles in urban logistics

4.1 Economic valuation

As mentioned previously, the break-even analysis of the investment of the electric vehicles in urban logistics involves two important parties, the manufacturers as suppliers and the urban logistics service providers as business users, and both are profit driven. Thus, the payback for their investments must be fully considered. The excessively long payback period of either party will cause them to give up the investments in electric vehicles in urban logistics. Only if they can achieve their break-even relatively simultaneously can there be enough driving force to make the marketization of electric vehicles in urban logistics sustainable. Hence, when studying the market development of electric vehicles in urban logistics from the viewpoints of manufacturers and business users, we need to comprehensively consider the operating conditions and payback periods of both the parties.

The investment in electric vehicles in urban logistics reduces emissions and internalizes environmental costs. Meanwhile, the internalization of environmental costs will have certain impacts on business cashflows. To make the marketization of electric vehicles in urban logistics economically feasible in the competitive market, the government imposes penalties on conventional fuel vehicles to have them bear environmental costs and increase their marginal costs. The incentive policies encourage the investment of electric vehicles in urban logistics by making up for the extra operating costs that manufacturers must pay to produce electric vehicles, thus reducing their marginal costs. It can be seen that in order to make electric vehicles in urban logistics competitive in the market and to raise the awareness of environmental protection, it is essential in the initial stage to implement government policies so that both the production and the usage of electric vehicles in urban logistics are well motivated toward their economic feasibility.

In the next section, our model formulation and analysis will be presented. For convenience, notations in Table 1 are used for defining variables and parameters.

4.2 Model analysis from the viewpoint of manufacturers producing electric vehicles in urban logistics

4.2.1 Manufacturer investment evaluation model

We first formulate an investment valuation model by the net present value (NPV) approach from the perspective of the manufacturers referring to Ding et al. (2014). It is considered that the lifecycle of the electric vehicles in urban logistics consists of the initial stage and the steady growth stage. At the initial stage of producing electric vehicles in urban logistics, the NPV of this project is negative, assuming that the sales volume of electric vehicles in urban logistics has not reached the expected level due to substantial upfront investment, business uncertainties, and lower market penetration. As the sale volume of logistics electric vehicles increases and the public gradually recognizes logistics electric vehicles driven by government incentive policies, the manufacturers' cash flow will gradually increase until the time point $t = n$ at which $NPV_m = 0$, which means they break-even. Beyond this point of time, electric vehicles in urban logistics come into its steady growth stage and earn economic profits. Our research will only focus on the decision issues in the initial stage.

In the early development stage, to enable the survival of electric vehicles in urban logistics in the market competition and promote its rapid spread, the government offers incentive policies in the form of subsidies (in T_{et}) for electric vehicles, and on the other hand, increases taxes or imposes fines (in T_o) on environmental pollution caused by conventional fuel vehicles. Since we assumed the electric vehicles in urban logistics will gradually replace conventional fuel vehicles, the manufacturers' annual operating cash flows can be expressed as $P_{et}Q_{et} + P_o(Q_t - Q_{et}) - [C_{et}Q_{et} + C_o(Q_t - Q_{et})] + [T_{et}Q_{et} - T_o(Q_t - Q_{et})]$, and the investment valuation of producing electric vehicles in urban logistics should be based on

TABLE 1 Variables and parameters.

Notation	Variables and parameters
Notations for manufacturers	
I	An initial investment in the production of electric vehicles in urban logistics
Qt	The market size of logistics vehicles in year t
Qet	The sales volume of electric vehicles in urban logistics in year t
Cot	The unit variable cost of fuel logistics vehicles in year t
Cet	The unit variable cost of electric vehicles in urban logistics in year t
Po	The sales price of fuel logistics vehicles
Pet	The sales price of electric vehicles in urban logistics (decision variable)
r_1	Risk-adjusted discount rate for manufacturers
Notations for business users	
S	Average revenue of business users per vehicle per ton per kilometer
Get	Cargo capacity per electric vehicle in urban logistics
Go	Cargo capacity per fuel logistics vehicle
Det	The average mileage of electric vehicles in urban logistics per year
Do	The average mileage of fuel logistics vehicles per year
Aet	Operating cost per electric vehicle in urban logistics in year t
Aot	Operating cost per fuel logistics vehicle in year t
r_2	Risk-adjusted discount rate for business users
n	Number of years for manufacturers and business users to break-even (producing electric logistics vehicles)
Notations for government policies	
To	Government fines for fuel logistics vehicles per vehicle
Tet	Government subsidy for electric vehicles in urban logistics per vehicle
β	The current government subsidy ratio factor
α	The rationalized government subsidy ratio factor
C	Average incremental cost per unit of electric logistics vehicles
Z	Annual carbon cap (in ton) (maximum amount of allowable carbon emissions allocated by the government)
e^e	Carbon emissions of electric vehicles in the life cycle, in tons per vehicle
e^o	Carbon emissions of fuel logistics vehicles in the life cycle, in tons per vehicle
h_t	Per ton purchase price of carbon emission rights in a fair market in year t
q_t	Carbon credits purchased from external sources in year t
H_t	The purchase cost of carbon credits in year t

the incremental net cash flow, which excludes the opportunity cost of only producing conventional fuel vehicles ($P_oQ_t - C_oQ_t - T_oQ_t$). For the manufacturers, the net present value of producing electric vehicles in urban logistics during the initial stage, denoted by NPV_m, can be expressed as:

$$NPV_m = -I + \sum_{t=1}^{n} \frac{(P_{et} - P_o)Q_{et} - (C_{et} - C_o)Q_{et} + (T_{et} + T_o)Q_{et}}{(1 + r_1)^t}. \quad (1)$$

4.2.2 Government subsidy model: Current *vs.* rationalized

In practice, it is found that manufacturers' battery procurement cost is proportional to the production cost of electric vehicles, and is also proportional to battery capacity. The current government subsidy scheme for electric vehicles (in $T'et$) is based on the total capacity density of the power battery. The government subsidy is briefly proportional to the production cost of electric vehicle, which can be expressed as $T'et = \beta Cet\ (0 < \beta \le 1)$.

In principle, the government subsidy policy should compensate the cost advantage of electric vehicles in urban logistics compared with fuel vehicles, and further promote the market penetration process of electric vehicles in urban logistics. In order to do that, the government subsidy scheme should be granted on the incremental cost basis for producing electric vehicles in urban logistics. That is, the government only compensates for the additional costs incurred by investing in electric vehicles in urban logistics to be competitive relative to conventional fuel vehicles in the market place. Therefore, with the increasing sale volume of electric vehicles in urban logistics, the incremental cost of producing electric logistics vehicles per unit gradually decreases, and thus the government subsidy will also gradually decrease until it is completely withdrawn when the manufacturer reaches break-even. In this way, the government policy is more in line with reality and promotes the market penetration process of electric vehicles in urban logistics. Assuming that the government subsidy is proportional to the average increment cost of producing electric logistics vehicles, the proportion coefficient is defined by α. It reflects the variation of market demand, investment intensity, energy utilization, pollution reduction efficiency, and commercial risks of electric logistics vehicles. The formula for the rationalized government subsidy (in T_{et}) can be expressed as $T_{et} = \alpha C\ (0 < \alpha \le 1)$. C is the average increment cost per unit of electric logistics vehicles, which is presented by allocating the total accumulated increment costs to the total sale volume during the initial stage. The rationalized government subsidy per unit can then be expressed as follows:

$$T_{et} = \alpha C = \frac{\alpha\left[I + \sum_{t=1}^{n}(C_{et} - C_o)Q_{et}\right]}{\sum_{t=1}^{n}Q_{et}}\ (0 < \alpha \leq 1). \quad (2)$$

4.2.3 Electric logistics vehicles planning sales forecasting model

In order to estimate the appropriate value of government subsidies, we need to forecast the annual sales volume of electric vehicles in urban logistics based on the actual situation in China. The sales volume of electric vehicles in urban logistics theoretically undergoes a growth trend during a certain time period due to government promotion and environment regulation enforcement in the initial stage, and after that, with the withdrawal of government subsidy, the growth trend gradually slows down, and then the market reaches saturation. The dynamics of the adoption process can be explained by the Bass diffusion model (Bass, 1969), which is commonly used for market analysis and demand forecasting of new products. Therefore, we adopted the Bass diffusion model to estimate the market trend of electric vehicles in urban logistics. Its general form is as follows:

$$n(t) = \frac{dN(t)}{dt} = p[m - N(t)] + \frac{q}{m}N(t)[m - N(t)], \quad (3)$$

where m, p, and q are parameters. m represents the market potential of electric vehicles in urban logistics, p represents the innovation coefficient, q represents the imitation coefficient, n(t) represents the predicted annual sales in year t as Q_{et}, and N(t) is the market holdings same as $\sum_{t=1}^{n}Q_{et}$. Solving Eq. 3, we can obtain Q_{et} expressed as follows:

$$n(t) = \frac{M\frac{(p+q)^2}{p}e^{-(p+q)t}}{\left(1 + \frac{q}{p}e^{-(p+q)t}\right)^2}. \quad (4)$$

According to the disclosed data from China Association of Automobile Manufacturers (CAAM) as shown in Table 2, the sales volume of China's electric vehicles in urban logistics continued to rise from 2014 to 2018. However, affected by the "subsidy fraud" scandals in 2017, the actual sales in 2017 and 2018 should be less than those in the disclosed data because some manufacturers made fraudulent sales reports to seek more subsidies. Subsequently, the sharply shrinking subsidy from 2018 results in a sharp decline of the sales in 2019. When the subsidy standards stopped tightening in 2020, the sales rose again. These abnormal fluctuations in sales also reflected the problem brought by the current subsidy scheme, which is not conducive to the market development. If the government subsidy was rationalized as Eq. 2, the problem of excess initial subsidy with steep fall coming afterward would have been alleviated, and the same is true for the sales trend.

Using the Bass diffusion model, we forecast the sales volumes of the electric vehicles in urban logistics from 2022 and so on. We even the abnormal values in the existing data as mentioned previously and fit the equation model to match the trend as follows:

$$Q_{et} = \frac{73937500e^{-0.825t}}{(1 + 64e^{-0.825t})^2}. \quad (5)$$

The predicted sales volumes of the electric vehicles in urban logistics from 2022 to 2025 are obtained from Eq. 5, and the forecasted sales trend (with smooth curve) is shown in Figure 1, where the parameters are set by m = 3,500,000, p = 0.005, and q = 0.32. Equation 5 will be used for estimating the government subsidy and the net present values of the manufacturers and business users.

Theoretically, the value of the rationalized government subsidy can then be calculated by Eq. 2. With the market promotion and sales growth of the electric vehicles in urban logistics, it is predicted that the NPV of investment of the electric logistics vehicles will gradually be close to zero from negative, and up to this point of time, the government will no longer subsidize electric logistics vehicles.

4.3 Model analysis from the view of business users of electric vehicles in urban logistics

Similarly, from the perspective of business users, the investment valuation of electric vehicles in urban logistics is also estimated in terms of the incremental difference in revenue and cost, compared with conventional fuel vehicles. For the convenience of comparison and analysis, we assume that all electric vehicles in urban logistics produced by the manufacturers are sold in the market. Regarding transportation cost measurement, we assume that it is charged in terms of the maximum allowable load carried by vehicles. Influenced by battery power consumption and charging time, the mileage of electric vehicles in urban logistics is shorter than that of conventional fuel vehicles on average. In addition, business users also bear the fine *(in* T_o*)* brought by conventional fuel vehicles that have not yet been replaced.

When electric vehicles in urban logistics are put into operation and begin to partially replace the conventional fuel vehicles in the market, for year t, the business users will hold electric logistics vehicles *(in* $\sum_{t=1}^{n}Q_{et}$*)* accumulatively purchased up to t years, the business users' annual operating cash flow can be expressed as follows: $SG_eD_e\sum_{t=1}^{n}Q_{et} + SG_oD_o(\sum_{t=1}^{n}Q_t - \sum_{t=1}^{n}Q_{et}) - [P_{et}Q_{et} + P_o(Q_t - Q_{et})] - [A_e\sum_{t=1}^{n}Q_{et} + A_o(\sum_{t=1}^{n}Q_t - \sum_{t=1}^{n}Q_{et})] - T_o(\sum_{t=1}^{n}Q_t - \sum_{t=1}^{n}Q_{et})$, where $(\sum_{t=1}^{n}Q_t - \sum_{t=1}^{n}Q_{et})$ is the amount of conventional fuel vehicles that have not been replaced. By deducting the opportunity cost of only holding conventional fuel vehicles $SG_oD_o\sum_{t=1}^{n}Q_t - P_oQ_t - A_o\sum_{t=1}^{n}Q_t - T_o\sum_{t=1}^{n}Q_t$, the business users' annual cash flow can be simplified as $[S(G_eD_e - G_oD_o) - (A_e - A_o)]\ \sum_{t=1}^{n}Q_{et} - (P_{et} - P_o)Q_{et} + T_o\sum_{t=1}^{n}Q_{et}$. Then, from the view of logistics service providers as the business users, the net present value of investing in electric vehicles in urban logistics, denoted by NPV_u, can be expressed as follows:

$$NPV_u = \sum_{t=1}^{n}\frac{[S(G_eD_e - G_oD_o) - (A_e - A_o)]\sum_{t=1}^{n}Q_{et} - (P_{et} - P_o)Q_{et} + T_o\sum_{t=1}^{n}Q_{et}}{(1 + r_2)^t}. \quad (6)$$

4.4 Joint investment decision for electric vehicles in urban logistics

We refer to the sales price of manufacturers selling electric vehicles in urban logistics and the purchase price by business users

TABLE 2 Sale volume of logistics vehicles from 2014 to 2021 (unit: thousand vehicles).

	2014	2015	2016	2017	2018	2019	2020	2021
Conventional vehicle	1,798.4	1,322.1	1,970.5	2,401.9	2,561.3	2,536.6	2,906.2	2,715.0
Electric vehicles	1.75	21.2	34.5	87.7	126.2	34.4	56.9	131.2

collectively as the transaction price. As the suppliers and buyers of electric vehicles in urban logistics, both the manufacturers and the business users are facing the issue of jointly determining the optimal transaction price so that both of them can reach their break-even at relatively the same time, which is crucial to the sustainable development of electric vehicles in urban logistics market. Therefore, as the overall benefit of the integrated system including manufacturers and business users is optimum, both parties will come to collaboration only if the following holds:

$$NPV_m = -I + \sum_{t=1}^{n} \frac{(P_{et} - P_o)Q_{et} - (C_{et} - C_o)Q_{et} + (T_{et} + T_o)Q_{et}}{(1 + r_1)^t} \geq 0, \tag{7}$$

$$NPV_u = \sum_{t=1}^{n} [S(G_{et}D_{et} - G_oD_o) - (A_e - A_o)]\sum_{t=1}^{n} Q_{et} - \frac{(P_{et} - P_o)Q_{et} + T_o\sum_{t=1}^{n}Q_{et}}{(1 + r_2)^t} \geq 0. \tag{8}$$

These are the necessary prerequisites for a lasting collaborative relationship between the manufacturers and business users. The goal of the collaboration is to realize the unification of both individual interest and collective interest, and to finally achieve Pareto optimum. To satisfy Eqs 7, 8, the manufacturers and business users must negotiate a transaction price P_{et} that satisfies both parties. Since the determination of P_{et} goes through a negotiation process between the manufacturers and business users, we use the Rubinstein game approach (Rubinstein, 1982) to describe the bargaining process of negotiating P_{et}. First, we identify a feasible region that satisfies the interests of both parties. From Eqs 7, 8, we can obtain the lower and upper bounds of P_{et} denoted by $P_{e\text{-}min}$ (from $\triangle NPV_m \geq 0$) and $P_{e\text{-}max}$ (from $\triangle NPV_u \geq 0$), respectively, as follows:

$$P_{e-min} = \frac{I - \sum_{t=1}^{n} \frac{(T_{et}+T_o)Q_{et} - (C_{et}-C_o)Q_{et} - P_oQ_{et}}{(1+r_1)^t}}{\sum_{t=1}^{n} \frac{Q_{et}}{(1+r_1)^t}}, \tag{9}$$

$$P_{e-max} = \frac{\sum_{t=1}^{n} \frac{[S(G_eD_e - G_oD_o) - (A_{et}-A_{ot}) + T_o]\sum_{t=1}^{n} Q_{et} + P_oQ_{et}}{(1+r_2)^t}}{\sum_{t=1}^{n} \frac{Q_{et}}{(1+r_2)^t}}, \tag{10}$$

where $[P_{e\text{-}min}, P_{e\text{-}max}]$ is the feasible interval to find the optimal value of P_{et} within which the manufacturers and business users make a reasonable allocation of mutual benefits (profits). According to the Rubinstein's game theory, for both parties to coordinate, the individual portion of shared profits under coordination must be not less than that of a non-coordination scenario. Assuming an indefinite bargaining game between the manufacturers and business users in our case, let x^* $(0 \leq x^* \leq 1)$ be the profit share of the manufacturers and $1\text{-}x^*$ be the profit share of the business users. The unique sub-game perfect Nash equilibrium, namely, the optimal profit sharing ratio of the manufacturer, is expressed as $x^* = (1\text{-}\delta_2)/(1\text{-}\delta_1\delta_2)$ (if $\delta_1 = \delta_2$, then $x^* = 1/(1+\delta)$), where δ_1 and δ_2 are the discount factors of the manufacturers and business users, respectively (here, discount factor is the patience degree of participants for $0 \leq \delta \leq 1$, which can be seen as the cost of bargain). Considering that the determination of profit sharing depends on the transaction price that satisfies both the manufacturers and business users, the ratio of the profit allotment between the two parties can then be expressed in terms of the transaction price as follows:

$$\frac{x^*}{1 - x^*} = \frac{1 - \delta_2}{\delta_1 - \delta_1\delta_2} = \frac{P_{e-max} - P_e^*}{P_e^* - P_{e-min}}, \tag{11}$$

where P_e^* denotes the optimal value of the transaction price and $P_{e\text{-}max}$ and $P_{e\text{-}min}$ are shown in Eqs 9, 10. Rewriting Eq. 11 with the coordination of participants, the optimal transaction price is obtained as follows:

$$P_e^* = \frac{(\delta_2 - \delta_1\delta_2)P_{e-max} + (1 - \delta_2)P_{e-min}}{1 - \delta_1\delta_2} = (1 - x^*)P_{e-max} + x^*P_{e-min}. \tag{12}$$

As seen previously, the lower and upper bounds of P_{et} depend on the sales volume, initial investments of the manufacturers, production costs, government policies, incremental revenue, and operating cost of electric vehicles in urban logistics and also the price of fuel logistics vehicles. They have joint impacts on the determination of the optimal transaction price through the negotiation process. Given the production and sales volume and other parameters, the number of years for the manufacturers and business users to reach their break-evens can be obtained, which present their payback periods. The optimal coordinated transaction price is obtained when the game process comes to an equilibrium at which both parties reach their break-evens at relatively the same time.

4.5 Economic valuation of electric vehicles in urban logistics with carbon caps

In this section, in addition to the government subsidy offered to compensate for the cost disadvantages of electric vehicles, we further study the impact of introducing carbon trading on the economic valuation of the electric vehicles in urban logistics.

With the consideration of carbon emission and carbon cap, when introducing the electric logistics vehicles to gradually replace the conventional fuel vehicles, carbon credits for additional carbon emissions are involved. The carbon emissions at time period t $(t = 1,2, \ldots ,n)$ can be expressed as follows:

$$e^eQ_{et} + e^o(Q_t - Q_{et}) = q_t + Z \quad \text{for} \quad q_t \geq 0, \tag{13}$$

where $(Q_t - Q_{et})$ is the sales quantity of conventional fuel vehicles. Equation 13 states that the total carbon emissions in

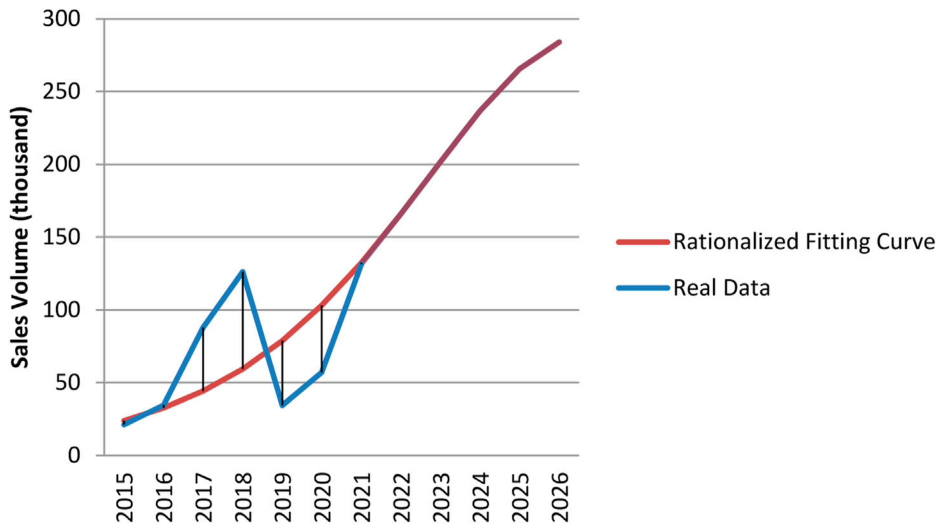

FIGURE 1
Sales trend of electric vehicles in urban logistics in the Chinese market.

TABLE 3 Data collection and estimation.

Initial investment of manufacturers (I) 12,000,000,000 RMB			
Item		Item	
Average revenue of logistics transportation	0.50 RMB/ton/km	Q_t	300,000
Annual mileage of urban logistics electric vehicles	36,000 km	T_o	5,000 RMB
Annual mileage of conventional fuel vehicles	45,000 km	H	100 RMB/ton
Average load of urban logistics electric vehicles	1.01 tons	Z	3,000,000 tons
Average load capacity of conventional fuel vehicles	1.26 tons	e^e	15.4 tons
Purchase tax of conventional fuel vehicles	7,000 RMB	e^o	39.7 tons
Usage cost of conventional fuel vehicles	40,600 RMB	r_1	8.68%
A_{et}	26,500 RMB	r_2	8.15%
P_o	93,500 RMB	δ_1	0.1
C_o	74,800 RMB	δ_2	0.6

Forecasted annual sales and variable costs of electric logistic vehicles											
Item	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Q_e (thousand vehicles)	23.94	32.60	44.13	59.25	78.69	103.01	132.32	165.90	201.77	236.52	265.54
C_e (thousand RMB)	166.15	149.54	134.58	121.13	109.01	98.11	93.21	88.55	84.12	79.91	75.92

Italic values are the same meaning as the Notations listed in Table 1.

year t is the sum of the emissions associated with producing both the electric logistics vehicles and the conventional fuel vehicles, which equals to the annual carbon cap plus the purchased carbon credits from an external source in year t. Carbon emission costs incurred from purchasing carbon credits (i.e., carbon emission rights) at time period t can then be expressed as follows:

$$H_t = h_t q_t = h_t [e^e Q_{et} + e^o (Q_t - Q_{et}) - Z]. \tag{14}$$

Equation 14 is derived from Eq. 13. As we assumed, the carbon cap can be either placed on the manufacturers or on the business users. Thus, we will discuss these two scenarios separately. If it is the manufacturer who participates in carbon trading, with the carbon credit purchase cost of Eq. 14 taken into consideration, we can obtain its NPV from Eq. 7 as follows:

TABLE 4 Results of the NPV break-even of electric vehicles in urban logistics with different subsidy scenarios (RMB).

		1	2	3	4	5	6	7	8	9	10	11
		2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Current subsidy scheme	Current subsidy (thousand)	108.00	108.00	79.00	47.00	21.00	21.00	18.90	15.12	—	—	—
	Market price (thousand)	122.50	122.50	122.50	122.50	122.50	122.50	122.50	122.50	122.50	122.50	122.50
	Manufacturers' NPV (million)	−10,884.51	−9,028.21	−7,198.96	−5,726.42	−4,647.62	−2,666.70	−118.05	2,897.16	5,251.52	8,223.66	11,718.64
	Business users' NPV (million)	−289.28	−470.78	−527.59	−436.56	−166.54	323.62	1,087.01	2,189.74	3,709.62	5,730.58	8,331.15
Under the rationalized subsidies												
α_1 = 15%	Rational subsidy (thousand)	88.90	44.11	28.70	20.64	15.53	11.90	9.35	7.46	—	—	—
	Coordinated price (thousand)	128.40	128.40	128.40	128.40	128.40	128.40	128.40	128.40	128.40	128.40	128.40
	Manufacturers' NPV (million)	−11,175.23	−10,919.48	−10,616.38	−10,012.63	−8,911.66	−7,130.83	−4,852.02	−1,986.93	930.25	4,509.43	8,631.50
	Business users' NPV (million)	−419.86	−765.79	−1,028.41	−1,192.89	−1,236.66	−1,126.31	−814.02	−234.26	697.49	2,080.99	4,019.84
α_2 = 23%	Rational subsidy (thousand)	136.31	67.63	44.01	31.65	23.81	18.25	14.33	—	—	—	—
	Coordinated price (thousand)	126.70	126.70	126.70	126.70	126.70	126.70	126.70	126.70	126.70	126.70	126.70
	Manufacturers' NPV (million)	−10,168.37	−9,310.36	−8,539.49	−7,540.39	−6,097.87	−4,026.57	−1,505.00	579.41	3,334.41	6,738.68	10,680.07
	Business users' NPV (million)	−382.24	−680.79	−884.11	−974.97	−928.32	−708.53	−266.27	464.18	1,565.39	3,132.57	5,262.08
α_3 = 30%	Rational subsidy (thousand)	177.80	88.21	57.40	41.28	31.05	23.80	—	—	—	—	—
	Coordinated price (thousand)	125.50	125.50	125.50	125.50	125.50	125.50	125.50	125.50	125.50	125.50	125.50
	Manufacturers' NPV (million)	−9,281.05	−7,888.11	−6,698.06	−5,340.83	−3,584.52	−1,241.10	132.73	2,114.85	4,755.39	8,036.19	11,850.03
	Business users' NPV (million)	−355.68	−620.79	−782.25	−821.14	−710.67	−413.63	120.39	957.20	2,178.03	3,874.86	6,138.96
Under the rationalized subsidies with the carbon cap set on manufacturers												
α_1 = 15%	Rational subsidy (thousand)	88.90	44.11	28.70	20.64	15.53	11.90	9.35	7.46	6.01	—	—
	Coordinated price (thousand)	129.90	129.90	129.90	129.90	129.90	129.90	129.90	129.90	129.90	129.90	129.90
	Manufacturers' NPV (million)	−11,908.50	−12,298.66	−12,554.57	−12,422.60	−11,705.34	−10,219.55	−8,147.90	−5,405.63	−1,961.92	1,634.02	5,817.15
	Business users' NPV (million)	−453.06	−840.80	−1,155.74	−1,385.18	−1,508.72	−1,494.93	−1,297.34	−850.53	−68.31	1,153.13	2,923.74
α_2 = 23%	Rational subsidy (thousand)	136.31	67.63	44.01	31.65	23.81	18.25	14.33	11.44	—	—	—
	Coordinated price (thousand)	128.70	128.70	128.70	128.70	128.70	128.70	128.70	128.70	128.70	128.70	128.70
	Manufacturers' NPV (million)	−10,890.64	−10,664.72	−10,435.69	−9,887.13	−8,802.36	−6,994.85	−4,643.50	−1,664.43	1,091.92	4,564.39	8,619.98
	Business users' NPV (million)	−426.50	−780.79	−1,053.88	−1,231.35	−1,291.07	−1,200.03	−910.69	−357.51	544.33	1,895.42	3,800.62

(Continued on following page)

TABLE 4 (*Continued*) Results of the NPV break-even of electric vehicles in urban logistics with different subsidy scenarios (RMB).

		1	2	3	4	5	6	7	8	9	10	11
		2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
α_3 = 30%	Rational subsidy (thousand)	177.80	88.21	57.40	41.28	31.05	23.80	18.70	—	—	—	—
	Coordinated price (thousand)	127.50	127.50	127.50	127.50	127.50	127.50	127.50	127.50	127.50	127.50	127.50
	Manufacturers' NPV (million)	−10,025.34	−9,292.10	−8,678.26	−7,814.03	−6,467.38	−4,450.26	−1,939.13	1,149.12	3,695.60	6,941.72	10,763.48
	Business users' NPV (million)	−399.94	−720.79	−952.02	−1,077.52	−1,073.42	−905.13	−524.03	135.50	1,156.97	2,637.71	4,677.50
Under the rationalized subsidies with the carbon cap set on business users												
α_1 = 15%	Rational subsidy (thousand)	88.90	44.11	28.70	20.64	15.53	11.90	9.35	7.46	6.01	—	—
	Coordinated price (thousand)	122.50	122.50	122.50	122.50	122.50	122.50	122.50	122.50	122.50	122.50	122.50
	Manufacturers' NPV (million)	−11,305.17	−11,212.26	−11,111.96	−10,758.78	−9,964.02	−8,552.01	−6,709.14	−4,346.96	−1,419.70	1,552.44	5,047.42
	Business users' NPV (million)	−1,059.35	−1,934.90	−2,611.31	−3,066.34	−3,269.29	−3,179.52	−2,745.19	−1,903.13	−581.22	1,295.27	3,792.05
α_2 = 23%	Rational subsidy (thousand)	136.31	67.63	44.01	31.65	23.81	18.25	14.33	11.44	—	—	—
	Coordinated price (thousand)	119.90	119.90	119.90	119.90	119.90	119.90	119.90	119.90	119.90	119.90	119.90
	Manufacturers' NPV (million)	−10,318.15	−9,647.80	−9,110.67	−8,400.37	−7,310.76	−5,664.55	−3,645.41	−1,165.77	940.58	3,645.21	6,863.85
	Business users' NPV (million)	−1,001.81	−1,804.89	−2,390.61	−2,733.04	−2,797.71	−2,540.57	−1,907.44	−834.93	746.16	2,903.56	5,691.95
α_3 = 30%	Rational subsidy (thousand)	177.80	88.21	57.40	41.28	31.05	23.80	18.70	—	—	—	—
	Coordinated price (thousand)	117.30	117.30	117.30	117.30	117.30	117.30	117.30	117.30	117.30	117.30	117.30
	Manufacturers' NPV (million)	−9,461.65	−8,295.02	−7,386.85	−6,377.85	−5,047.12	−3,216.30	−1,066.95	216.22	2,074.54	4,511.66	7,453.95
	Business users' NPV (million)	−944.26	−1,674.89	−2,169.91	−2,399.74	−2,326.14	−1,901.62	−1,069.70	233.28	2,073.53	4,511.85	7,591.85

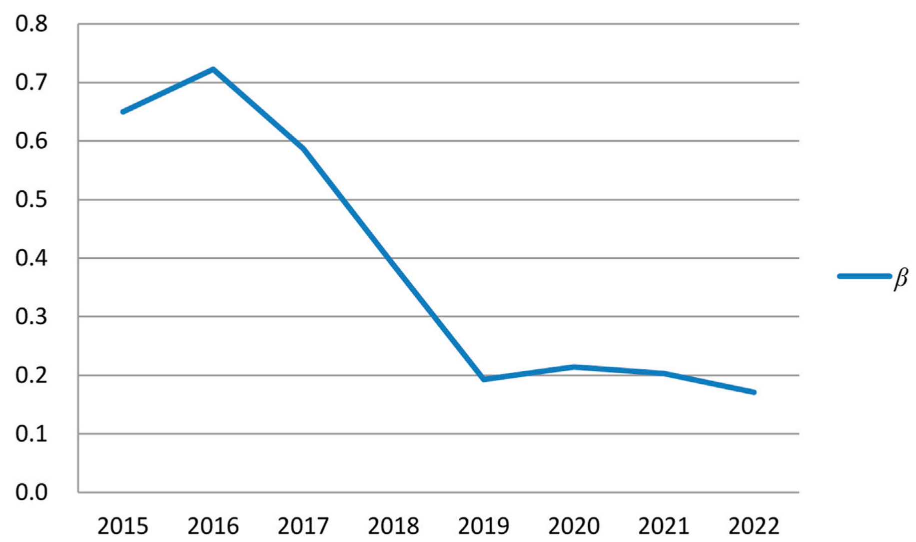

FIGURE 2
Trend of subsidy coefficient under the current subsidy scheme.

TABLE 5 Amount of government subsidies under different modes (thousand RMB).

Subsidy mode	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Total
Current subsidy program	108.00	108.00	79.00	47.00	21.00	21.00	18.90	15.12 (break-even)	0.00	0.00	0.00	418.00
Rationalized subsidy α1 = 15%	88.90	44.11	28.70	20.64	15.53	11.90	9.35	7.46	Break-even	0.00	0.00	226.00
Rationalized subsidy α2 = 23%	136.31	67.63	44.01	31.65	23.81	18.25	14.33	Break-even	0.00	0.00	0.00	336.00
Rationalized subsidy α3 = 30%	177.80	88.21	57.40	41.28	31.05	23.80	Break-even	0.00	0.00	0.00	0.00	419.60

TABLE 6 Payback year and transaction price under different scenarios (thousand RMB).

Subsidy mode	No carbon trading		Carbon trading for manufacturers		Carbon trading for business users	
	Payback year	Transaction price	Payback year	Transaction price	Payback year	Transaction price
Rationalized subsidy α1 = 15%	9	128.40	10	129.90	10	122.50
Rationalized subsidy α2 = 20%	8	126.70	9	128.70	9	119.90
Rationalized subsidy α3 = 25%	7	125.50	8	127.50	8	117.30

$$NPV'_m = -I + \sum_{t=1}^{n} \frac{(P_e - P_o)Q_{et} - (C_{et} - C_o)Q_{et} + (T_{et} + T_o)Q_{et} - H_t}{(1 + r_1)^t} \geq 0. \tag{15}$$

If it is the business user who participates in carbon trading, with the carbon credit purchase cost of Eq. 14 taken into consideration, we can obtain its NPV from Eq. 8 as follows:

$$NPV'_u = \sum_{t=1}^{n} \frac{[S(G_e D_e - G_o D_o) - (A_{et} - A_{ot})]\sum_{t=1}^{n} Q_{et} - (P_{et} - P_o)Q_{et} + T_o \sum_{t=1}^{n} Q_{et} - H_t}{(1 + r_2)^t} \geq 0, \tag{16}$$

where the impact of the cost of purchasing carbon credits is similar to the penalty cost imposed on carbon emissions. This is true in reality because if the carbon caps were not set low enough, then firms would not actively reduce carbon emissions.

In a way similar to Section 4.4, the optimal transaction price between the manufacturer and business user can be determined through negotiation using the Rubinstein game approach. For the case of the manufacturers to participate in carbon trading, we use Eq. 15 to develop the lower bound of the transaction price as follows:

$$P_{e-min} = \frac{I - \sum_{t=1}^{n} \frac{(T_{et}+T_o)Q_{et}-(C_{et}-C_o)Q_{et}-H_t-P_oQ_{et}}{(1+r_1)^t}}{\sum_{t=1}^{n} \frac{Q_{et}}{(1+r_1)^t}}. \tag{17}$$

Together with the upper bound of the transaction price as shown in Eq. 10, we can determine the optimal transaction price with the carbon cap set on manufacturers. On the other hand, for the case of business users to participate in carbon trading, we use Eq. 16 to develop the upper bound of the transaction price as follows:

$$P_{e-max} = \frac{\sum_{t=1}^{n} \frac{[S(G_eD_e-G_oD_o)-(A_{et}-A_{ot})+T_o]\sum_{t=1}^{n}Q_{et}-H_t+P_oQ_{et}}{(1+r_2)^t}}{\sum_{t=1}^{n} \frac{Q_{et}}{(1+r_2)^t}}. \tag{18}$$

Together with the lower bound of the transaction price as shown in Eq. 9, we can determine the optimal transaction price with the carbon cap set on business users.

5 Numerical illustration

In this section, we conduct a case analysis based on the real data of China's urban logistics vehicle market to demonstrate the economic valuation of electric vehicles in urban logistics and provide insight into government policies' effectiveness. We compare the incremental cost difference between electric vehicles in urban logistics and conventional fuel vehicles, and NPV models are used to estimate the break-even time periods of the manufacturers and business users under the current market price and government subsidy mode. Then, the theoretically rationalized government subsidy coefficient and pricing formula are used to optimize the government subsidy and transaction price, and the break-even time periods are recalculated for comparison. In the similar way, the carbon trading scenario is discussed to gain insight into the effectiveness of government policies.

5.1 Data collection

Electric vehicles in urban logistics include minivan and light truck, mainly used in the fields of intra-city express and fresh food logistics. The data are estimated on average based on real market situation shown in Table 3. With the development and market penetration of the electric logistics vehicles, its variable production cost gradually reduces as the battery cost decreases with technological improvement.

5.2 Impact of current implemented government subsidy

Table 4 shows that under the current subsidy scheme and pricing, the NPVs of the electric vehicles in urban logistics for the manufacturers and business users will become positive in 2024 and 2020, respectively, i.e., the former will achieve its break-even in 10 years and the latter in 6 years. This incurs unbalanced payback periods between the two parties and will result in unwillingness from the manufacturers, implying that the current subsidy scheme may be inappropriate in a certain sense.

Under the current implemented government subsidy mode with $T'_{et} = \beta C_{et}$ $(0 < \beta \le 1)$, i.e., the government subsidy is proportional to the production cost of electric vehicles. Using the unit variable cost and current actual government subsidy for the electric logistics vehicles, the value of the coefficient β can be calculated to show its trend in Figure 2. The current government subsidy seems illogical since it incurs unbalance in the market due to its being directly proportional to the production cost of the electric vehicle, which cannot be compatible with the reality and does not properly consider the market competition with fuel vehicles. The initial growth trend of β indicated that the battery costs fell faster than subsidies and also meant that the subsidies were excess than needed. The delayed reaction of the government resulted in the sharp drop from 2017 to 2019. Due to the market competition, it would be unlikely for the manufacturers to make adjustment of the sales price for the subsidy decline. The loss caused by the subsidy decline basically should be covered by production cost reduction or sales increase, which needs longer time periods. Hence, this may not be acceptable by the manufacturers who have to take much longer to achieve their break-even. Noticing that it is the manufacturers that make the initial investment of producing the electric logistics vehicles by undertaking heavy upfront cost relative to the business users, this implies that the manufacturers originally take longer time to reach its break-even than the business users, which is evidenced in reality.

5.3 Rationalizing government subsidy and transaction price

From the aforementioned analysis, we can see that the current implemented government subsidy scheme needs to be rationalized to follow the market mechanism. Therefore, Eq. 2 is used to rationalize the government subsidy on the incremental cost basis, and Eq. 12 is used to coordinate the transaction price for both parties so as to ensure that both parties can reach their break-evens at relatively the same time and achieve sustainable development when the subsidy ceases. Based on the incremental cost, the value of the subsidy coefficient α is set to be less than 1 with three levels of 15%, 23%, and 30% for sensitivity analysis. The rationalized government subsidy, coordinated transaction price, and payback time periods for both parties are calculated with the collected data.

The comparison in Table 5 shows that for the rationalized scheme with α levels of 23%, the accumulated subsidies during the time periods toward the break-even are 336,000 RMB, which is rather less than that under the current implemented subsidy scheme of 418,000 RMB. Their payback periods are relatively the same, which means the manufacturer is overcompensated under the current subsidy scheme.

Under the rationalized government subsidy, Table 4 shows that both the manufacturers and business users reach their break-even at the same time in 9, 8, and 7 years at the subsidy coefficient level of 15%, 23%, improve routing for urban logistics distribution using and 30%, respectively. The investment break-even time periods are shortened with the increase of the government subsidy, which leaves the room for negotiation between business organizations and governments regarding how long is acceptable for the manufacturers and business users to break-even while facing the risks they undertake. Under the rationalized subsidy scheme with α levels of 23%, the coordinated transaction prices of the electric vehicles are 126,700 RMB, higher than 122,500 RMB under the current subsidy scheme. This implies that the reduced government subsidies compensate manufacturers by the increased transaction prices. In contrast, the higher purchase price paid by the business users prolongs their payback periods. It explains that under the rationalized scenario, the incomes associated with electric logistics vehicles are rebalanced between the manufacturers and business users.

5.4 Rationalizing government subsidy combined with the carbon cap

The impact of environmental standards on decision performance can be analyzed by observing the number of years to reach break-even changes as the carbon cap is introduced. With the carbon cap enforced on either the manufacturers or on the business users, it is expected that their payback time periods will be prolonged due to the imposed cost impact of paying for carbon credits, as shown by the case example in Table 4 that their payback time periods are extended for one more year . The total carbon emissions were 11.3 million tons in 2015 and will be 5.5 million tons in 2025, which is cut in half in 10 years for the given estimated data. We could see the positive effect brought by the marketization of electric logistic vehicles under the carbon trading context.

The government subsidy is not affected by the enforcement of the carbon cap as assumed in Eq. 2. Compared to the previous scenario not considering carbon trading, as shown in Table 6, the coordinated transaction price is higher when the carbon cap is enforced on the manufacturers due to the carbon emission costs undertaken by the manufacturers. In contrast, the coordinated transaction price is lower when the carbon cap is enforced on the business users. These can be explained by Eqs 17, 18 where the impacts of the carbon costs paid due to excess emission over the carbon cap for the manufacturers and business users are opposite to the transaction price.

6 Discussion

In our case study, the payoff of participants engaged in the production and use of electric vehicles in urban logistics to replace conventional fuel vehicles is quantitatively analyzed. Government incentives tend to last only for limited time periods and be withdrawn when the participating firms reach their break-even. Since its purpose is to let the marketization on the "right" track, investigation of how incentive policies work would help policymakers make the right decisions.

Under the current implemented subsidy and pricing model in China, the manufacturers undertaking heavy upfront investment in electric vehicles in urban logistics will take a longer time to achieve its break-even than the business users, which implies that the business users bear less risk than the manufacturers. Therefore, the manufacturers are compensated by the government subsidy when it sells an electric logistics vehicle, so they would share the subsidy with the business users by coordinating the transaction price through negotiation.

When the government subsidies are significantly reduced, the manufacturers may not be able to break-even in an acceptable time period, if the sale price of electric vehicles is unchanged. This may result in economic infeasibility to the supply side and may not be conducive to the sustainable development of the market. Thus, there is a need to negotiate the transaction price between the manufacturers and the business users to help rid the imbalance incurred by the steep drop or sharp withdrawal of the government subsidies. Also, the government subsidy scheme should also be rationalized based on economic logic compatible with the market mechanism.

Our research findings show the importance of coordination of the transaction price combining with the rationalized government subsidy scheme. When considering government policy incentives in an integrated supplier–buyer system (different from the traditional models in extant literature), the coordinated transaction price plays a core role and is interrelated with the rationalized government subsidies through the negotiation process. Compared with the current subsidy scheme, under the rationalized subsidy scheme based on the incremental cost and with the consideration of upfront investment by the manufacturers, the reduced government subsidies are given to the manufacturers by increasing the coordinated transaction price; this higher transaction price is paid by the business users, prolongs their payback periods, and thus rebalances the business performances of both parties. In this way, the unbalanced income distribution of electric logistics vehicles is redistributed between the manufacturers and business users through the rationalized government subsidy scheme together with the optimal coordinated transaction price. This explicitly proves that the effect of the rationalized government subsidies on the incremental cost basis helps rebalance the profits between the manufacturers and business users *via* the coordinated transaction price, and the transaction price negotiation is crucial in sustaining their business collaboration.

For a business firm in pursuit of maximizing economic benefits, its commitment to reducing carbon emissions and complying with environment standards depends on the trade-off that involves the supplier and the user. In terms of achieving sustainable economic and environmental development, business firms in a supplier–buyer system should jointly fulfill their social responsibilities of protecting the environment. In the case of commercializing electric vehicles in urban logistics, the environmental responsibilities undertaken by business organizations are embodied in the transaction price coordination between the manufacturers and business users. As more electric vehicles are produced, more carbon reductions are achieved and less carbon credit costs are paid. In practice, to make the carbon trading scheme work, the threshold of carbon emission should be low enough and the purchase price of carbon credits should be relatively uneconomic. In this way, business firms that purchase a large amount of carbon credits will face greater economic pressure, which in turn will stimulate business firms to innovate and further reduce carbon emissions. The results of this study support the findings of past studies such as those by Bi et al. (2020), Duarte et al. (2016), Li et al. (2020), and Gao et al. (2022).

7 Conclusion

In this study, we aim to investigate the marketization mechanism of electric vehicles in urban logistics with the consideration of its economic and environmental performances. From the perspectives of both the manufacturers and business users, we carry out economic evaluation through investment break-even analysis by using the net present value approach and illustrate the role of government policies (regulation, incentives, and carbon trading) in bringing the urban logistic industry to be low carbon and environment-friendly.

Our research contributions lie in the following aspects: 1) Different from the existing literature, from the viewpoints of both manufacturers and business users, we evaluate the economic feasibility of electric vehicles in urban logistics, which considers the profit-driven feature of the business user as a buyer, and thus varies from the case of electric passenger vehicles. As a notable feature of our study, by focusing on the electric logistics vehicles' development, the distinction between buyers as business users and as passengers is identified, and this reflects that their motives and behaviors have different impacts on business transaction. 2) We address the pricing mechanism of electric vehicles in urban logistics that coordinates the transaction price between the manufacturers and the business users with government policies taken into consideration. The model proposed in this paper provides a framework for optimizing the government subsidy scheme and the transaction price of electric vehicles in urban logistics with enforcement of carbon trading system, and thus the manufacturers and the business users achieve their break-even in limited time periods and collaboratively reduce carbon emissions *via* investment in electric logistics vehicles production and operation. 3) By looking into the reality in China, we discuss the potential for improving policy making by analyzing the theoretical logic together with the real case, and investigating the inter-relations among market price, government policies, and production cost reduction with technology innovation, which is conducive to the policymaker making the right decision to be compatible with the market mechanism.

From the main findings, we can draw the following conclusions. 1) In order to realize the sustainable development of electric vehicles in the urban logistics market, it is important that government policies can effectively stimulate the benefit distribution of manufacturers and logistics service providers to achieve a win–win situation. 2) The government subsidy scheme should be rationalized based on economic logic compatible with the market development mechanism. 3) The impacts of the carbon emission costs paid over the carbon cap for the manufacturers and business users are opposite to the transaction price. It is relatively more conducive to the marketization process to introduce a carbon trading system to the business users rather than the manufacturers with green investment burden already. 4) Decline in government subsidies will have two-sided effects on the manufacturer, i.e., negative impact on its capital flow and possibly positive impact on driving its production cost reduction with technology innovation. 5) The manufacturers and the logistics service providers should not only actively participate in the production and usage of electric vehicles but also make compliance with environmental standards a high priority and a mandatory task and draw attention in improving their environmental performance by reducing pollutants and carbon emissions. Government regulation could have an incentive mechanism to encourage business firms to take their environmental responsibilities. This study has some limitations, for example, future studies could consider battery replacement and scrap issues from the perspective of an electric vehicle's life cycle. Furthermore, it is also worthwhile to investigate the multi-player collaborative decision problem that includes upstream suppliers of batteries. The future studies may compare the electric vehicle for urban and rural logistics.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material. Further inquiries can be directed to the corresponding author.

Author contributions

ZY, HD, and LC contributed to the conception and design of the study. ZY and LC collected the data. ZY, HD, and LC performed the case analysis. ZY wrote the first draft of the manuscript. All authors contributed to the manuscript revision, read, and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The spillover effects of uncertainty and globalization on environmental quality in India: Evidence from combined cointegration test and augmented ARDL model

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Environmental quality and climate change have become hot topics among academics in all scientific fields in recent decades due to their impact on human health and economic development. Hence, this paper investigates the key factors of carbon dioxide emissions in India from 1970–2020 through the Bayer-Hanck test and Augmented ARDL framework on an augmented STIRPAT model, introducing uncertainty and globalization. We employ a set of unit-root tests and a combination of cointegration techniques (DOLS and FMOLS), which permit us to estimate the long-run and short-run relationships. Empirical findings confirmed that the series is I(1) series and there is the existence of a long-run relationship between our variables using three cointegration tests, meaning that the variables have the same behavior in the long run term. The findings revealed that India has an inverse U shape of the Environmental Kuznets curve (EKC) due to the positive association between GDP *per capita* and CO_2 emissions until reaching a threshold, after which the link becomes inverse due to the negative impact of GDP square on CO_2 emissions. Furthermore, the findings demonstrated a positive influence of uncertainty and a negative impact of globalization on long-term environmental degradation. Besides, energy consumption and population density are positively associated with CO_2 emissions in the long and short run. We advocate for policies that promote more trade openness by entering new markets and cooperating with new trading partners.

KEYWORDS

CO_2 emissions, economic Uncertainty, globalization, environmental quality, STIRPAT model

1 Introduction

All the members of the United Nations, including India, have adopted the 2030 agenda for sustainable development, which focuses on mutual understanding among the nations to carry out future objectives where human lives are improved alongside protecting the environment. Out of the seventeen sustainable development goals, such as eliminating poverty, erasing hunger, reducing inequality, Grow Affordable and Clean Energy, and improving Clean Water and Sanitation, the thirteenth goal focused on acting against climate change and combating its effects on the environment. India has a dual role to play in global climate politics. Besides being a developing country with low levels of *per capita* emissions (Parikh et al., 2009), India is also an emerging economy with rising emissions (Dubash, 2013), and its greenhouse gas and carbon dioxide emission contribute to global warming. The impact of climate change on agriculture and human health is severe and varies significantly across various regions of the country (Dash and Hunt, 2007). In addition, Tripathi et al. (2016) reveal the deepening negative effect of global warming on agricultural production poses a serious threat to food security.

The largest source of greenhouse emissions in India is the electricity and heat sector, followed by the agriculture, manufacturing, and construction sector. About 3.21% of global cumulative carbon dioxide is emitted by India (Ritchie and Roser, 2020). Besides, the government has framed various policies to improve environmental quality, worsening daily. Hence, there is not much achievement in this regard because there is a massive gap between the aim of the policies implemented and the current measures taken (Reich and Bowonder, 1992). Moreover, in recent years, India has been very open to the outside world, with a large increase in foreign trade and significant foreign direct investment inflows, which shows the Government's approach to globalization in all its aspects. Two adverse effects have characterized the literature on the relationship between globalization and the environment. First, globalization contributes to economic growth by increasing countries' foreign trade and investment flows. In an attempt to satisfy foreign direct investment (FDI), governments, especially in developing countries, may overlook the environment by overlooking non-environment-friendly means of production, which causes environmental degradation in the long run. Secondly, globalization has excellent benefits in distributing clean means of production and new technologies that would improve the environment. In other words, globalization is considered an ideal solution for spreading environmentally friendly technologies in developing countries, which still use traditional production methods that harm the environment. This automatically means improved environmental conditions in the long run for developing countries.

Furthermore, many researchers have attempted to identify the factors that upsurge environmental degradation. Mohapatra and Giri (2009) investigated the link between economic development and CO_2 emissions using the EKC (Environmental Kuznets Curve) hypothesis. Shahbaz et al. (2015) used annual data from 1970 to 2012 to test the link between globalization and carbon dioxide emissions in India. They discovered that a rapid increase in globalization and energy consumption has significantly escalated carbon dioxide emissions. According to the study, economic growth is inversely related to carbon dioxide emissions. Villanthenkodath and Mahalik (2020) used annual data covering 1980 to 2018 to study the association between technological innovations and environmental quality in India. Tourism development and structural change also have a pivotal role in environmental degradation; thus, Villanthenkodath et al. (2021) discovered that tourism degrades environmental quality in their study. According to current literature, the demand for environmental quality is low in countries such as India due to poverty, so less attention is paid to this issue (Jalan et al., 2009).

It is clear that in recent years, particularly following the 2008 financial crisis, the issue of economic uncertainty has become a sensitivetopic in any economic study, as many studies have emerged attempting to understand the impact of this uncertainty on various economic indicators. Moreover, as is well known, anything that affects the economy automatically impacts the climate and the environment. This has resulted in some recent studies attempting to investigate the impact of economic uncertainty on climate change (Ayad et al., 2023; Wang K. H. et al., 2020; Liu and Zhang, 2022 and Syed and Bouri, 2021). Economic policy uncertainty (EPU) is defined by Gulen and Ion (2016) as the inability of economic agents to predict the possible economic consequences, timing, and content of policy decisions. This situation causes these agents to take precautionary and preventive procedures to avoid future shocks related to any doubt or suspicion in economic activities. As a result of the previous crises that the global economy has faced (the Gulf war of 2003, the financial crisis of 2008, and the COVID-19 crisis, for example), economic uncertainty has become a key factor in determining production and even government decisions. Furthermore, the EPU can influence CO_2 emissions.

Conversely, economic policy uncertainty (EPU) can affect CO_2 in contradictory ways. On the one hand, economic uncertainty can inhibit investment and production, which reduces energy consumption and thus automatically reduces carbon emissions. On the other hand, EPU can stop 'companies' interest in alternative energies and energy transition, which are considered. According to them, high costs can be avoided usingtraditional and cheap energy sources of production using petroleum products, which increases carbon emissions. Despite the great importance of economic uncertainty, we find a relative scarcity of studies that deal with its impact on climate change, especially in major polluting countries such as India. India was included among other countries in a few studies, but no study estimated the impact of EPU on environmental quality in India.

As a result, we intend to contribute to the current literature on climate change by exploring the effect of economic uncertainty [as measured by the Ahir et al. (2022) index] and globalization [as measured by the Dreher (2006) index] on environmental quality measured by CO_2 emissions in the context of India over the last half-century, from 1970 to 2020. Notably, this is the first attempt to study the effect of uncertainty and globalization in one model on CO_2 emissions in one of the world's largest carbon emitter countries, using an augmented STIRPAT model. Latterly, India has experienced massive ups and downs in its economy due to the succession of Governments and their relentless pursuit of economic and social revival, especially in light of the country's high poverty rates. For this reason, the study attempts to gauge the impact of these trends by improving citizens' living conditions and increasing the country's welfare on environmental conditions. Consequently, developing countries like India have a vast and devastating impact on the environment in their early stages. Furthermore, the most important thing that has characterized India in these years is the rapidly growing economic growth, the exploding population, the enormous energy consumption, the great opening up to the outside, and the growing uncertainty in all aspects of economic life. Hence, this gives an essential edge to this study by looking at some of the most significant environmental impacts in India in recent years.

In addition, unlike previous research, this study employs the combined cointegration test proposed by Bayer and Hanck (2013) and the augmented ARDL (Auto-Regressive Distributed Lag) model proposed by McNown et al. (2018).

The rest of the paper is structured in six sections. Section 2 presents the literature review. Section 3 and Section 4 describe the data and methodology of the study. Study results are presented in Section 5, while section 6 highlights the conclusions and recommendations.

2 Literature review

Environmental degradation and climate change have become humanity's most pressing concerns in the last 20 years (UN Chronicle, 2007; Chan, 2018). According to numerous studies, our planet has experienced a considerable rise in global temperatures in recent years, which has become an enormous threat to all world countries regarding environmental, economic, social, and even security concerns. Besides, the economy is widely regarded as the primary and most significant contributor to environmental deterioration (Khan MB. et al., 2022a; Ullah I. et al., 2022a; Irfan et al., 2023; Zhang et al., 2023), as seen by natural resource depletion (Liang et al., 2022) on the one hand and rising energy use in industrial and agricultural activities on the other. As a result, economic studies to discover the most important causes of the continual deterioration of the environment have exploded in recent years.

Many studies examined how economic expansion affects carbon emissions. Mahmood et al. (2019) argue that economic growth may reduce environmental damage after a certain point, confirming an inverted U-shaped connection. In contrast, previous research discovered that economic growth and environmental damage are connected, and that industrial structure adjustments may mitigate climate issues (Wang et al., 2016). The energy-economic growth-pollution trilateral relationship is well known, as economic growth is based on energy consumption, while pollution is generated mainly by fossil fuels-generated energy (Al-Mulali et al., 2013; Wang et al., 2016). At the same time, the transition to renewable energy sources for fueling economic growth is widely recognized as one of the main solutions for ensuring both economic expansion and mitigation of climate change (Yuan et al., 2014; Wang et al., 2020; Abban et al., 2022; Ali et al., 2022; Khan I. etal., 2022b; Han et al., 2022). Meanwhile, investment openness is responsible for a surplus of carbon emissions associated with pollution-intensive industries, especially if the FDI destination is a developing or emerging country. Blanco et al. (2013) confirmed that after a certain threshold, the spillover effect will reduce environmental degradation (Xie et al., 2020). However, Haug and Ucal (2019) find evidence suggesting that FDI does not influence carbon emissions, while financial development and urbanization do. Previous research also supports the findings indicating financial development as a driver for carbon emissions (Zhang, 2011), even if indicates FDI as least threatening to the environment. On the other hand, Shahbaz et al. (2013) examine the impact of financial development on carbon emissions and find that the relationship benefits the environment, as the financial system may support green investments and energy-efficient technologies. Later, Boutabba (2014) also proves that financial development improves environmental degradation. Besides urbanization, population growth was considered as a feature influencing climate change. In this regard, Martínez-Zarzoso et al., 2007 argue that the increasing population attracts a higher environmental impact, yet it is not certain that a population reduction will reduce pollution. Other scholars emphasize the importance of population aging for carbon emissions, claiming that there is a positive relationship between the two features (Yu et al., 2018; Wang and Wang, 2021).

It is worth emphasizing that following the financial crisis of 2008, the world's economic activity entered a state of doubt and uncertainty. Similar to the Russian-Ukrainian war in early 2022, which produced great fear from all countries of the world, perhaps the rise in oil prices to 138 dollars per barrel is the best evidence of the impact of uncertainty on the global economy. As a result, researchers' interest in economic uncertainty has grown in recent years, particularly following Baker et al. (2016)'s study, which developed a statistical indicator to measure economic uncertainty created using the rate of recurrence of the word uncertainty in international newspapers as evidence of the rise or fall of uncertainty.

Despite the scarcity of research on the subject, the effect of (EPU) on CO_2 emissions has gained prominence in the last five years, leading to the conclusion that uncertainty plays a prominent role in institutional behavior toward environmental change. On the one hand, EPU may contribute to environmental degradation by increasing CO_2 emissions. However, many firms use cheap production methods that rely primarily on unclean energies to prevent any shocks that increase the cost of production in the long run (Jiang et al., 2019; Ulucak and Khan, 2020; Adams et al., 2020; Wang Q. et al., 2020; Amin and Dogan 2021; Anser et al., 2021; Atsu and Adams 2021; Syed and Bouri, 2021), while other studies considered the short run (Ashena and Shahpari, 2022).

Other studies, on the other hand, have found that the EPU may reduce CO_2 emissions while increasing environmental quality. In this case, high uncertainties may force institutions and companies to resort to clean energies to avoid any shortage in their supplies of fuels and petroleum products from global markets (Adeboyin and Zakari, 2020; Ahmed et al., 2021; Syed and Bouri, 2021; Liu and Zhang, 2022).

Even though India is one of the world's top ten carbon emitters, studies on the impact of economic uncertainty on CO_2 emissions in the country still need to be considered. This could be because the EPU index was not developed in India until the World uncertainty index indicator was proposed by Ahir et al. (2022). However, some studies on the subject, however, have focused on panel samples that included India. Anser et al. (2021), for example, evaluated the effect of WUI on CO_2 emissions in the top ten carbon emitter countries using pooled mean group ARDL (PMG-ARDL) modeling, depending on the STIRPAT model. The most notable finding of the researchers is the distinction between the short and long-term effects of WUI on CO_2 emissions, as economic uncertainty reduces carbon emissions in the short run, allowing for climate improvement. However, in the long run, the influence positively affects CO_2 emissions (Udeagha, M. C. and Muchapondwa, 2022), where economic uncertainty is regarded as a cause of environmental degradation in the study sample. Syed et al. (2022) studied the impact of EPU and geopolitical risks (GPR) on CO_2 emissions in BRICST countries from 1990 to 2015. The findings showed that EPU has a negative impact on CO_2 emissions at the lower and middle quantiles but a positive impact at the upper quantiles. Adams et al. (2020) investigated the causal link between EPU, CO_2 emissions, and energy consumption in ten resource-rich countries from 1996 to 2017. According to the findings, EPU has a long-term positive impact on CO_2 emissions, and a bidirectional causal relationship between EPU and CO_2 emissions was also pointed out.

Furthermore, Atsu and Adams (2021) explored the cointegration relationship between EPU, CO_2 emissions, energy consumption, financial development, innovations, and institutional quality in BRICS countries from 1984 to 2017. They used a cross-sectionally augmented ARDL model with panel data. According to the findings, EPU contributed to CO_2 emissions during the study period.

In recent years, globalization has become a significant aspect of the global economy since the world has become a small village because of the easy movement of capital, commodities, and individuals between the world's five continents. Hence, It should be unsurprising that globalization has a huge impact on the climate and the ecosystem (Aslam et al., 2021; Jahanger et al., 2022; Usman et al., 2022). Therefore, according to McAusland (2010), globalization hasthree probable consequences on CO_2 emissions. First, the scale effect states that globalization increases economic activities and subsequently surges energy consumption escalating CO_2 emissions. Second, the composition effect reveals that the impact of globalization on CO_2 emissions is linked to how globalization affects production structure. If globalization transforms the production structure from industrial to service sectors, CO_2 emissions fall; conversely, if globalization shifts the production structure from agricultural to industrial, CO_2 emissions rise. Third, in the technique effect scenario, globalization can affect production processes by introducing new technologies from international partners; these technologies could enhance energy efficiency by employing environmentally friendly procedures, leading to lower CO_2 emissions. In addition, Shahbaz et al. (2018) introduced a fourth effect known as the comparative advantage effect, which states that dirty industrial technologies can be transferred to developing and emerging countries in exchange for being rejected in their home countries; these countries' carbon emissions have soared.

Remarkably, there is a severe lack of research on the impact of globalization on CO_2 emissions in India, with only two studies found. Shahbaz et al. (2015) considered the relationship between globalization, as measured by the Dreher index (2006), energy consumption, CO_2 emissions, financial development, and GDP growth from 1970 to 2012. Unlike social and political globalization, the findings showed that economic globalization had a negative long-term impact on CO_2 emissions. In contrast to Shahbaz's (2015) findings, Sahu and Kumar (2020) used the ARDL model and the Dreher index (2006) to explore the effect of globalization on environmental quality from 1971 to 2014. According to this study, the results revealed that political and social globalization negatively influences CO_2 emissions. Also, Ullah S. et al., (2022b), studying two group's lower globalized economies (LGE) and highly globalized economies (HGE) found similar positive impact on CO_2 emmisions; however, economic globalization has a positive effect. In addition, Sharif et al. (2022) found that social globalization positively moderates the relationship between CO_2 emissions and economic output.

However, we only found a few additional articles in panel studies that looked at the impact of globalization on carbon emissions, including one from India. From 1972 to 2017, Khan Y. et al. (2022c) tested the association between globalization and CO_2 emissions in South Asian countries. Globalizationhad a positive impact on CO_2 emissions in all countries (Bangladesh, India, Nepal, Pakistan, and Sri Lanka), according to the findings. Juxtaposing, Haseeb et al. (2018) discovered the same result, revealing a positive link between globalization and CO_2 emissions in India and Russia but a negative one in Brazil, China, South Africa, and BRICS countries as a group. Conversely, Mehmood and Tariq (2020) concluded that globalization does not affect CO_2 emissions in India, Pakistan, and Bhutan in the long run, contrary to Bangladesh, Afghanistan, and Sri Lanka. Pata (2021) re-examined the same relationship in BRIC countries using Fourier ADL cointegration. The outcomes exposed no evidence of a cointegration relationship between the variables in India, in contrast to Brazil and China, with a positive impact of globalization on CO_2 emissions.

Furthermore, Muhammad and Khan (2021) discovered, using panel data from countries (developed and developing countries), that CO_2 emissions rise in industrialized countries while falling in developing countries as a result of economic globalization. Correspondingly, in a global data analysis covering 180 nations from 1980 to 2016, Farooq et al. (2022) confirmed the detrimental influence of globalization on environmental degradation, similar to Jahanger et al. (2022) results.

3 Data

To achieve our objective in this study, we use annual data from 1970 to 2020 in India to investigate the determinants of CO_2 emissions during the last half-century using the STIRPAT model. Therefore, our dependent variable is carbon dioxide emissions (CO_2) measured in metric tons, from Our World in Data and our independent variables are the world uncertainty index, from Economic Policy Uncertainty Index database, as well as the globalization index presented by Dreher (2006), from KOF Swiss Economic Institute website. Additionally, we include the three STIRPAT model components of technology, affluence, and population, as defined by Dietz and Rosa (1994). First, for the technology, we use the primary energy consumption (ENE) measured by oil equivalent consumption. Second, for affluence, we use the GDP *per capita* (GDP) and GDP *per capita* squared (GDP2), from World Bank to examine the Environmental Kuznets Curve EKC. Finally, for the population, we use population density (POP) by dividing the total population on the surface. Hence, the empirical model used this described in the equation below:

$$logCO2_t = \gamma_1 + \alpha_1 logGDP_t + \alpha_2 logGDP2_t + \alpha_3 logENE_t + \alpha_4 logPOP_t + \alpha_5 logWUI_t + \alpha_6 logGLO_t + \mu_t \quad (1)$$

Where γ_1 is the constant term (intercept), α_i are the slope coefficients, μ_t is the white noise of the estimation, and *log* denotes the logarithmic form.

4 Methodology

4.1 Combined cointegration test Bayer-Hanck (2013)

Since Engle and Granger (1987) developed it to evaluate the long-run association among variables, the cointegration concept has become dominant in time series analysis. Therefore, the Engle and Granger (1987) test (EG) demands that all the series under investigation have the same integration order I(1) or I(2). However the EG test can produce biased results due to its explanatory power properties. In 1991, Johansen introduced a novel approach (J) for examining cointegration relationships and solving EG test problems. The fundamental superiority of the J test on EG is that it detects multiple cointegration relationships among variables. Furthermore, Boswijik (1994) (Bo) presented a new procedure to estimate Error Correction Model (ECM) using F test, and Banerjee et al. (1998) (Ba) enforced the Boswijik work by the addition of ECM model based on *t*-test.

Based on these four tests, Bayer and Hanck (2013) combined all these tests in a single test to avoid possible different results for the unique tests. In this case, the Bayer-Hanck test gives us two test statistics as follows:

$$EG - J = -2\left[\ln\ (P_{EG}) + ln(P_J)\right] \quad (2)$$

$$EG - J - Bo - Ba = -2\sum \ln\ (P_i) = -2\left[\ln(P_{EG}) + ln(P_J) + \ln\ (P_{Bo}) + \ln\ (P_{Ba})\right] \quad (3)$$

Where, P_{EG}, P_J, P_{Bo}, and P_{Ba} indicate the probability values (*p*-values) for every single test, the Bayer-Hanck test uses the F statistic to test the existence of cointegration relationship to compare with critical values proposed by Bayer and Hanck, implying that the null hypothesis of no cointegration link should be rejected if the test statistic is higher than the critical value at α%.

4.2 Hatemi-J (2008) cointegration test

Conversely, the previously described cointegration tests presume that the estimated parameters do not vary over time (Hicham, 2020), implying that structural breaks in long-run relationships are discounted. Gregory and Hansen (1996) proposed a new process to test cointegration relationships with one structural break using three tests ADF (Augmented Dickey-Fuller), Za, and Zt. This procedure was developed by Hatemi-J (2008) by introducing two structural breaks in the equations below:

$$y_t = a_0 + a_1 D_{1t} + a_2 D_{2t} + \beta_0^{'} x_t + \beta_1^{'} D_{1t} x_t + \beta_2^{'} D_{2t} x_t + \varepsilon_t \quad (4)$$

Where D_{1t} and D_{2t} are the dummy variables defined for the structural breaks.

4.3 Augmented ARDL model

The augmented ARDL model (AARDL) is a new extension of the ARDL procedure presented by Pesaran et al. (2001). The standard auto-regressive distributed lags (ARDL) model examines two null hypotheses to detect cointegration relationships: the overall F-test for all the lagged variables and the *t*-test for lagged dependent variable. Nevertheless, Pesaran et al. (2001) assumed that the dependent variable must be an I(1) series, that no degeneration cases exist, and that the independent variable is exogenous. Remarkably, according to McNown et al. (2018), many researchers ignored these assumptions, resulting in inaccurate estimates. To avoid a generalized Dickey-Fuller equation when only the lagged dependent variable is significant, McNown et al. (2018) proposed a supplementary test to investigate the significance of the independent variables. This third test avoids the degenerate case reliance on the I(1) dependent variable notion. Given that all three tests accept significance, there is a strong confirmation of long-run association among the variables. Consequently, the model we used to examine the cointegration connection among our variables, as well as long and short-run estimation, for our framework is as follows:

$$\begin{aligned}\Delta \ln CO2_t = &\gamma_1 + \alpha_1 CO2_{t-1} + \alpha_2 GDP_{t-1} + \alpha_3 GDP2_{t-1} + \alpha_4 ENE_{t-1} \\ &+ \alpha_5 POP_{t-1} + \alpha_6 WUI_{t-1} + \alpha_7 GLO_{t-1} \\ &+ \sum\nolimits_{i=1}^{p} \beta_{1i} \Delta CO2_{t-i} + \sum\nolimits_{i=1}^{p} \beta_{2i} \Delta GDP_{t-i} \\ &+ \sum\nolimits_{i=1}^{p} \beta_{3i} \Delta GDP2_{t-i} + \sum\nolimits_{i=1}^{p} \beta_{4i} \Delta ENE_{t-i} \\ &+ \sum\nolimits_{i=1}^{p} \beta_{5i} \Delta POP_{t-i} + \sum\nolimits_{i=1}^{p} \beta_{6i} \Delta WUI_{t-i} \\ &+ \sum\nolimits_{i=1}^{p} \beta_{7i} \Delta GLO_{t-i} + \tau_i D_t + \mu_t \end{aligned} \quad (5)$$

Where γ_1 is the intercept of the equation; β_{ji} represents the short-run estimators; α_j indicates the long-run estimators and μ_t is the white noise of estimation while Δ representing the first difference operator. In addition, D_t denotes possible structural breaks in the model. Thus, the three hypotheses are as bellow:

First, The null hypothesis for the overall F test on all variables is H_{0A}: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = 0$;

Second, the null hypothesis for the *t*-test on only the dependent variable is H_{0B}: $\alpha_1 = 0$;

Third, the F-test on independent variables is: H_{0A}: $\alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = 0$.

TABLE 1 Unit root tests results.

Variables	Bootstrap ADF		Zivot-Andrews		Lumsdain-Pappel	
	Test	5% cri. v	Test	Break	Test	Breaks
CO_2	−1.306	−1.806	−1.488	2014	−2.799	2001–2014
Δ (CO_2)	−4.416***	−3.025	−6.210***	2012	−7.110**	1997–2012
ENE	−0.935	−1.771	−3.662	1988	−4.183	1988–2007
Δ (ENE)	−6.845***	−3.093	−8.535***	1991	−9.382***	1988–2004
POP	−1.446	−3.791	−1.254	1994	−2.652	1985–2003
Δ (POP)	−4.001***	−2.249	−5.535**	2015	−6.872**	2007–2014
GDP	1.908	−1.948	−3.531	1979	−4.355	1979–1991
Δ (GDP)	−4.965**	−2.996	−7.158***	2015	−6.850**	1990–2014
GDP2	2.220	−1.936	−3.281	1991	−3.869	1979–1991
Δ (GDP2)	−4.274**	−2.996	−6.628***	2015	−6.858**	2004–2014
GLOB	−0.608	−2.585	−2.456	1979	−6.254	1989–2008
Δ (GLOB)	−3.610**	−3.086	−5.384**	1993	−7.056**	1981–1993
WUI	−4.071***	−3.139	−5.177**	2000	−6.329*	1995–2012
Δ (WUI)	−10.102***	−3.054	−10.428***	1997	−10.624***	1982–1997

Δ indicates the first differences; *, **, *** represents significance at 10, 5% and 1% respectively; Critical values for the ADF test are simulated based on 10,000 bootstrap replicates. For the Zivot-Andrews test, critical values are −5.57(1%), −5.08(5%) and −4.82(10%); For theLumsdain-Pappel test, critical values are −7.19 (1%), −6.75 (5%) and −6.48 (10%).

5 Findings and discussion

5.1 Stationarity tests

Because the ARDL methodology demands that all variables must be I(0) or I(1) series with no I(2) series, the first stage in our investigation is to guarantee that our variables are not stationary at the second difference. Therefore, to avoid any misleading outcomes, we use three-unit root tests. The first is the bootstrap unit root test proposed by Park (2003) ADF to obtain bootstrap critical values for each variable. Second, to handle probable structural breaks in the data, the Zivot-Andrews (ZA) (1992) and Lumsdain-Pappel (LP) (1997) tests are also used. Table 1 shows the results, and it is evident that our series is not stationary at their levels, excluding the WUI, which is stationary at its level by the ADF and ZA tests but not by the LP test, which has two structural breaks. Accordingly, all the series are I(1) series, and there is no I(2) variable. Hence, we can run the ARDL procedure in addition to both Bayer-Hanck and Hatemi tests to test the cointegration link in our series.

5.2 Cointegration tests

Once we have confirmed the integration order of the variables, which are I(1) series, it is important to examine the cointegration behavior to explore the long-run association between them. This paper demonstrates the cointegration between variables by using three different tests. Initially, we use the combined test proposed by Bayer and Hanck (2013) based on four previous tests. Hatemi-J's (2012) test with two structural breaks accounts for possible long-term relationship breakdowns, as we cannot use Maki's (2012) tests for five structural breaks due to the short study period. McNown et al. (2018) presented the Augmented ARDL (AARDL) instead of the standard ARDL to support the results of the first two tests. A

TABLE 2 Co-integration tests results.

Bayer-Hanck test				
Tests	Engel-GrangeEG	Johansen J	Banerjee BA	Boswijk BO
Test statistic	−3.748	70.098***	−3.765	25.208**
p-value	0.470	0.000	0.165	0.048
EG-J	56.769***	5% critical value 10.352		
EG-J-BA-BO	66.437***	5% critical value 19.761		
Hatemi test				
Tests	Test statistic	5% critical value	Break 1	Break 2
ADF	−9.158***	−7.903	1987	2004
Zt	−11.444***	−7.903	1990	2004
Za	−135.968**	−123.870	1990	2004
AARDL				
Hypothesis	Test statistic	I (0) 5% crit. val	I (1) 5% crit. val	
F overall	4.292**	2.764	4.123	
t dependent	−4.867**	−2.86	−4.38	
F independent	4.998**	2.32	4.03	

*** symbolizes significance at 10, 5%, and 1% respectively.

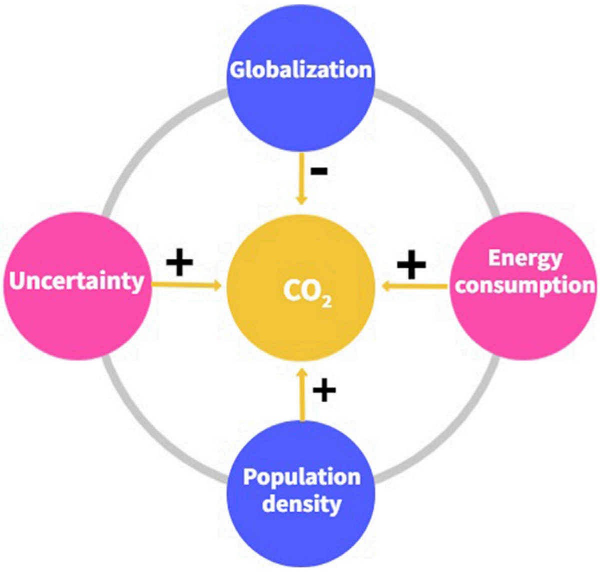

FIGURE 1
Graphical presentation of empirical results.

Bayer-Hanck test revealed that EG-J test statistics are greater than critical values at a 1% t significance level, as illustrated by Table 2's results, which unquestionably showed long-run relationships between variables tested under the three tests. Using three tests with a 5% significance level, the Hatemi tests also revealed the cointegration nexus with two structural breaks in 1990 and 2004.

Moreover, the results showed evidence of rejecting the three null hypotheses of the AARDL procedure at a 5% significance level using bootstrapping critical values with 10,000 replications. Consequently, the alternative hypothesis of the cointegration relationship among our variables should be accepted at a 5% significance level, meaning that our variables have the same long-term behavior and do not diverge from one another.

5.3 Long-run estimations

Following that, under the assumption of a cointegration relationship, we apply three estimating approaches to estimate the long-term impacts in our model: FMOLS, DOLS. The fully modified ordinary least square (FMOLS) regression is developed as a residual-based test with better efficiency in estimating results for cointegrated variables (Pedroni, 2001). DOLS that are very useful in the case of co-integrated variables with I(1) process, in addition to and AARDL, with the introduction of structural breaks for the first two estimations. In this context, the long-run estimations yielded the following results. According to the empirical results (Figure 1), any increase in energy consumption by 1% increases CO_2 emissions by 0.98%–1.27% in India, as seen in Table 3, which is in line with the results of Shahbaz et al. (2021), Jayasinghe and Selvanathan (2021) and Kanjilal and Ghosh (2013). There was a significant energy demand across all sectors, particularly manufacturing, industry, and transportation, which supported economic growth and thus increased carbon emission rates. As a result, the direct impact of energy consumption on environmental degradation can be seen in the post-liberalization period.

Furthermore, the results revealed the existence of an inverted U shape of EKC based on the positive GDP coefficient and the negative GDP square coefficient. CO_2 emissions rise monotonically with GDP up to 3.44 (1.6174/2*0.235 = 3.44) but diminish once income exceeds this level. However, it is essential to note that economic growth throughout the study period did not reach this threshold. Besides, the findings revealed that GDP is the most critical determinant in environmental degradation in India over the research period, with any rise in GDP of 1% leading to an upsurge in CO_2 emissions up to 2.53%. This result is in line with Ohlan's (2015) and Akalpler and Hove, 2019 results.

Economic globalization reduces India's CO_2 emissions by 0.13%–0.21% for every one percentage point increase in Economic globalization as determined by the three estimation methods. For Shahbaz et al. (2015), this study supported their findings in India, and Zaidi et al. (2019) findings in the Asia Pacific Economic Cooperation countries. Thus, given the negative correlation between globalization and CO_2 emissions, it is clear that new approaches to entering global markets and gaining new trading partners can help improve environmental quality.

Moreover, the results indicate that the world uncertainty index affects CO_2 emissions in India only with the dynamic OLS regression, whereas the increase in WUI by 1% escalates CO_2 emissions by 0.0086%. Principally, the contribution of WUI to environmental degradation can be explained by two possible mechanisms, as described by Muhammad and Khan, 2021. First, uncertainty can be seen as an impediment to R&D, innovation, and the transition to renewable energy sources to prevent uncertainty shocks that might hinder economic growth. As a result, these precautionary policies increase carbon emissions. Second, a high WUI encourages firms to adopt traditional production methods, such as machines that use oil, gas, or coal energy sources to minimize production costs and absorb uncertainty shocks that can raise raw material prices, increasing CO_2 emissions.

Finally, population density positively influences environmental degradation only, with AARDL estimation showing that 1% augmentation in population density escalates CO_2 emissions by 0.78% in India. Additionally, the R-squared coefficient shows that the variations of the independent variables explain 99.9% of the variation in dependent variables.

5.4 Short-run estimations

As shown in Table 4, we used two error correction models to detect the short-run effect on CO_2 emissions. The best outcomes are found in the AARDL-ECM (AARDL Error Correction Model) estimation, which has an R-squared of 0.7336, and most estimators are significant. Notably, the results are presented with only one lag because the higher lags are insignificant. An important finding is that the model corrects 73% of its deviations from long-run equilibrium each year, which is statistically significant at 1%, meaning that after any shock, the system will be back to its equilibrium state after 17 months. This result is in line with the

10.3389/fenvs.2023.1144201

TABLE 3 Long run estimation results.

Variables	FMOLS		DOLS		AARDL	
	Coefficient	Probability	Coefficient	Probability	Coefficient	Probability
ENE	1.0715***	0.000	0.9835***	0.000	1.2739***	0.000
GDP	1.6174***	0.007	1.3777**	0.013	2.5350***	0.008
GDP2	−0.2350**	0.011	−0.2006**	0.012	−0.397***	0.007
GLO	−0.1355**	0.021	−0.1561***	0.000	−0.2168***	0.006
POP	−0.3524	0.195	−0.0890	0.668	0.7889**	0.038
WUI	0.0007	0.601	0.0086***	0.000	0.0004	0.8347
C	3.5705***	0.000	3.7867***	0.000	1.3268***	0.000
D1990	−0.0030	0.660	−0.0179***	0.000	/	/
D2004	−0.142**	0.032	0.0020	0.545	/	/
R-squared	0.9995		0.9999		0.9997	
LM test	/	/	/	/	0.0577	0.944
ARCH	/	/	/	/	0.2408	0.787

D1990 and D2004 structural breaks obtained from Hatemi tests; LM test Lagrange Multiplier test for autocorrelation of errors and ARHC is the heteroscedasticity test of errors.

TABLE 4 ECM model for short-run estimation results.

Variables	ECM		AARDL-ECM	
	Coefficient	Probability	Coefficient	Probability
ECT	−0.648***	0.000	−0.7903***	0.000
Δ(ENE)	0.6704***	0.000	0.6421***	0.000
Δ(GDP)	0.3944	0.797	2.0034**	0.013
Δ(GDP2)	−0.0252	0929	−0.3141**	0.011
Δ(GLO)	−0.1158	0.428	−0.1714**	0.011
Δ(POP)	0.5542	0.809	0.6234**	0.037
Δ(WUI)	0.0001	0.851	0.0003	0.835
C	0.0018	0.932	2.2314**	0.032
D1990	−0.0008	0.860	−0.0132*	0.070
D2004	0.0003	0.948	−0.0009	0.886
R-squared	0.5752		0.7336	

ECT denotes the Error Correction Term for adjustment speed and Δ denotes the differences series.

cointegration outcomes in Table 2, which shows that the model corrects 73% of its deviations from long-term equilibrium each year. The ECM method is remarkable in that it achieves the same results in the short and long term. However, estimates show that in the short term, energy consumption, GDP *per capita*, and population density worsen environmental degradation, whereas globalization decreases CO_2 emissions and improves environmental quality. Furthermore, the EKC hypothesis testing revealed an inverse U shape with a threshold of 3.19 in the short run.

6 Conclusions

Environmental quality and climate change have become hot topics among scholars in all scientific fields in recent decades due to their impact on human health and economic development. Hence, this paper investigated the key determinants of CO_2 emissions as one of India's most significant environmental degradation characteristics over the last half-century, 1970–2020. Furthermore, using a STIRPAT model, we investigated the relationship between carbon dioxide emissions and energy use, GDP *per capita*, population density, and the world uncertainty and globalization indexes. We used various cointegration techniques such as Bayer and Hanck (2013), Hatemi-j (2008), and Augmented ARDL methods to explore the presence of a long-run connexion between our variables. Moreover, the bootstrap ADF test (2003), Zivot and Andrews (1992), and Lumsdain and Pappel (1997) tests were employed to explore the integration order of the series in order to deal with unit roots and structural breaks.

The tests used in our empirical results confirmed the cointegration relationship among our variables. There was a negative correlation between carbon emissions and GDP *per capita* square after a threshold of 3.44, indicating that India has an inverse U-shaped EKC hypothesis. However, the threshold was not reached yet, which justify further economic growth policies. For not affecting the environment further, it is critical for these policies to include carbon mitigation goals and environmental protection goals. The positive link between GDP *per capita* and CO_2 emissions is responsible for this. There is also evidence that CO_2 emissions are linked to energy consumption and population density in both the long and short term. As a result of the Indian government's post-liberalization policies over the last fifty years, particularly the expansion of energy demand, especially for energy derived from oil, gas, and coal sources, energy use and population growth are key determinants of environmental degradation in India.

In addition, the findings revealed that the economic uncertainty index contributes to an escalation in carbon dioxide, particularly in the long run. This is due, as previously stated, to firms adopting precautionary policies to avoid uncertainty shocks by reducing production costs through the use of non-environmentally friendly production methods. Conversely, all of the measuring methodologies utilized in our study demonstrated that globalization contributes to enhancing environmental quality in India in the short and long term. Hence, this result emphasizes the necessity for the Indian government to pursue policies that promote more trade openness by entering new markets and cooperating with new trading partners, imposing at the same time a strict environmental protection regulation to promote new technologies, better energy efficiency and carbon emissions mitigation targets.

While the study emphasizes the impact of uncertainty on environmental degradation and the contribution of globalization to curb carbon emissions, it has some limitations. Globalization could be analyzed on three dimensions—economic, social, and overall—to better understand the drivers that policymakers may use in mitigating environmental issues but also in shaping economic growth options. Future research could be oriented to describe the impact of globalization on environmental degradation, economic growth, and social welfare to comprise all three major development needs of India.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://worlduncertaintyindex.com/data/ https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html https://data.worldbank.org.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The reviewer MU declared a past co-authorship with the author DB to the handling editor.

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Literacy rate impact on innovations and environmental pollution in China

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This study examines the impact of literacy rate and innovations on environmental pollution in China from 1990 to 2021. We applied the Quantile Autoregressive Distributed Lag method for the analysis, and our findings suggest that an increase in literacy rate leads to short- and long-term innovations. At the same time, literacy has a positive effect in 1st to 4th quantile in the long run. Furthermore, innovation has a positive effect on environmental pollution. However, in the short run, the literacy rate has negative implications for environmental pollution. These findings imply that education is essential to increase innovation in the economy. Besides, the literacy rate increases the standard of living, and thus, it is recommended that government should adopt environmental protection laws to reduce environmental pollution along with literacy increase. Additionally, China has achieved significant economic growth in the last few decades. To ensure sustainable economic growth government should introduce a carbon tax to minimize production externalities such as environmental pollution.

KEYWORDS

literacy rate, Innovations, environmental pollution, QARDL, China

1 Introduction

Chinese economic growth in recent years has been attributed to recent investments in physical and human capital investments. However, human capital's contribution is low compared to physical assets. (Wei et al., 2001; Arayama & Miyoshi, 2004). According to Ding & Knight (2011), human capital is measured by the number of people enrolled in secondary and higher education, the number of science and technology workers in the labor force, and the amount of money on education and science. This is significantly associated with the number of innovations that occur within a nation. CHI (2008) synthesizes contradictory evidence: higher worker education does contribute to economic growth and innovations; however, its impact may be indirect, which explains its minimal direct effect on growth. Human capital, following the endogenous growth hypothesis, is hypothesized to motivate the development of new technologies and their dissemination, both of which, in turn, stimulate economic expansion. However, there is scant evidence that human capital affects innovation, and there is no evidence that education has any indirect positive effects on innovation-driven economic growth. Education plays a significant role in innovation at the regional level. Invention patent applications *per capita* were significantly correlated with the number of people who had earned advanced degrees (Chi & Qian, 2010). symptoms at presentation, physical exams and lab results.

Increasing prosperity in China has a trickle-down effect, bringing new management techniques and cutting-edge technologies that can bolster innovation in other parts of the world. Innovations are the main engine attributed to a higher level of economic growth in China (Zhu et al., 2019). State Environmental Status Bulletin reported that in 2018, environmental air quality regulations were met in just 121 out of 338 prefecture-level cities in China, or 35.8% of the country's urban areas. There were 822 days in 338 cities where pollution levels were dangerously high, 20 more than in 2017. Sixty percent of the time, PM2.5 was the main pollutant on days with severe pollution. The endogenous growth theory posits that technological progress is crucial to stimulating economic expansion (Malamud & Zucchi, 2019). There is a long history of research into how technological progress impacts the natural world. Holdren and Ehrlich (1971) suggested an association between the three variables (IPAT) theory, which posits that technological progress can mitigate the increase in pollution caused by a growing human population. The author classified the causes of environmental pollution into three categories: large-scale impacts; structural effects; and technological effects; with the latter two categories receiving particular attention because of the importance of technology in improving environmental quality. There is consensus among academia on how technological progress might enhance environmental quality.

There has been a rise in studies examining the correlation between pollution reduction investments and creative output. Tursun et al. (2015) estimated the impact of engineering technology on pollution reduction from 2005 to 2010. Their results support the hypothesis that technical progress contributes to a 60% decrease in CO_2 and SO_2. Levinson investigated the environmental impacts of the United States' industrial sector in light of global trade and technological progress in 2009. The findings of that study show that technological progress has had a substantial positive influence on the environment of the United States' manufacturing sector, with SO_2 emissions decreasing by 39% between 1987 and 2001. Pollution levels were inversely related to environmental research funding (Peng SJ, 2006). Increasing one's potential for independent innovation can reduce the carbon dioxide intensity of the industrial sector, according to the results of a study done in China by Yang et al. (2014). Because of their increasing complexity and difficulty in assessment, environmental concerns are usually reduced to sound bites rather than being dealt with in a sensible matter. This is because their complexity is expanding. People with a substantial stake in a sort of economic development that is not sustainable and extracts resources can sometimes successfully derail efforts to address environmental concerns equitably. This is because they have a vested interest in the manner in which economic progress takes place. In order to ensure that education can play an essential part in defining and analyzing environmental issues and producing solutions to environmental challenges, the challenge is to convey this complexity in appealing and understandable ways to the audience that will be receiving this information.

Even though significant progress has been made in protecting aquatic ecosystems, additional problems are still to come due to the growing human population and increased industrial production. Besides, several reforms have been made to protect the environment. Despite the perception that it is "soft" and garnering less attention than other activities to preserve the environment, environmental education develops future environmental problem solutions. Environmental education needs to be successful in the twenty-first century in terms of its goals of cultivating the next-generation of environmental leaders and increasing public awareness and concern for environmental issues (Hudson, 2001). Research, development, and innovations have been growing in China for the last few decades. In addition, the literacy rate in China has reached the highest level in the region, and the recent trade openness and industrialization bring a significant increase in the country, which puts pressure on the environment and leads to increases the environmental pollution such as CO_2 emissions. The past literature suggested a close association between innovations and CO_2 emissions. However, the relationship between literacy rate and CO_2 emissions relationship needs to be clarified in the literature. Therefore, the study aims to investigate the nexus between literacy rate, innovations, and environmental pollution in China. This study contributes to the existing literature from the following points; first, according to the best of our knowledge, this first study evaluates the nexus between literacy rate, innovations, and environmental pollution in China for the first time. This will help understand the implications of innovations and literacy for the CO_2 emissions in China. The study suggests policy implications that could help to reduce air pollution and speed up innovation activities in the country. Second, this study uses a novel QARDL method for analysis, which provides both short-run and long-run estimations. The QARL provides more robust estimations than the conventional ARDL method and better policy recommendations.

2 Literature review

The term "academic literacy" has been given several different definitions and interpretations, all of which may be discovered scattered throughout the many bodies of scholarly literature. There are many different ways to interpret the term "content-area literacy." However, the most comprehensive interpretation is that the term refers to skills connected to having a solid command of a subject and higher-level reasoning. There are many different ways to interpret the term "content-area literacy" (Shanahan & Shanahan, 2008). The development of several abilities, such as critical and analytical thinking, linguistic fluency, social awareness, and involvement in the community, are all aspects of an education in literacy that should be comprehensive and well-rounded (Kiili et al., 2013). As a result, the concept comprises not just the fundamental literacy skills of reading and writing but also a wide range of academic capabilities in addition to those two specific literacies. In an effort to pin down just what we mean when we talk about "academic literacy," various techniques have been tried throughout the years. It is a widely held view that to achieve academic literacy, one must possess a particular set of linguistic talents desirable in the employment market (Li, 2022). In various academic subfields, the idea of innovation has been the subject of research and discussion. Innovation can be defined as the process of coming up with new ideas, processes, or tools, as well as making use of those new ideas, methods, or technologies. There are many various types of innovation, some of which have been recognized in earlier research (De Vries et al., 2016), such as product and service innovation. Among the many different types of innovation, product innovation and service innovation are two of the most common. The creation and distribution of one-of-a-kind goods and services are the focus of the concepts known respectively as product innovation and service innovation. Process innovation refers to the development of new concepts, frames, or paradigms to assist in defining the nature of a problem and possible solutions, as opposed to conceptual innovation, which refers to shifts in the established procedures, techniques, routines, structures, or roles within an organization or administration. Conceptual innovation refers to developing new concepts, frames, or paradigms to assist in defining the nature of a problem and possible solutions (Liddle, 2013).

Higher education in China has advanced tremendously since the turn of the century, and the country has also made significant strides in technological innovation. Between 1978 and 2000, and again between 2000 and 2018, the average yearly growth rate of the total number of conventional universities was 2.55 percent. Since 1998, there has also been an uptick in the number of students enrolling in traditional forms of higher education. The average annual growth rate of patents was 20.73% from 2000 through 2018, much greater than the average annual growth rate of 12.77% from 1985 through 2000 (WIPO IP Statistics Data Center, n.d.). The period covered by this study was from 2000 through 2018. China's educational system has benefited from several measures taken by the Chinese government. The Chinese government recommended putting into action the Strategy of Developing the Country *via* Science and Education in 1995 when it realized the significance of education in fostering a culture of innovation. The decision to accelerate the advancement of science and technology considered this recommendation and included it. The same year, as an essential component of the strategy, the Chinese government launched the "211 Project," which prioritizes the expansion of approximately one hundred institutions and a wide variety of essential academic specialties. China's "985 Project" was initiated in 1999 to create several top-tier universities. Currently, the project intends to encourage the establishment of 39 prestigious academic institutions located all over the country. In the meantime, the Ministry of Education in China published its Action Plan for Education Promotion for the 21st century. This plan gave "university expansion" the highest priority in China's higher education reforms and hurried up the development of traditional universities. From 44.92 percent in the year 2000 to 94.48 percent in the year 2010, the percentage of Chinese inhabitants who hold a college degree has skyrocketed, as shown by statistics from both the Chinese National Bureau of Statistics and the United States Census Bureau. On the other hand, reports from the World Intellectual Property Organization reveal precisely the opposite of what was stated (Pan et al., 2020). One essential variable that drives corporate innovation is macro-level education at the higher education institution level. To begin, partnerships between universities and businesses, academic conferences, and attempts to train employees all contribute to an increase in the innovative capacity of companies. As a second thing to consider, educational institutions can supply businesses with trained workers. The majority of China's high-tech development zones can be found in areas that are home to a significant number of highly regarded educational institutions and research labs (Grimpe & Sofka, 2009). The Chinese economy had witnessed consistent and rapid growth since 1978, when it started reforming and opening up to the outside world. Even though the long-term extended model played a part in China's economic miracle, the country is currently grappling with the burden of delayed development and worsening environmental quality. This is although the model played a part in China's economic miracle. Even though this paradigm was the primary impetus for China's miraculous economic rise, this is the result (Zhang et al., 2020). Since the beginning of China's economic reforms, the potential of the country to innovate has considerably expanded. This can be seen in the rise in both the input and the output indicators of innovation systems, such as the number of people working in research and development, the amount of money spent on research and development, patents, high-tech and service exports, and scientific and technical journal articles. These are all indicators of innovation systems. However, although increasing quantity is always the first stage in every catch-up approach, the quality of many indicators has been called into question. This is despite the fact that increasing quantity is always the first step (Fan, 2015). Liu et al. (2022) analyzed the role of renewable energy and eco-innovation in Environmental performance and international trade in China. Their findings suggest that innovation and renewable energy improve the environmental quality, while trade increases the CO_2 emissions in China. Liu et al. (2022) investigated the relationship between infrastructure development, CO_2 emissions, and HDI in China; they reported that infrastructure development increases CO_2 emissions and HDI in China. Zeraibi, Ayoub, et al. (2022) reexamine the EKC hypothesis by adding China's fiscal, monetary, and environmental development policies. Their results indicate a long-run relationship between fiscal and monetary expansion, economic growth, and CO_2 emissions. Past research focuses on education's effect on economic growth and development, such as Stites & Semali (1991), Coman Nuta et al. (2022); Treiman (2007), and Mazumdar (2005) found the literacy rate improves the economic growth and development. Some other researchers such as Mughal et al. (2022); Wang and Wang (2022); Ibrahim and Vo (2021) and Xin et al. (2022) investigated the innovations and environmental pollution. There are mixed findings. Some research suggests that innovation reduces environmental pollution, while others suggest that innovation has either a negative or no effect on environmental pollution. In contrast to past research, the current study analyzes the nexus between literacy rate, environmental pollution, and innovation in China.

3 The trend of literacy rate on innovations and the environment in China

Economic development has adverse implications for environmental quality in China and raises environmental concerns. The incompatibility of economic growth and environmental quality is a pain point in China's economic transition and development. The key to overcoming the pain point is to achieve innovation-driven development. In other words, economic growth and environmental quality are not compatible with one another. Human capital's impact on creative ability is a very popular area of study. The primary premise of the endogenous growth hypothesis, which states that gains in human capital led to increases in technical innovation, which in turn led to increases in economic growth, receives only a small amount of

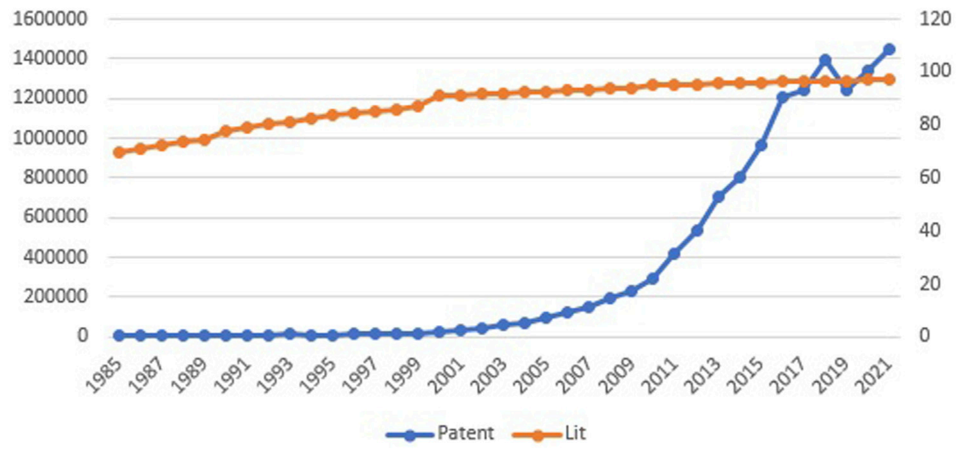

FIGURE 1
Patent and CO_2 emissions in China.

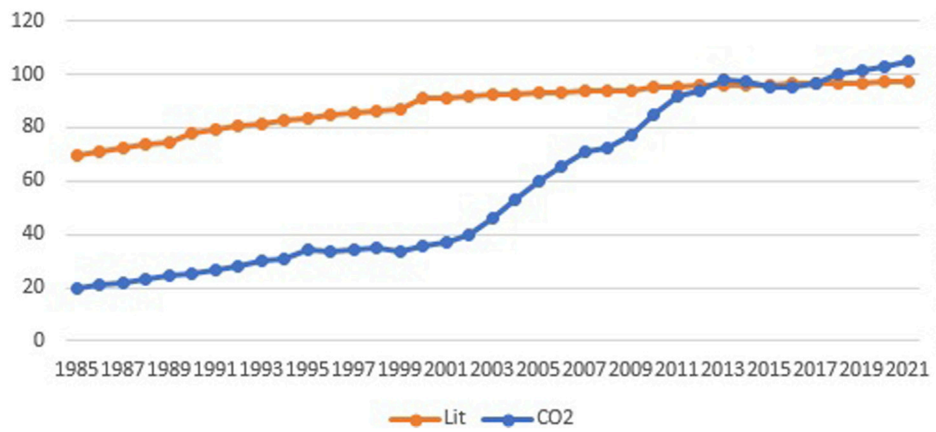

FIGURE 2
Patent and literacy rate in China.

support from empirical research. Several studies have investigated China's human capital's role in the country's capacity to absorb foreign knowledge and increase domestic production. However, the impact of human capital on a nation's capacity to produce its own unique body of knowledge has received little attention from researchers. In order to resolve this issue, we made use of data on patent applications and education at the province level, as well as methodologies from the field of spatial econometrics, to take into account the spatial dependence of observations. Figure 1 presents patent and CO_2 emissions in China, while Figure 2 shows the patent and literacy Rate in China from 1985 to 2021. We found a strong correlation between the educational level of workers and the amount of innovation activity in the province, which was measured by the number of invention patent applications submitted for every 10,000 residents. The impact of higher education on innovation is far greater than that of primary and secondary schools combined. We also discovered something less encouraging: during the past decade, the significance of workers' post-secondary education to the innovation process has decreased. More research is required to assess whether higher education's impact on innovation has lessened and the reasons for this (Chi & Qian, 2010). Pan et al. (2020) explored the criteria that education plays a role in Promote Firm Innovation in China. They identified that The United Nations established seventeen goals for sustainable development in 2015, and many of them are interconnected.

Two of these goals are increasing access to education at a high level and discovering alternative sources of energy that are not dependent on fossil fuels. This study's objective is to investigate the connection between the amount and quality of higher education and the innovative capacity of businesses. Data from the one-of-a-kind Chinese Patent Census Database (1991–2018), the Chinese Industrial Enterprise Database (1995–2013), and provincial-level schooling statistics were utilized in the empirical investigation. Inferences such as the following can be drawn from these

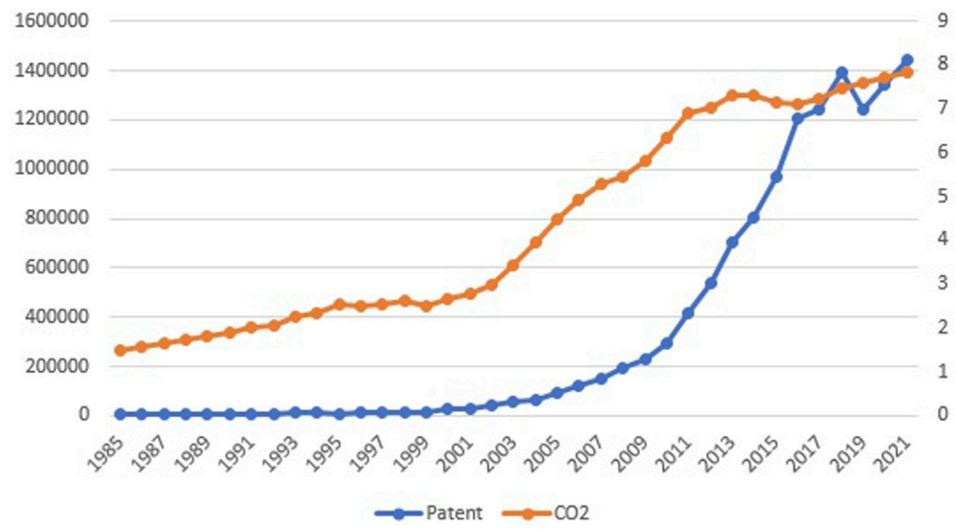

FIGURE 3
Literacy Rate and CO_2 emissions in China.

findings of empirical research: The quality of higher education that was made available in those provinces was the key factor that contributed to the lack of average innovation outcomes achieved by Chinese businesses on a provincial level. The rapid increase in the number of persons with post-secondary educations from institutions that are not among the nation's elites is one hypothesis that may help to explain this phenomenon. People who did not graduate from a prestigious university are less likely to be inventive. However, they have a higher likelihood of being employed by businesses that have this quality in common. Graduates typically find work in fields related to advanced technology. To put it another way, China's efforts to expand access to education have placed excessive emphasis on expanding enrollment and insufficient attention on improving the standard of education being offered. Second, having a college degree was positively related to company innovation; however, having a degree from a less prestigious university was negatively connected with company creativity. There is a possibility that the Chinese government is increasing its support for famous universities in part because these institutions serve as experimental locations for educational reform programs meant to stimulate innovative thinking among students. Third, whereas prestigious higher education had almost little bearing on the innovative activities of SOEs and FOEs, it had a significant and positive role in the creative endeavors of POEs. This is because Chinese higher education institutions that are not considered to be of elite status place a greater focus on educating students for the workforce than they do on scientific inquiry and the development of new products. State-owned enterprises (SOEs) in China are frequently subject to significant amounts of influence from the government, and they provide little incentive for innovative personnel to produce. On the other hand, foreign-owned enterprises (FOEs) in China may obtain technology from their overseas parents. The implications of our empirical findings, both in terms of theory and in terms of practice, are significant. To begin, we separated the several hypotheses that endogenous growth models rely on. The unique qualities of each student's selected school and institution will determine the extent to which they are encouraged to think creatively. Second, after successfully expanding the higher education sector, the Chinese government should shift its focus from education quantity to education quality and pay more attention to improving innovative capabilities in teaching and research, particularly for non-elite higher education institutions. This should be done because the Chinese government has successfully expanded the higher education sector. In the meantime, the most prestigious educational institutions continue to be crucial for the creativity of developing countries.

As a result of China's rise to prominence as a major producer on the global market, the country's environmental conditions have deteriorated considerably in recent decades, placing the country's population in grave danger and contributing to a variety of ongoing socioeconomic problems. In the past 20 years, there have been significant shifts, most notably in the execution of environmental and emission standards, which have gone from weak to robust. These changes have been particularly notable in the United States.

In recent years, China's environmental issues have emerged as a matter of national significance, making it necessary for the country to take action. The Air Pollution Prevention and Control Action Plan, the Environmental Protection Law of 2015, the Environmental Protection Tax Law of 2017, and several other significant efforts on national policy have all been passed and made operationally (Jin et al., 2016). China, the country with the largest industrial sector in the world, continues to face significant environmental difficulties even though numerous efforts and ambitious plans have been made at various periods at the local, provincial, and federal levels. China is particularly susceptible to the effects of SO_2 and CO_2 emissions on civilization. These consequences can be felt worldwide, but China is particularly at risk. Therefore, to solve the issue before it is too late, new environmental standards based on objective criteria need to be developed. The issues that were caused by pollution and smog in the country were balanced out by addressing the issue of carbon trading, which has added a significant agenda item to the government's ambitions for the next 5 years. Environmental non-governmental organizations can help facilitate a more objective assessment of environmental problems and possible solutions to such problems.

The quick increase in CO_2 emissions caused environmental degradation in past few decades. Chinese government have made significant efforts to reduces the emissions in the country. According to the findings of this study, there is a significant gap in effectiveness between the various regulatory agencies. However, government agencies now have greater leeway to initiate legal action against those who violate environmental regulations. The Environmental Protection Tax Law, which was just passed into law, includes a provision that proposes expanding the scope of environmental levies to include carbon dioxide emissions. It is necessary to make a payment for the carbon tax. However, the government should prioritize creating an economy with a minimal carbon footprint and a society that is, sympathetic to the environment. A better environmental future for China and the rest of the world requires paying attention to ensuring implementation compared to analyses of the results, public interest, participation, transparency, and efficiency in suggesting penalties on the responsible and then reviewing compatibilities of the environmental laws. Figure 3 presents the trend between literacy rate and CO_2 emissions in China from 1985 to 2021. This is necessary to achieve the ultimate environmental goals (Khan & Chang, 2018). China's environmental protection law (EPL) aims to improve the environment through a legal system. Share the environmental database that accurately measures environmental pollution; effectively implement the environment laws; close monitoring of industries that may affect the environment. Strict measures and extremely high accountability standards should be implemented to maintain the country's emission level. Implementing carbon tax in industries to mitigate emissions is a good decision.

Even if the revised EPL satisfies China's environmental protection requirements, there is still a significant amount of potential for improvement. The following are a few suggestions that were made throughout this inquiry that might be of some use:

- Consistent legislative actions aiming at improving the legal system, with a primary emphasis on the approach for implementing the EPL;
- Establishing a framework for numerous government agencies to share environmental database information is essential to achieve the most effective harmonization, which must then be followed by the proper measures in order to build an inter-regional environmental enforcement mechanism;
- Increasing environmental intelligence is necessary in order to enforce laws more effectively and identify instances of contamination in the environment.
- The state's economic authorities should encourage firms that are sustainable and beneficial to the environment, and they should phase out inefficient industrial methods.
- The non-governmental organizations (NGOs) that work to safeguard the environment play an important role in society and must receive funding. It is essential to make the most of their potential by increasing their capacities and fortifying their pathways;

TABLE 1 Descriptive analysis.

Variables	P	CO2	LI	NR	GDP
Mean	11.1132	1.3129	4.4765	6.3875	28.3498
Median	10.9468	1.2318	4.5231	6.4853	28.1380
Maximum	14.1844	2.0596	4.5788	7.3922	30.5065
Minimum	8.1588	0.3951	4.2424	4.8090	26.3326
Std. Dev	2.0122	0.5745	0.1022	0.7043	1.4034
Skewness	0.1538	−0.0275	−0.9176	−0.4881	0.0648
Kurtosis	1.5217	1.4459	2.5754	2.2260	1.5641

- Polluters need to be held to extremely high accountability standards for installing suitable environmental monitoring equipment and maintaining accurate emission records when pollution is produced.
- In order to safeguard the environment to the greatest extent feasible, it is imperative that polluters be incentivized to work together and that efforts to educate the general public about the myriad of laws governing environmental protection be strengthened.
- Obtaining insurance is an excellent way to prepare for the approaching carbon tax. The world's economy and the monetary system will undergo shifts as a direct consequence of the imposition of a price on carbon. China's government is responsible for seizing the opportunity for a global low-carbon economy by identifying policies and activities pertinent to the issue.
- Building a low-carbon economy and culture on a large scale is needed. Before selecting how to impose a carbon tax, it is necessary to analyze both the benefits and the drawbacks of such a tax because its implementation is a foregone conclusion. The government has to prioritize raising the amount of support it provides for low-carbon innovation and providing aid to partnerships working to increase energy consumption and production.
- Second, we need to move forward with production methods that are cutting-edge, low-carbon, and ecologically benign while simultaneously building upon and boosting industries that are already well-established. In conclusion, the industry should devise, create, and distribute low-carbon products to eliminate trade barriers, increase market share, and advance the industry (Environmental Law: 2 Years On - China Water Risk, n.d.).

4 Materials and methods

The study uses the nexus between literacy rate, innovation, and environmental innovation in China; this study develops two models to analyze the data

$$P = \alpha_1 + \beta_1 Li + \beta_2 GDP + \beta_3 R\&D + \beta_4 NR + \varepsilon_1 \quad (1)$$

$$Env = \alpha_2 + \beta_5 Li + \beta_6 GDP + \beta_7 Pop + \varepsilon_2 \quad (2)$$

Where,

L = Literacy Rate is the independent variable,

TABLE 2 ADF estimation.

	Level		Difference	
	t-Statistic	Prob.*	t-Statistic	Prob.*
P	−0.56953	0.8648	−4.37824***	0.0072
ENV	−1.00462	0.7409	−2.93713*	0.0512
LI	−5.4463***	0.0001	−6.02288***	0.0001
NR	−2.45342	0.1351	−5.31539***	0.0001
GDP	−0.10932	0.9406	−3.61592**	0.0104

R&D = R&D spending.
Pt = Patent (innovation)
NR = number of researchers in a country (per million people)
Env = Environmental pollution–CO2.
GDP = GDP.
E = Energy consumption.

The expected sign of the coefficients suggests holding a positive LI, GDP, R&D, and NR. At the same time, GDP and population have positive expected signs, and literacy rate is assumed a negative relationship with CO2 emissions. Further, the literature suggests that literacy can enhance environmental quality in China. Therefore, this study aims to measure the implications of literacy on innovation and the environment for the period 1985-2021. The study applied the QARDL model suggested by Hashmi et al. (2022). QARDL method allows us to investigate the long-run and short-run relationship between literacy rate, GDP, R&D, NR, and innovation. QARDL is a more advanced method than ARDL and measures variations in explanatory variables. We use two separate models in this study; the simplified version of ARDL can be written as

$$P_t = \phi + \sum_{i=1}^{n} \vartheta_{1i} LI_{t-i} + \sum_{i=0}^{m} \vartheta_{2i} GDP_{t-i} + \sum_{i=0}^{k} \vartheta_{3i} R\&D_{t-i} + \sum_{i=0}^{l} \vartheta_{4i} NR_{t-i} + \sum_{i=0}^{l} \vartheta_{4i} CO_{2t-i} + \mu_t \quad (3)$$

$$P_t = \phi + \sum_{i=1}^{n} \vartheta_{1i} LI_{t-i} + \sum_{i=0}^{m} \vartheta_{2i} GDP_{t-i} + \sum_{i=0}^{k} \vartheta_{3i} R\&D_{t-i} + \sum_{i=0}^{l} \vartheta_{4i} NR_{t-i} + \sum_{i=0}^{l} \vartheta_{4i} CO_{2t-i} + \mu_t \quad (4)$$

The Quantile ARDL is the extension of the basic ARDL method; following these two models in Equations (1), (2), we can rewrite as follow,

$$Q_{Pt} = \lambda(\tau) + \sum_{i=1}^{r} \vartheta_i(\tau) P_{t-i} + \sum_{i=0}^{t} \vartheta_i(\tau) LI_{t-i} + \sum_{i=0}^{d} \vartheta_i(\tau) R\&D_{t-i} + \sum_{i=0}^{s} \vartheta_i(\tau) NR_{t-i} + \kappa_t(\tau) \quad (5)$$

$$Q_{ENVt} = \pi(\tau) + \sum_{i=1}^{e} \vartheta_i(\tau) LI_{t-i} + \sum_{i=0}^{n} \vartheta_i(\tau) GDP_{t-i} + \sum_{i=0}^{h} \vartheta_i(\tau) P_{t-i} + \varpi_t(\tau) \quad (6)$$

To account the possibility of serial correlations, the QARDL model in equations (2)&3) needs to be generalized, demonstrating the QARDL-ECM model:

$$Q\Delta P_t = \theta(\tau) + \gamma(\tau)(P_{t-1} - \beta_{LI}(\tau) LI_{t-1} - \beta_{GDP}(\tau) GDP_{t-1} - \beta_{R\&D}(\tau) R\&D_{t-1} - \beta_{NR}(\tau) NR_{t-1}) + \sum_{i=1}^{n-1} \lambda_i(\tau)\Delta P_{t-i} + \sum_{i=0}^{m-1} \lambda_i(\tau)\Delta LI_{t-i} + \sum_{i=0}^{k} \lambda_i(\tau)\Delta GDP_{t-i} + \sum_{i=0}^{k} \lambda_i(\tau)\Delta R\&D_{t-i} + \sum_{i=0}^{k} \lambda_i(\tau)\Delta NR_{t-i} + \varphi_t(\tau) \quad (7)$$

$$Q\Delta ENV_t = \theta(\tau) + \gamma(\tau)(P_{t-1} - \beta_{LI}(\tau) LI_{t-1} - \beta_{GDP}(\tau) GDP_{t-1}) + \sum_{i=1}^{n-1} \lambda_i(\tau)\Delta P_{t-i} + \sum_{i=0}^{m-1} \lambda_i(\tau)\Delta LI_{t-i} + \sum_{i=0}^{k} \lambda_i(\tau)\Delta GDP_{t-i} + \varphi_t(\tau) \quad (8)$$

Whereas short-term cumulative effects of historical and present P, LI, R&D, NR, and ENV levels are calculated by:

$$\gamma = \sum_{i-1}^{n-1} \kappa\gamma_j \qquad \nu^* = \sum_{i-1}^{g-1} \alpha\kappa_j,\ \theta^* = \sum_{i-1}^{d-1} \alpha\theta_j,\ \varpi^* = \sum_{i-1}^{k-1} \alpha\varpi_j \quad (9)$$

To determine the long-term parameter for P, LI, R&D, NR, and ENV, we use the formula:

$$\delta_{P^*} = -\frac{\delta_P}{\rho},\ \delta_{LI^*} = -\frac{\delta_{LI}}{\rho},\ \delta_{GDP^*} = -\frac{\delta_{GDP}}{\rho},\ \delta_{R\&D^*} = -\frac{\delta_{R\&D}}{\rho},\ \delta_{NR^*} = -\frac{\delta_{NR}}{\rho},\ \delta_{ENV^*} = -\frac{\delta_{ENV}}{\rho} \quad (10)$$

ECM's coefficient (p) is expected to have a significant negative value. The first step is to perform a unit root test in the estimation. However, no strict same odder integration is required, just like the Johansen test requires. The unit root test is applied to check the order of integration of the variables in the system. The unit root is essential for the reliability of long-term forecasting. It should be noted that the prediction may not be applicable and reliable when the series is unstable or when there are random shocks within the data. ADF method is used to test stationary properties of the data.

$$\Delta \mathrm{AF_t} = \nu_0 + \kappa \mathrm{AF_{t-1}} + \sum_{i=1}^{\sigma} \varphi_i \Delta \mathrm{AF_{t-1}} + \mu_t \quad (11)$$

$$\Delta \mathrm{AF_t} = \nu_0 + \mathrm{T} + \kappa \mathrm{AF_{t-1}} + \sum_{i=1}^{\sigma} \varphi_i \Delta \mathrm{AF_{t-1}} + \mu_t \quad (12)$$

Equations (7) and (8) suggest the ADF unit root estimation of series based on intercept and trend in all series.

Additionally, Lee Strazicich is more efficient for detecting a break in the data than Zivot Andrews (ZA). ZA test measures the discontinuity in the dataset at trend or intercept, but Lee Strazicich tests the data break exogenously by applying the trend and intercept simultaneously. Mathematically Lee Strazicich expressed as.

$$y_t = \beta_0 + \beta_1 t + \beta_2 a_{1t} + \beta_3 a_{2t} + \beta_4 a_{3t} + \beta_5 a_{4t} + \varphi y_{t-1} + \sum_{j=1}^{n} d_j \Delta y_{t-j} + \varepsilon_t \quad (13)$$

However, to measure the overall significance of included variables in the model we used the Wald test, which provides joint significance. The significance of the Wald test implies that explanatory variables jointly determine the dependent variables. The test is applicable to multiple models, including those with binary variables.

TABLE 3 LS estimation.

Variables	t-stat	Year
P	−5.07634***	2009
CO_2	−6.58556***	2001
LI	−7.52756***	2002
NR	−11.7316***	2008
GDP	−5.34941***	2002

$$WL_t = \frac{\left[\hat{\nu} - \nu_0\right]^2}{1/I_n(\hat{\nu})} = I_n(\hat{\nu})\left[\hat{\nu} - \nu_0\right]^2 \tag{14}$$

In addition, series data may face autocorrelation problems, indicating the two-time series are correlated.

$$\mathrm{ACR_t} = \phi_1 + \sum_{k=2}^{p} \nu_j \mathrm{ACR_{jt}} + \alpha_t$$

$$\alpha_t = \beta_1 + \sum_{k=2}^{p} \beta_j \mathrm{R_{jt}} + \pi\alpha_{t-1} \tag{15}$$

Testing linearity is also important; the study test assumes that non-linear combinations of explanatory variables respond to dependent variables. The model uses a polynomial or another non-linear functional form to the linearity of the model.

$$x = \alpha z + \gamma_1 \hat{x}^2 + \cdots + \gamma_{k-1} \hat{x}^k + \varepsilon \tag{16}$$

5 Results and discussion

This section provides results and discussion; the first part of estimations is descriptive statistics. The estimations mainly discuss the overall trend, deviation in data, and symmetrical properties such as skewness and kurtosis. Table 1 provides descriptive statistics.

The descriptive statistics suggested following the standard value, implying that included variables are in the acceptable range. The symmetrical pattern suggests that its value lies in standard value. JB statistics also suggest that the model is consistent with the data. The Augmented Dickey-Fuller (ADF) test is used to check stationarity in data. The stationarity status of a variable assumes that the variable should have mean and constant over time. For the non-stationary series, mean and variance do not remain constant. The outcomes of ADF are reported in Table 2.

The information in Table 2 elaborates that at a 1% significance level, LI is stationary level. Although all the factors have zero mean and constant variance at the first difference, indicating that the statistical characteristics of the data do not change with time. The ADF results suggest that all variables are non-stationary at level and become stationary at first difference. Additionally, another test known as the Lee-Strazicich test (LS) is used to verify the stationary properties of the data further. The LS is used for stationarity testing if the data has structural breaks. The LS results are reported in Table 3.

Table 3 presents that innovation, environment, literacy rate, number of researchers, and gross domestic product, have a break in their continuity. The Autoregressive Distributed Lag (ARDL) bounds test determines the long-run and short-run relationship between variables. This method determines whether one variable has a statistically significant effect on another variable (the dependent variable) over time. The results are reported in Table 4.

Table 4 shows Model 1 and 2 bound tests which test the hypothesis of the long run; cointegration estimates the long-run relationship between the variables, and the bound test results indicate the existence of a long-run relationship. This indicates that innovations, CO_2 emissions, and literacy rate has a long-run association. If cointegration exists in the model, it implies that all variables move together over time. However, there might

TABLE 4 Estimations of model 1 and model 2.

F-Bounds Test		Null Hypothesis: No levels of relationship		
Test Statistic	Value	Signif. (%)	I (0)	I (1)
Model 1			Asymptotic: n = 1000	
F-statistic	8.377,729	10	2.2	3.09
k	5	5	2.56	3.49
		2.50	2.88	3.87
		1	3.29	4.37
Model 2				
			Asymptotic: n = 1000	
F-statistic	5.043174	10	2.37	3.2
k	3	5	2.79	3.67
		2.50	3.15	4.08
		1	3.65	4.66

TABLE 5 Q-ARDL for model 1.

Long term	Variable	Coefficient	Std. Error	t-Statistic	Prob		Variable	Coefficient	Std. Error	t-Statistic	Prob
	LI	2.588	1.457	5.896	0.000		LI	2.828	0.587	2.327	0.000
	GDP	1.485	0.311	4.767	0.000		GDP	1.467	0.151	9.739	0.000
q = 0.25	R&D	0.052	0.094	0.550	0.086	q = 0.5	R&D	0.198	0.175	1.128	0.267
	NR	1.137	0.459	2.477	0.019		NR	0.744	0.653	1.139	0.263
	LI	3.485	0.463	4.162	0.000		LI	2.119	0.459	3.494	0.000
q = 0.75	GDP	1.466	0.139	10.578	0.000	q = 0.85	GDP	1.444	0.129	11.181	0.000
	R&D	0.287	0.176	1.628	0.113		R&D	0.348	0.171	2.037	0.050
	NR	0.527	0.662	0.796	0.432		NR	0.381	0.621	0.614	0.043
Short											
	D (LI)	1.522	6.245	1.685	0.105		D (LI)	2.353	3.834	1.657	0.010
	D (GDP)	0.122	0.663	0.183	0.856		D (GDP)	0.133	0.622	0.215	0.832
	D (R&D)	-0.073	0.214	-0.341	0.736		D (R&D)	-0.056	0.190	-0.293	0.772
	D (NR)	-0.004	0.318	-0.014	0.989		D (NR)	0.321	0.312	1.029	0.313
	P (-1)	0.397	0.273	1.452	0.159	q = 0.5	P (-1)	0.431	0.265	1.629	0.116
q = 0.25	LI (-1)	-13.324	27.678	-0.481	0.634		LI (-1)	-5.309	4.488	-1.183	0.248
	GDP (-1)	-0.077	0.417	-0.184	0.855		GDP (-1)	0.511	0.475	1.075	0.293
	R&D (-1)	0.461	0.823	0.561	0.580		R&D (-1)	0.282	0.184	1.534	0.038
	NR (-1)	0.130	0.395	0.329	0.745		NR (-1)	-0.059	0.244	-0.242	0.811
	ECT (-1)	0.759	0.733	1.036	0.310		ECT (-1)	-0.325	0.453	-0.718	0.080
	D (LI)	9.927	18.622	0.533	0.599		D (LI)	10.851	17.358	0.625	0.538
	D (GDP)	-0.194	1.028	-0.188	0.852		D (GDP)	-0.115	0.945	-0.121	0.904
	D (R&D)	-0.229	0.622	-0.368	0.716		D (R&D)	-0.276	0.583	-0.474	0.639
q = 0.75	D (NR)	0.612	0.325	1.884	0.071	q = 0.85	D (NR)	0.601	0.309	1.946	0.063
	P (-1)	0.605	0.402	1.505	0.045		P (-1)	0.641	0.363	1.764	0.090
	LI (-1)	-7.785	5.845	-1.332	0.095		LI (-1)	-6.407	5.792	-1.106	0.079
	GDP (-1)	1.019	0.586	1.738	0.095		GDP (-1)	0.908	0.543	1.674	0.107
	R&D (-1)	0.246	0.156	1.579	0.027		R&D (-1)	0.193	0.161	1.200	0.041
	NR (-1)	0.105	0.236	0.446	0.660		NR (-1)	0.162	0.228	0.709	0.185
	ECT (-1)	-0.273	0.455	-0.600	0.054		ECT (-1)	-0.222	0.426	-0.521	0.007

possibility of short run deviation from the long run equilibrium, which ECM can measure.

The information in Table 5 reveals that LI, GDP, R&D, and NR influence innovation in the long run. The estimation discloses that in the 1st quantile, LI, GDP, R&D, and NR are significant and positively affecting innovation. In 2nd, 3rd and 4th quantile, LI, and GDP also have a positive association with innovation. These results imply that in the long run LI, GDP, R&D, and NR determine innovation in China. In addition, the short-run findings report that only literacy rate has a positive effect on innovations in 3rd quantile; similarly, R&D spending affected innovations only in 3rd quantile. This indicates that short-run estimations innovations need a large period.

Table 6 contains results for Model 2, which indicates that in the long run, literacy has a positive and significant effect on environmental pollution. While in the short run, GDP can have a positive and significant effect on environmental pollution in 4th quantile. At the same time, the literacy rate has no effect on environmental pollution in the short run. These results imply that with the literacy rate increase in the long run, people attain higher living standards and increase their income level, raising energy consumption and environmental pollution. However, in

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TABLE 6 Q-ARDL estimations for model 2.

Long Term	Variable	Coefficient	Std. Error	t-Statistic	Prob		Variable	Coefficient	Std. Error	t-Statistic	Prob
	LI	0.4626	0.4109	1.1257	0.2684		LI	1.0336	0.5534	1.8676	0.0707
q = 0.25	GDP	0.0949	0.0988	0.9608	0.3437	q = 0.5	GDP	0.1268	0.1078	1.1764	0.2478
	P	0.1783	0.0607	2.9364	0.006		P	0.1321	0.0673	1.9629	0.0581
	C	-5.4826	2.0784	-2.6379	0.0126		C	-8.3827	2.56112	-3.2730	0.0025
	LI	0.9764	0.7562	1.2912	0.2056		LI	0.88467	0.7071	1.2509	0.0197
q = 0.75	GDP	0.2427	0.1531	1.5869	0.1221	q = 0.85	GDP	0.229	0.1224	1.8705	0.0703
	P	0.0715	0.1248	0.573	0.5705		P	0.0904	0.0994	0.9101	0.0694
	C	-10.6706	4.7437	-2.2494	0.0313		C	-10.0635	3.8489	-2.6146	0.0134
Short Term											
	D (LI)	1.0257	0.8163	1.2564	0.2197		D (LI)	0.5864	0.8004	0.7326	0.4701
	D (GDP)	-0.0017	0.129	-0.0134	0.9894		D (GDP)	0.0532	0.1592	0.3346	0.7405
	D(P)	0.0337	0.0712	0.4732	0.0399		D(P)	0.0716	0.0592	1.2085	0.2373
q = 0.25	ENV(-1)	0.649	0.2327	2.7894	0.0096	q = 0.5	ENV(-1)	0.6197	0.2046	3.0283	0.0054
	LI (-1)	-0.8298	0.8983	-0.9237	0.3638		LI (-1)	-0.2250	0.9680	-0.2325	0.0179
	GDP (-1)	-0.1075	0.1286	-0.8364	0.4102		GDP (-1)	0.0286	0.1574	0.1816	0.8572
	P (-1)	0.0265	0.0872	0.3033	0.764		P (-1)	-0.0249	0.1266	-0.1967	0.8455
	ECT (-1)	-0.2192	0.1193	-1.8373	0.0772		ECT (-1)	-0.0972	0.1139	-0.8532	0.4011
	D (LI)	1.1943	1.7429	0.6853	0.499		D (LI)	2.43221	2.63325	0.92365	0.3638
	D (GDP)	-0.0137	0.1307	-0.1047	0.9174		D (GDP)	0.11342	0.09689	1.17057	0.252
	D(P)	0.0992	0.0574	1.7266	0.0957		D(P)	0.10243	0.07679	1.33399	0.1934
q = 0.75	ENV(-1)	0.7127	0.1835	3.8834	0.0006	q = 0.85	ENV(-1)	0.51541	0.2679	1.92391	0.065
	LI (-1)	-0.9011	1.0159	-0.887	0.3829		LI (-1)	-1.16647	1.24476	-0.93711	0.357
	GDP (-1)	0.0671	0.1319	0.5086	0.6152		GDP (-1)	0.19391	0.09436	2.05491	0.0497
	P (-1)	0.0242	0.1096	0.2203	0.8273		P (-1))	-0.03702	0.06288	-0.58885	0.5609
	ECT (-1)	-0.1614	0.1108	-1.4559	0.1569		ECT (-1)	-0.28346	0.13624	-2.08056	0.0471

the short run, the literacy rate does not affect the living standard and energy consumption; thus, literacy does not affect environmental pollution. Innovation is often seen as a critical driver of economic growth and competitiveness, allowing businesses and societies to continuously improve and adapt to changing circumstances. It is also essential in addressing global challenges such as climate change, health epidemics, and food and water security. Our results suggest a long-run association between innovations and environmental pollution in China. This implies a strong association between literacy and innovation. Highly literate societies tend to be more innovative, which enables individuals to access new information and knowledge. It also helps people to communicate their ideas effectively and collaborate with others, which leads to successful innovation. The positive association between literacy rate and innovation is supported by other studies (Cheung et al., 2021; Guzmán-Simón et al., 2020; Swain & Cara, 2019; Lau & Richards, 2021; Højen et al., 2021; Liu et al., 2021; Tian et al., 2020; García-Pérez-de-Lema et al., 2021; Fitriasari et al., 2021). Literate societies consider to be aware of environmental issues and more aware of understanding and addressing them. In addition, literate individuals tend to make more sustainable choices regarding consumption and disposal habits. In addition, literacy can assist people in understanding the science behind environmental problems and finding solutions.

The expenditure on R&D, however, is often viewed as a key element of innovation. Research and development projects involve creating new ideas and transforming them into innovative products, processes, or services. R&D contributes to the development of new technologies, improving existing products, and creating new businesses. R&D investments lead to innovative products and services, which enable organizations to gain a competitive advantage in the market. The findings are supported by other studies (Babelytė-Labanauskė & Nedzinskas, 2017; Hammar & Belarbi, 2021; Vrontis & Christofi, 2021; Heij et al., 2020). Innovation can also solve environmental problems; For example, developing new technologies, such as renewable energy sources or more efficient methods of production, can help reduce production's impact on the environment. Innovation finds new ways to utilize resources sustainably and reduces the negative effect of the environment on societies.

6 Conclusion

China has made significant progress in increasing literacy rates in recent decades. Similarly, a significant achievement has been made in R&D and innovations. World Intellectual Property Organization reported that in 2019 China devoted about 2.18% of its GDP to R&D spending, which is the highest among all middle-income countries. Trade openness and sustained economic expansion over the last few decades resulted in a high level of environmental pollution. Therefore, this study analyzes the relationship between literacy rate and innovation and environmental pollution from 1985 to 2021. We applied Quantile ARDL method for data analysis and used two models; the first model takes innovations as the dependent variable, while literacy rate, GDP, R&D spending, and the number of researchers (NR) are taken as independent variables. While in the second model, we took environmental pollution (CO2) as the dependent variable, and literacy rate, GDP, and population as independent variables. Our study's outcomes suggest a long-run relationship between innovations, literacy rate, and environmental pollution. However, the literacy rate does not affect environmental pollution in the short run. These findings have some useful policy implications; firstly, the literacy rate is essential in establishing innovations in China. Therefore, the government should make an effort to increase the literacy rate, especially in rural areas. Secondly, innovations have a positive and significant effect on environmental pollution, indicating that innovations are mostly taken to produce CO_2 emissions-related products. Therefore, the government should focus on innovations, renewable energy sources, and sustainable products which reduce the country's environmental pollution. Since the literacy rate does not affect environmental pollution in the short run, the government must add environment awareness-related content to the syllabus in the education system, especially at the primary and secondary education levels. The study has some limitations; this study focuses on a single country case, and future studies may use many countries and compare the region-wise relationship between literacy rate and innovation and environmental pollution. Future studies may use other advance methodologies for the data analysis and compare the results with past studies' findings.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Research on network capacity, absorptive capacity and service innovation performance of technology business incubators—based on PLS-SEM and fsQCA methods

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Introduction: In the new economic normal, technology incubators are an important support to achieve the growth of strategic emerging enterprises. On the basis of resource based theory, organizational learning theory, inter-organizational relationship theory, and network capability theory, this study constructs a theoretical framework and hypotheses of the impact of network capability within the "resource-capability-relationship" perspective, absorptive capacity on service innovation performance of technology business incubators.

Methods: This study uses 234 Chinese incubators in the incubator network as samples and applies partial least squares structural equation modeling (PLS-SEM) and fuzzy-set qualitative comparative analysis (fsQCA) to explore the questions mentioned above.

Results: The results verify the relationship between network capacity, absorptive capacity, and service innovation performance. Furthermore, the results yield four paths that lead to high service innovation performance, such as "network capability orientation" and "high absorption orientation", which are different combinations of network capacity and absorptive capacity.

Discussion: The research results are important for improving the innovation performance of technology incubator services and ensuring the stable and effective operation of incubated enterprises.

KEYWORDS
network capability, absorptive capacity, technology business incubators, service innovation performance, fsQCA, PLS-SEM

1 Introduction

Technology business incubators have become an institutionalized part of innovation-driven policies worldwide to promote innovation, entrepreneurship, and economic growth (Mian et al., 2016). Technology business incubator, as an important carrier of industry and enterprise innovation capability improvement and innovation system construction in the new normal situation of "Mass Entrepreneurship and innovation" (Fu et al., 2021). It has created excellent professional service platforms such as resource knowledge and technology for China's small, medium and micro technology incubators, promoting the incubators to rapidly grow into gazelle enterprises, accelerating the transformation and innovation of traditional industrial structure (Hausberg and Korreck, 2021). By the end of 2019, there were more than 7,000 technology business incubators worldwide, most of which are supported by local and central governments Li. (2020). Traditional technology business incubators provide incubators with the resources and services necessary for business operations (infrastructure management services and technical know-how, *etc.*). At the same time, it helps incubators achieve resource integration and supports incubators to survive and grow in the fierce market competition (Tang et al., 2021). The upgrade and restructuring of technology business incubators through service innovation is the best way and most feasible path for incubators to gain heterogeneity, differentiation, and sustainable competitiveness, which is expected to break through the traditional "nanny" service model, achieve leapfrog development, enhance the service capacity of the incubator and accelerate the growth of incubators (Yuan et al., 2022).

Based on social network theory, Granovetter. (2008) argues that all economic activities of incubators are embedded in social networks of relationships. The study pointed out that an external social network of relationships is an important vehicle for incubators to obtain scarce resources such as knowledge and to carry out innovative activities (Adler and Kwon, 2002). It was found that through incubator networks, incubators gained more opportunities for business collaboration and gained more access to scarce resources, which in turn improved innovation performance (Bruneel et al., 2012; Ayatse et al., 2017). Thus, it is clear that how to improve the innovation performance of incubators in incubator networks is an important issue facing current research. Lavie. (2007) pointed out that firms with similar network partners have a large gap in the innovation performance they obtain, which is mainly due to the differences in the network capabilities of firms. However, based on the perspective of incubators in incubator networks, few scholars have further explored the mechanisms through which network capabilities affect innovation performance (Hoffmann, 2007; Lavie, 2007), resulting in the role of network capabilities of incubators in incubator networks remains full of unknowns.

Based on resource-based theory, Barne. (1991) argues that resource acquisition and development help incubators enhance their competitive advantage. It was found that external resources acquired through social networks can effectively contribute to the competitive advantage of incubators only if they form a complementary effect with the internal resources of incubators (Lin et al., 2012; Wu et al., 2021). However, scholars studying the internal capabilities of incubators hold a different view, arguing that the network theory school overemphasizes the role of external ties in influencing the innovation performance of incubators while ignoring the central role played by absorptive capabilities. Further research has found that incubators differ in their absorptive capacity and that it is these differences in the capacity that leads to differences in the innovation performance of incubators (Miranda et al., 2022). Zahra and George (2002) suggest that firms with higher absorptive capacity have better innovation performance and will have a much better chance of winning in the competitive market. However, based on the perspective of incubators in incubator networks, there is a paucity of scholarly research on how network capabilities affect innovation performance through absorptive capacity. Therefore, this study aims to answer the following questions:

- How does network capacity affect innovation performance?
- How does absorptive capacity affect innovation performance?
- What is the relationship between network capacity and absorptive capacity?
- How do network capability and absorptive capacity jointly contribute to innovation performance?

In view of the special role of technology business incubators in the process of innovation, entrepreneurship, and industrial transformation and upgrading, this study constructed a theoretical analysis framework of "resource-capacity-relationship" based on strategic management theory, and resource-based theory, network capability theory, and absorptive capacity theory. Taking 234 Chinese incubators as the research object, this study discusses the impact of the relationship between network capability and service innovation performance of technology business incubators under the coupling of "resource-capability-relationship" and empirically tests the mediating role of absorptive capacity. In this study, fuzzy set qualitative comparative analysis (fsQCA) and structural equation modeling (PLS-SEM) was used for data analysis. It was found that network resource patching ability, network cross-organization learning ability, network relationship interaction ability, potential absorptive capacity, and actual absorptive capacity impact service innovation performance. In addition, absorptive capacity mediates the relationship between network capability and service innovation performance. This study helps to deepen the understanding of incubators to realize network capability and service innovation performance through absorptive capacity, and has profound theoretical and practical value.

The rest of this paper is organized as follows: Section 2 provides the research hypothesis and theoretical framework construction. Section 3 describes the data and method. Section 4 presents the result and stability checks. Section 5, we present the discussion of the findings and research implications. Section 6, we present conclusions. Finally, in Section 7, we set forth the limitation of the research and the direction of the next research.

2 Theoretical analysis and hypothesis

2.1 Theoretical framework of network capabilities in the framework of "resource-capability-relationship"

The dynamic and complex cooperative relationships of service innovation networks require technology business incubators to use their network capabilities for reasonable management and control to achieve the strategic goals of service innovation (Franco et al., 2018; Chereau and Meschi, 2021; Cepeda-Carrion et al., 2022). Since Ritter et al. (2004) proposed the concept of network capability, many scholars have conducted extensive research on the structure of network capability dimensions (Ávila, 2022), the influence mechanism between network capability and other weighting factors (Yu and Chong, 2005) and the mechanism of network capability operation in different contexts from multiple perspectives and levels (Al-Mubaraki and Busler, 2017), but there is a lack of integration research from a multi-theoretical coupling perspective (Branstad and Saetre, 2016). This study deconstructs network capabilities from three aspects: Resource-based theory, capability theory, and inter-organizational relationship theory. The resource-based theory argues that heterogeneous resources are the root cause for firms to gain competitive advantage (Barney, 1991). Capability theory argues that value arises from a firm's ability to allocate heterogeneous resources (Grant, 1991). Inter-organizational relationship theory suggests that "relational transactions" can spontaneously interact with each other from disorderly and chaotic external relationships, effectively integrating the absorbing capabilities distributed in innovation network relationships and creating new capabilities (Oliver and Ebers, 1998). In the innovation-driven context, the innovation of technology business incubator services is essentially dependent on the incubator's ability to effectively allocate and coordinate the heterogeneous resources, knowledge, and relational rents in the external innovation network with reasonable network resources, and then realize internal and external knowledge exchange, integration and engineering. This paper integrates resource-based theory, dynamic capability theory, and inter-organizational relationship theory, and proposes a theoretical analysis framework of "resource patchwork, absorption capability, and relationship interaction" from the perspective of external network relationship, referred to as "resource, capability, and relationship" theoretical framework.

Network resource patching ability refers to the incubator's ability to fully utilize and develop internal and external resources, and to reorganize and absorb existing resources (Vicentin et al., 2021). The network resource patchwork ability of science and technology business incubators not only creates the environment but also co-evolves with the external environment. It can help incubators identify the form, type, and substitution of resources and carry out resource evaluation, providing strong resource base support for the growth and development of incubators, and then promoting the service innovation of science and technology business incubators. Network cross-organization learning ability refers to the technology business incubators to provide the incubated enterprises innovation learning, and the guest room and third-party professional service (such as technical support, talent recruitment, talent training, production management, marketing management, business consulting, *etc.*) the ability of to the incubated enterprises rapidly correct organizational behavior and change the backward organizational routines, graduated with an acceleration in the incubated enterprises and growth (Zhan and Xie, 2022). It aims to realize the innovation of technology business incubator service. Network relationship interaction capability refers to the ability of technology business incubators to construct an external value relationship network, which aims to build a high-quality network relationship platform for incubators, accelerate the formation of an "active knowledge field" between incubators themselves and network relationship partners, and promote incubators to quickly embed value relationship network. Better access to external heterogeneous resources, specific knowledge, skills, services, *etc.*, to accelerate the development of incubated enterprises.

2.1.1 Network resource patching ability and service innovation performance

If incubators lack network resource patching ability, it will be difficult to identify innovative activities and opportunities in the incubator network. Bøllingtoft and Ulhøi. (2005) proposed that network resource patching ability is the basic ability of incubators to deal with network changes. Through this ability, incubators can better understand the network environment. Teece. (2007) found that network resource patching ability helps incubators to discover the value and potential of partners in the incubator network from a strategic level, and then grasp the evolution trend and development direction of the incubator network (Theodorakopoulos et al., 2014). Therefore, incubators with strong network resource patching ability can better perceive the strategic opportunities in the incubator network (van Weele et al., 2020), so that the services innovation performance of the incubator can be effectively improved. Based on this, the following hypothesis is proposed.

Hypothesis 1. (H1): Network resource patching ability positively affects service innovation performance.

2.1.2 Network resource patching ability and service innovation performance

Liebeskind et al. (1996) argued that network cross-organization learning ability can help incubators complete a relationship network with a sufficient number and type of partners. Oliver and Ebers. (1998) found that enterprises can effectively manage the linkage density of incubators and network partners through network cross-organization learning ability. Ndubisi et al. (2020) suggested that the network cross-organization learning ability of incubators positively influences firms' service innovation. Based on this, the following hypothesis is proposed.

Hypothesis 2. (H2): Network cross-organization learning ability positively affects service innovation performance.

2.1.3 Network relationship interaction capability and service innovation performance

Tsai. (2001) suggests that network relationship interaction capability facilitates knowledge transfer between incubators and partners, thus promoting innovation. Ford. (1980) found that the deepening of partnership helps to complete long-term technology project collaboration and gives firms a competitive advantage. Dhanaraj and Parkhe. (2006) found that stable relationships between partners help incubators' knowledge acquisition and innovation performance. Based on this, the following hypothesis is proposed.

Hypothesis 3. (H3): Network relationship interaction capability positively affects service innovation performance.

2.2 Network capability and absorptive capacity

The concept of absorptive capacity first appeared in a paper published by Cohen and Levinthal. (1990). Absorptive capacity is defined as an enterprise's ability to identify, evaluate and absorb external new knowledge and then apply it in commercial output.

Zahra and George (2002) defined absorptive capacity as the dynamic ability of enterprises to create and apply knowledge to obtain and maintain competitive advantages, which has been recognized by most scholars. Lane et al. (2006) proposed that absorptive capacity is the ability of enterprises to apply external new knowledge through exploration, transformation, and development learning processes. Based on the research of Zahra and George (2002), this paper summarizes absorptive capacity as the dynamic ability of enterprises to acquire, digest and transform external new knowledge and technology, and integrate it into commercial output. In this paper, absorptive capacity is divided into two dimensions: potential absorptive capacity (knowledge acquisition and digestion) and actual absorptive capacity (knowledge conversion and application). The following will study the influence on the two dimensions of absorptive capacity from the three dimensions of network capacity.

2.2.1 Network relationship interaction capability and service innovation performance

As a strategic network capability, network resource patchwork capability focuses on the strategic thinking of incubators' networks (Tavoletti, 2013). Dyer and Nobeoka. (2000) found that the ability to assemble network resources can further clarify the identity of incubators in the enterprise network, to obtain in-depth information and knowledge, thus promoting knowledge acquisition. Mohr and Sengupta. (2002) proposed that the ability to put together network resources can help incubators analyze the knowledge they need from a strategic perspective, enhance learning intention and motivation, and thus promote the digestion and application of knowledge. Based on this, the following hypothesis is proposed.

Hypothesis 4a. (H4a): Network resource patchwork capability positively affects potential absorptive capacity.

Hypothesis 4b. (H4b): Network resource patchwork capability positively affects actual absorptive capacity.

2.2.2 Network resource patching ability and absorptive capacity

As the network capability at the structural level, network cross-organization learning ability can help incubators establish a relationship network with a sufficient number of partners and diverse types (Mohr and Sengupta, 2002). Through the network cross-organization learning ability, incubated enterprises can select key partners and establish direct connections with them to acquire more valuable knowledge, thus promoting the acquisition and digestion of knowledge. Dyer and Singh. (1998) found that network cross-organization learning ability helps incubated enterprises to establish a network of relationships, and promotes joint learning and knowledge exchange among partners, thus promoting knowledge learning and transfer. Kohtamäki and Bourlakis. (2012) proposed that the network cross-organization learning ability builds a platform for mutual learning between incubators and partners, significantly improves the dynamic ability of network organizations, and then promotes knowledge learning and application. Based on this, the following hypothesis is proposed.

Hypothesis 5a. (H5a): Network cross-organization learning ability positively affects potential absorptive capacity.

Hypothesis 5b. (H5b): Network cross-organization learning ability positively affects actual absorptive capacity.

2.2.3 Network relationship interaction capability and absorptive capacity

As network capability at the relationship level, network relationship interaction capability can assist incubated enterprises to deal with, coordinating, controlling, and deepening the connection with partners (Mu and Di Benedetto, 2012). Ebers and Maurer. (2014) first proposed the concept of "relational absorptive capacity", which integrates the connotation of network relationship interaction capacity and absorptive capacity. "Relational absorptive capacity" indicates that the absorptive capacity of an enterprise must be placed in the cooperative relationship of network partners to effectively play the role of network relationship interaction capacity. That is, network interaction ability has a significant impact on absorptive capacity. Yli-Renko et al. (2002) found that for incubators and partners, a high-level network relationship can not only guarantee the efficiency of information acquisition but also improve the quality of information exchange, thus enhancing the potential absorption capacity. Uzzi. (1997) pointed out that the network interaction ability of incubators contributes to the communication and interaction between network partners, thus promoting the transformation and application of external knowledge of incubators and enhancing their actual absorption capacity. Based on this, the following hypothesis is proposed.

Hypothesis 6a. (H6a): Network relationship interaction capability positively affects potential absorptive capacity.

Hypothesis 6b. (H6b): Network relationship interaction capability positively affects actual absorptive capacity.

2.3 Absorptive capacity and service innovation performance

Potential absorptive capacity consists of knowledge acquisition capacity and knowledge digestion capacity (Zahra and George, 2002). Stock et al. (2001) proposed that knowledge acquisition ability can enable enterprises to have a deeper understanding of customers' needs and further promote enterprises to develop new products in a more targeted manner. Dyer and Singh. (1998) found that knowledge acquisition ability, on the one hand, promoted the reduction of product defects in enterprises; On the other hand, shorten the product development cycle effectively and improve the innovation performance. Atuahene-Gima. (2003). believes that knowledge digestion ability can help enterprises in the following two aspects: first, it can help enterprises to speed up problem-solving in new product development; The second is to helps enterprises update the knowledge base in time so that the repetitive work can be effectively avoided. To sum up, the potential absorptive capacity can improve the service innovation performance of enterprises. Actual absorptive capacity consists of knowledge conversion capacity and knowledge application capacity. Todorova and Durisin. (2007) believe that knowledge transformation ability can not only help enterprises restructure their cognitive structure, but also help enterprises get rid of their dependence on knowledge path, to further enhance their competitive advantages. Neergaard. (2005) proposed that knowledge

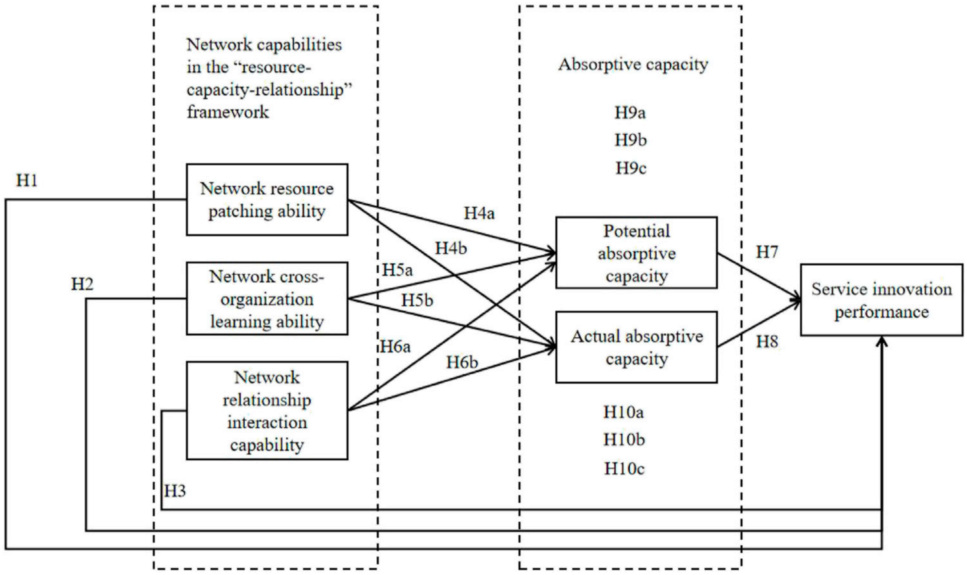

FIGURE 1
Research model.

application is indispensable in the process of transforming resources and information into new products or new ideas for enterprises. Lichtenthaler. (2009) found in his study that to cope with changes in the external environment, enterprises can develop new products only by continuously enhancing their knowledge conversion ability and knowledge application ability. To sum up, the actual absorptive capacity can improve the service innovation performance of enterprises. Based on this, the following hypothesis is proposed.

Hypothesis 7. (H7): Potential absorptive capacity positively affects service innovation performance.

Hypothesis 8. (H8): Actual absorptive capacity positively affects service innovation performance.

2.4 The mediating role of absorptive capacity

This paper constructs the influence mechanism framework of network capability, absorptive capacity, and service innovation performance of technology business incubators under the framework of "resource-capability-relationship", as shown in Figure 1.

3 Data and method

3.1 Data collection and variable measurement

This paper focuses on the influence mechanism between network capacity, absorptive capacity, and service innovation performance, uses the conceptual model proposed by multiple observation variables to measure, draws on mature scales to design and compile questionnaires, and draws on the on-the-job engineering master, MBA, EMBA, *etc.* A total of 65 students took the pre-test, and based on the results of the pre-test, the items of the questionnaire were perfected and revised to form the final questionnaire. The subjects of this survey are technology business incubator executives (chairman, general manager, and senior management), executives of incubating companies, and core members of the innovation team. The research area involves national technology business incubators such as Xi'an High-tech Industrial Park, Shaanxi Province, Qinchuangyuan Innovation Drive Platform of Xixian New District, Shaanxi Province, and University Science and Technology Industrial Park, Shaanxi Province. From June to December 2021, the subject group 6 in-depth interviews were conducted with the research objects and questionnaires were distributed.

The foundations of the study design are in the literature review section. This study utilizes and adjusts scales from earlier studies in which the items and responses were measured range is from "very dissatisfied" to "very satisfied" corresponding to the numbers "1" to "7". Table 1 lists the variables and their measurement methods used in this study. At the same time, a questionnaire survey was conducted on the target enterprises by E-mail. A total of 500 questionnaires were issued, 350 were finally recovered, 116 invalid questionnaires were removed, and 234 valid questionnaires were finally obtained, with an effective rate of 46.8%. The descriptive statistics of the sample are as follows: In terms of gender, males and females accounted for 65.81% and 34.19%; From the scale of the surveyed enterprises, 10% have more than 500 employees, 20% have 301–500 employees, 25% have 151–300 employees, 25% have 50–150 employees, and 20% have less than 50 employees. In terms of positions surveyed, senior executives account for 5.98%, department heads for 36.32%, project managers for 42.73%, and innovation team members for 9.97%.

TABLE 1 Survey variables and measures.

Variable	Measurement item	Sources
Network resource patching ability	Our enterprise can use the resources of the incubation network to develop solutions to new challenges such as the innovation needs of incubators	Senyard et al. (2009)
	Our enterprise can cope with new challenges through the integration and utilization of existing resources and incubation network resources	
	Our enterprise can effectively deal with the incubation problem by integrating and utilizing existing resources that were originally used for other aspects	
Network cross-organization learning ability	Our enterprise can quickly and accurately gain valuable knowledge and experience from the incubation network	Liebeskind et al. (1996)
	Our enterprise is good at coming up with creative improvement measures and solutions	
	Our enterprise can effectively build incubator-wide shared knowledge, experience methods, systems, and platforms	
	Our enterprise often reflects on the past work and draws out the corresponding experience and lessons	
Network relationship interaction capability	Our enterprise is good at identifying intermediaries who hold a lot of related resources	Ritter and Gemünden (2003)
	Our enterprise has set up a functional department dedicated to handling external cooperation relations	
	Our enterprise regularly communicates and interacts with external incubation network organizations in various forms	
	Our enterprise continuously builds, deepens, and improves relationships with external incubation network organizations based on our experience	
Potential absorptive capacity	Our enterprise can pay attention to and collect new technologies and knowledge emerging in the industry promptly	Ritter et al. (2004)
	Our enterprise can accurately assess the value of new technologies and knowledge	
	Our enterprise is in constant contact with the outside world to acquire new technologies and knowledge	
	Our enterprise can quickly analyze and understand the new technologies and knowledge that has been acquired	
	Our enterprise can learn new technologies and knowledge acquired at a faster pace	
Actual absorptive capacity	Our enterprise regularly discusses market trends and new product development matters	Ritter et al. (2004)
	Our enterprise can effectively integrate its existing relevant knowledge and technology with the new technology and knowledge after digestion	
	Our enterprise is better able to use new knowledge to develop new markets	
	Our enterprise can use the new knowledge to improve existing profitability models or launch new business models	
Service innovation performance	New services to meet the dynamic needs of incubators	Voss and Voss (2000), Monica Hu et al. (2009)
	The quality and level of new services exceeded the expectations of incubators	
	incubators are satisfied with the quality of new services provided by the incubator	
	The incubators are satisfied with the new service implementation and cooperation	
	Service innovation has led to a greater increase in the incubation capacity of the incubator	

3.2 Method research

Compared with traditional statistical methods, the qualitative comparative analysis (QCA) method is more suitable for this study. The reasons are as follows: First, different from the traditional regression method which focuses on exploring the "net effect" of a variable, QCA is based on the "configuration theory" and makes a reasonable explanation of the complex causes of the outcome variables by dealing with the multi-factor linkage relationship. Second, unlike the large sample data requirements of traditional statistical methods, QCA only needs small sample data (at least a dozen samples) to establish a causal relationship between the antecedent variables and the outcome variables. Thirdly, compared with the traditional regression method which can only

TABLE 2 Reliability and validity.

Variable	Item	Convergent validity			Cronbach's alpha	Multicollinearity
		Cross loadings	Composite reliability	AVE		VIF
Network resource patching ability (NRPA)	NRPA1	0.931	0.942	0.843	0.907	3.377
	NRPA2	0.942				3.774
	NRPA3	0.881				2.473
Network cross-organization learning ability (NCOLA)	NCOLA1	0.817	0.882	0.651	0.821	1.728
	NCOLA2	0.823				1.811
	NCOLA3	0.795				1.691
	NCOLA4	0.792				1.664
Network relationship interaction capability (NRIC)	NRIC1	0.850	0.915	0.729	0.875	2.110
	NRIC2	0.794				1.693
	NRIC3	0.895				3.719
	NRIC4	0.872				3.268
Potential absorptive capacity (PAC)	PAC1	0.848	0.926	0.717	0.900	3.719
	PAC2	0.883				4.476
	PAC3	0.892				3.397
	PAC4	0.881				2.819
	PAC5	0.718				1.556
Actual absorptive capacity (AAC)	AAC1	0.837	0.904	0.702	0.858	2.162
	AAC2	0.868				2.440
	AAC3	0.849				2.096
	AAC4	0.796				1.686
Service innovation performance (SIP)	SIP1	0.879	0.950	0.792	0.934	4.269
	SIP2	0.884				4.587
	SIP3	0.900				3.610
	SIP4	0.913				4.746
	SIP5	0.873				3.625

deal with the symmetric relationship between variables, QCA allows and can deal with asymmetric causality well.

According to the variable type, QCA is divided into three operation methods: fuzzy set (fsQCA), crisp-set qualitative comparative analysis (csQCA) and multi-value qualitative comparative analysis (mvQCA). Among them, csQCA and mvQCA are suitable for dealing with binary categorical variables and multi-category variables respectively. fsQCA deals with partial membership problems and degree changes by using the membership degree between 0 and 1 to represent the possibility of causal conditions. The variables involved in this study are mostly continuous variables, and there are problems of partial membership and degree changes. Therefore, fsQCA is used to more fully observe the subtle effects of changes in variable combinations under different conditions (Ragin, 2008).

In this paper, PLS-SEM (Hair et al., 2019) and fsQCA (Fiss, 2011) are selected to conduct causal and path analysis of network capacity and absorptive capacity on service innovation performance (Schlittgen et al., 2016). This study employs partial least squares structural equation modeling (PLS-SEM). Like most theoretical exploratory studies, the sample size of this study is relatively small, and the PLS-SEM model is suitable for the empirical analysis of this paper because it applies a non-parametric inference method for exploratory research characteristics (Woodside, 2016), and the sample data do not need to satisfy the normal distribution (Ringle et al., 2012). In this paper, the PLS-SEM model was constructed using SmartPLS3.0 software (Rigdon, 2012). This study employs fsQCA to address H9a-H9c and H10a-H10c. Seny Kan et al. (2016) argue that fsQCA is a novel way to access knowledge on organizations and management issues.

TABLE 3 Discriminant validity—Fornell-Larcker Criterion and Heterotrait - Monotrait Ratio.

	Mean	S.D.	1	2	3	4	5	6
1. Actual absorptive capacity	4.72	1.11	**0.838**	0.811	0.352	0.486	0.607	0.716
2. Network cross-organization learning ability	4.9	1.15	0.681**	**0.807**	0.345	0.438	0.634	0.694
3. Network relationship interaction capability	5.43	1.05	0.307**	0.294**	**0.854**	0.233	0.384	0.443
4. Network resource patching ability	3.81	1.55	0.429**	0.376**	0.21**	**0.918**	0.417	0.567
5. Potential absorptive capacity	5.17	1.17	0.539**	0.548**	0.339**	0.387**	**0.847**	0.634
6. Service innovation performance	5.04	1.06	0.644**	0.611**	0.402**	0.527**	0.589**	**0.89**

Note: Significant level:$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$, Bold diagonal entries are square root of AVEs, Heterotrait-Montrait ratios (HTMT) (Underlined) are below 0.85.

TABLE 4 Significant testing results of the structural model path coefficients.

	Path coefficient	t-value	*p*-value	95% BCa confidence interval	Conclusion
AAC - > SIP	0.257	2.941	0.003	(0.084,0.425)	H8 supported
NCOLA - > AAC	0.581	9.599	0.000	(0.454,0.689)	H5b supported
NCOLA - > PAC	0.426	6.263	0.000	(0.298,0.561)	H5a supported
NCOLA - > SIP	0.192	2.147	0.032	(0.017,0.365)	H2 supported
NRIC - > AAC	0.064	1.87	0.061	(0.015,0.196)	H6b not supported
NRIC - > PAC	0.174	2.649	0.008	(0.045,0.299)	H6a supported
NRIC - > SIP	0.148	2.608	0.009	(0.034,0.258)	H3 supported
NRPA - > AAC	0.191	3.383	0.001	(0.086,0.305)	H4b supported
NRPA - > PAC	0.191	3.036	0.002	(0.068,0.314)	H4a supported
NRPA - > SIP	0.235	4.026	0.000	(0.114,0.343)	H1 supported
PAC - > SIP	0.204	2.927	0.003	(0.061,0.333)	H7 supported

SRMR composite model = 0.067.
$R^2_{PAC} = 0.366$; $Q^2_{PAC} = 0.252$.
$R^2_{AAC} = 0.507$; $Q^2_{AAC} = 0.347$.
$R^2_{SIP} = 0.586$; $Q^2_{SIP} = 0.453$.
5000 bootstrap samples.

4 Result

4.1 Evaluation of measurement model

Using SmartPLS 3.0 for reliability analysis (see Table 2), all construct factor loadings took values ranging from 0.718 to 0.942 (Fornell and Larcker, 1981), all reaching a significance level of $p < 0.001$, Cronbach's alpha took values ranging from 0.821 to 0.934, and composite reliability (CR) took values ranging from 0.882 to 0.950. The internal consistency and combined reliability of the variables were high. The average variance extracted variance (AVE) of all the constructs was greater than the threshold of 0.5, indicating good convergent validity of the model; the square root of AVE of all the variables was greater than the correlation coefficients of the constructs with other constructs, indicating good discriminant validity of the model (see Table 3). The Heterotrait-Monotrait ratio was used to assess the discriminant validity, which is more sensitive for dealing with the validity of variance-based structural equations, and it was found that the ratios were all below the threshold of 0.85 (see Table 3). In summary, the measurement model met the basic requirements of reliability and validity.

4.2 Evaluation of measurement model

The predictive power of the model in this study was evaluated by the internal model explanatory efficacy using R^2 (multiple coefficients of determination), where a higher value of R^2 indicates that the measured variables explain the latent variables better. In this study, AAC explained the model to the extent of 0.507, PAC explained the model to the extent of 0.366, and SIP explained the model to the extent of 0.586 (see Table 4). In general, R^2 is weak between 0.25 and 0.5 and moderate between 0.5 and 0.75 (Afonso et al., 2018). Similarly, all VIF values are below the common cutoff threshold of 5 (Hair et al., 2012). Similarly, results from blindfolding with an omission distance of 7 yield Q^2 values well above zero (Table 4). In summary, the explanatory power of the model in this study is generally in line with the requirements.

TABLE 5 Calibration positioning points of case variables.

Variables		Locating point		
		Full membership	Crossover point	Full non-membership
Outcome variables	SIP	7	5	3.71
	NCOLA	6.5	5	3.5
	AAC	6.25	4.75	3.25
Conditional variables	NRPA	6	4	1.33
	PAC	7	5	3.89
	NRIC	7	5.5	4

4.3 Fuzzy set qualitative comparative analysis (fsQCA) approach

QCA is based on set theory and holistic perspective (Fiss, 2011) and is able to explain the composition of antecedents that lead or do not lead to a certain outcome. Based on the research model, fsQCA is used to analyze the complex antecedents of service innovation performance of technology incubators by taking service innovation performance as the outcome variable, as follows: firstly, the raw data are calibrated to obtain fuzzy affiliation scores; secondly, all antecedent variables are tested for necessity conditions; finally, the combination of sufficient conditions is determined using truth table analysis (Rihoux and Ragin, 2009).

4.3.1 Calibration procedure

"Calibration is the process of assigning an ensemble affiliation score to a case" (Fiss, 2011). Ragin. (2008) defines fuzzy sets as fully affiliated, intersection, and fully unaffiliated to establish the association of variables with fuzzy sets. It is centered on combining multiple aspects to select 3 reasonable anchors and explanations for the variables, typically 95% high-quantile, median (50%), and 5% low-quantile of the sample data.

The results and calibration information for each conditional variable are listed in Table 5.

4.3.2 Analysis of necessary conditions

The QCA method includes two types of analyses, necessity analysis of conditions and group state analysis of conditions, which are performed separately and necessity analysis is performed prior to group state analysis of conditions. The necessity test identifies the extent to which a single factor or variable influences the results. The QCA method is case-oriented, and the results of the QCA path analysis may be erroneous if a single variable plays a decisive role in the results. Therefore, in the early studies of the QCA method of necessity analysis, scholars had different views on whether the necessary conditions should be retained or not, and when the necessary variables are not identified and the group analysis is performed directly, there is a risk that the necessary conditions will be eliminated by the minimization process. The necessity test usually requires a minimum value of 0.9 for consistency, above which the variable is considered necessary for the outcome to occur, and its corresponding coverage is an important indicator of the empirical relevance of the necessity condition in the

TABLE 6 Analysis of necessary conditions.

Conditional variable	High-level SIP	
	Consistency	Coverage
NCOLA	0.789263	0.810349
~ NCOLA	0.616619	0.555546
AAC	0.813991	0.801877
~ AAC	0.580062	0.542719
NRPA	0.761614	0.749419
~ NRPA	0.565902	0.530049
PAC	0.851667	0.763229
~ PAC	0.546508	0.564550
NRIC	0.748524	0.719329
~ NRIC	0.632815	0.606535

necessity analysis (see Table 6). Following the recommendations from Ragin. (2008) and Fiss. (2011), this study sets consistency and PRI consistency thresholds to 0.8 and 0.5, respectively, thus identifying the solutions that lead to high service innovation performance.

4.3.3 FsQCA solution

The results of high service innovation performance were calculated by fsQCA3.0, and since the intermediate solution is more likely to reflect the actual results, the intermediate solution was used for the analysis (Rihoux and Ragin, 2009), resulting in four antecedent condition groupings of high service innovation performance (see Table 7). the consistency values of the four high service innovation performance groupings were 0.924, 0.925, 0.910, and 0.940, with an overall consistency of 0.881. This indicates that the four histories are sufficient conditions for achieving high service innovation performance when the majority of cases are satisfied; the overall coverage is 0.766, thus explaining 76.6% of high service innovation performance. From the results, fsQCA effectively identifies the four histories of high service innovation performance and has strong explanatory power, which validates the antecedent construct of high service

TABLE 7 Configurations of high service innovation performance.

Conditional configuration	Path			
	Network capability orientation		Absorptive capacity orientation	
	Configuration 1	Configuration 2	Configuration 3	Configuration 4
NCOLA	●	●	●	
AAC	●		●	●
NRPA	●	●		●
PAC		●	●	●
NRIC				⊗
Raw coverage	0.599223	0.600318	0.644775	0.424682
Unique coverage	0.0488294	0.0499247	0.0943816	0.0221214
Consistency	0.923954	0.925465	0.910224	0.939979
Solution coverage	0.765651			
Solution consistency	0.880854			

Note: The black circles (●) denote the presence of a condition, whereas the crossed-out circles (⊗) indicate the absence of one (Ragin, 2008). Core elements of a configuration are marked with large circles (prime implicants), peripheral elements with small ones and blank spaces are an indication of a "don't care" situation in which the causal condition may be either present or absent (Mikalef et al., 2015).

innovation performance due to the asymmetric characteristics of the histories.

Configuration 1 and configuration 2 are network capability orientation configurations. Configuration 1: Network cross-organization learning ability, network resource patching ability, and actual absorptive capacity are the core conditions. Configuration 2: Network cross-organization learning ability, network resource patching ability, and potential absorptive capacity are the core conditions. This sort of configuration shows that in the "network capability orientation" incubator network, the two dimensions of incubators' network competence are the key to achieving high service innovation performance. That is, if the network capability of the incubator network is based on network cross-organization learning ability and network resource patching ability as the main index, then the incubators should also pay attention to the cultivation of the network capability in terms of learning, coordination, and resources. This highlights the truth that "It takes a good blacksmith to make good steel."

Regarding core conditions, configuration 3 and configuration 4 embody the feature of "high absorption". They indicate that when potential absorptive capacity and actual absorptive capacity play a prominent role in the incubator network, the incubators' network-network resource patching ability and network cross-organization learning ability are the key to achieving high service innovation performance. It further shows that when incubators value "absorptive capacity", orchestrating resources (network resource patching ability) and maintaining cooperative relations (network cross-organization learning ability) are the necessary competencies for incubators to achieve high service innovation performance. Specifically, configuration 3 shows that if potential absorptive capacity and actual absorptive capacity are important network capacity elements, incubators need strong network cross-organization learning ability to make up for it. Conversely, as shown in configuration 4, if network relationship interaction capability is not important, network resource patching ability should become the important factor of the network capacity to ensure the realization of high service innovation performance.

This study concludes on the asymmetrical nature of the causal relationships leading to high service innovation performance. Overall, the fsQCA results provided in Table 7 support H9a, H9b, H9c, H10a, and H10b, and not support H10c. The results of fsQCA once again support the results in PLS-SEM.

4.4 Robustness test

We used standard methods to conduct a robust analysis of QCA results. The commonly used methods are: Adjust the calibration threshold, change the consistency threshold, add or delete the shell, change the frequency threshold, and add other conditions. Method 1: Referring to the practice of Fiss, the robustness test is carried out by adjusting the crossing point of calibration. Specifically, the crossing point is adjusted from 0.5 to 0.55. The number of configurations and the neutral permutations with the same core conditions but different edge conditions all changed slightly, but the changes were not enough to support meaningful and completely different substantive interpretation method 2. Referring to the set relation and quasi-sum difference of configurations proposed by Schneider and Wagemann. (2012) as the judging criteria, this paper reduced the consistency threshold from 0.8 to 0.75 and found that the research configurations were still supported. Therefore, the research conclusions of this paper are still robust.

5 Discussion

5.1 Theoretical contribution

The important theoretical contribution of this work is twofold.

Firstly, Network capacity has a significant positive impact on absorptive capacity under the framework of "resource, capacity and relationship", and absorptive capacity as a mediating variable has a significant positive impact on the service innovation performance of technology business incubators. In the service innovation process of technology business incubators, the absorption and application of knowledge by subjects build cross-organizational network cooperation based on trust (Nicotra et al., 2014; Ratten, 2016; Proeger, 2020). Only technology business incubators can fully utilize their own multi-dimensional and multi-module network capabilities to plan, coordinate and operate inter-organizational network relationships, thus facilitating incubators to fully develop their matching absorption capabilities (Dell'Anno and del Giudice, 2015; Franco et al., 2018; Kastelli et al., 2022). In turn, it can meet the real needs of incubators, improve incubation capacity and gain sustainable competitive advantages. First, the key to achieving innovation in technology business incubator services is to fully draw on and utilize the various value-based resources in the innovation incubation network relationships. The ability of technology business incubators to use network resources can help promote the aggregation and sharing of external horizontal and vertical innovation resources, enhance the effect of heterogeneous resource flow and transfer, and achieve efficient resource allocation and high-speed knowledge flow in the context of open innovation networks; second, the realization of knowledge accumulation in technology business incubators is based on the organizational learning ability of innovation incubation networks. Network organizational learning ability is an important method and path for technology business incubators to acquire value-based knowledge from external innovation networks, which can effectively prompt incubators to draw and store knowledge. At the same time, through knowledge integration, new knowledge and technologies are internalized into its own knowledge capabilities to provide quality incubation services for incubators and then realize service innovation; thirdly, technology business incubators make full use of network relationship interaction capabilities to maximize the integration and configuration of innovation incubation network relationships through comprehensive, multi-dimensional and multi-level in-depth interaction and communication, and are committed to building value co-creation. The "relationship rent" innovation network, with close cooperation and interdependence among them, lays the foundation for the technology business incubator to be in the active "knowledge field", and then realize knowledge accumulation and achieve the service innovation goal.

5.2 Management implications

This paper shows that the network capacity and absorptive capacity of incubators play an important role in the process of service innovation performance improvement. Therefore, the following 2 insights can be drawn.

Firstly, Technology incubators should strengthen resource acquisition and accumulation, and numerous studies have shown that incubator service innovation in China lacks the necessary capital, technology and talent. This study shows that incubator service innovation relies more on external resources, and with the construction of a large science and technology country to a strong science and technology country, network capacity and absorptive capacity are bound to become the source of competitive advantage for enterprises. First, incubators should focus on internal resource accumulation, strengthen the investment in the elements needed for service innovation, and strive to build core capabilities for service innovation. Second, external resources should be actively incorporated into the incubator service innovation network, and exchanges and learning with external incubators should be strengthened through building third-party platforms and supply chain collaboration to enhance the incubator's service innovation capabilities; finally, incubators should choose a service innovation enhancement path suitable for their own characteristics based on their own resource endowments. Secondly, incubators should pay attention to and enhance absorptive capacity. incubators should not only pay attention to and enhance the potential absorptive capacity to strengthen the acquisition and digestion of knowledge, but also pay attention to and enhance the actual absorptive capacity to strengthen the conversion and application of knowledge, thus enhancing service innovation performance.

6 Conclusion

This study constructs a theoretical framework and hypotheses of the impact of network capability within the "resource-capability-relationship" perspective, absorptive capacity on service innovation performance of technology business incubators. This study uses 234 Chinese incubators in the incubator network as samples and applies partial least squares structural equation modeling (PLS-SEM) and fuzzy-set qualitative comparative analysis (fsQCA) to explore the questions mentioned above. The following conclusions are drawn:

Firstly, according to the empirical results, it can be seen that 12 hypotheses in the conceptual model of this study passed the statistical test and 2 hypotheses did not pass the statistical test. The results show that the conceptual model proposed in this paper is better validated.

Secondly, in the service innovation process of technology business incubators, network capability (network resource patching ability and network cross-organization learning ability) has a significant positive impact on the service innovation performance of technology business incubators through the mediating role of absorptive capacity, and network relationship interaction capability has a positive impact on the service innovation performance through potential absorptive capacity.

Thirdly, the findings of this paper have important theoretical significance and practical value for the construction and management of innovation incubation network and efficient allocation of innovation resources, and the improvement of service innovation performance of technology business incubators. It provides policy suggestions and practice paths for incubator managers and decision makers.

7 Limitations and future research

There are still some shortcomings and areas for improvement in this paper. Firstly, the research sample of this paper is mainly selected from strategic emerging industries, and the single industry makes the scope of application of this paper needs to be further discussed and verified, and future research can try to expand the scope of industry research. Second, this paper only uses cross-sectional data in the empirical study, which may be biased, and future studies can try to use longitudinal comparative data. Finally, there may be collaborative effects of network capacity and absorptive capacity on the innovation performance of incubator services, which are considered but not in depth in the fsQCA approach, and their substitution or synergistic effects can be further studied in the future.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the participants was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

Methodology and software, HD and RM; formal analysis, HD and JL; resources and data curation, HD; investigation, HD; writing-original draft preparation, HD; writing-review and editing, HD and RM; supervision and project administration, JL; All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

Authors HD, RM, and JL are employed by Shaanxi Provincial Land Engineering Construction Group Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Empirical analysis of R&D spending, transport infrastructure development and CO_2 emissions in China

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Over the past few decades, the transportation sector has been the largest contributor to CO_2 emissions in China. Research and Development spending leads to technological innovation in the country and could affect the CO_2 emission in the country. Therefore, this study analyzes the nexus between CO_2 emissions, transport infrastructure and R&D spending in China. A QARDL approach was used for the data analysis, which revealed Research and Development and Transport infrastructure has a positive impact on CO_2 emissions. R&D was only significant in the first 25% quantile, while transportation was significant in almost all quantiles. These results suggest that R&D spending in China is mainly allocated to the sectors that emit the CO_2 emission. It is recommended that government should allocate more R&D to carbon-reducing sectors. Furthermore, the government should consider green transportation investments and renewable energy projects in the transportation sector to reduce CO_2 emissions in the country.

KEYWORDS

R&D spending, transport infrastructure development, CO_2 emissions, QARDL, China

1 Introduction

Research and development (R&D) spending has been attracting interest in research and academic contexts due to its impact on innovations in different sectors of the economy. In the transport sector, R&D spending has played a significant role in developing new tools, designs, and solutions that promote transport infrastructure efficiency and reduce CO_2 emissions (Lin and Chen, 2020). R&D investments have been associated with improvement in different aspects of infrastructure. The government's expenditure on generating innovations, knowledge and processes is essential in providing solutions to current challenges facing transport infrastructure (Saboori et al., 2014). Through R&D, new transport infrastructures can help provide cost-effective, disaster-resilient, long-lasting, environmentally friendly, and safe roads and railways. Consequently, a high level of service and efficiency can be achieved, contributing to developing a sustainable transport

Abbreviations: CO_2—, Carbon Dioxide; FS—, Fossil Fuel; R—, Research and Development Spending; T—, transport development; QARDL—, Quantile ARDL; SCP—, Structure-Conduct-Performance; ECM—, Error Correction Model; WDI—, World Development Indicator; JB—, Jarque-Bera.

system (Frazier, 2010). Furthermore, R&D spending can be used to address the problems associated with the cost and durability of infrastructure. In order to realize self-healing and self-monitoring transport systems, new tools, methods, and test procedures can be developed through research. Long-life, high-performance, and advanced materials for infrastructure construction can reduce reconstruction and maintenance costs (Lounis and McAllister, 2016). Nevertheless, research indicates that R&D spending coast is high and maintaining such a budget may increase government expenditure (Rust and Sampson, 2020). High-speed rails and highways have been developed in China as a model for other countries. As of 2021, the country had highways exceeding 169,000 km (Liu and Wang, 2022). According to Mouhamed et al. (2017) Chinese transportation infrastructure has replaced the traditional transport structure; the port infrastructure has evolved into one of the most modern ports, the highway mileage used by traffic has increased to the second position, and the railway business has reached the third position, which includes the largest passenger and freight traffic as well as establishes the most important airports and aviation services in the world. Due to the rapid development and improvement of infrastructure in China during the last 4 decades, it is essential to examine how R&D has contributed to development and innovation in the transport sector. Although transport infrastructure has brought significant prosperity of economic growth and social development, it is the main factor responsible for environmental degradation (Ozcan et al., 2020).

There are significant externalities associated with the construction of transport infrastructures, as well as a long operational cycle and large-scale investment that have irreversible effects on the environment (Luo et al., 2018). For instance, constructing roads, rails, and ports requires using machines powered by fuel, which emit significant amounts of carbon dioxide into the environment (Huang et al., 2020). A recent study has revealed that China has the highest level of CO_2 emissions from the transportation sector in the world (Xu et al., 2022). Since the Chinese transport sector is experiencing rapid growth, issues such as traffic flow, demand for transport, active transportation, and increased usage of diesel and gasoline will contribute to high levels of CO_2 emissions (Khanali et al., 2021). The expansion of highway and rail networks contributes to CO_2 emissions by promoting inter-regional activities, for example, the transportation of goods and industrial and manufacturing processes dependent on transportation. However, Kim and Lee, (2019) found that increased road and rail mileage results in increased transport mobility and reduced distance and travel time, which leads to decreased CO_2 emissions. In contrast Tao and Chao, (2019) reported that transport infrastructure development does not have a direct impact on the amount of CO_2 emissions generated by the users of roads, airlines, rails, and ports. There further argued that various factors, including the ability of people to purchase more vehicles, planes, water vessels, and trains, can affect the amount of CO_2 emissions produced. Due to these conflicting viewpoints, there is a need for additional research to fill these gaps. In spite of the fact that green transport infrastructure is still at an early stage of development, the costs associated with implementation are high (Melo et al., 2020). Consequently, countries like China, which have heavily invested in non-green transport infrastructures, are increasingly using normal transport infrastructures despite the negative impact on the environment. To support green infrastructure, it is necessary to understand the extent to which infrastructure contributes to environmental pollution. There is a conflicting debate regarding whether R&D development and digitalization reduce or increase CO_2 emissions, despite the positive impacts of R&D development, particularly in the business world (Umar et al., 2020; Ramos-Meza et al., 2021). The important aspect of R&D activities is that it makes recommendations regarding green transport infrastructures, such as electric rails and electric vehicles. In the transport sector, these green solutions contributed to significant reductions in CO_2 emissions. (Sohail et al., 2021). However, the implementation of green transport infrastructure is limited due to its high cost. Research and development spending in the field of green transportation focuses on the design, production, and commercialization of new technologies that can reduce the environmental impact of transportation. This can include investments in the development of electric vehicles, hybrid powertrains, and sustainable transportation infrastructure, as well as efforts to improve the efficiency of existing technologies and systems. Governments, private companies, and research institutions can all contribute to research and development spending in the field of green transportation. The goals of these efforts typically include reducing greenhouse gas emissions, reducing dependence on fossil fuels, improving energy efficiency, and reducing the overall environmental impact of transportation. Petrović and Lobanov (2020) found that 1 percent of R&D investments reduces CO_2 emissions by 0.09%–0.15% on average. In addition, studies have found that R&D activities in the transport sector can only have a significant impact on reducing CO_2 emissions in the long run, while it may not affect CO_2 emissions. Other studies have found that increased R&D expenditures increase CO_2 emissions; For instance, Koçak and Ulucak (2019) Research, revealed no significant relationship between renewable energy, R&D expenditures and CO_2 emissions. Research and development activities could increase emissions if the R&D activities involve the use of resources which contribute to the CO_2 emissions. R&D activities at a higher level are expected to reduce pollution in the country; however, it may take a long time to achieve certain environmental objectives due to various social and economic constraints. Since literature has conflicting results on R&D spending, transport infrastructure and CO_2 emissions. It is essential to re-examine this phenomenon with advanced statistical techniques. Co_2 emissions and R&D spending both have an increasing trend in China economic history; therefore, it is essential to estimate the relationship between R&D spending, transport infrastructure development, and CO_2 emissions in China, which may help to understand the impact of R&D spending and infrastructure development on the environment. As one of the largest economies and emitters of greenhouse gases, China's actions in these areas could have global implications. The study could suggest some policy recommendations and contribute to efforts to reduce emissions and promote sustainable development. Therefore, the main objective of this paper is to investigate the relationship between R&D spending, transportation infrastructure and CO_2 emission in China. There are several ways in which this research could provide new insights that can help to bridge the existing research; firstly, according to the best of our knowledge, there is no study that interlinks the R&D spending and transportation infrastructure in the context of China. Secondly, we use the case of China for our study; since infrastructure has significantly improved in China, the transport infrastructure has significantly increased in the last few decades in China; therefore, this study will provide implications of transport infrastructure for the CO_2 emission in China. Thirdly, we applied a novel QARDL technique, which provides robust results compared to the past studies, and better policy recommendations can be established in the reliable results. The rest of the paper is organized as section 2 contains the review of the literature. The second three trend of transportation, CO_2 emission and R&D in and four and four provides methodology, results and discussion; respectively, the section explains the conclusion of the study.

2 Review of literature

Marrero et al. (2021) investigated the relationship between road transport and CO_2 emissions among 22 countries in Europe. Their finding reveals that road transport and related infrastructure released 27% of the total emissions in the countries. Furthermore, they concluded that most of the CO_2 emissions associated with road transport are caused by the burning of fossil fuels, which implies that the amount of CO_2 released into the atmosphere is primarily determined by the amount of energy consumed.

Pani et al. (2021) analyzed the ten largest countries of the world to determine how freight transport impacts carbon emissions. CO_2 emissions from freight transport and infrastructure construction are the most significant contributors to CO_2 emissions in these countries. Truck vehicles were mainly responsible for stimulating the demand for energy in transportation and shipments. Therefore, these trucks deteriorate the environment by burning fossil fuels. Cardenete and López-Cabaco (2021) investigated the case of Spain and reported that freight transport is one of the most cost-effective methods of transporting cargo, but it contributes 30% more CO_2 emissions than other means of transportation. Arvin et al. (2021) also found similar results for Germany. The diesel and gasoline transport system released the most significant amount of CO_2 into the atmosphere. According to these findings, highways and roads used by trucks and other types of vehicles indirectly impact transport infrastructure. Umar et al. (2020) Examined the impact of fossil and biomass energy consumption on CO_2 emissions in the United States. transportation sector for the period 1981–2019 and used Spectral Breitung Candelon causality test, cointegration regression. The results of their study indicated that biomass energy is negative to carbon dioxide emissions. However, fossil energy consumption had a significant and positive impact on CO_2 emissions. In addition, they found a U-shaped inverted curve relationship between total energy consumption and carbon dioxide emissions. The study conducted by Hussain et al. (2020) found contrasting results. In their study, different dimensions of infrastructure were considered, such as soft and hard infrastructure in Asian countries. Their findings suggest that transportation infrastructure and CO_2 emissions were negatively correlated. Additionally, their results indicated that infrastructure development is a significant factor in CO_2 emissions. Still, increased climate change in Asia was found to reduce the level of transport activities, reducing emissions through critical infrastructure. Despite these findings, it was found that level of transport activities reduces climate change in a given Asian region, thereby reducing the emission levels through critical infrastructure.

Churchill et al. (2019) investigated the relationship between R&D intensity and CO_2 emissions in the transport sector in selected seven countries for the period 1870–2014, and results are extracted using non-parametric linear estimates. It was found that between 1955 and 1990, the intensity of R&D led to an increase in CO_2 emissions, and between 1990 and 2014, CO_2 emissions decreased. This suggests that other factors could have contributed to the variation in results. Koçak and Ulucak (2019) investigated how R&D expenditures affected energy consumption in transport infrastructures and transport in member countries of the OECD using the period 2003–2015. They applied regression analysis and suggested no relationship between R&D spending and CO_2 emissions in the OECD countries. Nevertheless, they discovered that R&D expenditures on storage and power contributed to reducing CO_2 emissions. Petrović and Lobanov (2020) examine the relationship between R&D spending and CO_2 emissions for 16 OECD countries. The study used panel data from 1981 to 2014 and applied regression models for analysis. According to their findings, growth in R&D investments reduced the amount of CO_2 emissions in the long run. Nevertheless, the results from individual countries indicated that the impact could either be negative or positive. Based on their study, "in most cases, higher R&D expenditures result in lower CO_2 emissions, but this does not apply to 40% of countries. Sohail et al. (2021) studied the association between green transport and environmental pollution, suggested that green transport helped to reduce the amount of CO_2 emissions. Specifically, their findings indicated that countries investing heavily in green energy, such as electricity, could have a minimal impact on CO_2 emissions. Similarly, Oryani et al. (2021) explored the effectiveness of renewable energy in promoting a sustainable environment. They reported the adoption of green transport CO_2 emissions *per capita* in the country. In the literature, it has been found that transport infrastructure is positively related to CO_2 emissions. In addition, R&D and CO_2 emission have mix findings.

Hidalgo Nuchera et al. (2009) examined the impact of adopting R&D on the transport and logistics industry. Their study adopted Structure-Conduct-Performance (SCP) model. In the transport and logistics sector, the level of IT knowledge and skills among employees was among the most important factors in facilitating R&D adoption. Additionally, their findings suggested new transportation models, new knowledge and supply chains emerging in the industry due to the adoption of R&D. Rust and Sampson (2020) used a system-based R&D management model to investigate the role of road and transport engineering in helping communities access roads and other transportation services. Their findings revealed that the systems-based approach had been demonstrated to improve the impact assessment indicators of R&D programmes for community access roads and transportation. In other words, the transport system is improved to provide solutions to the challenges facing road users. Parast, (2020) examine R&D mitigated challenges and disruptions experienced by United States firms. R&D was found to be a key

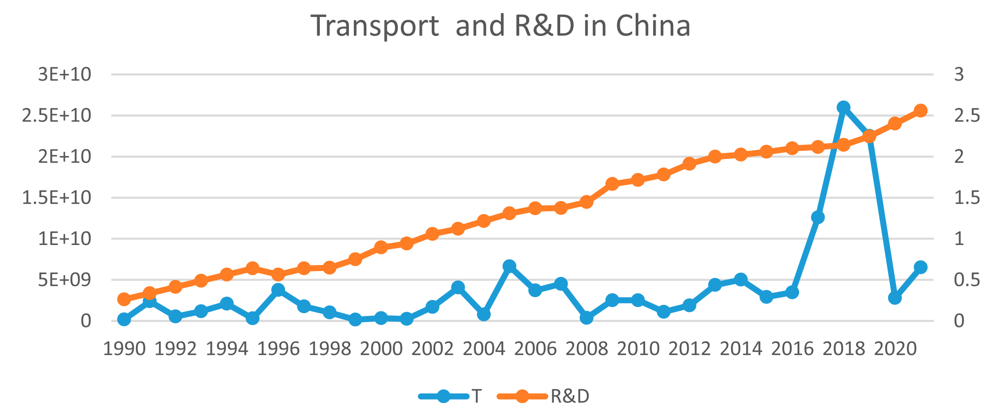

FIGURE 1
Transport and research and development (R&D) spending in China.

factor in the development of new models that contributed to improving the transport sector's resilience capabilities. Innovations improve resilience; it helps address challenges such as disruptions in demand, supply, and processes.

Kahouli, (2018) examine the impact of innovation on carbon emissions in the transportation industry, both in developed and developing Mediterranean countries. The results suggest that increases in innovation in developing nations lead to a reduction in carbon emissions from transportation. In developed countries, more innovation in the transportation sector is expected to result in a reduction in carbon. R&D innovation has long been recognized as an essential tool in reducing carbon emissions from transportation. The transportation sector can improve its energy consumption patterns through scientific research. J. Zhang et al. (2022) suggests that the growth of the digital economy lowers carbon emissions because it improves the energy structure by reducing the demand for fossil fuels. Arslan et al. (2022a) suggested that growing urban populations, merchandise trade, and financial development contribute to environmental degradation. Arslan et al. (2022b) argued that in modern research, the adverse impacts of climate change had increased the importance of sustainability disclosures. Furthermore, Bilal et al. (2022) suggests that companies with more carbon emissions have better financial reporting quality, indicating a negative relationship between carbon emission disclosures and discretionary accruals. Adebayo et al. (2022) among the other factors, the recent emergence of COVID-19 effect CO_2 emissions, and they suggested that COVID-19 decreases the CO_2 emissions in United Kingdom.

3 Trend of transpiration, R&D and Co2 emission in China

Figure 1 illustrates the trends in transportation and research and development (R&D) in China from 1990 to 2021. According to the data, R&D has increased significantly from 1990 to 2021, although this trend levelled between 1995 and 1996. China has significantly invested in R&D for the past 20 years, which explains this trend. China's National Bureau of Statistics reports that investment in R&D accounted for 2.4% of the total gross domestic product. For instance, the country had 350 national engineering research centres and 522 national key laboratories in 2020 (Daily, 2022). According to a 10-year comparison with European countries, China's R&D is currently higher than the Europeans' average. According to Shead (2021), in 2020, China's spending on research and development increased 10.3% to 2.44 trillion Chinese yuan ($378 billion). China invested $405 billion in research and development in 2020, which is 14.6% increase over the previous year. It should be noted, however, that despite this rising trend in research and development, the trend in transportation shows fluctuating in the given period. Based on the information provided in the data, it is difficult to conclude that R&D contributed to the improvement of the transport system in China. For instance, in the graph, China's transport went to zero in the years 1990, 1992, 1995, 1999–2004, and 2008 despite rising investments in R&D. However, between 2004 and 2005 there was a rising trend in the improvement of transport. Also, there is an upward trend from 2013 to 2018, which then drops dramatically in the year 2020. The drop-down in public and private transport investment after 2018 mainly occurred because the Chinese government gave attention to the cross-border transportation infrastructure. Since China introduced its Belt Road initiative, which led to the development of tarns-continental passages connecting China with Asia and Europe by land and sea (Zhao, 2020), these initiatives created investment opportunities in aboard, and large investments have been diverted abroad. China reported that "in 1949, the total railway length of the country was only 21,800 km, of which half was barely functional. A total of 52,000 km of railway were operational by the end of 1978. Approximately 132,000 km of railways were in operation in China by 2018, five times longer than in 1949, with a 2.6% annual growth rate. (Special Report, 2019). Still, the introduction of high-speed trains in the country had reached 29,000 km, which was more than two-thirds of the total. In terms of roads, specifically expressways, China has the longest expressway in the world at 143,000 km (Ke and Yan, 2021). It is difficult for a country like China to achieve such innovative transport infrastructure without the help of R&D, despite the

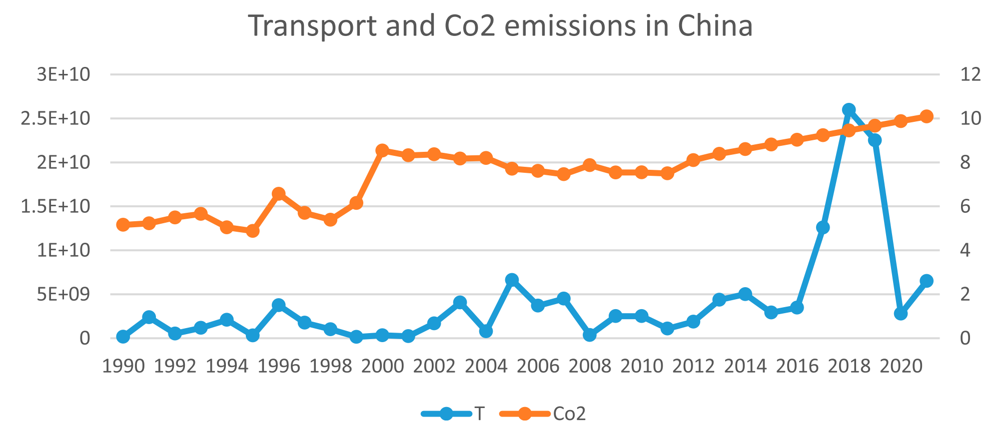

FIGURE 2
Transport and CO_2 emissions in China.

graphical data barely illustrating the impact of R&D and transport improvements. Thus, the statistical analysis is required to understand the linkages between R&D and transport upgradation.

Figure 2 shows trends in transport and CO_2 emissions in China between 19,990 and 2021. In general, the graph shows that transport and CO_2 emissions tend to follow similar trends. Between 1990 and 1992 there was a spike in transport development and the amount of CO_2 emissions. There was a slight decline in both transport and CO_2 emissions between 1994 and 1995, which was followed by an increase in both. There was a gradual decrease in CO_2 emissions between 2000 and 2011, transport had a rising and dropping trend during this period, and between 2016 and 2020, the transportation sector is expected to experience a rapid increase. CO_2 emissions, however, remain the same during this period. The trend of CO_2 emissions has generally been rising from 1990 to 2021, while the trend for transport has been rising and dropping, and there have been several spikes or fluctuations during this period. In China, the transport sector accounted for 9% of all CO_2 emissions, which makes it the third largest source after the building sector and the industrial sector. Considering that the construction of transportation infrastructures typically requires the use of fossil fuels and it is expected that it might have a higher percentage. Additionally, China's vehicle ownership ratio is a major contributor to its current and future CO_2 emissions. Based on the study, only 200 people out of a thousand own a vehicle, which is a bit lower than in other countries such as United States and the European Union.

According to Bank (2021), it is challenging to decarbonize the transportation sector, particularly as the number of people purchasing vehicles in middle income countries like China continues to increase rapidly. It is projected that China will consume 50% less energy and emit 80% less CO_2 by 2050 in the transportation sector (K. Zhang et al., 2019). In response to the increased emission of CO_2 in the transportation sector, China has adopted a series of mitigation measures, including the adoption of CO_2 emission standards and the acceleration of the electrification of vehicles. Although China's EV market share is set to exceed 80 percent by 2050, soaring motorization rates would still result in excessive carbon dioxide emissions from transportation by 2050. Consequently, China faces a challenging situation due to the increased number of vehicles on the roads.

Figure 3 above shows the trends in CO_2 emissions and R&D spending in China between 1990 and 2021. According to the graph above, there is an overall upward trend in the amount of CO_2 emissions and R&D spending in China. The country's R&D expenditures increased continuously between 1990 and 1995. In 1996, this trend slightly decreased, after which a rising trend continued until 2021. In the period 1990–1993, CO_2 emissions increased steadily. CO_2 levels slightly declined between 1994 and 1995, followed by a spike; there was a gradual decrease in CO_2 emissions between 2000 and 201, while CO_2 emissions steadily increased after 2012. These trends go beyond the expectations that R&D would help reduce CO_2 emissions to the environment. Research indicates that most environmental innovations in China were successful in reducing carbon dioxide (CO_2) emissions. Li and Wang (2017) examined 95 countries between 1996 and 2007 for the impact of technology shifts on CO_2 emissions.

The results indicate that technological progress has a negative effect on CO_2 emissions when only magnitude and intensity are considered. Lee and Min (2015) studied the influence of green research and development investment on CO_2 emissions and the financial performance of Japanese manufacturing enterprises. Their findings indicate that funding green research and development negatively impacts carbon dioxide emissions. Garrone and Grilli, (2010) analysed the public spending in energy R&D on carbon emissions for 13 industrialized countries between 1980 and 2004. This study indicates that government investments in energy R &D do not affect CO_2 emissions.

4 Methodology

Climate change, environmental dextrorotation, and temperature are continuously increasing, and it is recognized that carbon emission is a crucial factor in determining environmental pollution. Therefore, to enlist the influence of fossil fuel utilization, transportation, research and development are

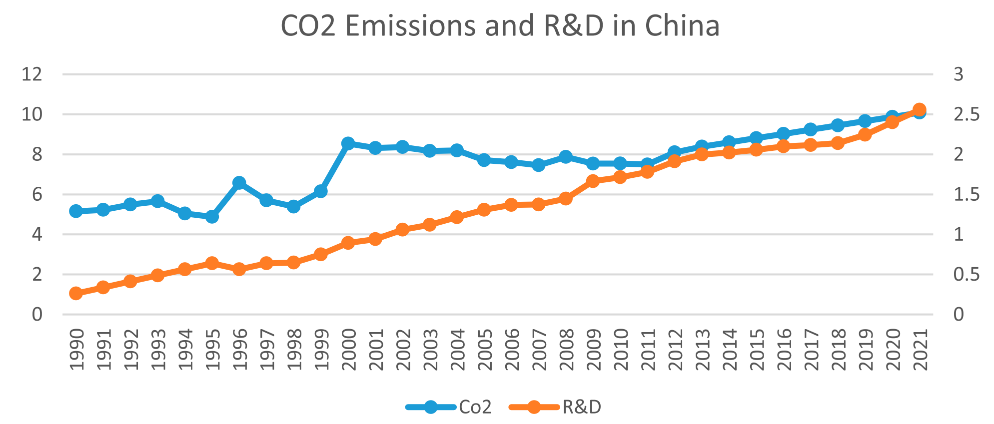

FIGURE 3
CO_2 emissions and R&D Spending in China.

arranged to capture the impact on carbon emissions. Several researchers employed various methods to investigate the implication of R&D, and transportation on CO_2 emission. The following model is used for the data analysis

$$CO_2 = \beta_0 + \beta_1 FS + \beta_2 T + \beta_3 R + \mu \tag{1}$$

The above equation presents a linear form of the baseline model; the CO_2 presents the CO_2 emissions in the country, which is the dependent variable. FS is the fossil fuel consumption; T is the transport development and R is the research and development spending China, FS, T and R are the explanatory variables. According to theory, FS and T has a positive effect the CO_2 emissions. While is assumed either positive or negative association with CO_2 emissions. μ is the error term which is assumed to uncorrelated with explanatory variables. The current study used the QARDL model formulated by Hashmi et al. (2022). Quantile ARDL is preferred over conventional ARDL in several aspects. Firstly, quantile ARDL provide more a more comprehensive analysis by allowing for the estimation based on different quantiles of the distribution. Secondly, Quantile ARDL is particularly useful in cases where the relationship between variables is non-linear and heterogeneous, as it allows estimation at different points of the distribution. Thirdly, the advantage of quantile ARDL over conventional ARDL is that it provides a better understanding of the distributional characteristics of the data, such as skewness and kurtosis properties of the data. Fourthly, the QARDL the estimations are based on the various quantiles, and there is possibility that each quantile may provide dissimilar results, which help to suggest suitable policy recommendations based on the outcomes and variations in the results in different quantiles. This method allows us to investigate the long-term equilibrium quantile relation between transportation and R&D on carbon emissions. QARDL is a more sophisticated type of the "ARDL model" that checks for variations in transportation carbon dioxide emissions and R&D spending. It will be helpful when investigating temporal and spatial symmetry and the simplified version of ARDL looks like this:

$$CO2_t = \varepsilon + \sum_{i=1}^{n} \vartheta_{1i} CO2_{t-i} + \sum_{i=0}^{m} \vartheta_{2i} FS_{t-i} + \sum_{i=0}^{k} \vartheta_{3i} T_{t-i} + \sum_{i=0}^{l} \vartheta_{4i} R_{t-i} + \eta_t \tag{2}$$

Cho et al. (2015) suggested the quantile form QARDL (*p*,q,r,s,u) for the model presented in Equation 1, which is an extension of the original model.

$$\begin{aligned} Q_{CO2t} = {} & \varepsilon(\tau) + \sum_{i=1}^{n} \vartheta_i(\tau) CO2_{t-i} + \sum_{i=0}^{m} \vartheta_i(\tau) FS_{t-i} + \sum_{i=0}^{k} \vartheta_i(\tau) T_{t-i} \\ & + \sum_{i=0}^{l} \vartheta_i(\tau) R_{t-i} + \eta t(\tau) \end{aligned} \tag{3}$$

The QARDL model depicted by Equation 2 is generalized due to the possibility of serial correlation.

$$\begin{aligned} Q\Delta CO2_t = {} & \eta + \beta_1 CO2_{t-1} + \beta_{2FS} FS_{t-1} + \beta_{3T} T_{t-1} + \beta_{4R} R_{t-1} \\ & + \sum_{i=1}^{n} \lambda_{1i} CO2_{t-i} + \sum_{i=0}^{m} \lambda_{2i} FS_{t-i} + \sum_{i=0}^{k} \lambda_{3i} T_{t-i} + \sum_{i=0}^{k} \lambda_{3i} R_{t-i} \\ & + \varepsilon(\tau) \end{aligned} \tag{4}$$

The following is a generalized restatement of Equation 3 demonstrating the QARDL-ECM model:

$$\begin{aligned} Q\Delta CO2_t = {} & \eta(\tau) \\ & + \gamma(\tau)\left(CO2_{t-1} - \beta_{FS}(\tau) FS_{t-1} - \beta_T(\tau) T_{t-1} - \beta_R(\tau) R_{t-1}\right) \\ & + \sum_{i=1}^{n-1} \lambda_i(\tau) \Delta CO2_{t-i} + \sum_{i=0}^{m-1} \lambda_i(\tau) \Delta FS_{t-i} + \sum_{i=0}^{k} \lambda_i(\tau) \Delta T_{t-i} \\ & + \sum_{i=0}^{k} \lambda_i(\tau) \Delta R_{t-i} + \varepsilon(\tau) \end{aligned} \tag{5}$$

Whereas short-term cumulative effects of historical and present FS, T, R, and CO_2 levels are calculated by:

$$\chi = \sum_{i-1}^{p-1} \lambda \chi_i$$
$$K^* = \sum_{i-1}^{s-1} \alpha K_j, \theta^* = \sum_{i-1}^{h-1} \alpha \theta_j, \varpi^* = \sum_{i-1}^{n-1} \alpha \varpi_j \tag{6}$$

To determine the long-term parameter for FS, T, R, and CO_2, we use the formula:

$$\delta_{CO2^*} = -\frac{\delta_{CO2}}{\rho}, \delta_{FS^*} = -\frac{\delta_{FS}}{\rho}, \delta_{T^*} = -\frac{\delta_T}{\rho}, \delta_{R^*} = -\frac{\delta_R}{\rho} \tag{7}$$

The ECM parameter (ρ) should have a significant negative value.

Moreover, to determine the stationary in the data, Augmented Dicky Fuller (ADF) is utilized, mathematically expressed in Equations (7), (8). In order to start the empirical analysis, the unit root test will be estimated at the beginning. Theoretically, it is assumed that a series should have no unit root. To start, the unit root test reveals if certain data are integrated. To test the random shocks in the data, the unit root test combines them at many scales. Such consistent results may be more useful for long-term forecasting. However, the proposed strategies may be unsuitable if the series is not stable, and the data contains random shocks. The unit root test estimates the unit root properties of the variable.

$$\Delta S_t = \kappa_0 + \rho S_{t-1} + \sum_{i=1}^{\sigma} \lambda_i \Delta S_{t-1} + \eta_t \tag{8}$$

$$\Delta S_t = \alpha_0 + T + \rho S_{t-1} + \sum_{i=1}^{\sigma} \lambda_i \Delta S_{t-1} + \eta_t \tag{9}$$

Equations (7) and (8) examine the series on the intercept, trend, and intercept to capture the unit root in all series. The Zivot-Adrews test is applied in this scenario to determine if the data has a structural break. The data should be transformed by differencing the variables before being included in the regression model if the unit root tests determine that a series has a single unit root. One of the limitations of ADF unit root tests is that structural discontinuities may be incorrectly interpreted as indicators of non-stationarity. It is possible that they will not be able to reject the unit root hypothesis in the case of a structural break that exists in the data. If the structure break on a given variable is related to a specific event, such as a change in policy, a currency crisis, or a war, the process may identify the exact moment when the break occurred. The Zivot-Andrews test permits only a single crack in the structure.

$$\Delta Zt = \mu + \alpha Z_{t-1} + \delta_t + \vartheta DU_t + \sum_{j=1}^{l} c_j \Delta Z_{t-1} + \eta_t \tag{10}$$

$$\Delta ZAt = \mu + \alpha Z_{t-1} + \delta_t + \lambda DT^* + \vartheta DU_t + \sum_{j=1}^{l} c_j \Delta Z_{t-1} + \eta_t \tag{11}$$

$$\Delta Z_t = \eta + \beta Z_{t-1} + \delta_t + \theta DU_t + \gamma DT_t + \sum_{m=1}^{g} c_m Z_{t-m} + e_t \tag{12}$$

The Wald test is used to determine if the explanatory variables in a model are statistically significant; the significance of variables indicates that they contribute to the model in some way. Multiple models, including ones with binary variables, are suitable for the test. Mathematically expressed as.

TABLE 1 Descriptive analysis.

Variables	CO_2	FS	T	R
Mean	1.9979	4.4348	21.3715	0.1226
Median	2.0530	4.4584	21.6173	0.2911
Maximum	2.3112	4.5603	23.9800	0.9389
Minimum	1.5845	4.3152	18.7950	−1.3422
Std. Dev	0.2201	0.0719	1.3148	0.6327
Skewness	−0.5509	−0.0966	−0.1889	−0.6228
Kurtosis	2.0074	1.7891	2.5890	2.3030
Jarque-Bera	2.9325	2.0047	0.4155	2.7164

$$Wl_t = \frac{\left[\hat{\kappa} - \kappa_0\right]^2}{1/I_n(\hat{\kappa})} = I_n(\hat{\kappa})\left[\hat{\kappa} - \kappa_0\right]^2 \tag{13}$$

Autocorrelation refers to the correlation between two-time series over a range of time. An autocorrelation analysis determines how closely a variable's present value relates to its historical values.

$$SR_t = \nu_1 + \sum_{k=2}^{P} \nu_j R_{jt} + \varepsilon_t$$
$$\varepsilon_t = \lambda_1 + \sum_{k=2}^{P} \lambda_j R_{jt} + \rho \varepsilon_{t-1} \tag{14}$$

In particular, it determines if the response variable can be explained by combining non-linear combinations of the fitted values. The idea behind the test is that the response variable can be described using only non-linear combinations of the explanatory variables. Then the model is incorrectly specified, and a polynomial or other non-linear functional form would better approximate the process by which the data were generated.

$$x = az + \gamma_1 \hat{x}^2 + \cdots + \gamma_{k-1} \hat{x}^k + \varepsilon \tag{15}$$

5 Results and discussion

The current study investigates the influence of transportation infrastructure and research and development expenditures on carbon emissions in consideration of the Chines economy. In order to achieve this objective, a time series dataset (1990–2021) has been compiled from the World Development Indicator (WDI). To summarize the variables statistics, the study employed descriptive analysis. A descriptive statistic is composed of three segments; the first segment defines the tendency of the data, which includes on mean, median, maximum, and minimum statistics. Secondly, descriptive elaborates the standard deviation, which measures the deviation of factors values from the mean. Thirdly, this analysis captures the symmetry of data (skewness) and high or low-tailed (kurtosis) data spread. Lastly, Jarque-Bera (JB) measures the model's goodness of fit. The outcomes are articulated in Table 1.

TABLE 2 Augmented dicky fuller test.

ADF	At level		At 1st difference	
Variables	t stat	prob	t stat	prob
CO_2	−1.341	0.597	−5.490***	0.0006
FS	−0.830	0.795	−3.739**	0.0348
T	−2.039	0.269	−8.753***	0.000
R	−4.142**	0.003	−5.283***	0.0009

TABLE 3 Zivot andrew test.

ZA	Intercept			Trend		
Variables	t stat	Prob	Year	t stat	Prob	Year
CO_2	−4.51**	0.01	2000	−3.37**	0.04	2001
FS	−3.93***	0.00	2012	−2.69**	0.02	2004
T	−5.76	0.12	1999	−5.93**	0.04	2002
R	−5.35***	0.00	1999	−4.45***	0.00	2010

Table 1 shows the tendency of data ranges between the maximum and minimum values since the average values of each factor are within the defined ranges. While the deviation from means also lies in the thumb rule statistics value such as 2. Moreover, the symmetry of the data lies in thumb rule values such as 3. Whereas the high or low tailed of the dataset also lies in the accepted statistics range such as 10. Additionally, JB discloses the model's goodness of fit, which is one more positive aspect of the study. Therefore, it can be concluded that the overall spread of the dataset, deviation from the mean, and central tendency, along with the model's fitness, all support the validity of the data results and estimations. The pre-requisite condition of time series is that data should be stationary before performing baseline estimation. For this purpose, the study employed the unit root test. The outcome is reported in Table 2.

The result in Table 2 elaborates that only R has a unit root at a 1% level of significance. At the same time, all the factors have zero mean and constant variance at first difference. Moreover, FS is stationary at 5%, and CO_2, T, and R have a unit root at a 1% significant level. Next, the study uses the Zivot Andrew test to determine the discontinuity in the dataset. The results are mentioned in Table 3.

The information in Table 3 suggests that all the variables have a break in different years at the intercept and the on-trend break in the dataset. Consequently, it concludes that all the factors have unit roots at first differences and a break in the dataset. Recently, the QARDL model has gained considerable traction in the field of time series analysis. It is a flexible model for autocorrelation, separating long- and short-term connections and handling asymmetry relationships. The result of Q-ARDL is reported in Table 4.

We calculate the long-term and short-term effects of FS, T, and R&D on carbon emission in quantiles by using quantile ARDL. The results are presented in table 4, which suggests that in the long run, first quantile (Q = 0.25), only research and development spending influences carbon emission, and it has no effect second, third and fourth quantiles. In addition, in the second quantile (q = 5), all the factors like FS and T influence carbon emission. More importantly, the coefficient of FS, T, and R&D is significant at 1, five and10 percent, showing the long-term impact on carbon emission, respectively. Additionally, FS has a 1% significant impact on carbon emission in the third quantile (q = 75). While FS has a 5% significant impact on carbon emission in the fourth quantile (q = 85). However, in the short run, FS with one lag significantly affected the carbon emanation at 5%. In contrast, transportation infrastructure at a 5% significant level affects carbon emission in the first quantile of the short run. In the second quantile, T (−1) is associated with carbon emission, with a 5% significance level. Spending on research and development also interlinks with the carbon emission at a 1% significant level. Moreover, the association of FS and R has a connection with carbon emission in the third quantile at 10% and 1% significant levels. However, in the fourth quantile (q = 85), all the factors FS, T, and R are affected by carbon emission. The outcomes indicate that fossil fuel consumption, transportation system, and research and development expenditures are affecting the CO_2 emission by 5% and 10% level of significance. Besides, the study performs numerous tests to determine the reliability of results and stability of the model. For this purpose, the study used Wald, serial correlation, and the Ramsey test. The outcomes are reported in Table 5.

The Wald test in Table 5 reported that all the datasets of factors significantly influencing the carbon emission, rejecting H0, i.e., this implies that all variables jointly affect the CO_2 emission. Whereas the outcomes of Ramsey and serial correlation also show no autocorrelation problem in the data. Furthermore, diagnostic tests (residual, stability, and coefficient) are all positive for the research. There is a continuous increase in fossil fuel consumption in China. Moreover, the transportation infrastructure, which assists in transporting and stimulating the business, also consumes a considerable quantity of fossil fuel (Rahman, 2019). By contrast, R&D expenditures are increasing to locate modern methods of production, distribution and to introduce the latest technologies to affect CO_2 emissions (Anser et al., 2020). Climate change, environmental degradation, and increased temperatures are the major threats that the world faces today; tremendous carbon emissions represent the primary threat to the environment (Hwei et al., 2021). On the contrary, carbon emission is increasing significantly in developing economies due to the expansion of economic activities and industrialization. In general, all nations are experiencing high levels of carbon emissions.

The results reported that fossil fuel consumption, R&D, and transportation play a positive role in emitting carbon in China. Undoubtedly, each factor is responsible for emitting carbon in the economy, but fossil fuel consumption is at the top because of its high utilization. Every economic sector utilizes fossil fuels, especially industry and transportation. The energy shortage in developing economies is one of the reasons they heavily rely on fossil fuels. The outcomes elaborate that with a 1% growth in fossil fuel utilization, carbon emission in the economy increased by 0.19%. A rise in fossil fuel consumption will lead to an increase in carbon emissions, which pollute the environment and threaten the environment, causing environmental degradation. These findings are in support by Qiu

TABLE 4 Q-ARDL estimation.

	Long run										
	Variable	Coefficient	Std. Error	t-Statistic	Prob		Variable	Coefficient	Std. Error	t-Statistic	Prob
	1. FS	0.011	0.008	1.345	0.189		1	0.019***	0.005	3.976	0.000
q = 0.25	2. T	0.033	0.030	1.098	0.281	q = 0.5	2	0.007*	0.018	0.431	0.069
	3. R	0.174**	0.056	3.083	0.004		3	0.220***	0.035	2.853	0.007
	1	0.024**	0.007	3.121	0.004		1	0.029**	0.011	2.695	0.011
Q = 0.75	2	−0.004	0.027	−0.146	0.884	Q = 0.85	2	−0.011	0.041	−0.284	0.777
	3	0.029	0.070	0.425	0.673		3	−0.097	0.101	−0.965	0.342
Short Run											
	1. FS	0.012	0.031	0.404	0.689		(FS)	0.004	0.033	0.145	0.885
	2. FS(-1)	−0.022**	0.022	−1.003	0.025		FS(-1)	0.022**	0.034	−0.659	0.015
	D(T)	−0.007	0.015	−0.460	0.649		D(T)	0.030	0.018	0.017	0.986
Q = 0.25	T (-1)	0.001**	0.012	0.105	0.017	Q = 0.5	T (-1)	0.003*	0.017	−0.188	0.052
	R	−0.154	0.267	−0.578	0.568		D(R)	0.269***	0.401	0.670	0.009
	ECT (-1)	−0.054*	0.136	−0.396	0.094		ECT (-1)	−0.088**	0.186	−0.474	0.039
	FS	0.014	0.032	0.452	0.654		FS	0.008**	0.046	0.191	0.049
	FS1(-1)	−0.004*	0.030	−0.146	0.084		FS(-1)	0.021	0.048	0.003	0.997
Q = 0.75	T	0.005	0.017	0.319	0.752	Q = 0.85	T	0.011*	0.027	0.435	0.066
	T (-1)	0.030	0.017	0.015	0.987		T (-1)	−0.010	0.023	−0.435	0.666
	R	0.455***	0.353	1.290	0.009		R	0.990*	0.568	1.742	0.094
	ECT (-1)	−0.258*	0.189	−1.363	0.085		ECT (-1)	−0.391**	0.295	−1.327	0.019

TABLE 5 Diagnostic test.

Wald test				
Test Statistic	Value	df	Probability	
F-statistic	5.542	(3, 28)	0.07	
Chi-square	6.628	3	0.06	
Breusch-Godfrey Serial Correlation LM Test				
Null hypothesis: No serial correlation at up to 2 lags				
F-statistic	5.272,517	Prob. F (2,26)		0.012
Obs*R-squared	9.233,569	Prob. Chi-Square (2)		0.0099
Ramsey				
F-statistic	0.267,658	(2, 26)	0.0673	
Likelihood ratio	0.652,161	2	0.0717	

et al. (2020); Martins et al. (2021), Koondhar et al. (2021); Atsu et al. (2021); Rehman et al. (2019), and RAHMAN, (2019).

A total of 37% of CO_2 emissions are attributed to terminal sectors in 2021, and transportation is the industry that is most

TABLE 6 Pairwise granger causality tests.

Null hypothesis	F-statistic	Prob
FS does not Granger Cause CO_2	1.23035	0.3093
CO_2does not Granger Cause FS	7.58390	0.0027
R does not Granger Cause CO_2	2.53514	0.0933
CO_2does not Granger Cause R1	0.73954	0.4875
T does not Granger Cause CO_2	2.58357	0.0908
CO_2does not Granger Cause T	0.25669	0.7756
R does not Granger Cause FS	2.51014	0.1015
FS does not Granger Cause R	2.34386	0.1167
T does not Granger Cause FS	0.76293	0.4768
FS does not Granger Cause T	3.72632	0.0383
T does not Granger Cause R	1.98578	0.1583
R does not Granger Cause T	3.14583	0.0604

dependent on fossil fuels (Zhao et al., 2022). Following a historic decline in 2020, transportation-related CO_2 emissions increased by approximately eight percent in 2021 as pandemic restrictions were relaxed and passenger and freight operations resumed (Huang et al., 2021). While the transportation sector is forecast to grow by nearly 20% by 2030, to meet the Net Zero Scenario, the sector's emissions will need to decline by almost 20% to less than 6 metric tons (Zhao et al., 2022). The findings are in line with Li et al. (2021); Jiang et al. (2019); Huang et al. (2021); Wang et al. (2021); and Zhang et al. (2021).

Based on the projections, it appears that R&D spending has a negative average influence on CO_2 emissions. The average CO_2 emissions are reduced by 0.09%–0.15% for every 1 percent increase in R&D spending (Petrović and Lobanov, 2020). Estimated regressions for individual countries show that R&D spending can positively or negatively impact CO_2 emissions, ranging from 0.79% in Denmark to 0.52% in Belgium (Petrović and Lobanov, 2020). In other words, increased spending on R&D often results in lower CO_2 emissions in the long run, albeit this is not the case for around 40% of nations (Petrović and Lobanov, 2020). The estimate of the short-run time-varying coefficient panel data models also showed that the influence of R&D might be positive, negative, or neutral (insignificant) over a long period. The analysis finds that R&D positively affects carbon emission, indicating that as a 1% upsurge in R&D, carbon increased by 0.02% in the economy. However, the findings of the study are supported by Artha et al. (2021); Shahbaz et al. (2020); Qin et al. (2021); Gan and Smith (2011); and Aldakhil et al. (2019). Table 6 presents the Granger Causality Tests results, which is used for the robustness of baseline results. The Granger Causality test suggests a unidirectional causality from CO_2 to FS. There is unidirectional causality from R to CO_2 emissions, which indicates that R&D spending causes the CO_2 emissions. In addition, there is causality running from T to CO_2 emissions which indicates that transport development causes the CO_2 emissions in China. Furthermore, R is causing T, which implies that research and development cases transportation development. These findings reported the validity of the bassline results.

6 Conclusion

Literature suggests that carbon plays an important role in environmental degradation in developed and developing countries. Among the number of factors, transportation and R&D are the main factors that determine the CO_2 emission. Therefore, the study mainly focuses on the nexus between transport infrastructure, CO_2 emissions and R&D spending in China. Modern econometric approaches, such as the ZA test and Q-ARDL, are used for the data analysis. The finding suggests that transportation infrastructure and R&D both have positive implications for CO_2 emissions. The spending on research and development also influences carbon emissions. Because of more expenditure in the research and development sector, countries are producing modern machinery for production purposes, which has an inverted U-shape affiliation with the environment. The condition of the transportation network affects the emission of carbon dioxide, and transportation infrastructure upgradation increases the number of vehicles, stimulating business activities and heavy fissile fuel consumption that leads to higher CO_2 emissions in the country.

These findings suggest a few policy recommendations; firstly, the positive association of R&D implies that most of the R&D is allocated to projects that contributed to the CO_2 emission in the country. Besides, the R&D spending ignores the environmental factor engaged in the innovation's activities. Therefore, it is necessary that R&D spending should allocate to green energy projects such as green technologies, green energy, and green vehicles to improve environmental quality, which would help the economy to mitigate CO_2 emissions. Secondly, the transport infrastructure is positively related to CO_2 emission, which indicates with the transport infrastructure upgradation; the CO_2 emission in the country increases. Therefore, the government should focus on green transportation and other modes such as "electrification of vehicles, etc. Thirdly R&D government should allocate R&D activities to the electrification of vehicles and green transportation that could help to achieve the transportation and environmental goals. In this study, there are some limitations since the focus is only on one country; in the future, the study may be expanded to include multiple countries as well. It is also possible that future studies may adopt this new technique in order to reexamine this relationship by applying the advanced statistical technique. This study has some limitations; firstly, this study focuses on one country, and the results of the study may not be generalizable to other countries and regions with different cultural, economic, and political conditions. Future studies may test this hypothesis by including multiple countries that allow the comparison of results across different countries. This can help to identify any country-specific effects and to better understand the underlying factors that influence the relationship between variables. Secondly, this study uses QARLD method future studies may advance techniques such as Quantile on Quantile approach, which provide more robust results and policy recommendations. Thirdly, future studies can also consider incorporating additional variables and control variables to better account for relationship between R&D spending, Transport development and CO_2 emissions to increase the robustness of the analysis.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JY, JM, YF, and SW conceptualized the contribution. LH wrote and edit the manuscript. All authors listed have made a substantial, direct and intellectual contribution to the work, and approved the submission of the manuscript.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Nexus between health poverty and climatic variability in Pakistan: a geospatial analysis

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Studies investigating the interconnection of health poverty and climatic variability are rare in spatial perspectives. Given the importance of sustainable development goals 3, goal 10, and goal 13, we explored whether the geographic regions with diverse climate structure has a spatial association with health poverty; whether spatial disparities exist across districts of Pakistan. We implied the A-F methodology to estimate the MHP index using the PSLM survey, 2019–20. The climate variables were extracted from the online NASA website. We applied the spatial techniques of Moran's I, univariate and bivariate LISA, to address the research questions. The findings revealed that the magnitude of MHP differs across districts. Punjab was found to be the better-ff whereas Baluchistan was the highest health poverty-stricken province. The spatial results indicated positive associations of MHP and climate indicators with their values in the neighbors, whereas a negative spatial association was found between the MHP and climate indicators. Also, spatial clusters and outliers of higher MHP were significant in Baluchistan and KP provinces. Government intervention and policymaker's prioritization are needed towards health and health-related social indicators, mainly in the high poverty-stricken districts, with high temperature and low humidity and precipitation rates, especially in Baluchistan.

KEYWORDS

health poverty, climate change, alkire-foster methodology, univariate and bivariate LISA, inequalities, Pakistan

1 Introduction

Climate change and health poverty are the two central goals among the United Nation Sustainable Development Goals (SDGs). The first is to ensure healthy lives and promote wellbeing for all ages, and the second is to take urgent action to combat climate change and its impact (UNDP, 2015a; UNDP, 2015b). Climate change occurs in different ways, such as temperature, rainfall, humidity/precipitation, CO2, air pollution, wind/pressure, etc. Global warming, or global rise in temperature, has become an incontrovertible fact, and it had been predicted that global warming would rise in the 21st century from human activities (Hansen et al., 1981). There is growing evidence that climate change has a significant impact on human health and economic growth (Sheridan and Allen, 2015; Kjellstrom et al., 2016; Gilmont et al., 2018; Kinney, 2018; Jones, 2019; Patrick et al., 2019; Sangkhaphan and Shu, 2019; Nuță et al., 2021; Abban et al., 2022; Dankyi et al., 2022; Li et al., 2022; Khan et al., 2023; Zhang et al., 2023). Climate change has an inverse bearing on the health sector, particularly in developing countries. By 2050 climate change will mostly aggravate the prevailing health difficulties, and the population affected by climate-related sicknesses will increase (Barros et al., 2014). Climate change influences health-related outcomes through air pollution, changing exposure to heat and cold, food safety hazards, pollen, emerging infections and functioning of health services and facilities, and other reasons such as water-borne diseases and increased exposure to Ultra-Violence radiations, changing prices of and access to nutrition (Hames and Vardoulakis, 2012; Morris et al., 2015; Kovats and Osborn, 2016).

Changes in the climate distress the social and environmental attributes of healthcare, such as safe drinking water, clean air, secure shelter, and adequate food and nutrition (WHO, 2021). Such climate-sensitive health risks are typically felt by the deprived and most vulnerable women, children, and poor societies, especially from low- and middle-income countries (WHO, 2021). Increasing access to primary healthcare services and acute hospital care mitigate the impact of temperature on mortality (Paterson et al., 2014; Cheung et al., 2020; Mullins and White, 2020). Recently, (Boyles et al., 2021), stated that environmental attributes are related to maternal health impacts such as pregnancy, infertility, breast cancer, and metabolic disorders. A bunch of previous literature has shown that climate change has a substantial impact on child health (Thompson et al., 2012; Bennett and Friel, 2014; Davenport et al., 2017; Bhandari et al., 2020; Helldén et al., 2021), or maternal health (Giulia et al., 2020; Khan et al., 2011; Kuehn and McCormick, 2017; Rylander et al., 2013; Watt and Chamberlain, 2011). Access to hospitals and family planning centers were also associated with climate change (Peters et al., 2008; Chen et al., 2020; Wang et al., 2021; Wu et al., 2022).

Nations throughout the globe face several problems in achieving good human health and accessibility to health-related indicators in general, particularly in developing countries. Lack of access to health facilities tends researchers to construct multidimensional health poverty (MHP) index to measure the extent of accessibility to health across various countries. MHP index is predicated on the most popular Alkire-Foster theoretical framework of multidimensional poverty index (MPI), which had been constructed to measure the extent of poverty in the three dimensions of health, education, and living standard (Alkire and Foster, 2011a; Alkire and Foster, 2011b; Alkire and Roche, 2013; Alkire and Santos, 2013). However, with the emergence of innovations, the health dimension has been considered a broad subject matter as it plays a pivotal role in economic development and the human wellbeing of any country. As a result, many researchers have constructed a separate MHP index (Simões et al., 2016; Weziak-Bialowolska, 2016; Clarke and Erreygers, 2020; Chi et al., 2021; Mustafa et al., 2021). Many nations have reduced health poverty in the last 3 decades, but health problems persist. Population growth and global urbanization threaten 'people's accessibility to health-related social indicators (Klasen and Lawson, 2007; Leon, 2008; Das Gupta et al., 2011; Liddle, 2017). For example, approximately 400 million people do not have access to basic health facilities (Balakrishnan et al., 2019), and more than 15 million people with HIV have no access to medical treatment (UNDP, 2015b; WHO, 2020). Moreover, approximately 7 million people die each year due to air pollution (WHO, 2018), nearly 844 million people have no access to safe drinking water (UNDP, 2015b), and approximately 2.3 billion people lack access to sanitation facilities (UNDP, 2015b). Also, more than 3 billion people, mostly from low- and middle-income countries, use solid fuels for cooking (WHO, 2018). Assessment of health poverty in this regard captured significance because it covers the two fundamental global SDGs, the end of poverty in all its form anywhere (SDG goal 1) and ensuring healthy lives and promote wellbeing for all at all ages (SDG goal 3) (UNDP, 2015b).

MHP is dynamic that varies across geographical boundaries within the countries. Considerable variations exist in the incidence of health poverty at geographical levels (Iqbal and Nawaz, 2017; Jewczak and Korczak, 2020; Khan and Hussain, 2020; Mustafa et al., 2021; Chen et al., 2022). Inequalities in health poverty exist across various regions within the countries. In the presence of such severe inequalities, the United Nation's SDGs Agenda of 2030 universally agreed on a need to diminish these drastic inequalities, i.e., reduce inequality within and among countries (SDG goal 10) (UNDP, 2015a; UNDP, 2015b). Thus, it is necessary to identify the disparities in MHP from spatial perspectives. The mounting acceptance of spatial analysis has played a crucial role in almost every field of research, particularly in the social sciences. The spatial analysis identifies atypical clusters and hotspots (outliers) concerning MHP, thus appearing as a new hot topic. Several studies have explored the spatial perspectives of health poverty, but they are rare in low- and middle-income countries (Weeks et al., 2012; Sharma, 2014; Jewczak and Korczak, 2020; Dong et al., 2021; Morrow et al., 2022). Most studies mainly focused on the impact of various health and social determinants of health in non-spatial perspectives. Thus, it is desirable to recognize the spatial patterns of health poverty at the regional level. On one side, health poverty is dynamic and changes across countries. On the other side, climate change is diverse and also varies across regions. As noted above, both the impact and association of climate change and health-related attributes vary across geographical locations; there is an urgent need to look at the spatial connection of climatic variability with multidimensional health poverty at the geographical boundaries of any country.

Pakistan is a developing economy, with more than half of the population living in rural areas. The country is divided into four provinces and Federally Administered Tribal Areas (FATA). These provinces and FATA regions are further administered into divisions and sub-divisions (districts). Pakistan has a very diverse climate and is as varied as its topography. Mainly, there are four different types of weather, i.e., 1) dry winter (from December to February), 2) a hot, dry spring that starts in March and ends in May, 3) the summer rainy season, also called the southwest monsoon season which occurs from June to September, and 4) retreating monsoon lasts from October to November (Climatology, 2020). There are considerable differences in the mean, minimum, and maximum temperature, precipitation, rainfall, and wind pressure across various geographies. For instance, the northern areas of Pakistan are blessed with hilly and/or cold areas such as Murree, Swat, Naran, Malam Jabba, Kalam, Shogran, Neelum Valley, Ayubia, Chitral, Quetta, Kalat. The mean, minimum, and maximum temperatures are low, and the rainfall is high in such areas. The Kharan, Thar, Cholistan, Sibbi, Hyderabad, Jacobabad, Thal, etc., are hot and dry areas of Pakistan. Similarly, the rate of humidity/precipitation and wind pressure is also different in different climatic regions of Pakistan.

The past literature suggested a strong connection between climate change and health outcomes. Several climatic and environmental attributes, such as increasing temperature, growing carbon dioxide (CO_2) emissions, and air pollution, have significantly influenced health and health-related outcomes. Previous literature mainly investigated the relationship between health poverty and climate change from non-spatial perspectives. Very few efforts have been made in spatial terminologies towards these associations, particularly in developing countries. However, the association between climate change and health outcomes must be investigated further from spatial perspectives. Therefore, considering the importance of the United Nations SDGs (Goals 3, 10, and 13), this study investigates the spatial nexus between climate change and health poverty from different angles. First, it recognizes the spatial patterns of health poverty and climatic variability across districts of Pakistan. Second, it identifies the spatial clusters of hotspots/cold spots and spatial outliers both in climatic variability and health poverty. Finally, it examines the univariate and bivariate spatial associations between climatic variability and health poverty across study districts of Pakistan. This study contributes to the existing literature in two ways. First, according to our knowledge, this is the first attempt to recognize the spatial nexus between climatic variability and health poverty in Pakistan. Second, this study applies spatial econometric models instead of conventional ones to gain more robust results. This study is useful for the government in identifying locations with a strong (or weak) spatial connection between health poverty and climate change. Policy planners and government can also use these results to prioritize districts with severe health poverty and bad climate associations.

2 Literature review

A literature review is considered the backbone of any research study. This section comprehends detailed conversations on health outcomes and climate change. Human health is a broad sector, and numerous researchers are working from different perspectives and dimensions. Similarly, in many previous studies, climate change has been measured differently. Few studies demonstrate the link between health outcomes and climate variables.

Sarmiento (2023) recently analyzed the relationship between temperature, mortality, and access to healthcare in Colombia. He showed that an increase in the days of hot or cold temperatures increases mortality. Higher temperatures above the mean of 27°C boosted the mortality rates by about 0.24 deaths per 100,000 lives. Further, he also confirmed that access to healthcare services mediated between temperature and mortality. A similar study was conducted by Mullins and White (2020) in US counties in the 1960s and 1970s, in which they tested whether access to healthcare mitigates the temperature effects on mortality. Results of the study revealed that improved access to primary care services provided by community health centers moderated the association between temperature and mortality by about 14%. Besides, the findings suggested that improving access to primary care may be useful for reducing the relationship between mortality and temperature. In another study, Mullins and White (2019) examined the link between ambient temperature and mental health outcomes at the county level in the United States. Their results concluded that higher temperatures increase mental illnesses and self-rated poor mental health. The study's findings also confirmed that cold temperatures reduce the inverse mental health outcomes.

Moreover, they concluded that the impact of temperature on mental health differs from physical health and psychological and behavioral outcomes. Grace et al. (2015) investigated the association between birth weight, precipitation, and temperature in 19 African countries. Birth weights were recorded from the Demographic and Health Survey (DHS) from 1986 to 2010, and the monthly data on precipitation and temperature was derived from satellite and ground-based weather stations. Unlike the findings of Mullins and White (2019), their empirical findings suggested that precipitation and temperature did not affect birth weight. Nawaz (2021) examined the effects of multidimensional energy poverty and climate shocks on health poverty in Pakistan. Outcomes of the empirical analysis confirmed that climate change, including temperature, flood, and rainfall, has substantially and positively influenced multidimensional health poverty. In addition, the temperature has an adverse impact on child health.

Paavola (2017) examined how social and health disparities outline the health impacts of climate change in the United Kingdom. Exposure to heat, air pollution, pollen, and floods were considered to influence health outcomes. He found that the aging population and decreasing public expenditure on social and healthcare may aggravate disparities in health outcomes linked to climate change. Epstein et al. (2023) stated that precipitation anomalies (in the form of rainfall and drought) are related to poor health outcomes. In this regard, they examined the influence of precipitation on short-term health outcomes by using demographic and health survey data from 23 sub-Saharan African countries. The empirical results concluded that precipitation anomalies were correlated with short-term mobility among women, which in turn was associated with poor health outcomes. Goldie et al. (2015) explored the relationship between humidity, temperature, and health system in the context of climate variation in Darwin, Australia. The findings of the study indicated that humidity has significantly determined hospital morbidity. They suggested that in tropical regions of Australia, there is a need for heat-health policies to accommodate the influence of humidity at varied times of the day. Gao et al. (2014) conducted a review study to understand the impact of ambient humidity on child health. They selected 37 most relevant studies out of 2,797 articles from various electronic databases, including PubMed, Web of Science, ScienceDirect, and EBSCO. They found that 78% of the studies reported that ambient humidity played a significant role in children's prevalence and incidence of climate-related infectious diseases. Rylander et al. (2013) identified that climate change influenced human health differently, such as lack of food and safe drinking water, poor sanitation, and morbidity. Their results showed that climate change in precipitation, rainfall, and droughts will increase the risk of maternal and infant mortalities.

Bi et al. (2022) examined the relationship between wind speed in the context of air temperature and its severity on human health in the form of mortality in Shanghai, China. The study outcomes verified V-shaped associations between daily air temperature and cause-specific mortality. In addition, older ages were more sensitive to variations in air temperature. The authors suggested that air temperature is a substantial determinant of human mortality, especially for elders. Almendra et al. (2019) assessed the short-term impacts of air temperature on hospitalization for mental disorders in Portugal. The findings showed that hospital admissions significantly increased with higher air temperature. Compared to men, women were more vulnerable to changes in air temperature. However, they found no significant difference between different age groups concerning the impact of air temperature. Péres et al. (2020) measured the relationship between air temperature and health outcomes in terms of mortality in two Brazilian regions by performing a quasi-Poisson non-linear lag distributed model. The study results indicated that air temperature increasingly influenced human health, which enhanced the general and specific mortalities. They also noted the varied impact of air temperature on mortality in both regions. Other studies, including Gilmont et al. (2018); Jones (2019); Kinney (2018); Kjellstrom et al. (2016); Li et al. (2022); Patrick et al. (2019); Sangkhaphan and Shu (2019) and Sheridan and Allen (2015) have discussed the association between climate variability and health outcomes in their perspectives mainly depend on their study objectives.

Fonseca-Rodriguez et al. (2019) assessed the spatial relationship between oppressive weather types and health outcome in the context of total mortality in Sweden. Poisson regression with distributed lags model was used for time series dataset from 1991 to 2014. The study results showed that during summer, in the south, the moist tropical and dry tropical weather significantly increased the total mortality at longer lags and, in the north, dry tropical weather increased the mortality at shorter lags. During winter, in the south, dry polar and moist polar weather respectively raised mortality from lag 6 to lag 10 and from lag 19 to lag 26. In the north, no significnat effect of oppressive wather was noted. Their findings concluded varied effects of oppressive weather across regions and seasons. Huang et al. (2022) investigated the health disparities from effect of built environment on temperature-related mortality in the local geographic units in Hong Kong, China. Using Bayesian spatial models at local area level, the effects of local temperature on mortality were analyzed. The findings of the study showed that variations in local temperature did not significantly contribute towards mortality. However, green space density substantially influenced the non-accidentally and cardiovascular diseases mortalities. They also found that the spatial disparities in mortality within Hong Kong could be explained by geographical distribution of green space rathre than temperature. Their study results suggested further investigation of spatial impact of temperature on health outcome at small area boundaries. Wibawa et al. (2023) examined the impact of ambient temperature, relative humidity and preciptiation on incidence of diarrhea in five regions of Surabaya, Indonesia. Their study results showed higher incidnece rate of diarrhea in rainy season in east Surabaya. Weather condition was significantly varied across the study regions. Diarrhea risk was substantially associated with extremely high and low temperature in the eastern area. They also resulted that the extremely low humidity boosted the incidence of diarrhea with highest risk in western region. Moreover, they suggested local government an health sectors to construct weather-based early warning system to mitigate the rising risks of infectious diseases. Liu et al. (2016) conducted spatial-temporal analysis of climate change, air pollution and mortality in 120 counties of China by applying univariate and partial correlation analysis. The results showed a significant spatial clustering of Air Pollution Index (API) with highest API in northwest China and east China respectively in year 2012 and year 2013. API was inversely associated with heat index, precipitation and sunshine hours but directly correlated with air pressure. As compared to the areas with lower API concentrations, areas with high API had higher mortality rates. Their findings concluded that air pollution varied by across regions and substantially associated with mortality across the country.

In a nutshell, the above literature mainly focussed on the link between climate change and health outcomes. These studies measured climate change mainly by temperature, humidity, precipitation, rainfall, air temperature, wind position, floods and drought. Similarly, health outcomes have been measured from different angles, such as mental health, child health, maternal health, access to health infrastructure, hospitalization, and mortalities. However, all of these studies mainly assessed the association from non-spatial perspectives. Therefore, considering the climate diversity, this study tries to fill the gap between health poverty and climatic variability in spatial perspectives across districts of Pakistan.

3 Theoretical framework of multidimensional health poverty

Multidimensional health poverty is not predicated on a new method but rather built on a pre-determined methodology of the Multidimensional Poverty Index (MPI). MPI framework was introduced by Sabrina Alkire and James Foster in 2011 by criticizing unidimensional income poverty (Alkire and Foster, 2011a). Traditionally, poverty was considered a unidimensional monetary phenomenon. Nations with higher income *per capita* were considered to be better off economically and *vice versa*. Later, it was found that many countries with a higher *per capita* income have a lower quality of life.

In contrast, many nations with lower *per capita* income have enjoyed a quality standard of living, such as higher life expectancy, good education, and higher access to healthcare infrastructure. With the emergence of time, the traditional monetary approach has been strictly criticized, as Amartya Sen in 1994 pointed out that poverty is a multidimensional concept, and no single indicator is solely capturing its universal characteristics (Sen, 1994). By making Sen's statement of multidimensionality as a foundation, Sabrina Alkire and James Foster constructed a methodology to measure poverty in this perspective (Alkire and Foster, 2011b). First, this methodology was constructed for three dimensions (each with one or more than one sub-dimensions) of health, education, and living standards. There are several advantages of this framework. First, one can add as many variables as the dataset has. Second, the most

TABLE 1 Health deprivation matrix.

i \ j	1	2	3	4	5	6
1	0	1	0	0	0	0
2	1	1	0	0	0	1
3	0	0	0	0	1	0
4	1	1	1	0	1	0
5	0	0	1	1	0	0
6	0	0	1	1	1	1
7	1	0	0	1	0	0
8	1	1	1	1	1	1
9	0	1	0	0	1	1
10	1	0	1	1	1	1

Note. 1 and 0 denote if a person/individual is deprived and non-deprived respectively.

important characteristic is that one can decompose the index concerning dimensions and regions. These key characteristics allowed researchers throughout the globe to construct the MPI by including different variables which mainly depended on the dataset.

In the modern era, as innovations emerge, many researchers are of the view that MPI has narrowly explained the previously selected three domains of the composite index, and there is a need to explore these dimensions in depth. For instance, the health and energy sectors are the two important United Nations SDGs and play a pivotal role in the economic growth of all nations. There is a need to investigate separately the people's access to healthcare services as well as to energy sources. Resultantly, researchers have constructed separate indices for health and energy poverty. Different nations have constructed these indices by including a varied number of indicators mainly depending on the data availability (Simões et al., 2016; Weziak-Bialowolska, 2016; Pelz et al., 2018; Clarke and Erreygers, 2020; Lin and Okyere, 2020; Murias et al., 2020; Sokołowski et al., 2020; Chi et al., 2021; Karpinska et al., 2021; Mustafa et al., 2021; Qurat-ul-Ann and Mirza, 2021; Awan and Bilgili, 2022). Based on the SDGs' importance to health and wellbeing, this study has implemented the Alkire-Foster methodology to construct multidimensional health poverty. This composite index is composed of the health and health-related social indicators (mainly depending upon the data availability) to gauge the severity of districts' health poverty. The higher the index value in a specific district is, the more the district is health deprived in terms of healthcare services and *vice versa*.

As this study uses the framework of multidimensional poverty index, it is necessary to initiatively define the traditional Alkire-Foster theoretical concept of MPI. According to the Alkire-Foster approach MPI can be defined as: when an individual (or a household) is deprived in one health services dimension, the individual/household is identified as health poor in at least one dimension. Further, if the individual/household is deprived in two or more than two dimensions of health or health-related services, the individual/household is considered as multidimensionally health poor. This phenomenon can be easily understood by an example described in Table 1 and Table 2.

TABLE 2 Identification of multidimensional health poverty under different cut-off (k).

Dimension cut-off (k)	Individual/household under MHP
k = 1	1, 2, 3, 4, 5, 6, 7, 8, 9, 10
k = 2	2, 4, 5, 6, 7, 8, 9, 10
k = 3	2, 4, 6, 8, 9, 10
k = 4	4, 6, 8, 10
k = 5	8, 10
k = 6	8

Table 1 shows the health deprivation matrix of ten individuals/households for six dimensions. Each row represents i^{th} person or household and each column represents j^{th} indicator or dimension. The two elements (0 and 1) of the health deprivation matrix are explained as follow: if a person/household has access to a specific health indicator, the score is assigned as 0 (non-deprived), whereas if an individual/household has no access to that health facility, the score is assigned as 1which means the household is deprived in that indicator. Multidimensional health poverty is sensitive to the size of the deprivation cut-off (k) (Khan and Sloboda, 2022). Table 2 shows the identification of MHP at different k values. As the deprivation cut-off (k) increases the extent of multidimensional health poverty decreases. For instance, when k = 1, almost all individuals/households are considered to be multidimensionally deprived; whereas when k = 6, only 8th individual/household is multidimensionally deprived.

The extensive literature showed a significant association between health services and worldwide climate variability (temperature, rainfall, flood, drought, humidity, precipitation, and air temperature). Pakistan also has a diverse climate structure, which may or may not has a connection to health poverty. Keeping in view the importance of SDGs and previous literature, this study proposed the following hypotheses to be tested:

Hypothesis 1: There is a significant spatial agglomeration among the districts of Pakistan concerning the MHP score.

Hypothesis 2: The contiguous districts of Pakistan are significantly spatially correlated with one another regarding climate variability.

Hypothesis 3: There is a significant spatial bivariate relationship between the MHP score and climate variability at the district level.

4 Methodology

4.1 Study area

This study explores the spatial association of MHP and climatic variability across districts from four provinces and districts of the FATA region of Pakistan. There may be significant spatial differences in the extent of MHP across districts because capital districts from all

FIGURE 1
Area of the study (districts of Pakistan).

provinces are relatively well-off concerning access to health and health-related social dimensions. Thus, information on health-related indicators was gathered from four provinces and FATA regions. However, Gilgit Baltistan, Azad Jammu, Kashmir, and some of the districts from four provinces were excluded. These districts were either restricted due to the law-and-order situations or sufficient information on the study variables was unavailable. The rest of the districts were considered the study areas, shown in Figure 1.

TABLE 3 Profile of MHP dimensions, indicators, deprivation cut-off, and weights.

Dimensions	Indicators	Deprivation cut-off	Weights
Use of health services	Doctor consultation	If a person is consulted by a doctor, the assignment is 0, otherwise 1	1/21
	LHW accessibility	If a household has access to Lady Health Worker (LHW), the assignment is 0, otherwise 1	1/21
	Delivery assistance	If a woman has given birth in the presence of a doctor or nurse, then 0, otherwise 1	1/21
Quality of health services	Institutional delivery	If a woman has given birth in govt/a private hospital, the assignment is 0, otherwise 1	1/14
	Satisfaction of family planning services	If a household is not satisfied with the services of the family planning center, then 1, otherwise 0	1/14
Cost of health services	Cost of time (distance to clinic/ hospital)	If the distance from household to clinic/hospital is more than 30 min, the assignment is 1, otherwise 0	1/14
	Cost of time (distance to family planning center)	If the distance of the household to the family planning center is less than 30 min, then 0, otherwise 1	1/14
Child health	Child immunization	If the children of a household under 5 years old are immunized, then 0, otherwise 1	1/14
	Diarrhea consultation	If a household is consulted (from govt/a private hospital) for diarrhoea, the assignment is 0, otherwise 1	1/14
Maternal health	Pre-natal consultation	If a woman (in pregnancy) has no access to consultation (from the hospital, clinic, or family planning center) before delivery, the assignment is 1, otherwise 0	1/14
	Post-natal consultation	If a woman has access to proper consultation after delivery, the assignment is 0, otherwise 1	1/14
Housing services	clean drinking water	If a household has access to clean drinking water, the assignment is 0, otherwise 1	1/14
	Toilet facility	If a household has no access to a toilet facility, the assignment is 1, otherwise 0	1/14
Energy services	Cooking fuel accessibility	If a household has no access to the gas facility, the assignment is 1, otherwise 0	1/14
	Lighting accessibility	If a household has access to electricity, the assignment is 0, otherwise 1	1/14

Source: Authors' own computations based on "Pakistan Social and Living Standard Measurement (PSLM) surveys, 2019–20"

4.2 Data sources

This study used two types of data sources: one for health-related social indicators to construct the MHP index and the other for climatic variability across various geographies. Health-related indicators were extracted from the most recent Pakistan Social and Living Standard Measurement (PALM) survey, Round VII, 2019–20, conducted by the Pakistan Bureau of Statistics, Islamabad (Pakistan Bureau of Statistics,G.O.P, 2020). Though the survey was not conducted to identify the spatial clusters of health poverty, sufficient information on health-related social dimensions fulfilled our study objectives. The survey was conducted at the district level, and information on various sociodemographics, health, housing, water and sanitation, and environment were collected from households. Information on climatic variability was extracted from the most popular and well-known Online National Aeronautics and Space Administration (NASA) website established in the United States on 29 July 1958 (NASA). NASA has online information on climate-related attributes such as solar fluxes, solar cooking, mean, minimum, and maximum temperatures, earth skin temperature, humidity, precipitation, wind pressure, wind speed, and wind direction at different distances and dimensions.

4.3 Variables of the study

Before explaining the methodology of MHP in detail, choosing appropriate indicators to measure the MHP is of supreme importance. Therefore, based on the previous literature, our study has chosen seven dimensions (and 15 of their sub-dimensions) (Iqbal and Nawaz, 2017; Chi et al., 2021; Mustafa et al., 2021; Khan and Sloboda, 2022). All the study dimensions are weighted equally. A detailed picture of these dimensions (and their sub-dimensions), their deprivation cut-offs, and assigned weights are given in Table 3. Similarly, based on the data availability, six climate-related variables have been selected for this study. The first three variables were the maximum, minimum, and mean temperature of districts, all measured in degree centigrade (oC). The humidity rate of the district was measured in grams of vapor per kilogram (g/kg), precipitation of the district was scaled in millimeters per day (mm/dd), and wind speed in the district was measured in meters per second (m/s). The selected climate-related variables influencing health poverty are described in detail in Table 4. Ten years of data (from 2011 to 2021) on these indicators were extracted, and then used their averages as the study observations.

4.4 Multidimensional health poverty

The MHP index was formulated for the districts of Pakistan through the widely used Alkire-Foster methodology (Alkire and Foster, 2011a; Alkire and Foster, 2011b; Alkire and Santos, 2013). This approach is comprised of two steps; the Identification step and the Aggregation step.

TABLE 4 Profile of climate related indicators of the study.

Variable name	Description	Measurement unit
Mean temperature	Average of the 10 years annual mean temperature of a district	˚C
Max: temperature	Average of the 10 years annual maximum temperature of a district	˚C
Min: temperature	Average of the 10 years annual minimum temperature of a district	˚C
Humidity	Average of the 10 years annual humidity rate of a district	g/kg
Precipitation	Average of the 10 years annual precipitation rate of a district	mm/dd
Wind speed	Average of the 10 years annual wind speed of a district	m/s

Source: Authors' own computations based on information extracted from online National Aeronautics and Space Administration (NASA) website. "˚C", "g/kg", "mm/dd", and "m/s" denotes "degree centigrade", "grams of vapor per kilogram of air", "millimeters per day", and "meters per second" respectively.

The identification step (also known as the dual cut-off) is further divided into two thresholds. The first threshold was used to choose the deprivation cut-off of indicators and assign a weight to each indicator. A household *i* is called to be deprived for indicator x_i, if its attainment in that indicator is beneath the cut-off, where the cut-off is represented by z_i, i.e., if $x_i < z_i$. Following, all study dimensions were equally weighted, i.e., ($w_i = \frac{1}{no.\,of\,dimenstions} * \frac{1}{no.\,of\,indicators}$), where w_i is the weight assigned to i^{th} indicator. The cut-off z_i scores and assignment of equal weights were fixed by following previous literature on poverty in Pakistan (Khan et al., 2014; Khan et al., 2015; Iqbal and Nawaz, 2017; Khan and Akram, 2018; Khan and Sloboda, 2022). The study indicators were weighted so their sum equals 1, i.e., $\sum_1^n w_i = 1$, where n is the total number of indicators.

The second threshold was used to choose the poverty cut-off to identify the poor from the non-poor. From poor to non-poor identification, a deprivation score was assigned to households according to their deprivations in component indicators. The deprivation score was designed by taking the weighted sum of household deprivations. Statistically,

$$c_i = \sum\nolimits_1^n w_i ind_i \tag{1}$$

where c_i denotes the deprivation score of the i^{th} household, w_i is the weight assigned to i^{th} variable, and "ind_i" is the i^{th} indicator. If a household is deprived in i^{th} indicator, i.e., if $x_i < z_i$ the $ind_i = 1$, otherwise $ind_i = 0$. Next, a cut-off score was determined to identify if a household is multidimensionally health poor. The i^{th} household is considered multidimensionally health poor if its deprivation score is higher than or equal to the poverty cut-off k, i.e., if $c_i \geq k$ and *vice versa*. According to the A-F censoring approach, the c_i of multidimensionally non-poor households were exchanged as 0, even if their c_i is non-zero. By applying the censored deprivation score $c_i(k)$ technique, if $c_i \geq k$, then $c_i(k) = c_i$, and "0" otherwise.

In the second (Aggregation) step, two elements were computed. The first one was the incidence of households facing multiple deprivations denoted by $H = \frac{q}{n}$, and the second was the average share of households' weighted deprivations (deprivation intensity) denoted by $A = \frac{\sum_i^n c_i(k)}{q}$. H is the headcount ratio, q denotes the number of multidimensionally healthy poor, n is the total number of households, and $c_i(k)$ is the censored deprivation score of i^{th} household. The MHP, denoted by M_o, is the product of both H and A. Statistically,

$$M_o = H \times A \tag{2}$$

This study's analysis unit is the district, but the MHP index has been constructed at the household level. Therefore, the MHP scores of all households were aggregated at the district level. The mean is used to recognize the spatial association of MHP and climate change at the district level. The statistical notation of mean is written as under,

$$Mean = \frac{1}{n}\sum_{i=1}^{n} MHP_i \tag{3}$$

Where n is the number of households i = 1, 2, 3, . . . , n and MHP_i is the multidimensional health poverty score of i^{th} households.

4.5 Spatial analysis

Global and local univariate Moran's I test statistics were applied to test whether MPH and climatic variability have spatial clusters and/or spatial outliers. The global univariate Moran's I examined if a spatial association exist between the MPH and/or climate variable(s) of a specific district and the MPH and/or climate variable(s) of the surrounding/neighboring districts. Statistically, the global univariate Moran's I is written in Eq. 3 as under,

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i - \bar{x})^2}, i \neq j \tag{4}$$

where n is the number of districts; x_i and x_j are the MPH or climate indicator scores of i^{th} and j^{th} districts, respectively; $\bar{x}$ denotes the mean score of MPH or climate indicator of all districts; w_{ij} is the weighted queen contiguity matrix. If i^{th} and j^{th} districts share a common boundary, the assignment $w_{ij} = 1$, otherwise $w_{ij} = 0$. I represent the global univariate Moran's I score ranges between +1 and −1, i.e., $1 \leq I \geq -1$. When Moran's I = 0, it means that the MPH or climate indicator is randomly and/or irregularly dispersed, when 'Moran's I > 0, it means that the MPH or climate indicator scores are positively agglomerated, and when Moran's I < 0, it means that the MPH or climate indicator scores of neighboring regions are negatively associated. To check the significance of Moran statistic, a null hypothesis (H_o) of spatial randomness was tested against the alternative hypothesis (H_1) of spatial clusters/patterns.

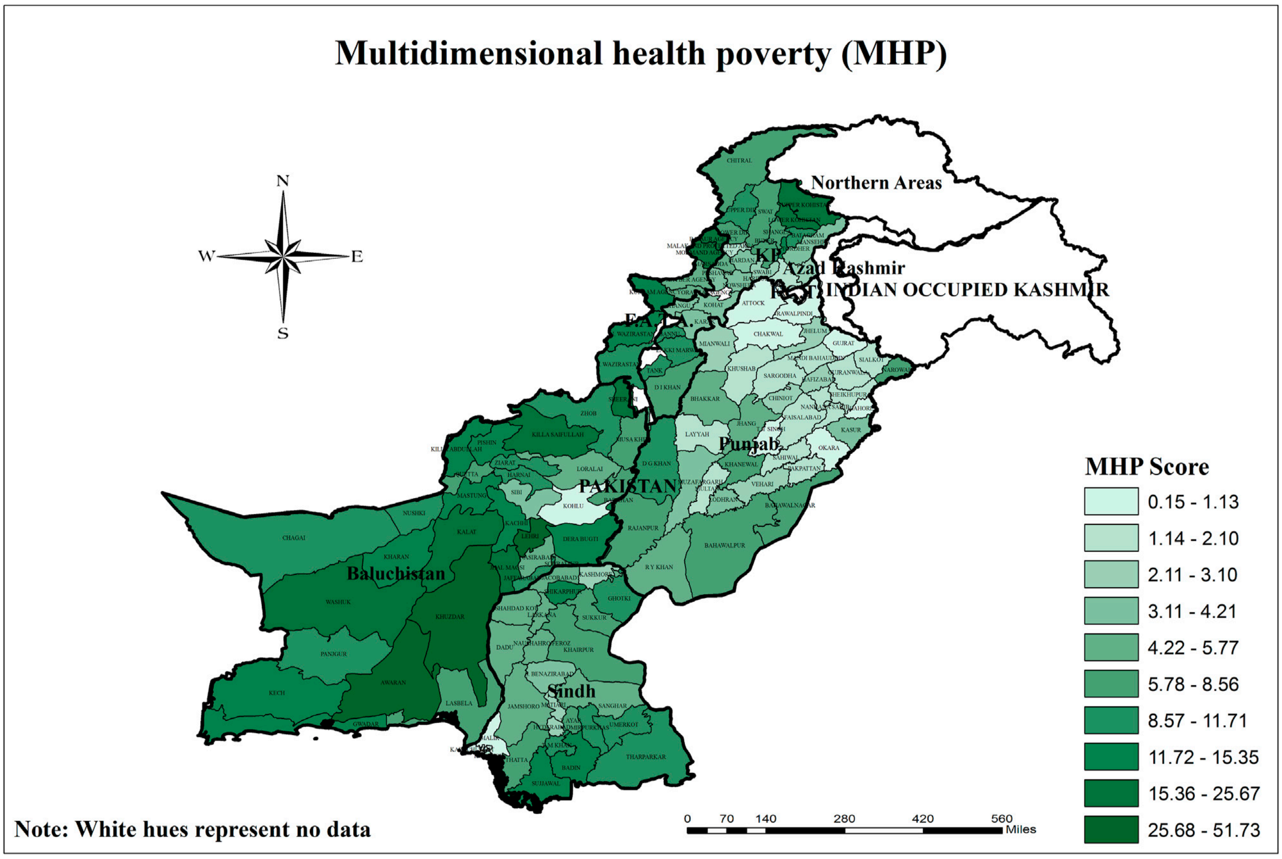

FIGURE 2
Spatial distribution of multidimensional health poverty across districts of Pakistan.

The local univariate Moran's I statistic identified the districts' significant spatial clusters and/or spatial outliers concerning MPH or climate change variables. Econometrically, the local univariate Moran's I is written in Eq. 4 as under,

$$I_i = \frac{n(x_i - \bar{x})\sum_{i=1}^{n} w_{ij}(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}, i \neq j \tag{5}$$

where n is the number of districts; x_i and x_j are the MPH or climate indicator scores of ith and jth districts, respectively; $\bar{x}$ represents the mean score of MPH or climate indicator of all districts; w_{ij} is the queen contiguity weight matrix. I_i is the extent of spatial association between each ith and its surrounding districts. Some studies (Anselin, 1995; Anselin et al., 2010) suggested dividing the Local Indicators of Spatial Association (LISA) results into four quadrants, i.e., high-high (H-H) or hot spot, low-low (L-L) or cold spot, high-low (H-L) or outlier, and low-high (L-H) or an outlier. The H-H and L-L quadrants mean that the MPH or climate indicator score of a district and its adjacent districts are significantly spatially agglomerated. In contrast, the quadrants of H-L and L-H mean that the contiguous districts are heterogeneous or randomly dispersed.

The statistical concept of bivariate global and local Moran's I is similar to the univariate ones. Although, in univariate analysis MPH or climate indicator(s) score of a specific district was tested with its MPH or climate indicator(s) values in the neighboring districts, while in bivariate analysis MPH scores of a district were tested with another (say climate-related) variable(s) scores in the surrounding districts. Some studies (Anselin et al., 2002; Anselin et al., 2010) proposed bivariate global and local Moran's I tests, given in Eqs 5, 6, respectively,

$$I_{xy} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(y_j - \bar{y})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i - \bar{x})^2}, i \neq j \tag{6}$$

$$I_{xy(i)} = \frac{n(x_i - \bar{x})\sum_{i=1}^{n} w_{ij}(y_j - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}, i \neq j \tag{7}$$

where n is the number of districts; x_i and y_j are the MPH and climate indicator scores of ith and jth districts, respectively; $\bar{x}$ and $\bar{y}$ represents the mean score of MPH and climate indicator of all districts, respectively; w_{ij} is the queen contiguity weighted matrix.

5 Results

5.1 Spatial distribution of multidimensional health poverty

Figure 2 displays the spatial distribution of MHP scores of all districts on the map. The map clearly showed varied patterns of

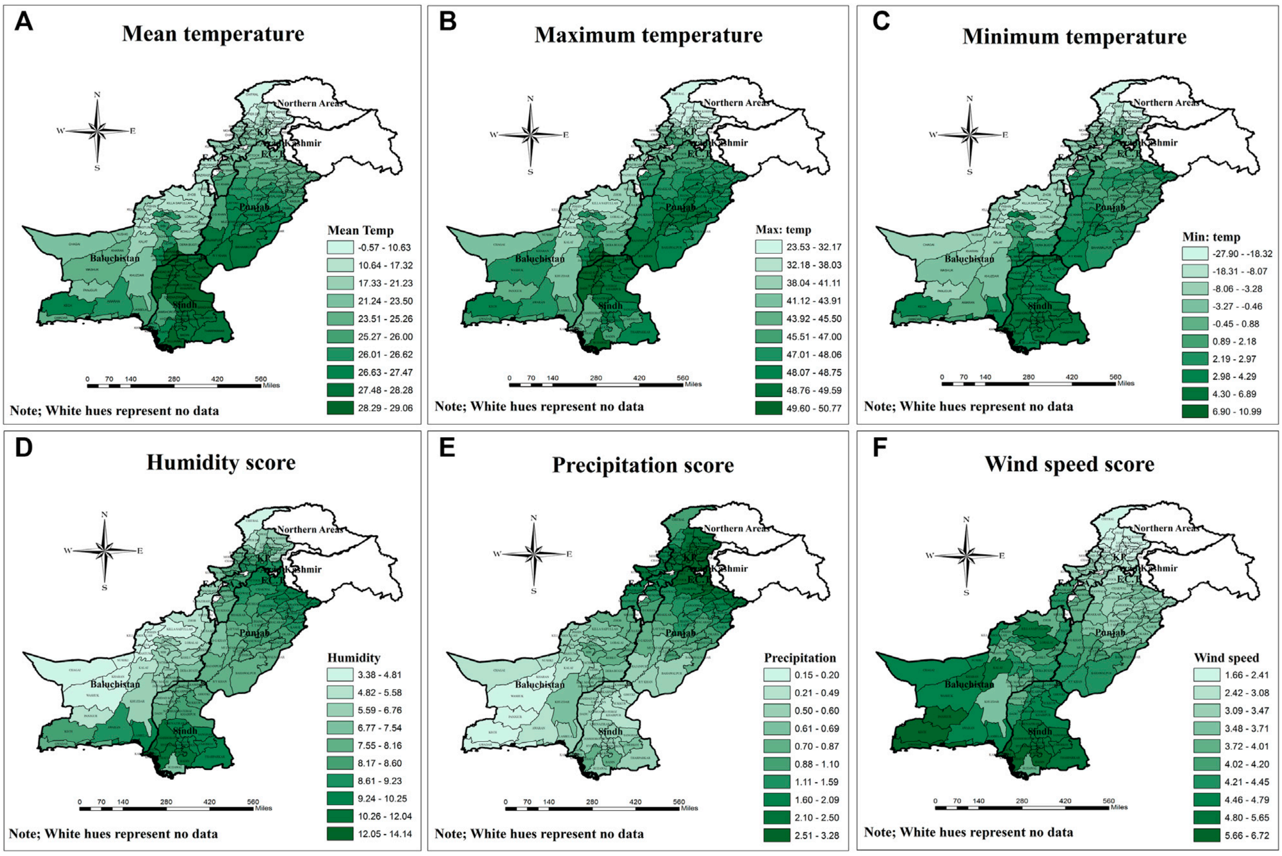

FIGURE 3
Spatial distribution of **(A)** Mean temperature **(B)** Maximum Temperature **(C)** Minimum temperature **(D)** Humidity score **(E)** Precipitation scores and **(F)** Wind speed score across districts of Pakistan.

MHP across all districts of Pakistan. MHP was higher in districts of Baluchistan, FATA, and some of the districts from Khyber Pakhtunkhwa (KP). These districts are mostly located in the country's west-southern, western, and northern areas. The highest health poverty-stricken districts were found in Baluchistan and KP, which range from 25.68% to 51.73%. Residents of these districts were found to be health poor, which means that people in these areas have relatively less access to health and health-related social indicators.

In contrast, MHP was lower in the districts in the country's eastern, eastern-south, central, and southern parts. These districts are mainly located in Punjab and Sindh. The lowest health poverty-stricken districts were found mainly in Punjab, which ranges from 0.15% to 1.13%. Inhabitants of these districts have relatively higher access to health and health-related social determinants.

5.2 Spatial representation of climate variables

Figure 3 displays the spatial distribution of climate variables of the study. Figures 3A–C displayed all districts' mean, maximum, and minimum temperatures. All three panels of the figure showed almost similar patterns though slight variations were found, especially in Sindh. However, within provinces, there is a clear picture of disparities in the mean, maximum and minimum temperatures across districts. Mean, maximum and minimum temperatures were recorded to be higher in Punjab and Sindh districts, mainly located in the country's eastern, south-eastern, and southern parts. The highest mean, maximum, and minimum temperatures ranged from 28.29°C to 29.06°C, 49.60°C to 50.77°C and 6.90°C to 10.99°C in regions of Sindh and Punjab. On the other hand, districts from Baluchistan, KP, and FATA have comparatively lower mean, maximum and minimum temperatures. These districts are mainly located in the country's northern, west-northern, and western parts. The ranges of lowest mean, maximum, and minimum temperatures were calculated as −0.57°C to 10.63°C, 23.53°C to 32.17°C and −27.90°C to −18.32°C respectively.

The humidity rate of all the districts is shown in Figure 3D. There are considerable differences in the rates of humidity in all provinces. Districts from Punjab and Sindh made a spatial pattern of higher humidity compared to Baluchistan, KP, and FATA districts. Some of the districts from Baluchistan also have relatively higher humidity. Almost all regions from Baluchistan, FATA, and KP showed a spatial cluster of lower humidity rates. The highest humidity range (12.5 k/kg to 14.14 k/kg) was seen in Sindh province, whereas the lowest humidity range (3.38 k/kg to 4.81 k/kg) was found in the regions of Baluchistan. The precipitation rate displayed a similar pattern to the humidity rate, though considerable

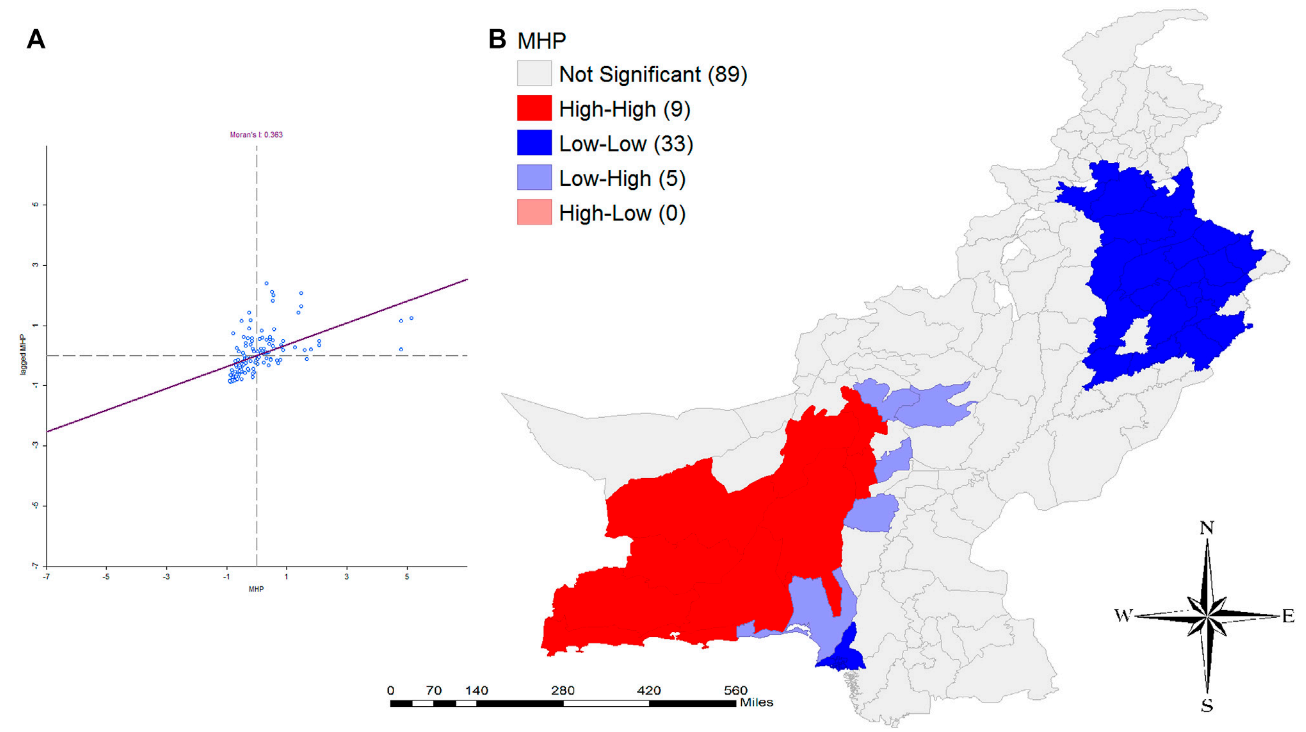

FIGURE 4
Author's own calculations based on the Pakistan Social and Living Standard Measurement (PSLM) survey (Pakistan Bureau of Statistics,G.O.P, 2020). Spatial analysis of **(A)** Global Moran's I of multidimensional health poverty and **(B)** Local Moran's I of multidimensional health poverty across districts of Pakistan.

disparities were noted in the districts of KP and Sindh provinces (Figure 3E). Humidity was found to be lower in KP and higher in Sindh, whereas precipitation was the opposite. The precipitation rate was found to be higher in the districts of Punjab, KP, and FATA.

In contrast, districts from Sindh and Baluchistan showed a spatial pattern of lower precipitation rates. The higher precipitation (2.51 mm/day to 3.28 mm/day) and lower precipitation (0.15 mm/day to 0.20 mm/day) ranges were noticed in KP and Baluchistan, respectively. Finally, Figure 3F displays the wind speed across all districts of Pakistan. Like other climate variables, wind speed presented evident variations across the districts. The northern and eastern areas of the country presented a clear cluster of districts with lower wind speeds. Some of the districts from Baluchistan also have lower speed rates. In contrast, almost all districts from Sindh and Baluchistan made a spatial pattern of districts with higher wind speeds. The lowest wind speed range (1.66 m/s to 2.41 m/s) was found in the northern regions of Pakistan, whereas the highest range (5.66 m/s to 6.72 m/s) of wind speed was noticed in the areas of the southern part of Pakistan.

5.3 The univariate spatial relationship of MHP and climate indicators

Figures 4A,B, respectively, show the results of global and local Moran's scores of MHP in Pakistan. The Moran's I statistic score indicated that concerning MHP, the contiguous districts were significantly spatially associated by 36% with a significance level of Pseudo p-value of 0.001 (Table 5). The scatterplot of Moran's I score of MHP is shown in Figure 4A. The univariate LISA analysis classified the spatial clusters into four quadrants (Figure 4B). A spatial cluster of H-H districts was found in the western part of the country, located in Baluchistan, which means that these districts and their surrounding districts are highly health-poverty-stricken areas. A significant spatial cluster of L-L districts was found in Punjab. In other words, districts in this cluster are relatively better off regarding health poverty. Furthermore, a spatial pattern of L-H districts was found in Baluchistan, where neighboring districts with higher health poverty scores surround the district with a lower MHP score.

Univariate Moran's I test scores of climate variables are shown in Table 5. The scatterplots of these indicators are provided in Appendix A, Figure A1. Table 5 indicates a solid spatial association between a specific district and its neighboring districts. All variables have a higher (than 75%) Moran's I scores. The highest univariate spatial association was recorded for precipitation rate, and the lowest spatial relationship was calculated for minimum temperature. Figure 5 displays the univariate local Moran's clusters of climate variables. It is evident from the figure that a spatial cluster of L-L districts concerning mean, minimum, and maximum temperatures was found mainly in KP and Baluchistan (Figures 5A–C).

In contrast, an H-H spatial pattern of districts for mean and maximum temperature was found in Sindh and Punjab (Figures 5A,B), whereas, for minimum temperature, it is found only in Sindh

TABLE 5 Test for significance of spatial clusters and outliers with 999 random permutations.

Variable	Moran's I	E(I)	Sd(I)	z-score	Pseudo *p*-value
Multidimensional health poverty (MHP)					
MHP	0.363	−0.0074	0.0520	7.0832	0.001
Univariate Moran's I = Climate indicators					
Mean temperature	0.797	−0.0074	0.0527	15.2736	0.001
Max: temperature	0.782	−0.0074	0.0527	15.0076	0.001
Min: temperature	0.783	−0.0074	0.0536	14.7794	0.001
Humidity	0.878	−0.0074	0.0553	16.0589	0.001
Precipitation	0.929	−0.0074	0.0556	16.8232	0.001
Wind speed	0.871	−0.0074	0.0528	16.6578	0.001
Bivariate Moran's I = MHP * Climate indicators					
MHP*Mean temperature	−0.182	−0.0074	0.0394	−4.6607	0.001
MHP*Max: temperature	−0.095	−0.0074	0.0389	−2.4563	0.012
MHP*Min: temperature	−0.274	−0.0074	0.0410	−6.7317	0.001
MHP*Humidity	−0.387	−0.0074	0.0422	−9.2399	0.001
MHP*precipitation	−0.157	−0.0074	0.0413	−3.7950	0.001
MHP*wind speed	0.031	−0.0074	0.0411	0.7474	0.217

Source: Authors' own computations based on "Pakistan Social and Living Standard Measurement (PSLM) surveys, 2019–20".

(Figure 5C). The clusters of H-L and L-H were very small, showing fewer districts where the mean, maximum and minimum temperatures are high (low) but low (high) neighbors surround them. Unlike the temperatures, humidity indicated different shapes of clusters (Figure 5D). Almost all districts from Baluchistan (and some from KP) province were spatially clustered in L-L quadrants. A spatial pattern of H-H districts was found in the province of Sindh. The precipitation rate is highly clustered across the districts of Pakistan (Figure 5E). Almost all the districts from Sindh and Baluchistan presented a spatial cluster of L-L districts. A higher precipitation rate is found in northern areas of Pakistan, significantly surrounded by districts with higher precipitation. Finally, the spatial clusters of wind speed are presented in Figure 5F. H-H spatial clustered districts were located in Sindh and Baluchistan, whereas L-L clustered districts were mainly found in KP and Punjab. Only one district in the south was clustered as L-H.

5.4 Bivariate spatial association between health poverty and climate change

Table 5 shows the bivariate global Moran's I result of health poverty and climate attributes. MHP has a negative significant spatial association with all the climate variables of the study except wind speed which is insignificant. The highest inverse spatial association (38%) was found between the MHP score and humidity, whereas the lowest negative relationship (10%) was recorded between MHP and maximum temperature. The bivariate Moran scatterplots of multidimensional health poverty with the climate indicators are provided in Appendix A, Figure A2.

Figure 6 shows the bivariate local Moran's I result of MHP scores and climate variables. Districts with L-L spatial clusters in the north and central part of Pakistan indicated that MHP is lower in these districts, which are surrounded by lower mean temperature districts (Figure 6A). The H-H clustered districts, mainly from Sindh, showed higher health poverty surrounded by neighbors with higher mean temperatures. A strong L-H spatial outlier was found in Punjab and Sindh provinces, which indicated that MHP is lower in these areas but is surrounded by the districts with higher mean temperatures. Also, a spatial collection of H-L districts in the north and central parts exhibited that the lower mean temperature districts surround higher health poverty. The spatial correlation of MHP and maximum temperature displayed in Figure 6B is almost similar to the behavior found in Figure 6A; however, it is different for MHP and minimum temperature presented in Figure 6C. A weak cluster of H-H districts was found in the southern part, where the higher minimum temperature of the neighbors encircled high MHP. L-H spatial cluster was also found near the H-H cluster. The H-L spatial outlier in the northern and central parts confirmed that higher MHP is encircled by the contiguous areas where the minimum temperature is low.

Figure 6D displayed the spatial bivariate local Moran's of MHP and Humidity rate. Almost all districts from Baluchistan presented a strong spatial pattern of H-L districts, indicating that higher MHP is surrounded by the lower humidity rate in their neighboring districts. L-L clustered districts were mainly found in KP and Baluchistan. A spatial cluster of H-H regions was found in Sindh, where the higher MHP was covered with neighbors with high humidity rates. The spatial correlation between MHP and precipitation is similar to the association found in Figure 6D. However, considerable variations were found in the

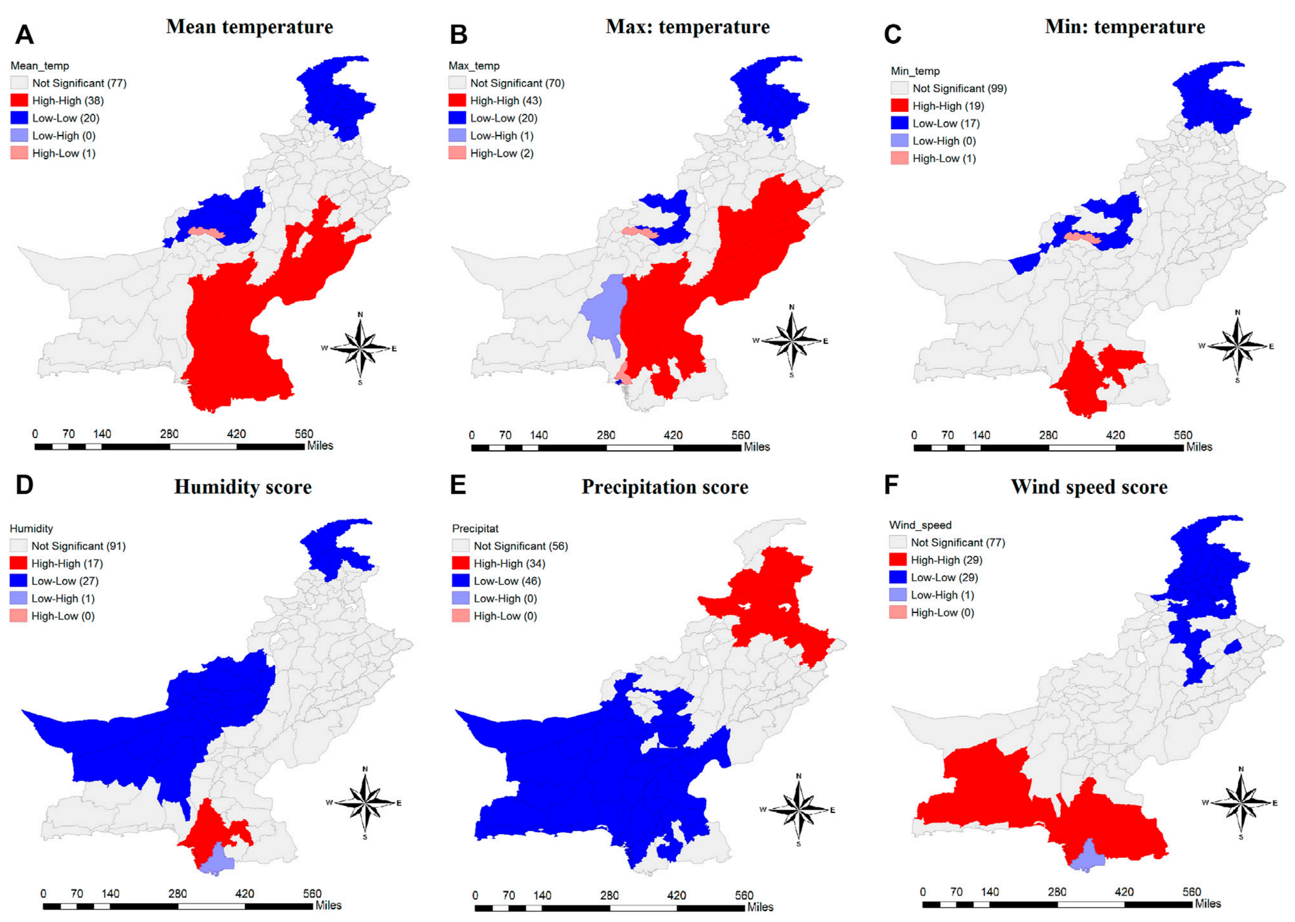

FIGURE 5
Spatial representation of univariate local Moran'I of **(A)** Mean temperature **(B)** Maximum temperature **(C)** Minimum temperature **(D)** Humidity score **(E)** Precipitation score and **(F)** Wind speed score across study districts of Pakistan.

number of districts in each cluster except H-H (Figure 6E). A strong outlier of H-L districts in Baluchistan and Sindh exhibited that higher MHP was bounded by neighbors with lower precipitation rates. A cluster of L-L districts was also seen in these provinces, showing that lower precipitation neighbors encircle the lower health poverty. A strong spatial outlier of L-H areas was seen in the northern and east northern parts where lower MHP was covered, with the districts having higher precipitation rates. Few districts presented the cluster of H-H regions, mainly in KP and some in the FATA. Finally, a very different result of MHP and wind speed were noted in Figure 6F. H-H clusters were mainly found in Sindh and Baluchistan. The l-H outlier was also seen in Sindh, which indicated that lower MHP was shielded with districts with higher wind speeds. Districts from Punjab and KP presented a cluster of L-L districts. Also, a spatial outlier of H-L districts was seen in KP, which indicated higher health poverty walled by districts with lower wind speed.

6 Discussion

This study is the first examination of the spatial nexus between Pakistan's MHP and climate indicators. Because this study addresses the fundamental question of whether the diverse climate across various geographies of Pakistan has spatial connectivity with the varied MHP. Another novelty is that this study identifies the regions where MHP is positively and/or negatively associated with climatic variability.

The results confirmed that people in Baluchistan and FATA have less accessibility to health and health-related indicators. In other words, inhabitants in these regions are multidimensionally health-deprived. On the other hand, residents in districts from Punjab are better off in terms of MHP scores. They have higher accessibility to health and healthcare services. Our results are consistent with the outcome of previous research (Khan and Hussain, 2020). The government of Pakistan has launched different health programs such as the "sehat sahulat program" and "family planning and primary healthcare" to improve the accessibility of all people to various healthcare services (GOP, 2015; NADRA, 2016). Despite such initiatives, significant differences exist across Pakistan districts which challenge the UNDP's Sustainable Development Goals (SDGs). According to UNDP's SDG 1, each nation must ensure healthy lives and promote wellbeing for all ages (UNDP, 2015a; UNDP, 2015b). Our findings suggest that Pakistan is far from the SDG that needs to be achieved. Not only the accessibility to various health-related social indicators is less, but there were disparities in such

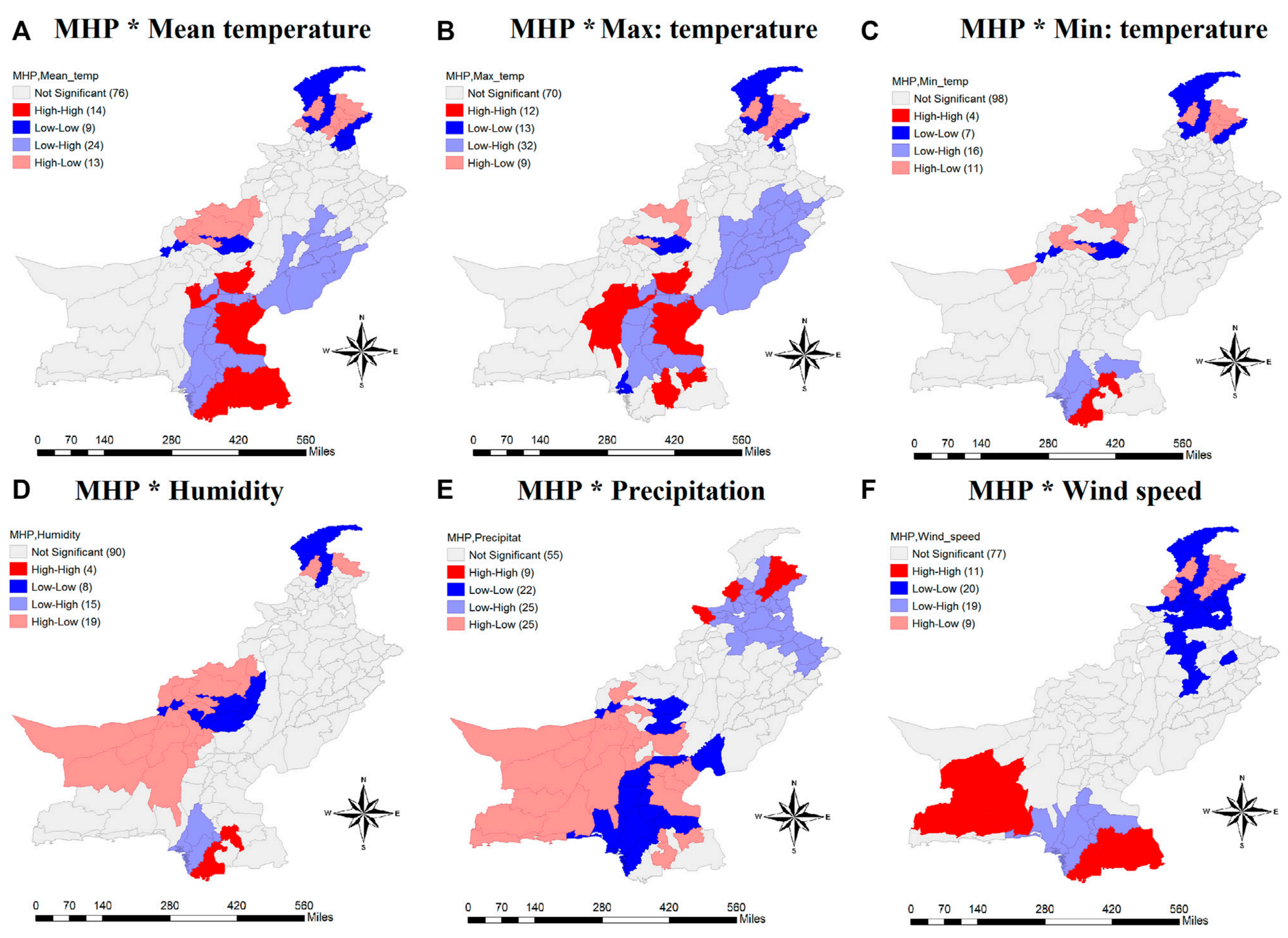

FIGURE 6
Spatial analysis of bivariate Moran's I of **(A)** MHP*Mean temperature **(B)** MHP*Maximum temperature **(C)** MHP*Minimum temperature **(D)** MHP*Humidity rate **(E)** MHP*Precipitation rate and **(F)** MHP*Wind speed rate across all districts of Pakistan.

accessibility across different geographical regions. Districts from some geographical regions achieved higher access to healthcare infrastructure and got lower MHP values, whereas others still have a substantially high MHP score.

The climate in Pakistan is diverse. It changes across geographical locations. Our study results also presented varied patterns of various climatic attributes, including temperature, humidity, precipitation, and wind speed. It is confirmed that mean, maximum, and minimum temperatures are higher across the districts of Punjab and Sindh (mostly smooth areas or no hilly areas) whereas lower in most of the districts from Baluchistan, KP, and FATA, as these provinces have mostly hilly areas. Humidity and precipitation presented similar disparities across districts, whereas the wind speed provided different patterns. Districts across Baluchistan and Sindh collectively made a pattern of higher wind speed, whereas northern and northeastern districts depicted a pattern of lower wind speed.

A critical analysis component was identifying the spatial clustering in multidimensional health poverty and its connection to climate attributes. First, we conducted a univariate global and local spatial analysis to check whether significant spatial clusters and outliers exist in study indicators. According to the results, health poverty in a specific district was spatially positively associated with the MHP scores of its surrounding districts. The LISA results confirmed the location of the hot spots, cold spots, and spatial outliers. The H-H cluster in Baluchistan province showed that these districts are multidimensionally health deprived. Such findings were also found in previous studies in Pakistan (Iqbal and Nawaz, 2017; Mustafa et al., 2021). Also, the cluster of cold spots (L-L) districts in Punjab indicated that the residents of Punjab are relatively well-off in terms of MHP scores. Such spatial disparities are against one of the most important SDGs, i.e., Goal 10 of reducing inequality within and among countries (UNDP, 2015a; UNDP, 2015b).

Our findings exposed a strong spatial positive correlation between the contiguous neighbors concerning all climate-related variables. Mean, and maximum temperatures were highly clustered mainly in Sindh and Punjab, whereas minimum temperature was clustered as H-H only in Sindh. In contrast, all the temperature indicators in the northern and some central districts were clustered in L-L quadrants. The results concluded opposite outcomes for humidity and precipitation. Lower humidity and precipitation areas were found in Baluchistan and Sindh, which were surrounded by districts with lower humidity and precipitation rates. However, the case for the H-H cluster was different. Higher precipitation districts were seen in the northern and northeastern areas.

Interestingly there was no spatial outlier in terms of precipitation rate. The wind speed was also significantly spatially associated with its neighboring districts. It is confirmed that wind speed was higher in the areas of Sindh and Baluchistan whereas lower in the districts of KP and some of Punjab, which spatially clustered in L-L quadrants.

A key contribution of the study is to identify the spatial cross-correlation between multidimensional health poverty and various climate indicators. For this purpose, we conducted a bivariate global and local spatial analysis. Results of the study confirmed that all the climate-related indicators have a significant negative spatial association with MHP, except wind speed has a positive but insignificant spatial association with the MHP score. Results from earlier studies also supported our findings (Weck et al., 2008; Thompson et al., 2012; Bennett and Friel, 2014; Farooq et al., 2019; Majeed and Ozturk, 2020; Li et al., 2022). Our results suggested that the higher the temperatures, humidity, precipitation, and wind speed, the lower the MHP scores throughout Pakistan. However, separate bivariate LISA analysis of all climatic indicators with MHP provided insight into the spatial clusters and outliers.

The results show that higher MPH was clustered by neighboring areas with higher mean and maximum temperatures (Figures 6A,B). In contrast, the L-L cluster of MHP is surrounded by a lower mean and maximum temperature of the neighbors. Such districts were seen in the northern areas of Pakistan. In contrast, H-L and L-H outliers were strong because of the negative spatial association of MHP and temperature. Previous studies also supported our findings of the inverse association of health outcomes and temperature (Martiello and Giacchi, 2010; Wondmagegn et al., 2021). Most regions were clustered such that lower (higher) MHP scores were surrounded by higher (lower) mean or maximum temperature districts. The spatial clusters and outliers of MHP with minimum temperature were found to be very small. The majority of the districts were insignificant. Though, spatial outliers of lower (higher) MHP covered by the higher (lower) minimum temperature were seen in the southern and central parts of the country. Moreover, almost all districts from Baluchistan presented a spatial outlier of H-L districts which confirmed the inverse relationship between the higher MHP in specific districts surrounded by districts with lower humidity rates. Previous studies also supported the inverse association of humidity and health poverty in terms of health outcomes and health infrastructure (Barreca, 2012; Gao et al., 2014; Derby, 2017; Wolkoff, 2018). MHP with precipitation rate made a strong outlier of H-L districts, mainly in Baluchistan, which depicted a strong negative association between the two. Such inverse outcomes are consistent with previous studies (Abiona, 2017; Schramm et al., 2021). A higher MHP score lowers the precipitation rate in adjacent regions. Not only was the H-L outlier seen, but the L-H spatial outlier was also found in the country's northern and northeastern areas, which confirmed that lower MHP is surrounded by neighboring districts with higher precipitation rates. Also, a good spatial cluster of H-H was seen in the southern regions where high MHP districts were covered by lower precipitation districts.

7 Limitations

This study has several limitations. First, there may be other health-related indicators of MHP. However, this study used only 15 health and health-related social indicators, as the available dataset did not provide sufficient information on other health-related variables. The same is true for the selection of climate-related attributes. Several other climate variables (such as CO2, air pollution, drought, and flood) also significantly determine the health services but are not included in the present study due to the unavailability of data on the NASA website. Second, the spatial analysis was performed at the district level because the shapefiles and coordinate information were unavailable at a more micro level, such as municipal or household. Third, this study only considered the districts from four provinces and the FATA region, as data on other districts were not collected due to law-and-order situations. Fourth, the spatial analysis was limited to geographical location and did not consider the time because the PSLM survey is cross-sectional.

8 Conclusion

Previous studies investigated the association between climate variability and health outcomes mostly from non-spatial perspectives. Also, health outcomes are mostly measured by a single indicator. This study assessed the relationship between climate variability and multidimensional health poverty in spatial terms by considering health poverty a multidimensional phenomenon. Therefore, we constructed a multidimensional health poverty (MHP) index to measure the overall health status of the districts. We used mean temperature, minimum temperature, maximum temperature, humidity, precipitation, and wind speed as indicators of climate variability. We applied the spatial univariate and bivariate global Moran's I and Local Indicators of Spatial Association (LISA) tests to assess the significant spatial clusters and outliers of climate variability and MHP.

The instant results concluded that there is a considerable geographical disparity in terms of health poverty. Punjab was considered the well-off, whereas Baluchistan was considered the highly poverty-stricken province. Such a conclusion was also drawn based on the univariate spatial results. H-H cluster was found in Baluchistan, whereas L-L spatial cluster was seen in the districts of Punjab. Moreover, the study results concluded an inverse spatial association between MHP and temperatures. Bivariate spatial outliers of H-L and L-H confirmed the clusters of a significant negative relationship, especially in Baluchistan and KP. Most importantly, the results also concluded an inverse spatial association of MHP with humidity and precipitation rates. A strong spatial outlier (H-L) was seen in the districts of Baluchistan and Sindh. It is concluded that a lower humidity or precipitation rate, the higher the MHP scores.

The above results have some policy recommendations. Firstly, based on the conclusion from univariate global and local results, the government of Pakistan is recommended to set priorities to mitigate health poverty. More preferences must be given to the districts making an H-H cluster to reduce the disparities in access to health-related social indicators. Secondly, based on the significant bivariate spatial association between MHP and temperature, government and policymakers (in order to reduce health poverty) are needed to set priorities by giving more preferences to areas under H-L outliers. Thirdly, keeping the importance of bivariate relationship between MHP and precipitation and humidity rates in view, to mitigate the health poverty, policy planners are needed to adopt such steps that improve the people's accessibility to health-related social indicators by setting priorities in Baluchistan and Sindh provinces, especially in the districts where the humidity and precipitation rates are low.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://www.pbs.gov.pk/publication/pakistan-social-and-living-standards-measurement-survey-pslm-2019-20-provincial and https://climate.nasa.gov/.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2023.1180556/full#supplementary-material

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Has building innovative provinces reduce environmental pollution?--evidence from a quasi-natural experiment in China

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The implementation of innovative provinces as a pivotal pilot measure to promote the in-depth advancement of ecology in China is a critical undertaking. An accurate assessment of the environmental effects of these innovative provinces is necessary to obtain a comprehensive understanding of the impact of pilot policies and facilitate the promotion of future policies with precision. In this study, the difference-in-differences method and the mediation model are employed to analyze the effect and mechanism of the pilot policies for innovative provinces on regional environmental pollution in 30 provinces in China from 2008-2020. The results demonstrate that the innovation provincial policies have resulted in an average reduction of 14.6% in environmental pollution annually in the pilot areas. This conclusion is still valid after robustness tests are eliminated. Furthermore, the mediation effect model provides evidence that the innovation provinces pilot policy reduces environmental pollution through technological innovation and industrial structure upgrading. Additionally, the heterogeneity analysis finds that innovation provinces pilot policy have led to a reduction of 17.4% in environmental pollution in coastal regions and a reduction of 11.7% in inland regions annually. Overall, this research contributes to the existing literature by underscoring the importance of innovation-driven development for environmental governance and effectively promoting the construction of a resource-saving and environment-friendly society.

KEYWORDS

innovative provinces, industrial structure upgrade, environmental pollution, quasi-natural experiment, DID model

1 Introduction

In recent decades, the global economy has experienced significant growth and development. However, this growth has been accompanied by serious environmental challenges, including rising levels of greenhouse gas emissions, declining air quality, and deteriorating ecosystems. To address these global challenges, innovative development has become an inevitable choice for countries to solve problems related to population, resources, and the environment, and ensure sustainable development (Wang and Luo, 2020). For instance, the United Kingdom has promoted innovative green technologies, such as clean energy applications, to address the haze problem (Foxon et al., 2005). The German government places significant importance on technology development and innovation to achieve energy saving and emission reduction. Since 2005, the energy conservation program has focused on energy efficiency and renewable energy, with the German government supporting the use of renewable energy by establishing large-scale wind and solar power generation facilities to reduce the threat to the environment from energy-intensive and polluting emission resources (Lehr et al., 2008). Similarly, China has highlighted the importance of promoting green development through innovation and promoting the harmonious coexistence of humans and nature at the 20th National Congress of the Communist Party (Dessein et al., 2022). Current research suggests that an increasing number of countries are responding to the deteriorating environmental and climate issues by adopting innovative development approaches.

China has adopted a new development concept that emphasizes innovation, coordination, green growth, openness, and sharing, as part of its broader efforts to establish an ecological civilization system and promote harmonious coexistence between people and nature. The Central Committee of the Communist Party of China (CPC) and the State Council issued the "Outline of National Innovation-driven Development Strategy" in May 2016, which called for the construction of a regional innovation demonstration and leading highland, as well as the establishment of innovative provinces. The implementation of this policy represents a crucial step towards establishing a modern innovation system in China, and aligns with the strategic objective of advancing the nation's innovation capabilities. At the highest level of policy design, innovation-driven development is recognized as the primary catalyst for achieving high-quality and sustainable economic growth. It is important to note that such growth cannot come at the expense of environmental degradation. Thus, the policy prioritizes pollution prevention and emission reduction as integral components of high-quality economic development.

Innovation development provides new impetus and direction for environmental pollution control (Zhang M. et al., 2022). The role of innovation development in environmental protection has been extensively studied in the literature (Lin et al., 2021). Chiou et al. (2011) used a spatial error model to discuss the impact of innovation on green development, and found that green innovation can significantly promote the improvement of environmental performance. Additionally, Jordaan et al. (2017) found that technological innovation is a key driver in reducing greenhouse gas emissions globally. Moreover, in the field of renewable energy, innovative development can significantly reduce carbon emissions, promote low-carbon economic development, and improve environmental quality (Xu and Lan, 2023). To summarize, numerous prior studies have identified innovation development as a crucial and effective means of mitigating environmental pollution (Ibrahim and Vo, 2021). These findings underscore the significance of innovation in promoting sustainable and high-quality development (Liu et al., 2022).

Despite the abundance of literature on the impact of innovation on environmental pollution, three areas still need to be addressed. First of all, the existing literature on the relationship between innovation development and environmental pollution has primarily focused on direct effects, while mediation effects have been largely neglected. Such as previous research has indicated that innovation has a positive impact on improving the emission standards of industrial enterprises in handling pollutants (Zhang K. et al., 2019), reducing greenhouse gas emissions (Gu and Wang, 2018), and improving the environment (Bhupendra and Sangle, 2015). The extant literature has predominantly centered on examining the direct impacts of innovation, as evidenced by studies conducted by Shahbaz et al. (2018) and Wang and Luo (2020). However, there remains a need for further investigation into the mediating mechanisms through which innovation development can drive environmental protection.

Secondly, while some scholars have delved into exploring the impact of innovation on pollution reduction at the individual level and at the firm level, there is a dearth of research investigating these effects at the macro-level of provinces. For instance, Heidenreich and Kraemer (2015) explicate the micro-individual level by which innovation development can furnish consumers with a wider array of options and facilitate the adoption of environmentally-friendly behaviors, thereby promoting consumer environmental behavior. Additionally, at the meso-firm level, Wang K. L. et al. (2021) and Sahoo et al. (2023) have examined the effect of firm technological innovation on environmental performance. It is important to note that there are clear distinctions between provincial and corporate innovation, individual innovation. The construction of innovative provinces can lead to stronger innovation regional convergence effects (Chen et al., 2020) and regional knowledge spillover effects (Shang et al., 2012). Furthermore, the construction of innovative provinces is a major development decision made at the regional level in China, which can result in a more rational allocation of regional resources and potentially have more significant environmental effects compared to the construction of corporate innovation (Xu et al., 2020). But the impact of innovative province construction on environmental governance remains understudied.

Thirdly, it is worth noting that there is still a lack of research on measuring the extent of the environmental effects of innovation development in developing countries. Research on the relationship between innovation development and pollution reduction has been predominantly conducted in developed countries due to their advanced technology (Ashford, 2002; Popp, 2006). A study focusing on Japan found that the enhancement of technology innovation is conducive to the development of low-carbon technologies, leading to a reduction in carbon emissions and improvement in air quality (Lee and Min, 2015). However, it is noteworthy that developed countries have placed too much emphasis on the role of technological innovation in innovation development and pollution reduction, while neglecting the importance of social and policy innovation (Barykin et al., 2022). Moreover, developed countries have tended to rely too heavily on market mechanisms and have lacked government and social involvement in pollution control (Kvasničková Stanislavská et al., 2023). Studies have found that the dominant role of governments in environmental governance is more pronounced in developing countries than in developed ones, and this government-led environmental governance model can better guarantee the implementation of environmental policies, resulting in more effective improvement of environmental quality (Spilker, 2012; Li et al., 2023). Currently, as the world's largest developing country, the Chinese government has incorporated innovation development into its national development plan, attempting to use innovation development to break through resource and environmental bottlenecks and achieve a transition to high-quality economic development (Chen et al., 2022). This makes it all the more necessary to use Chinese data to summarize the development patterns in China and provide more references for other developing countries to develop innovation development policy.

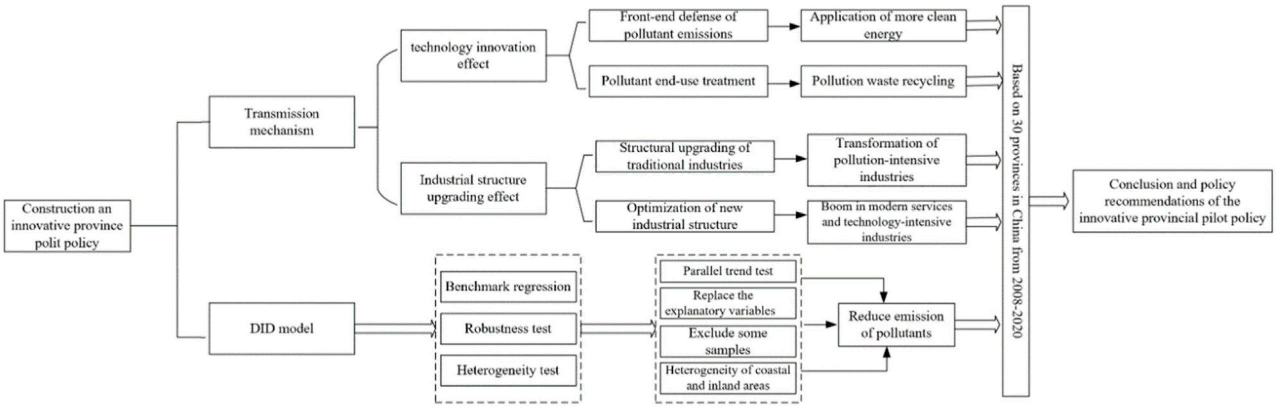

FIGURE 1
Research framework.

Given the research gaps observed above, this research contributes significantly to the existing literature in three ways: Firstly, this study expands the research on the construction of innovative provinces by examining the impact of innovation on environmental governance at the provincial level. By doing so, it attempts to provide further evidence for the study of innovation development and environmental governance at the regional level. Secondly, this study elucidates the mediating mechanisms of environmental governance in pilot policies implemented in innovative provinces through the lenses of endogenous growth theory and ecological economics. It delves into the intricate workings of innovation-driven development, unpacking the "black box" with depth and rigor. Exploring these effects and mechanism can generate new insights into more differentiated and effective decision-making related to innovation development. Finally, this paper utilizes a difference-in-difference (DID) approach to quantitatively assess the environmental effects of innovative provincial policy. This study employs the Difference-in-Differences (DID) model to mitigate pre-test sample discrepancies between the treatment and control groups, thereby eliminating model endogeneity through quadratic differencing. As a result, our analysis provides a more precise assessment of the environmental impacts of innovative provinces.

The subsequent sections of this paper are structured as follows: Section 2 reviews relevant literature, explains the integrated impact of innovative provincial policies on environmental governance; Section 3 explains the econometric model, variable selection, and data sources; The empirical results are introduced in Section 4. Section 5 is the discussion; Finally, the conclusion and policy recommendations are in Section 6. The specific research framework is shown in Figure 1.

2 Policy background and research hypotheses

2.1 Policy background

China has established a strong foundation for the development of innovative provinces, which aligns with the country's overall strategy of building an innovative and technology-driven economy. The implementation of an innovation-driven development strategy was first proposed at the 18th National Congress of the Communist Party, and has been consistently reinforced and perfected since then. In March 2015, the CPC Central Committee and the State Council issued the "Several Opinions on Deepening the Reform of Institutional Mechanisms to Accelerate the Implementation of the Innovation-Driven Development Strategy," which aimed to fully realize the innovation-driven development strategy and create a new engine for economic growth. In May 2016, the CPC and the State Council published the "National Innovation-driven Development Outline," which provided systematic planning and deployment for the implementation of the innovation-driven development strategy in the medium and long term. The construction of innovative provinces then entered a pilot development stage, with Zhejiang, Jiangsu, Sichuan, Guangdong, and other provinces being selected by the central government as pilot regions for this initiative. The Ministry of Science and Technology of China has explicitly stated in the "Guidelines for the Construction of Innovative Provinces" that one of the primary objectives of innovative pilot provinces is to promote "green and low-carbon, harmonious development." The guidelines highlight that scientific and technological innovation can help solve environmental issues and accelerate the construction of a resource-saving and environment-friendly society.

The policy of constructing innovative provinces is anticipated to have significant implications for China's economic development and ecological civilization construction. One of the primary benefits of the policy is that it directly improves the level of regional innovation, which is essential for promoting industrial upgrading. Through this policy, the provincial governments are expected to create a conducive environment that fosters innovation and creativity, which in turn will lead to the development of new and improved products and technologies. Furthermore, the emphasis on economic transformation and industrial upgrading in the construction of innovative provinces is expected to promote the development of more energy-efficient and environmentally friendly technologies and products. This is expected to provide new technical means and solutions for environmental protection, thereby contributing to the country's ecological civilization construction. It is worth noting that an accurate assessment of the environmental effects of innovative provinces is crucial for providing a comprehensive and in-depth understanding of the impact of the pilot policies. This will also facilitate the precise promotion of future policies that are aimed at promoting sustainable development in the pilot provinces and across the country. In conclusion, the pilot construction policy of innovative provinces in China is expected to have significant implications for the country's economic development and ecological civilization construction. Additionally, the policy's emphasis on environmental protection and sustainability is expected to provide new technical means and solutions for promoting ecological civilization.

2.2 The effect of construction of innovative provinces on environmental pollution

The core requirement of building an innovative province in China is to promote a development model led by innovation drive, guaranteed by openness to rise and oriented by green development. Theoretically, the construction of innovative provinces can accelerate the pace of innovation and development in pilot provinces, improving the resource utilization efficiency, and supporting the development of energy-saving and environmental protection industry, accelerating the development of the industrial clean technology, and advocating a resource-saving and environment-friendly society and achieve the goal of ecological civilization (Zhao, 2016; Zhang L. et al., 2022). This is not only conducive to exploring a regional development model tailored to local conditions, but also capable of achieving sustainable economic, social and environmental development (Lei et al., 2020; Gao and Yuan, 2021). Specifically, the innovative provinces reduces regional environmental pollution in the following two ways.

On the one hand, the construction of innovative provinces can stimulate enterprises to invest more in new product development, thereby enhancing their innovation capacity (Liao and Li, 2023). This improved innovation capability not only reduces the emission of pollutants such as wastewater, waste gas, and solid waste (Ge, 2019), but also facilitates better management of environmental pollution emissions (Zhang G. et al., 2019), ultimately leading to a reduction in environmental pollution. In addition, Prakash and Potoski (2006) and Bhupendra and Sangle (2015) that innovation can improve the environment through pollution prevention, pollution control, and the use of clean technology in firms Hodson et al. (2018), based on data from the U.S. energy industry, found that an increase in the level of innovation will enable firms to more efficient use of energy while producing less carbon emissions, thereby improving regional air quality.

On the other hand, in order to achieve the goal of building an innovative province, the government will actively increase its investment in the field of green innovation and pool the green innovation elements in each region. Additionally, the government will further promote environmental protection by formulating and implementing environmental regulations and other environmental regulatory actions to restrain the pollutant emissions of enterprises (Waxman and Markey, 2009; Abbass et al., 2022).

H1: Innovative provincial policies has a significant effect on environmental pollution.

The construction of innovative provinces represents a notable example of achieving the "win-win" goal of economic development and environmental protection. This policy not only fosters development through innovation but also acknowledges the responsibility of serving as a "demonstration zone" for pollution control. According to Porter's hypothesis, stimulating the "innovation compensation" effect of enterprises through technological innovation constitutes a critical means of achieving pollution reduction and improving enterprise competitiveness (Porter and Linde, 1995). Furthermore, industrial pollutant emissions significantly decrease with the upgrading of industrial structure, which enhances environmental quality (Wang et al., 2018). Hence, this study proposes a mediating mechanism to elucidate the regional environmental effects of innovative province policies from the perspectives of technology innovation and industrial structure upgrading. Specifically, the policy reduces environmental pollution through the following measures.

2.3 Mediating effect of technology innovation

The development of innovative provinces can play a vital role in improving the local science and technology innovation capacity. One important factor contributing to this improvement is the creation of a favorable environment and adequate conditions for the advancement of science and technology. For instance, the construction of science and technology parks, innovation centers, and research and development institutions, as well as offering higher salaries and improved working conditions for researchers can attract and retain talented researchers. This, in turn, can provide a rich pool of human capital that can enhance the quality of scientific research and technological development (Ponomariov and Boardman, 2010). Additionally, Kuzma et al. (2020) found a positive correlation between better innovation facilities in a region and the number of patents invented by researchers. Furthermore, the construction of innovative provinces can provide strong external incentives for research and development in the area of environmental technology (Borghesi et al., 2015). With these incentives, companies with core technologies and a commitment to environmental innovation may be attracted to enter the region and make breakthroughs in clean energy, environmental equipment, and green manufacturing processes. Finally, the development of innovative provinces will create more opportunities for science and technology exhibitions and forums to promote the exchange and diffusion of scientific and technological information. This will further enhance regional technological innovation capabilities.

Technological innovation is the main driving force to reduce regional environmental pollution. Ehrlich and Holdren (1971) proposed the population, affluence, and technology (PAT) model, which suggest that technological progress can alleviate environmental pollution caused by population growth. Grossman and Krueger (1991) decomposed the factors affecting environmental pollution into scale effects, structural effects, and technology effects and highlighted the important role of technology effects in improving environmental quality. Specifically, this study argues that technological innovation reduces regional pollution in two main ways: On the one hand, defense at the front end of pollution emissions, by improving production levels to reduce pollutant emissions; And on the other hand, strengthening the terminal treatment of pollution, improving the efficiency of pollutant treatment. Improving technology levels can stimulate clean production processes and increase the frequency and scope of clean energy use (Hao et al., 2020). The advanced technology creates clean energy to prevent more pollution (Valentin and Elena, 2020), while improving pollution treatment technology solves the recycling of polluted waste (Wang S. et al., 2021) to achieve the purpose of emission reduction and environmental protection. Specifically, the development of renewable energy sources, new biofuels, and energy-efficient vehicles and appliances will be promoted through the improvement of science and technology guided by innovative development, and these measures will reduce pollutant emissions (Ibrahim and Vo, 2021).

H2: Construction of innovative provinces policy will further reduce environmental pollution through technological innovation.

2.4 Mediating effect of industrial structure upgrading

The development of innovative provinces is a catalyst for the upgrading of the regional industrial structure. Firstly, innovative provinces can upgrade industrial structure by cultivating and attracting high-level talents. According to the innovative talent theory, talent plays a crucial role in driving economic development and industrial upgrading (Cubas et al., 2016). Through the establishment of research institutions and centers, innovative provinces provide a favorable environment for attracting and cultivating high-level talent. Secondly, the construction of innovative provinces can stimulate enterprises' willingness to innovate and facilitate the transformation of industrial innovation outcomes, thereby promoting industrial structure upgrading (Liao and Li, 2023).

Industrial structure upgrading, with its "structural effect," is considered an important approach to reducing environmental pollution (Yu and Wang, 2021). The construction of innovative provinces is expected to further this process by promoting the upgrading of both traditional heavy industries and highly polluting industries, as well as the optimization of new industrial structures. On the one hand, provinces will actively promote the transformation and upgrading of industrial structure, and the secondary industries represented by pollution-intensive industries will achieve green transformation of production by choosing clean production application, pollution treatment technology transformation, and direct exit (Bhupendra and Sangle, 2015). On the other hand, the pilot policy has given rise to low-pollution industries represented by modern services and technology-intensive industries, which will lead to an increase in the proportion of tertiary industries and reduce pollution emissions such as waste gas, wastewater, and solid pollution generated during industrial development. Previous studies have found that industrial restructuring can bring about a rational distribution of resources among industries, leading to their full utilization and ultimately reducing environmental pollution (Lind, 2002; Pasche, 2002).

H3: Construction of innovative provinces policy will further reduce environmental pollution through industrial structure upgrading.

3 Methodology and data

3.1 Econometric methodology

In 2018, 14 provinces were selected as pilot areas for innovative provincial policies, providing a quasi-natural experiment for studying the environmental effects of the construction of innovative provincial policies. Specifically, we used the Difference-in-Differences (DID) method to evaluate the environmental performance of the innovative provincial policies (Bertrand et al., 2004; Wang et al., 2019). According to Wooldridge (2007), the fundamental concept behind the DID approach involves measuring the variation in outcomes between a control group and a treatment group both prior to and subsequent to the implementation of a policy, and subsequently generating difference-in-differences statistics that reflect the impact of the policy. The DID method uses the idea of a quasi-natural experiment, which divides the entire sample data into two groups: one group that is affected by the intervention, the treated group, and another group that is not affected by the same intervention, the control group (Conley and Taber, 2011). The DID model is set as follows:

$$Y_{it} = \beta_0 + \beta_1 did_{it} + \sum_{i=1}^{N} \beta_j X_{it} + \mu_i + \gamma_t + \epsilon_{it} \tag{1}$$

$did_{it} = Treat_{it} \times Time_{it}$, where i is the region, and t is the year. Besides, the policy shock variable is regarded as did_{it}. did is a dummy variable equal to 1 if a city has a policy on construction of innovative provinces, and 0 if it does not. μ_i is the province fixed effect, ϵ_{it} is the time fixed effect, and the ϵ_{it} is the random perturbation term. X_{it} represents the other control variables that affect environmental pollution.

3.2 Variable selection

3.2.1 Environmental pollution

In this study, the "three wastes," namely, sulfur dioxide emissions, general industrial solid waste generation, and total wastewater discharge, were analyzed dimensionlessly based on the methodology used by Khatun (2009). Principal component analysis was applied to these three variables to obtain weighting coefficients for each region, which were then used to calculate a comprehensive pollution emission index for each year. This index serves as a measure of the regional pollution level for each region.

3.2.2 Construction of innovative province

China put forward the concept of construction of innovative provinces in 2016, and in 2016–2018, 16 provinces (municipalities) have been established as innovative provinces in China one after

TABLE 1 Explanations and data sources of all basic variables.

Variable		Symbol	Measured methods
Dependent variable	Environmental pollution	EPdid	Based on the emissions of "three wastes," the principal component analysis method is used to calculate
Independent variable	Policy for construction of innovative provinces	IP	The province is defined as 1 during the pilot year and thereafter; otherwise, the value is 0
Control variables	Government Intervention	GI	The logarithm of the ratio of fiscal spending to GDP.
	Openness	OP	The amount of actual foreign capital used in the current year as a proportion of GDP
	Human capital	HC	Logarithms of students enrolled in higher education institutions
	Economic development	ED	The logarithm of GDP *per capita*
Mediation variables	Technology innovation	TI	R&D input
	Industrial structure upgrading	IS	The ratio of the value added of the tertiary industry to the value added of the secondary industry

TABLE 2 Descriptive statistics and correlation analysis.

	1	2	3	4	5	6	7	8
EPdid	1.000							
IP	0.024	1.000						
TI	−0.067	0.354***	1.000					
IS	−0.185***	0.268***	0.808***	1.000				
ED	0.650***	0.321***	0.405***	0.245***	1.000			
OP	−0.014	0.103**	0.735***	0.782***	0.307***	1.000		
GI	−0.499***	−0.198***	−0.400***	−0.248***	−0.725***	−0.407***	1.000	
HC	0.110**	0.193***	0.247***	0.364***	0.297***	0.240***	−0.0804	1.000
Obs	390	390	390	390	390	390	390	390
Mean	0.051	0.108	0.016	3.712	1.386	0.278	0.254	7.792
Std. Dev	0.897	0.310	0.011	4.903	0.108	0.322	0.111	0.324
Min	−1.562	0.000	0.002	0.480	1.034	0.008	0.100	6.876
Max	2.200	1.000	0.064	30.830	1.570	1.671	0.758	8.817

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

another. This study characterizes the state of innovative provinces construction in the form of dummy variables. The province is defined as 1 during the pilot year and thereafter; otherwise, the value is 0.

3.2.3 Mediation variables

(1) technology innovation: R&D activities are often considered as one of the important manifestations of the improvement of science. Therefore, this research uses R&D input to measure the level of technology innovation by referring He et al. (2022). The larger the indicator, the higher the level of technology innovation in the region.
(2) Industrial structure upgrading: Drawing on Zhang G. et al.'s (2019) findings, the process of industrial upgrading is typically accompanied by a shift towards the service industry, with the growth rate of the tertiary industry often surpassing that of the secondary industry. In this study, the extent of industrial structure upgrading is measured by the ratio of the value added of the tertiary industry to the value added of the secondary industry, as an increase in this ratio is indicative of industrial structure upgrading.

To avoid the problem of omitted variables in the model that lead to biased regression results, the following variables are included as control variables in the environmental pollution governance model in this paper.

3.2.4 Control Variable

(1) Government intervention

The government can encourage companies to adopt environmental protection measures, and reduce environmental

TABLE 3 VIF test.

Variable	VIF	1/VIF
IS	4.410	0.228
TI	3.820	0.262
OP	3.330	0.300
ED	2.620	0.382
GI	2.490	0.401
HC	1.340	0.747
IP	1.310	0.764
Mean VIF	2.760	

pollution by providing environmental protection subsidies and tax incentives (Pei and Pei, 2022). Referring to the Wang K. L. et al. (2021), Li et al. (2020), the share of government fiscal expenditure in GDP is used to represent the intensity of government intervention in the environment. The higher the share, the stronger the government control, the better it is for reducing environmental pollution.

(2) Openness

The degree of opening up has the following two views on environmental pollution. On the one hand, foreign investment can facilitate the introduction of advanced technology and promote the construction of regional environmental protection facilities, thereby contributing to the reduction of pollution (Letchumanan and Kodama, 2000; Chang, 2012). This phenomenon is often referred to as the "pollution halo" effect. On the other hand, developing countries may lower their environmental regulations in order to attract foreign investment and promote economic development, which may result in them becoming a "pollution haven" (List and Co, 2000; Levinson and Taylor, 2008). This research uses the ratio of foreign direct investment to GDP to measure the level of openness (Wu et al., 2020).

(3) Human capital

Human capital is a composite of various human resources, including education, training, skills, health, knowledge, and experience (Wößmann, 2003). As a crucial factor of production, human capital plays an indispensable role in both regional economic development and environmental pollution control. Research suggests that individuals with higher levels of education tend to exhibit greater awareness of environmental issues and are more inclined to participate in environmental protection behaviors, ultimately leading to a reduction in environmental pollution. Moreover, regions that possess higher levels of human capital tend to foster the development of environmentally friendly and energy-efficient technologies, thus improving regional environmental quality (Lan et al., 2012). Referring to Sarkodie et al. (2020), this research using the logarithms of students enrolled in higher education institutions to measure the regional human capital.

(4) Economic development level

The level of economic development is an important factor affecting environmental pollution. The Environmental Kuznets Curve (EKC) hypothesis suggests an inverse U-shaped trend between economic growth and environmental protection (Grossman and Krueger, 1995). The logarithm of GDP *per capita* is used to measure economic development in this paper (Hao et al., 2019).

The specific symbols and explanatory notes of each variable are shown in Table 1.

3.3 Data sources

To examine the effects of policies related to innovative province construction on regional environmental pollution management, this paper selects a sample of 30 provinces (excluding Hong Kong, Macao, Taiwan, and Tibet) in China from 2008 to 2020 for empirical analysis. The pilot construction batches and lists of innovative provinces were collected manually from the website of China's Ministry of Science and Technology and the websites of local governments at each province. Raw data were obtained from the China Statistical Yearbook, China Environmental Yearbook, China Statistical Yearbook and the website of the National Bureau of Statistics. Some data were supplemented according to the provincial (municipal) statistical yearbooks and the statistical bulletins on national economic and social development of the relevant local municipalities. The descriptive statistics and correlation analysis for each variable are shown in Table 2.

Table 2 presents the descriptive statistics and correlation analysis of the main variables. The results indicate that the explanatory variables have a wide range of variation, with the highest value of environmental pollution being 2.200 and the lowest value being −1.562, with a mean value of 0.051, indicating that the degree of environmental pollution varies widely across provinces. On the whole, the correlation between variables is strong, which indicates that the variables selected in this paper are appropriately chosen. In addition, this study used VIF to test for multicollinearity. Previous studies concluded that strong multicollinearity exists when VIF ≥ 10. As indicated in Table 3, all the variables have VIF values considerably below 10, signifying the absence of multicollinearity among the variables.

4 Empirical results

4.1 Parallel trend test

To verify the validity of the DID method employed in this research, a parallel trend analysis was conducted to assess the trends of pollutant emissions across the sample provinces (refer to Figure 2). Figure 2 shows that the pollutant emission trends of the control and treatment groups exhibited a similar pattern from 2008 to 2017. However, following the implementation of the innovative province policy in 2018, while the pollutant emission trends of the control group remained flat, the treatment group witnessed a marked decline. The parallel trend analysis results suggest that the pollutant emissions of the treatment and control groups were not significantly different before the policy implementation, thereby satisfying the fundamental prerequisite for utilizing the DID method in this research.

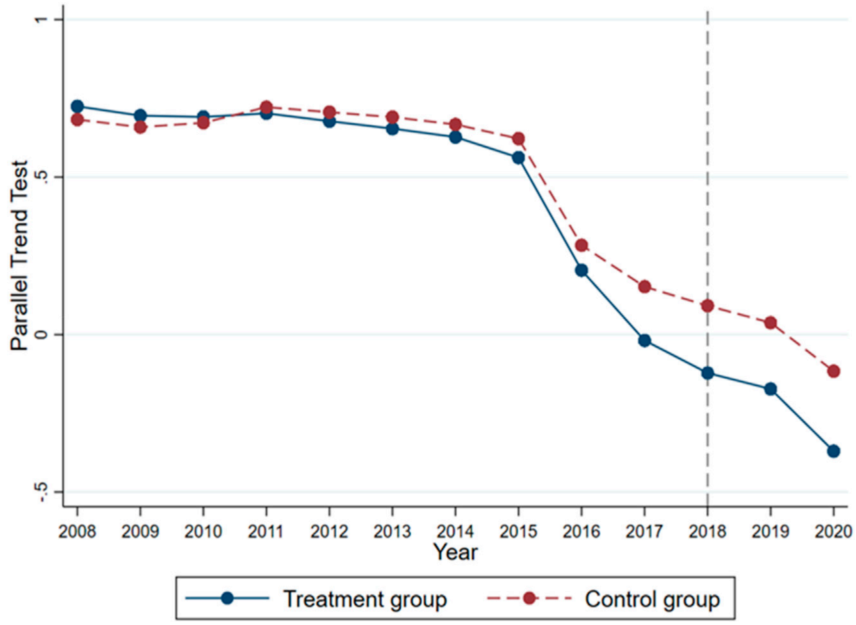

FIGURE 2
Parallel trend test.

TABLE 4 Benchmark regression estimation results.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
EPdid	−0.190***	−0.149***	−0.153***	−0.151***	−0.146***
	(−3.628)	(−2.991)	(−3.023)	(−2.960)	(−2.855)
ED		10.046***	10.294***	10.298***	10.540***
		(6.839)	(6.586)	(6.58)	(6.697)
OP			−0.064	−0.061	−0.053
			(−0.469)	(−0.447)	(−0.385)
GI				0.158	0.247
				(0.352)	(0.545)
HC					−0.167
					(-1.331)
CONS	0.057	−13.207***	−13.512***	−13.550***	−12.618***
	(1.429)	(−6.808)	(−6.598)	(−6.599)	(−5.823)
Observations	390	390	390	390	390
R-squared	0.037	0.151	0.152	0.152	0.157
Province FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.2 Benchmark regression

This paper use a two-way fixed-effects model to estimate Eq. 1 and analyze the impact of the construction of innovative provinces on regional environmental pollution. The results are shown in Table 4. Model (1) is the regression result without adding control variables, and Model (2)-Model (5) is the result of gradually adding control variables. The results show that in Model (1), the *EPdid*

TABLE 5 Heterogeneity test.

Variables	Coastal	Coastal	Inland	Inland
EPdid	−0.019	−0.174*	−0.145**	−0.117**
	(−0.213)	(−1.926)	(−2.444)	(−2.071)
ED		7.539**		6.707***
		(2.086)		(3.631)
OP		−0.386*		−0.087
		(−1.709)		(−0.568)
GI		−4.965***		1.423***
		(−3.701)		(3.168)
HC		0.384*		−0.581***
		(1.935)		(-3.494)
CONS	0.534***	−11.870***	−0.220***	−4.731*
	(8.413)	(−2.847)	(−5.052)	(−1.761)
Observations	143	143	247	247
R-squared	0.329	0.468	0.166	0.266
Province FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

coefficient is −0.190 and $p^{<}$ 0.01; In Model (5), the *EPdid* coefficient is −0.146 and $p^{<}$ 0.01. The *EPdid* term was always significantly negative at the 1% level during the stepwise inclusion of control variables. All the estimation results show that whether or not the control variable is added, the innovative provincial policies has a significant negative impact on pollution indicators. Therefore, H1 is verified.

4.3 Heterogeneity test

The results of the benchmark regression analysis suggest that the implementation of innovative provincial policies has significantly reduced environmental pollution. However, it is important to consider that coastal regions have played a central role in China's economic development since the reform and opening up. Coastal areas have distinct advantages over inland regions in terms of transportation infrastructure, international trade development, and access to foreign technologies. The Chinese government has implemented relatively liberal foreign trade policies in coastal regions, which has led to a significant divergence in economic development, infrastructure quality, and policy benefits between coastal and inland areas (Su and Jefferson, 2012). Therefore, it is crucial to investigate the impact of innovative province construction policies on environmental pollution under different geographical locations, as the effectiveness of such policies may vary based on regional characteristics. The results of regional heterogeneity are shown in Table 5. In coastal areas, the *EPdid* coefficient is −0.174, $p^{<}0.1$; While in inland areas, the *EPdid* coefficient is −0.117, $p^{<}0.05$. The obtained results suggest that the implementation of innovative province construction policies in both coastal and inland regions can effectively mitigate regional environmental pollution. It is important to note, however, that policies exhibit a stronger inhibitory effect on pollution levels in coastal areas compared to their inland counterparts.

4.4 Transmission mechanism test

The abovementioned empirical results show a strong global relationship between innovative provincial policies and environmental pollution. What is the mechanism of the innovative provincial policy to reduce regional pollution? As explained in the previous theoretical analysis, the innovative provincial policy affects the economic development and environmental governance of the regional through technological innovation effects and industrial structure upgrading effects. Ultimately, these effects reduce environmental pollution. This paper draws on Baron and Kenny (1986) and Zhao et al. (2010) to test for mediating effects in three steps. The specific formula is as follows:

$$Y_{it} = \alpha_0 + \alpha_1 did_{it} + \sum_{i=1}^{N} \alpha_j X_{it} + \mu_i + \gamma_t + \epsilon_{it} \tag{2}$$

$$M_{it} = b_0 + b_1 did_{it} + \sum_{i=1}^{N} b_j X_{it} + \mu_i + \gamma_t + \epsilon_{it} \tag{3}$$

$$Y_{it} = c_0 + c_1 did_{it} + c_2 M_{it} + \sum_{i=1}^{N} c_j X_{it} + \mu_i + \gamma_t + \epsilon_{it} \tag{4}$$

Eq. 2 serves as the base model that evaluates the cumulative impact of innovative provincial policies on environmental pollution. Building upon Eq. 2, we have incorporated two distinct mediating variables, resulting in Eqs 3, 4, respectively. Eq. 3 represents the effect of the policy of innovative province construction on the mediating variable M_{it}, which refers to technological innovation, and industrial structure upgrading. Besides, Eq. 4 indicates the inclusion of M_{it} in the model to analyze whether the construction of innovative provinces reduces environmental pollution through M_{it}. Eqs 2–4 together form the mediation model.

4.4.1 Transmission mechanism test of technological innovation

The transmission mechanism test of technological innovation is shown in Table 6. The total effect of the innovative provincial policy on regional pollution is −0.146 according to the Model (1), thus passing the significance level test of 1%, which is consistent with the previous conclusion. Model (2) is the result of the estimation of the technological innovation of the innovative provincial policy, and the empirical results revealing a significantly positive regression coefficient for the innovative provincial policy at the 1% level. These results suggest that the construction of innovative provinces promotes technology innovation. Model (3) is a regression analysis that explores the relationship between environmental pollution and both pilot policy and technological innovation. The results of Model (3) demonstrate that the coefficient of *EPdid* is negative and significant at the 10% level, whereas the coefficient of technological innovation is negative and significant at the 1% level. These findings suggest that enhanced technological innovation can effectively reduce environmental pollution. Further analysis by Bootstrap shows that intermediary effect is −0.268,

TABLE 6 Transmission mechanism test of technological innovation.

Variables	Model (1)	Model (2)	Model (3)
EPdid	−0.146***	0.002***	−0.090*
	(−2.855)	(5.199)	(−1.735)
TI			−27.616***
			(−3.969)
ED	10.540***	−0.039***	9.474***
	(6.697)	(−3.228)	(6.057)
OP	−0.053	−0.003***	−0.137
	(−0.385)	(−2.946)	(−1.012)
GI	0.247	−0.009**	0.007
	(0.545)	(−2.519)	(0.017)
HC	−0.167	−0.003***	−0.250**
	(−1.331)	(−3.170)	(−2.010)
CONS	−12.618***	0.089***	−10.160***
	(−5.823)	(5.405)	(−4.596)
Bootstrap (Indirect effect)			−0.268***
			(0.056)
Bootstrap (Direct effect)			−0.302***
			(0.093)
Observations	390	390	390
R-squared	0.157	0.691	0.194
Province FE	YES	YES	YES
Year FE	YES	YES	YES

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE 7 Transmission mechanism test of industrial structure upgrading.

Variables	Model (1)	Model (2)	Model (3)
EPdid	−0.146***	0.621	−0.144***
	(−2.855)	(1.41)	(−2.795)
IS			−0.004
			(-0.658)
ED	10.540***	−10.99	10.494***
	(6.697)	(-0.812)	(6.656)
OP	−0.053	−2.476**	−0.063
	(−0.385)	(-2.109)	(−0.457)
GI	0.247	−4.193	0.229
	(0.545)	(−1.076)	(0.505)
HC	−0.167	2.482**	−0.156
	(−1.331)	(2.304)	(−1.239)
Constant	−12.618***	−0.310	−12.620***
	(−5.823)	(−0.017)	(−5.818)
Bootstrap (Indirect effect)			−0.218***
			(0.068)
Bootstrap (Direct effect)			−0.352***
			(0.092)
Observations	390	390	390
R-squared	0.157	0.218	0.158
Province FE	YES	YES	YES
Year FE	YES	YES	YES

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

accounting for approximately 47% of the total effect. The bootstrap test are significant at the 1% level, which indicates that technology innovation plays a partially mediating effect in the process of reducing environmental pollution in the construction of innovative provinces. Therefore, H2 is verified.

4.4.2 Transmission mechanism test of industrial structure upgrading

The transmission mechanism test of technological innovation is shown in Table 7.

The results of Model 1 are the same as the analysis above. Model (2) tests the effect of the establishment of innovative provinces on the upgrading of industrial structure, but the results are not significant. Model (3) is a regression analysis that explores the relationship between environmental pollution and both pilot policy and industrial structure upgrading. The results of Model (3) demonstrate that the coefficient of *EPdid* is negative and significant at the 1% level, and the coefficient of industrial structure upgrading is −0.004, which is not insignificant. It is worth noting that the reason for the insignificant coefficient on industrial structure upgrading may be due to the use of stepwise regression to test for mediating effects, ignoring the “suppressing effects” (Spencer et al., 2005). Therefore, referring to the Zhao et al. (2010), this research use the bootstrap test to test whether there is a mediating effect. According to Eq. 4 and the bootstrap test results show that the coefficients c_1 and $b_1{*}c_2$ have the same sign and are significant at the 1% significance level, thus proving the existence of a partial mediation effect here (Fritz et al., 2012; Wen and Ye, 2014). The Bootstrap results shows that intermediary effect is −0.218, accounting for approximately 38% of the total effect. The bootstrap test are significant at the 1% level, which indicates that industrial structure upgrading plays a partially mediating effect in the process of reducing environmental pollution in the construction of innovative provinces. H3 were verified.

4.5 Robustness test

4.5.1 Placebo test

To further demonstrate that the decline in regional environmental pollution is attributable to the pilot policy of innovative provinces rather than other policies or incidental factors, this study draws upon the methodology of Chetty et al. (2009) and conducts a placebo test involving 1,000 random

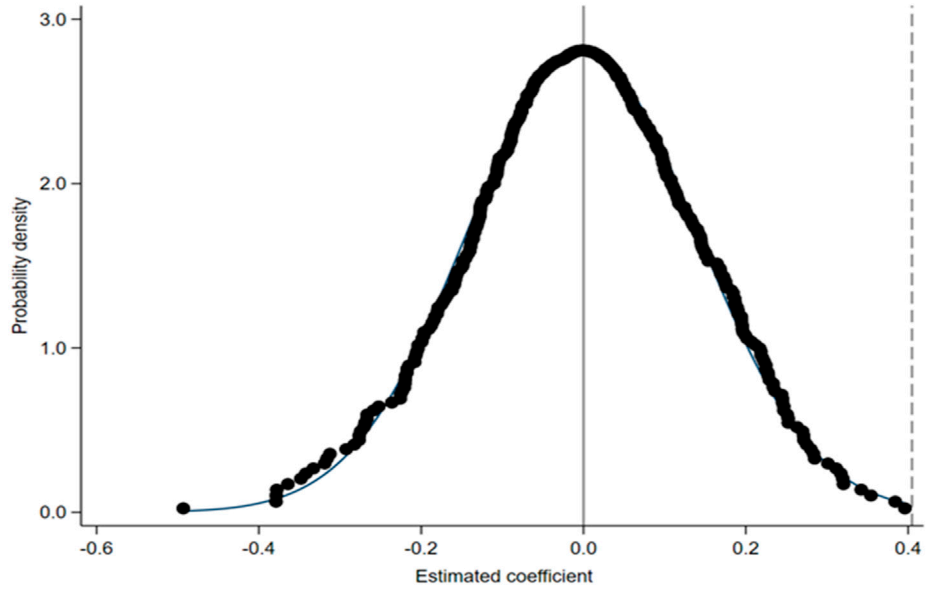

FIGURE 3
Placebo test.

TABLE 8 Test result of the propensity score matching balance.

Variables	Sample	Mean		Standardized deviation		*t*-test	
		Control group	Treated group	Standardized deviation	Reduction	T Value	*p*-Value
GI	Pre-match	0.184	0.315	−147.200	97.1	−14.170	0.000
	After Match	0.216	0.220	−4.200		−0.740	0.463
OP	Pre-match	0.451	0.128	112.300	94.4	11.420	0.000
	After Match	0.167	0.186	−6.300		−1.050	0.293
ED	Pre-match	1.447	1.334	124.300	95.500	12.050	0.000
	After Match	1.416	1.421	−5.500		−0.57	0.569
HC	Pre-match	7.832	7.758	22.600	39.100	2.250	0.025
	After Match	7.808	7.853	−13.800		−0.950	0.344

replications. As illustrated in Figure 3, the regression coefficients of the random samples cluster around 0 and exhibit a positive t-distribution. Furthermore, all of the regression coefficients exceed the baseline coefficient of −0.4. These findings suggest that the outcomes of this study are not subject to the influence of extraneous variables, and that the reduction in environmental pollution is indeed a result of the innovative province policy. Thus, the results of this research are robust.

5.5.2 PSM-DID test

To mitigate the potential influence of artificial selection bias on the experimental and control groups, this study employed the PSM (propensity score matching)-DID method to conduct robustness tests on the regression results, which are presented in Table 8. The results of the balance test indicate that the standard deviations of the variables significantly decreased after matching, and the *p*-values corresponding to the *t*-test of each variable were insignificant, suggesting that there was no significant difference between the treated and control groups after matching. These results signify that the matching process was effective and the PSM-DID method is suitable for robustness testing. Refer to Table 8 for the results of the propensity score matching balance test.

Based on PSM, this research continues to re-estimate Eq. 1 using OLS method and the results are shown in Table 9 below. The findings of Model (2) in Table 9 indicate that the *EPdid* coefficient is −0.082, which is statistically significant at the 1% level. This result suggests that the implementation of innovative provincial pilot policy can effectively alleviate regional environmental pollution.

TABLE 9 PSM-DID regression.

Variables	Model (1)	Model (2)
EPdid	−0.088***	−0.082***
	(−2.812)	(−2.625)
ED		2.920***
		(3.303)
OP		−0.386**
		(−2.168)
GI		0.018
		(0.074)
HC		−0.134
		(−1.613)
Constant	5.694***	3.009**
	(253.506)	(2.406)
Observations	298	298
R-squared	0.909	0.915
Province FE	YES	YES
Year FE	YES	YES

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

Notably, the estimated coefficients and significance levels obtained in Table 9 are consistent with those in Table 4, indicating the robustness of the research's results.

4.5.3 Replace the explanatory variables

This study further replace the explanatory variables to test the robustness. Specifically, raster data on annual average global PM2.5 concentrations, sulfur dioxide emissions, and carbon dioxide emissions from Columbia University were used as robustness indicators, drawing upon prior studies such as Ma et al. (2016), He et al. (2022), and Hanif (2018). The Robustness test are shown in Table 10 from Model (1) to Model (6). The results indicate that the inhibitory effects of innovative provincial policies on PM2.5, Sulfur dioxide emissions and Carbon dioxide emissions are −49.607, −0.134 and −0.086, respectively. Furthermore, these effects are statistically significant at the 1% and 5% levels. Thus, the construction of innovative provinces significantly reduces the emissions of all three pollutants, further supporting the robustness of the previous fifindings.

4.5.4 Exclude some samples

The results from Model 7 and 8 in Table 10 reveal that after excluding samples prior to 2012, the coeffificient of the innovative province policy is −0.172, and is significant at the 5% level, which significantly reduces the level of region environmental pollution. No significant difference exists between the results of replace the explanatory variables and the exclude some samples. This supports the empirical conclusion that the innovative provincial policies are effective in reducing pollution levels.

5 Discussion

5.1 Discussion for the results of the DID model

China's policy of constructing innovative provinces is a critical initiative aimed at enhancing regional innovation capacity and promoting China's position as a leading science and technology nation. The policy has important implications for China's economic development and ecological construction. This study contributes to a deeper understanding of whether the policy of constructing innovative provinces is conducive to environmental governance, and how the pilot policy affects the regional environment from a macro-perspective. To this end, the study employs the difference-in-difference method and the mediation model to analyze the effect and mechanism of the innovative provinces policy on regional environmental pollution.

Firstly, this research uses the difference in differences (DID) model to examine the impact of innovative provincial policies on regional pollution control. Distinguished from prior research that predominantly adopts regression models (Du et al., 2019; Albitar et al., 2022) and Spatial Econometric Model (Jin et al., 2022; Shi and Zhang, 2022), our study leverages the DID model, which is centered on China's policy of building innovative provinces. By adopting this approach, our study is able to effectively control for confounding factors that may influence the dependent variable, and also circumvent estimation bias arising from omitted variables that often characterizes fixed effects models (Stuart et al., 2014; Ge et al., 2022).

In addition, this research uncovers a significant positive effect of innovative provincial policies on enhancing regional environmental quality and curbing pollution, as revealed by DID model analysis. Innovation-driven development has emerged as a crucial means of addressing environmental issues, as it stimulates the synergistic development of economic growth and environmental governance through institutional and technological innovation (Ibrahim and Vo, 2021; Abbass et al., 2022). On the one hand, innovation-driven development facilitates the widespread application of novel energy and clean production technologies that can effectively reduce pollutant emissions and optimize resource utilization, thereby creating a mutually beneficial scenario for both environmental governance and economic development (Zhang L. et al., 2022; Jiang, 2022). On the other hand, innovation-driven development also fosters changes in consumption attitudes and behaviors of both businesses and consumers, while heightening public awareness and acceptance of eco-friendly products (Lorenczik and Newiak, 2012).

Moreover, our study reveals significant regional heterogeneity in the effects of innovative provincial policies on environmental governance, with the policy generally having a greater impact in coastal areas than inland areas. We can explain the following aspects. First of all, the coastal region has a larger population and a more developed economy, and consume more fossil energy (Zhao et al., 2018). Thus, the reduction of highly polluting elements through technological innovation and industrial upgrading under the guidance of innovative development is most effective in improving regional environmental quality. Second, from the perspective of human capital, it is evident that coastal regions, with their robust economy and accessible location, attract a

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TABLE 10 Robustness test.

	Replace the dependent variable						Exclude some samples	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	PM2.5	PM2.5	Sulfur dioxide emissions	Sulfur dioxide emissions	Carbon dioxide emissions	Carbon dioxide emissions	Remove samples prior to 2012	
EPdid	−48.211***	−49.607***	−0.192***	−0.134***	−0.092**	−0.086**	−0.144***	−0.127**
	(−4.505)	(−4.526)	(−5.788)	(−4.392)	(−2.298)	(−2.089)	(−2.679)	(−2.407)
ED		762.915**		3.010***		2.989**		10.468***
		(2.263)		(3.209)		(2.363)		(3.035)
OP		−39.825		0.578***		(0.043)		0.259
		(−1.363)		(7.106)		(−0.394)		(1.075)
GI		−24.302		−0.157		−0.31		−1.381*
		(−0.251)		(−0.580)		(−0.852)		(−1.848)
HC		60.213**		0.173**		−0.038		−0.206
		(2.245)		(2.325)		(−0.378)		(−0.832)
CONS	233.700***	−1,213.645***	5.702***	0.227	4.911***	1.331	0.051	−12.559**
	(28.818)	(-2.615)	(226.626)	(0.176)	(162.523)	(0.764)	(1.401)	(−2.483)
Observations	390	390	390	390	390	390	240	240
R-squared	0.527	0.542	0.875	0.903	0.1	0.117	0.034	0.129
Province FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

greater number of highly educated and skilled scientific and technological professionals (Salike, 2016). This influx of expertise provides vital technical support for the successful implementation of innovative provincial policies, while also expediting the process of policy transformation and execution (Mariz-Pérez et al., 2012). Additionally, compared to their inland counterparts, coastal regions possess more formidable financial resources, thereby enabling greater financial support for pilot policies and yielding a more tangible impact in the realm of environmental pollution control (Fan et al., 2011).

5.2 Discussion for the mediation effect results

Pilot policy for innovative provinces reduce environmental pollution through technological innovation effect and industrial structure upgrading effect respectively.

The research makes a contribution to the endogenous growth theory. Research found that the technological innovation effect of innovative provincial policies comes from the substitution of highly polluting elements by technological progress on the one hand (Zhang L. et al., 2022), and the advancement of clean technologies on the other, which brings good emission reduction effect and improves environmental quality (Abbass et al., 2022). Endogenous growth theory posits that economic growth is achieved not only through technological progress, but more importantly, through technological progress that brings about changes such as clean technologies, so as to better achieve the goal of reducing the environmental pollution (Driessen et al., 2013).

Besides, it is worth noting that industrial structure upgrading has a partially mediating role between innovation and environmental pollution. This study provides new ideas for developing countries to break the environment-economic trap from the perspective of ecological economics. Economic development drives the upgrading of industrial structure and reduces pollutants in the production process, thus achieving sustainable economic growth and environmental protection (Ran et al., 2023). Du et al. (2021) have also highlighted the importance of promoting industrial structure upgrading as a means to reduce environmental pollution, transform the economic development mode, and reconcile the conflict between economic growth and environmental protection.

6 Conclusion policy recommendations and study limitations

6.1 Conclusion

The policy of constructing innovative provinces in China is regarded as a crucial strategy to achieve the coordinated development of the economy and the environment through the application of science, technology, and human innovation. In this regard, this paper use the balanced panel data of 30 provinces in China from 2008 to 2020 and uses the DID model and the mediation effect model to analyze the effect and mechanism of the innovation provinces policy on environmental pollution. Based on this, the heterogeneity of the innovation provinces pilot policy on region environmental pollution is explored. The main findings can be summarized as follows.

First of all, the DID model shows that innovation provinces pilot policy significantly reduces environmental pollution after controlling for other factors and fixed effects. According to the specific findings, the innovation provincial policies have resulted in an average reduction of 14.6% in environmental pollution annually in the pilot areas. This conclusion is still valid after robustness tests are eliminated.

In addition, the mediation effect model shows that the innovation provinces pilot policy reduces environmental pollution through technological innovation and industrial structure upgrading. The findings revealed that the mediating effect contribution rates of technological innovation capability and industrial structure upgrading were 26.8% and 21.8%, respectively. These results respectively imply that a 1% increment in technological innovation capability and industrial structure upgrading in the pilot areas would lead to a reduction in environmental pollution by 0.268% and 0.218%.

Finally, the heterogeneity analysis finds that innovation provinces pilot policy have led to a reduction of 17.4% in environmental pollution in coastal regions and a reduction of 11.7% in inland regions annually. In conclusion, the innovation provinces pilot policy is more effective in coastal areas than inland areas in combating environmental pollution.

6.2 Policy recommendations

On the basis of the above conclusions, this research puts forward the following policy recommendations.

(1) The central government can distill effective measures for implementation, adjustment, and monitoring from the experiences of innovative pilot provinces to serve as a reference for non-pilot provinces. At the same time, the central government should expedite the promotion of innovative provinces, while also taking into account the location conditions, resource characteristics, and economic features of these provinces during the establishment of such pilot programs.
(2) During the construction of innovative provinces, local governments in pilot provinces should increase investment in science education and actively create innovative R&D platforms, to provide a conducive R&D environment for science and technology innovation. Moreover, it is recommended that local governments increase subsidies for enterprise technology innovation, foster the adoption of advanced technologies and clean production processes, optimize resource allocation of high-polluting enterprises using the “catfish effect,” and enhance resource utilization, which in turn reduces pollution emissions.
(3) To enhance the effectiveness of the policy of innovative provinces, the government should prioritize industrial transformation and upgrading. Coastal regions should focus on advancing high-tech industries and upgrading the industrial chain to the middle and high-end segments to foster an eco-

friendly industrial structure. Meanwhile, inland areas should phase out obsolete industries and expedite the transformation and upgrading of high energy-consuming and high-polluting industries. Additionally, inland regions should leverage the potential of coastal areas by adopting their technologies, based on their specific developmental needs, to ensure synchronized progress in economic growth and environmental protection across the region.

6.3 Study limitations

This research provides a preliminary exploration of the mechanism between innovation provinces pilot policy and environmental pollution, while two limitations still deserve to be further explored. First, this thesis has systematically explored the mediating role of technological innovation and industrial structure upgrading in the relationships between innovation provinces pilot policy and environmental pollution in China, while the other potential mediation variables such as foreign direct investment (Abbass et al., 2022), resource allocation (Sueyoshi and Yuan, 2015), employment Structure (Xue et al., 2019), regional human capital levels (Wei and Liu, 2022) may also be considered in the further studies which will lead to more useful and practical implications.

Second, this study focuses on the investigation of innovation development policies in developing countries, with China as a representative case. Future research can examine the relationship between innovation development and pollution reduction in developed countries such as the United States, Japan, and the United Kingdom. Exploring the differences between countries can provide a clearer demonstration of the role of government mechanisms in environmental governance (Song et al., 2023). Furthermore, it is essential to note that one of the limitations of the study is the unavailability of these data.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

LT: Conceptualization, Formal analysis, writing—original draft, Writing—review and editing and Funding; MT: Software, Methodology and Data analysis; WX (Corresponding author): Writing—review; Data curation and Funding. All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The effects of environmental regulation and environmental protection investment on green technology innovation of enterprises in heavily polluting industries—based on threshold and mediation effect models

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Introduction: Studying the influence and mechanism between environmental regulation, environmental protection investment, and enterprise green technology innovation is crucial to realize ecological civilization construction and sustainable economic growth.

Methods: Based on the green patent data and the corresponding enterprise data of A-share heavily polluting industry enterprises from 2010 to 2020, a comprehensive index of environmental regulation is constructed, and the system GMM estimation method, threshold effect test, and intermediary effect model are used. The impact and mechanism of environmental regulation on enterprise green technology innovation are studied, and the heterogeneity of property rights is analyzed.

Results: The following conclusions are drawn: 1) Environmental regulation presents a "U"-shaped relationship of first suppressing and then promoting enterprise green technology innovation, and there is only a single threshold effect, and the "inflection point" is 2.756. 2) There is an intermediary effect of environmental investment in the impact of environmental regulation on enterprise green technology creation; that is, environmental regulation affects enterprise green technology innovation by affecting the environmental protection investment behavior of enterprises. 3) State-owned enterprises are more sensitive to environmental regulation, and environmental regulation has a greater impact on enterprise green technology innovation.

Discussion: These conclusions play an important role in the formulation of environmental policies by governments and in the green development of enterprises.

KEYWORDS

environmental regulation, green technology innovation of enterprises, environmental protection investment, threshold effect, mediator effect

1 Introduction

Since the reform and opening up, China's economy has continued to develop rapidly, accompanied by extensive economic growth characterized by high input and high consumption, which has also brought about problems such as resource scarcity and environmental pollution. In particular, enterprises in highly polluting industries have become the main source of environmental pollution. At this stage, China's economy has shifted from a high-speed development stage to a high-quality stage, and environmental problems have become a bottleneck limiting the sustainable development of China's economy (Li et al., 2018). If we can effectively control the problem of corporate pollution, we will definitely be able to realize the ecological civilization concept of "gold and silver mountains are green water and green mountains" put forward by General Secretary Xi Jinping, and the government is trying to reduce carbon emissions and achieve carbon neutrality, promoting the coordinated development of economic development and ecological environmental protection. Sustainable energy use and technological innovation are considered important means to promote carbon neutrality (Muzzammil Hussain and Wang, 2022; Zhou et al., 2022). Enterprises are an important carrier of technological innovation. They are also the main body of environmental pollution management. Since the ecological environment has the characteristics of public goods, enterprises lack the motivation to actively manage the environment and need the "visible hand" of the government to compensate for the market failure caused by the single market, so the environmental regulation led by the government is of great significance to environmental governance. Government environmental regulation stimulates the green transformation of enterprises by internalizing the social costs of pollution and is considered an effective way to mitigate the conflict between environmental protection and sustainable economic growth (Zhang, 2022).

The most fundamental and effective way to control environmental pollution is green innovation (Magat, 1978). Technological innovation can effectively curb carbon emissions and contribute to carbon neutrality (Hasanov et al., 2021), and technological progress has a catalytic effect on economic growth (Ximei et al., 2022; Danish et al., 2023). For enterprises, compliance with environmental regulations will lead to an increase in operating costs of enterprises; enterprises can balance the cost of compliance with the efficiency improvement effect brought by environmental improvement and finally formulate enterprises' environmental policies, whether passive pollution emission reduction or active green technology innovation. Green technology innovation can also improve the efficiency of enterprises and promote the upgrading and transformation of enterprises while combating environmental pollution. Green technology innovation requires a large amount of capital investment. As a special investment activity, environmental protection investment can provide financial support for enterprises' green innovation. Environmental investments are also effective in reducing carbon emissions and promoting carbon neutrality (Hasanov et al., 2021). However, enterprises' investment decisions are affected by the intensity of environmental regulations. Therefore, we investigate the following question: how do the formulation of environmental regulatory policies and their intensity affect the green technology innovation of enterprises, and what are the characteristics and mechanisms of their impact?

The relationship between environmental regulation and green innovation is the focus of the current research. The incentive effect of environmental regulations on enterprises' green technology innovation is still controversial. Traditional institutional economics believes that the increase in the intensity of environmental regulation crowds out enterprises' production resources, increases production costs, and hinders technological innovation (Gollop and Roberts, 1983), while the "Porter hypothesis" (Porter, 1991) holds the opposite view, and moderate environmental regulation helps improve enterprises' innovation behavior. In order to avoid environmental regulation and drive enterprises to carry out technological innovation, thereby generating compensatory benefits for enterprises, technological innovation has also long contributed to enhancing the competitive advantage of enterprises. This has given rise to a controversy in the academic community about environmental regulation and enterprise green technology innovation. Many scholars have carried out many useful studies on the heterogeneity of environmental regulation and the mechanism of environmental regulation on green innovation (Guo and Yuan, 2020; Xu et al., 2023). However, further research can still be conducted: (1) Most of the research focuses on environmental regulation and green innovation at the provincial and municipal levels, and the research at the micro level of enterprises is not rich enough. (2) Some studies on the relationship between environmental regulation and green innovation still need to be deepened; for example, some scholars have proposed a "U"-shaped relationship, but there is a lack of more in-depth testing of the inflection point. (3) Environmental protection investment is an active means for enterprises to deal with environmental pollution, but some scholars pointed out that enterprises make environmental protection investments to respond to the government's environmental regulation and opportunism. What role does environmental protection investment play in the green innovation of environmental regulation enterprises? Literature studies are less involved regarding this issue.

Based on the aforestated problems, this paper selects enterprises in highly polluting industries, which are key industries monitored by government environmental regulation, to study the relationship between environmental regulation, environmental protection investment, and enterprise green technology innovation and deeply explore the mechanism of environmental regulation on enterprise green innovation. The research in this paper can contribute in the following aspects: (1) At the micro level, we propose that there is a "U"-shaped relationship between environmental regulation and enterprise green innovation, and we specifically propose the inflection point, which enriches the relevant research on environmental regulation and green innovation at the theoretical level. (2) We propose to study the mediating role of environmental investment in environmental regulation on enterprise green innovation and verify the role of environmental regulation on enterprise green technological innovation mechanism. (3) It is proposed that there are differences in the impact curves of environmental regulation on enterprise green technological innovation under different property rights characteristics. These conclusions have important guiding significance for the formulation of the intensity of government environmental regulation and the investment decision of enterprises' green transformation and upgrading. It has practical implications for promoting the coordinated development of economic growth and environmental protection.

The rest of this article is organized as follows. Section 2 provides a literature review of environmental regulation, environmental investment, and green technology innovation; Section 3 presents the theoretical analysis and research hypotheses; Section 4 presents the materials and methods; Section 5 presents the empirical results and discussion; Section 6 presents the heterogeneity analysis; and Section 7 presents the conclusions, policy recommendations, and future research directions.

2 Literature review

Looking back at the relevant literature at home and abroad, there is no unified conclusion on the relationship between environmental regulation and green innovation. The following views are the main conclusions: (1) the promoting effect; that is, environmental regulation can stimulate enterprises to "innovation compensation" effect, thereby promoting enterprise green technology innovation (Li et al., 2021; Li et al., 2023). (2) The inhibiting effect; that is, environmental regulation has a "crowding-out" effect on enterprise innovation and research and development because it increases the cost of enterprise pollution control, thereby inhibiting enterprise green technology innovation (Leeuwen and Mohnen, 2017). (3). A large number of scholars have proposed the "U"-shaped relationship between environmental regulation and green innovation through theory and empirical evidence, and the implementation of environmental regulation will crowd out innovative research and development due to the increase in expenditure costs, and with the increase of the intensity of environmental regulation, its impact on enterprise green technology innovation is transformed from an inhibition effect to an innovation effect (Ouyang and Du, 2020; Lyu et al., 2022; Xu et al., 2023). (4). Uncertainty; environmental regulation may not necessarily promote green technology innovation, green technology innovation is affected by a combination of factors, and the relationship between the two is not simply linear or nonlinear (Rexhäuser and Rammer, 2014).

Regarding the heterogeneity of the Porter hypothesis, some scholars believe that the establishment of the Porter hypothesis requires certain premises, and the effect of environmental regulatory innovation faces many constraints (Yuan et al., 2017). From the perspective of regional differences, the regions with better development in the east support the "Porter hypothesis," while the western region with relatively poor economic development does not (Wang and Wang, 2011). There are also differences in the impact of different types of environmental regulations on green technology innovation (Chen et al., 2022; Liping Wang and Chuang, 2022; Liu et al., 2022). Moreover, different forms of enterprise ownership and enterprises in different industries also have different green innovation performances under the same environmental regulation (Liping Wang and Chuang, 2022). In terms of research methods, scholars conducted panel data regression from the provincial (Shao et al., 2022), prefecture, and municipal levels (Xiaoxi Cao, 2022) and the industry (Lian et al., 2022) and constructed a dynamic panel regression model with the lag term of the explanatory variable to control the endogeneity effect.

Regarding environmental regulations and environmental investments: Based on Porter's hypothesis (Xie et al., 2017), pollution paradise hypothesis (Arouri et al., 2012), and factor endowment hypothesis (Wu et al., 2019), many scholars explain the impact of environmental regulation on environmental protection investment from three aspects: promotion, inhibition, and "double" marginal effect. Although the relationship between environmental regulation and environmental protection investment is different, it shows that the decision of enterprises on environmental protection investment is influenced by environmental regulation. Regarding environmental protection investment and green innovation, based on the perspective of resource base, capital support is the key factor of green innovation (Wang et al., 2022), environmental protection investment provides the basic platform and conditions for green innovation, and the amount of environmental protection investment invested by enterprises has become an important driving force for enterprise green technology innovation. It is a common belief that environmental protection investment will promote green technology innovation (Heinkel et al., 2001; Li et al., 2022), so more research focuses on innovation output and innovation efficiency and proposes time (Ma and Hou, 2018), government (Sun, 2016), loan interest rate (Huang et al., 2019), and other factors in the impact of environmental protection investment on the output and efficiency of green technology innovation.

3 Theoretical analysis and research hypotheses

3.1 Environmental regulation and corporate green innovation

The strengthening of environmental regulations will prompt enterprises to improve their processes and increase productivity, which will have a positive impact on the improvement of enterprises' green technological innovation capacity, and the improvement of technological innovation can compensate enterprises' compliance costs and also bring new market opportunities, thus improving the competitiveness of enterprises, which is the innovation compensation effect brought by environmental regulations (Porter, 1991; Horbach, 2008). Thus, the strengthening of environmental regulations stimulates enterprises to innovate green technology.

However, environmental regulations impose additional costs on enterprises and have a negative impact on them: first, environmental regulations require enterprises to reduce pollutant emissions and engage in clean production, which raises entry barriers for enterprises, hinders the initial development of SMEs with insufficient capital, and reduces market dynamism; second, environmental regulations inevitably lead to additional expenses for enterprises to control pollution, which also inevitably crowd out funds for technological research and development, *etc.* Thus, environmental regulations have a crowding-out effect on green technology innovation (Leeuwen and Mohnen, 2017). This hinders green innovation.

In summary, environmental regulations and enterprises' green technology innovation are affected by a combination of the innovation compensation effect and crowding-out effect. This paper reasonably speculates that the relationship between environmental regulation and corporate green innovation is not simply linear but that there should be an "inflection point" between the two, and when environmental regulation exceeds this point, the innovation compensation effect of environmental regulation on corporate green innovation is greater than the crowding-out effect, which shows that enterprise green innovation has a positive impact. Otherwise, it shows a negative impact. Based on this, this paper proposes hypothesis 1.

H1: Environmental regulation and enterprise green technology innovation have a "U"-shaped relationship.

3.2 The role of enterprise environmental protection investment in environmental regulation in the innovation of enterprise green technology

The strengthening of environmental regulations will affect the investment decisions of enterprises in environmental protection (Turken et al., 2020). First, in the face of the strengthening of local environmental regulations, it will restrict the investment of enterprises that have not carried out environmental management (Li et al., 2023), and second, environmental regulations will affect the financing environment of enterprises. With the strengthening of environmental regulations, enterprises will actively invest in environmental protection to obtain investment opportunities and reduce financing costs. Especially for heavily polluting industries and countries or regions with high environmental protection requirements, environmental regulations will promote environmental investment (Luo et al., 2021; Wang et al., 2022).

According to the literature, environmental investment can significantly promote green technology innovation. Environmental investment can provide the capital needed for enterprise green technology innovation and provide the infrastructure for talent to gather, so there is an input–output relationship between environmental protection investment and enterprise green innovation, and enterprise environmental protection investment is conducive to enterprise green technology innovation and further enhance enterprise value (Lee et al., 2015).

From the perspective of compliance costs, when enterprises face stricter environmental regulations, enterprises will weigh the benefits of environmental protection investment with the costs of environmental regulations (fines, environmental protection taxes, *etc.*), adjust the investment structure of enterprises, and increase strong environmental protection investment, thereby affecting the green technology innovation of enterprises.

According to the chain rule, environmental regulation will affect enterprises' environmental protection investment, and environmental protection investment will affect enterprises' green technology innovation, so this paper proposes hypothesis 2.

H2: Environmental protection investment plays an intermediary role in environmental regulation and green technology innovation of enterprises; that is, environmental regulation affects environmental protection investment and then affects green technology innovation of enterprises.

3.3 Heterogeneity of different enterprise ownership forms

In general, state-owned enterprises have more social responsibility, are more sensitive to government environmental regulations, will take more proactive measures in the face of environmental regulations, have more financial resources than passive measures, such as paying pollution discharge fees, and are more likely to make environmental protection investments, proactively innovating green technologies. Non-state-owned enterprises will be more cautious about environmental protection investment, preferring to invest in short-term income projects, while green innovation for enterprises is relatively conservative, and only when the benefits of green innovation are higher than the cost of environmental regulation, non-state-owned enterprises will take the initiative to carry out green innovation. Based on the aforestated analysis, this paper proposes hypothesis 3.

H3: Environmental regulations help to improve green technology innovation in SOEs but not in non-SOEs.

4 Materials and methods

4.1 Sample selection and data sources

Considering the availability of data, the data of listed companies in China's heavily polluting industries from 2010 to 2020 were selected as the research sample. According to the 2010 Guidelines for Environmental Information Disclosure of Listed Companies and the 2012 Revised Guidelines for the Classification of Listed Companies by Industry, the heavily polluting industries are defined as B mining, C manufacturing, D electricity, heat, gas, and water production and supply in three major categories of 16 sub-categories, as shown in Table 1. The samples were screened as follows: (1) ST, *ST companies during the exclusion period; (2) exclusion of samples with missing key data. In the end, 625 samples and 9,334 observations were screened. Among them, the environmental regulation is measured, the data of enterprise green technology innovation and enterprise environmental protection investment are manually screened, and the main sources of other enterprise data are the Guotai'an database, the Wind database, and the website of the National Bureau of Statistics.

TABLE 1 Classification of heavily polluting industries.

Code	Name	Code	Name	Code	Name
B06	Coal mining and washing industry	C22	Paper industry and paper products industry	C31	Ferrous metal smelting and rolling processing industry
B08	Ferrous metal mining and dressing industry	C25	Petroleum processing, coking, and nuclear fuel processing industries	C32	Non-ferrous metal smelting and rolling processing industry
B09	Non-ferrous metal mining and dressing industry	C26	Chemical raw materials and chemical products manufacturing	C33	Metal products industry
C13	Agricultural and sideline food processing industry	C27	Pharmaceutical manufacturing	D44	Electricity and heat production and supply industry
C17	Textiles	C28	Chemical fiber manufacturing		
C19	Leather, fur, feathers, and their products industry	C30	Non-metallic mineral products industry		

4.2 Variable setting

(1) Explained variable: enterprise green technology innovation (GTI).

Considering the delay in patent approval, the number of green patent applications is used instead to represent green technology innovation. Regarding the number of green patent applications obtained, first, the patent IPC classification number was searched from the State Intellectual Property Office (SIPO), and the patent applications of all enterprises in heavily polluting industries were manually obtained; second, the green patent IPC classification number was obtained from the "International Patent Green Classification List" launched by the World Intellectual Property Organization (WIPO) in 2010; finally, the types of patent applications of enterprises in heavily polluting industries obtained from the State Intellectual Property Office were matched with the green patent IPC classification number to obtain the number of green patents applied by enterprises in heavily polluting industries each year, according to Qi et al. (2018). In this paper, alternative energy production, waste management, and energy conservation patents are selected as the specific projects of green patents, and each enterprise is added according to the three aforementioned patent applications as a measure of enterprise green technology innovation. The number of green utility patent applications is used as an alternative index of enterprise green technology innovation for robustness testing.

(2) Explanatory variable: environmental regulation (Er)

Environmental regulation is based on the practice of Ye et al. (2018) to calculate the comprehensive index of environmental regulation intensity through the industrial wastewater discharge, SO2 emission, and industrial soot emission of enterprises. The larger the comprehensive index of environmental regulation, that is, the more polluting the emissions, the lower the intensity of environmental regulation, and *vice versa*. The specific measurement method of the specific environmental regulation comprehensive index is as follows.

① We standardize the industrial wastewater discharge, SO2 emission, and industrial smoke emission of the enterprise, and the standardized formula is as follows:

$$\mathrm{UE}^{s}_{\mathrm{ij}} = \left[\mathrm{UE}_{\mathrm{ij}} - \min\left(\mathrm{UE}_{\mathrm{j}}\right)\right] / \left[\max\left(\mathrm{UE}_{\mathrm{j}}\right) - \min\left(\mathrm{UE}_{\mathrm{j}}\right)\right], \quad (1)$$

where UE^{s}_{ij} represents the result of indicator standardization, UE_{ij} represents the emission of class J pollutants of enterprise i, and max (UE_j) and min $(\mathrm{UE_j})$ represent the maximum and minimum emissions of class J pollutants in all businesses, respectively.

② Calculating the weight of each pollutant:

$$W_j = \mathrm{UE}/\overline{UE_{ij}}, \quad (2)$$

where $\overline{\mathrm{UE}_{ij}}$ indicates the average amount of pollutant emissions from all enterprises in each year.

③ Through the standardization and weight of pollutant emissions, the comprehensive index of environmental regulation of the enterprise is finally calculated.

$$\mathrm{Er_i} = 1/3\sum_{j=1}^{3} W_j \mathrm{UE}^{s}_{ij}. \quad (3)$$

(3) Intermediary variable: environmental investment (EI) Environmental protection investment refers to investment in pollution control, emission reduction, resource conservation, *etc.* In the narrow sense, environmental protection investment refers to environmental protection capital expenditure, and in the broad sense, it includes not only environmental protection capital expenditure but also environmental protection cost expenditure. Here, we define corporate environmental protection investment as corporate environmental protection capital expenditure. The acquisition of capital environmental protection investment data adopts the practice of Zhang et al. (2019) and retrieves the environmental protection-related production line

TABLE 2 Study variable settings.

The variable type	The variable name	Aberrations	Relevant explanations
The variable being explained	Enterprise green technology innovation	GTI	Number of green patent applications
	Enterprise green technology innovation	GTIE	Number of utility model patent applications
Explanatory variables	Environmental regulation	Er	Comprehensive indicators of environmental regulation intensity
Mediation variables	Corporate environmental investment	EI	The sum of capital expenditures and expense expenditures
Control variables	Enterprise size	Size	The logarithmic number of employees in the enterprise
	Capital structure	Lev	Total liabilities/total assets
	Return on assets	Roc	Net profit/total net assets
	Enterprise value	Tobin Q	Tobin Q
	Cash flow level	Cash	Net cash flow from operating activities/total assets for the year
	Capital growth	Growth	Total revenue growth rate
	Market share	Market	Operating income/operating costs
	Capital intensity	Capital	Net fixed assets/number of employees

renovation, clean production equipment purchase, and other items from the "construction in progress" details in the company's financial statements as the amount of capital environmental protection investment. In order to eliminate the effect of enterprise size, the deflation of total assets at the end of the period is adopted.

(4) Control variables

Enterprise green technology innovation will also be influenced by other factors that need to be controlled variables. According to the results of research studies by Qi et al. (2018) and You and Li (2022), combined with the actual situation, we choose the enterprise size, capital structure, return on assets, enterprise value, cash flow level, enterprise growth, market share, and capital intensity as control variables, as shown in Table 2.

4.3 Model settings

(1) Benchmark model of environmental regulation for enterprise green technology innovation

We have analyzed the impact of environmental regulation on green technology innovation theoretically, but the relationship needs to be verified econometrically based on enterprise-related data. A multiple linear regression model usually uses a set of predictor variables to measure the response to a particular variable. While the relationship between environmental regulation and enterprises' green technology innovation is not a simple linear relationship, so we refer to the study by Ouyang and Du (2020) and add the square of environmental regulation to the linear regression model to construct a benchmark effect model for regression to test the effect of environmental regulation on enterprises' green technology innovation, which is as follows:

$$\mathrm{GTI_{it}} = \beta_1 Er_{it} + \beta_2 Er_{it}^2 + \beta \sum \mathrm{X_{it}} + \theta_i + \mu_t + \varepsilon_{it}. \quad (1)$$

Among them, i represents enterprise, t represents time, GTI represents enterprise green technology innovation, Er represents environmental regulation, θ_i represents individual fixed, μ_t means time fixed, and ε_{it} is random disturbance. Based on the theoretical analysis, the nonlinear relationship between environmental regulation and green innovation of enterprises is analyzed, and the quadratic term Er_2 of environmental regulation is added. If the coefficients β_1 and β_2 are significant and the signs are opposite, it means that environmental regulation and enterprise green technology innovation have a "U"-shaped relationship.

(2) Dynamic panel GMM model of environmental regulation and enterprise green technology innovation

The GMM estimation method can effectively solve the endogeneity problem by constructing equations parameters based on moment conditions without assuming the distribution of variables or knowing the distribution information of random disturbance terms (Roodman, 2009). Considering the possible endogeneity of environmental regulation and green technology innovation, in order to eliminate the influence of endogeneity and ensure the stability of the conclusion, this paper introduces the instrumental variables, selects the lag of one period of green technology innovation lag as the instrumental variable, and uses the more efficient systematic GMM estimation method to establish the dynamic panel GMM model of environmental regulation and enterprise green technology innovation for regression. The details are as follows:

$$\mathrm{GTI_{it}} = \alpha_1 \mathrm{GTI_{it-1}} + \alpha_2 Er_{it} + \alpha_3 Er_{it}^2 + \alpha \sum X_{it} + \eta_i + \sigma_t + \xi_{it}, \quad (2)$$

where η_i、 σ_t、 and ξ_{it} denote the individual fixed, time fixed, and random interference terms, respectively, and the names and meanings of the other variables are the same as described previously.

TABLE 3 Descriptive statistics for each variable.

Variable	Observations	Average value	Variance	Minimum	Maximum
GTI	9,334	0.492	0.840	0.000	5.762
Er	9,334	0.522	0.676	0.000	2.901
EI	9,334	8.767	8.410	0.000	27.064
Size	9,334	7.751	1.239	2.197	11.592
Lev	9,334	42.894	28.114	0.708	1199.500
Roc	9,334	1.049	208.833	−17638.300	2285.360
Tobin Q	9,334	22.801	1.043	20.426	27.207
Cash	9,334	0.055	0.097	−4.270	2.457
Growth	9,334	19.829	292.992	−97.022	26,327.130
Market	9,334	1.661	1.438	0.310	31.529
Capital	9,334	12.887	1.282	2.450	17.818

(3) The threshold effect model of environmental regulation on enterprise green technology innovation

There is a threshold for the incentive effect of environmental regulations on enterprises' green innovation. Theoretical analysis also suggests that there may be a "U"-shaped relationship between the two, and we need to further explore the specific inflection point values. In order to explore the "inflection point" of the "U"-shaped relationship between environmental regulation and green technology innovation, we analyze the impact of environmental regulation on green technology innovation at different intervals. According to the findings of Hansen (1999), we choose environmental regulation as the threshold variable and construct a threshold effect model:

$$GTI_{it} = \lambda_0 + \lambda_1 Er_{it} \cdot I(q_{it} < \gamma) + \lambda_2 Er_{it} \cdot I(q_{it} > \gamma) + \lambda \sum X_{it} + \delta_{it}, \tag{3}$$

where I ( ) represents the indicator function. When the expression in parentheses is positive, the value is 1; otherwise, the value is 0; q_{it} represents the threshold variable, that is, environmental regulation (Er), γ is the corresponding threshold value, and δ_{it} is the random disturbance term. The names and meanings of the remaining variables are the same as described earlier.

(4) The mediation effect model of enterprise environmental protection investment

We aimed to investigate the mediating role of environmental protection investment of enterprises in environmental regulation on enterprises' green technology innovation. To establish the mediation effect model, the traditional mediation effect generally adopts the stepwise regression method of Wen et al. (2004), and later, Jiang (2022) proposed to verify whether the regression coefficient estimate of the explanatory variable by adding the mediation variable to the explanatory variable is significant. The causal chain between the explanatory variable and the interpreted variable should not be too long, and the influence of the mediating variable on the interpreted variable should be obvious. In this paper, the suggestions of Jiang Boat are used to test whether the relationship between the environmental protection investment of enterprises in the mediation variable and the environmental regulation of the explanatory variable is significant. In addition, the relationship between the green technology innovation of the explanatory variable enterprises and the environmental protection investment of the mediation variable enterprises has been elaborated in the literature review, and there is a significant positive relationship between the two. The specific model is as follows:

$$EI_{it} = \tau_1 Er_{it} + \tau_2 Er_{it}^2 + \tau_3 \sum X_{it} + \varphi_i + \psi_t + \omega_{it}, \tag{4}$$

where φ_i、 ψ_t、 and ω_{it} denote the individual fixed, time fixed, and random interference terms, respectively, and the names and meanings of the other variables are the same as described previously.

5 Results and discussion

5.1 Descriptive statistics

The descriptive statistics of each variable are shown in Table 3. All data were dimensionless, and the results of descriptive statistics showed that different high polluting enterprises have different attitudes towards green technology innovation. A considerable number of enterprises have no idea of green technology innovation, and there are some enterprises that are more proactive in green innovation. The attitude to green innovation also affects the amount of environmental investment of enterprises, so the variables of environmental protection investment also vary widely.

5.2 Regression model results and discussion

The benchmark regression results according to model 1 are shown in Table 4. According to the results of the Hausman test, this paper selects the fixed-effects model to test the multiple regression

TABLE 4 Results of the regression model of environmental regulation on enterprise green technology innovation.

Variable	Benchmark regression model		Dynamic panel effect model	
	GTI	GTIE	GTI	GTIE
Lag (GTI/GTIE)			0.652*** (8.000)	0.124** (1.800)
Er	0.230*** (7.580)	0.406*** (12.560)	3.131*** (3.760)	6.798*** (6.070)
Er^2	−0.125*** (−8.630)	−0.196*** (−12.660)	−1.467*** (−3.790)	−3.354*** (−6.060)
Size	0.075*** (4.390)	0.082*** (4.490)	0.341** (2.000)	0.233 (0.980)
Lev	−0.002*** (−3.650)	−0.002*** (−3.090)	−0.011 (−1.290)	0.001 (0.010)
Roc	−0.001 (−0.170)	−0.001 (−0.370)	−0.001 (−1.300)	−0.001 (−0.390)
Tobin Q	0.139*** (9.430)	0.105*** (6.680)	0.131 (1.540)	0.106 (0.780)
Cash	0.018 (0.240)	0.047 (0.580)	0.157 (0.560)	−0.009 (−0.020)
Growth	−0.001 (−1.170)	−0.001 (−1.390)	0.001 (0.990)	0.001 (0.350)
Market	−0.016 (−1.470)	−0.016 (−1.420)	−0.001 (−0.000)	−0.003 (−0.020)
Capital	0.110*** (9.530)	0.110*** (8.920)	0.024 (0.280)	0.262* (1.680)
R-sq	0.250	0.280		
AR (1)			0.000	0.000
AR (2)			0.845	0.255
Hansen test			0.131	0.146
N	9,281	9,281	8,152	8,152

of environmental regulation on enterprise green technology innovation. From the results, it can be seen that the coefficient of the environmental regulation composite index on enterprise green technology innovation is significantly positive, and since the larger the environmental regulation composite index, the weaker the environmental regulation, the positive coefficient indicates that the environmental regulation is negatively significant on enterprise green technology innovation, and the negative coefficient of the quadratic term of environmental regulation on enterprise green technology innovation indicates positive significance. This indicates that environmental regulation has a "U"-shaped relationship that first inhibits and then promotes green technology innovation, and the result remains unchanged after substituting the variable being explained, which verifies the correctness of hypothesis 1. This result shows that in the face of tightening environmental regulations, enterprises cope with environmental regulations in the initial stage and continuously increase investment in pollution control costs and have a crowding-out effect on green R&D costs, leading to a reduction in enterprise green technology innovation; as the cost of pollution control increases, by comparing the long-term benefits of green innovation with the current costs of passive pollution control expenditures, companies will invest more in green innovation and improve green production technologies to produce green products, thus reducing the cost of pollution control, which is the "innovation compensation effect." The strength of environmental regulation affects enterprises' decisions on green innovation. In the long run, the government will continue to tighten environmental regulations, and enterprises will continue to improve their green innovation capability to meet the standards and make green technology innovation their core competitiveness. Therefore, the change in environmental regulations will lead to a nonlinear relationship of first inhibiting and then promoting the green technology innovation of enterprises.

From the regression results of the control variables in Table 4, the effect of capital structure on enterprise green technology innovation is significantly negative. It means that the lower the asset-liability ratio, the more sufficient funds enterprises have for green technology research and development. Enterprise size, enterprise value, and capital intensity have a positive effect on enterprise green technology innovation. The explanation for this is that the larger the scale of the enterprise, the more inclined to conduct green technology research and development for long-term development when faced with environmental regulations; enterprises with higher enterprise value pay more attention to investment in future technologies and pay more attention to green technology research and development; the more capital-intensive the enterprise, the stronger the financial capacity and the more funds are used for green technology research and development.

5.3 Dynamic panel model results and discussion

To solve the endogeneity problem, the dynamic panel model is used for further verification, and we use the systematic GMM

TABLE 5 Threshold effect test.

Model	F-value	*p*-value	Number of free samples	Threshold estimates	Different significance cut-offs		
					1%	5%	10%
Single threshold	61.970	0.000	400	2.756	16.928	16.928	16.928
Double threshold	11.260	0.587	400	1.345 2.756	9.878	9.878	9.878

estimation method. The specific results are reported as shown in Table 4. AR (1) passed the 0.01 test, and AR (2) did not pass, indicating that the residuals only had first-order sequence correlation and did not have second-order sequence correlation problems. The Hensen test was passed, indicating that there was no over-identification problem, which indicates the robustness of the results of the GMM estimation. From the results point of view, the impact of green technology innovation of enterprises lagging behind in the first period on the green technology innovation of the current period is significantly positive, indicating that the current technological innovation mode of enterprises has received the impact of technology transformation, research and development difficulties, or market advantages of new products, and will not change much in the short term. In the dynamic regression results, the quadratic terms of the environmental regulation composite index and the environmental regulation composite index are relatively significant, and the direction is consistent with the benchmark regression. It indicates that the results of the effect of environmental regulation on enterprises' green technology innovation are robust.

5.4 Threshold effect test results and discussion

According to the aforestated analysis, the impact of environmental regulation on enterprise green technology innovation shows a nonlinear relationship of first decline and then rise, but whether there are multiple inflection points of decline and rise, where are the specific inflection points, and what are the impacts of environmental regulation on enterprise green technology innovation in different intervals need to be further analyzed by the threshold effect model. Referring to the research by Yang Dan et al. [38], this paper analyzes the inflection point of environmental regulation on enterprise green innovation and examines the difference in the impact of environmental regulation on enterprise green innovation in different intervals. In this paper, the bootstrap self-help method was selected to sample 400 times to estimate the threshold and related statistics. The specific results are as follows: as can be seen from Table 5, the single threshold value is 2.756, and the F-statistic is significant at the 1% level, while the double threshold F-statistic is not significant. Therefore, it shows that there is a single threshold effect in environmental regulation. Figure 1 reports that a single threshold estimate passes the 95% confidence interval test; according to the regression results of the single threshold panel in Table 6, it can be seen that environmental regulation shows a "U"-shaped relationship of first decreasing and then increasing on enterprises' green technology innovation, which further verifies hypothesis 1.

The threshold effect regression results indicate that there is no multiple downward rising inflection point of environmental regulation on enterprises' green technological innovation, as can be seen in Table 5. The inflection point of "U" is 2.756, that is, when the environmental regulation is less than 2.756, the environmental regulation requirement is low, and enterprises passively accept environmental regulations and respond mainly by paying emission fees, fines, *etc.*, which also crowd out green R&D expenditures without changing overall costs. In addition, the impact of environmental regulation on enterprises' green technology innovation is inhibited in this interval; as the environmental regulation increases, the cost of pollution control and other entry barriers become higher, and enterprises need to improve green technology innovation to reduce costs and enhance competitiveness. When the environmental regulation is greater than 2.756, the impact of environmental regulation on enterprises' green technology innovation is mainly manifested as the "innovation compensation effect," which shows the promotion effect. The coefficient of the first interval is 0.057, and the coefficient of the second interval is 0.032, indicating that the rate of decrease in the first interval is higher than the rate of increase in the second interval. The possible reason is that at the beginning of environmental regulation, responding to pollution control, crowding-out the already small amount of green R&D costs, and as the cost of pollution control continues to rise and the cost of green R&D decreases, accelerating the reduction of green technology

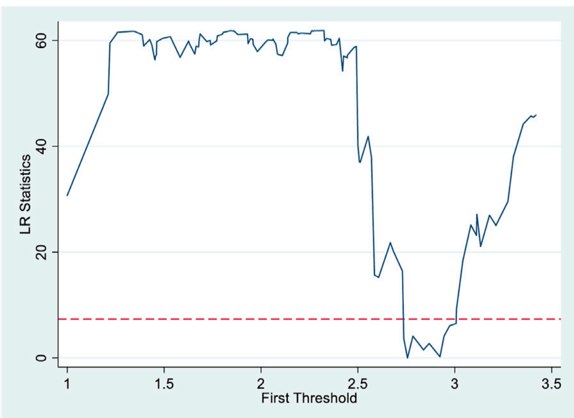

FIGURE 1
Single threshold estimate with 95% confidence intervals.

TABLE 6 Regression results of the single threshold panel.

Variable	Coefficient	Standard deviation	T-value	95% confidence interval
Er_1(Er < 2.756)	0.057***	0.017	3.270	[0.023 0.091]
Er_2(Er > 2.756)	−0.032***	0.014	−2.280	[-0.059–0.005]
Constant terms	−3.718***	0.332	−11.210	[-4.368–3.068]

TABLE 7 Test results of the intermediary effect of environmental protection investment.

Variable	GTI	EI	GTI
EI			0.007*** (6.900)
Er	0.313*** (10.100)	1.271*** (4.000)	0.303*** (9.810)
Er^2	−0.160*** (−10.720)	−0.580** (−3.800)	−0.155*** (−10.450)
Time control	YES	YES	YES
Individual control	YES	YES	YES
R-sq	0.100	0.120	0.050
N	9,334	9,334	9,334

innovation level; with the increase of environmental regulation, enterprises have increased their investment in green R&D. The level of green technology innovation of enterprises is increasing, but due to R&D inertia, the increase of green technology innovation is slower.

5.5 Mediation effect test results and discussion

Table 7 reports the mediating effect of environmental protection investment on enterprise green technology innovation, and it can be seen from the results that environmental regulation shows significant effects on both environmental investment and quadratic items of environmental investment, and the direction of change is consistent with the direction of the effect of environmental regulation on green technology innovation. According to the literature analysis, the positive impact of environmental protection investment on green technology innovation of enterprises is obvious. It also verifies the significant impact of environmental protection investment on green technology innovation, so we can conclude that environmental protection investment has a mediating effect on green technology innovation in environmental regulation, which verifies hypothesis 2. Changes in environmental regulations have affected the choice of environmental protection investment by enterprises. In the early stage of government environmental regulation, the cost of pollution control is lower than environmental protection investment. Therefore, enterprises are more inclined to invest more in pollution control costs and less in environmental protection. With strict environmental regulations, the government continues to guide enterprises to green innovation and subsidies for environmental investment, and enterprises aim to improve competitiveness and access to the threshold with increased investment in environmental protection. Environmental protection investment provides innovation platform, technology, capital, and other aspects of support for enterprise technological innovation so as to improve enterprise green technology innovation.

5.6 Robustness test

In order to verify the robustness of the empirical results, this paper conducts robustness tests from two aspects: (1) replacing the explanatory variables, using the number of green utility patent applications as the interpreted variables, and the test results are shown in Table 4, and the results are still stable. (2) To solve the endogenous problem and reverse causation, the instrumental variable method is adopted, and the first period of environmental regulation lag is used as a predetermined explanatory variable to construct a dynamic model, and the systematic GMM estimation method is adopted, the specific results are shown in Table 4, and the test results are consistent with the research conclusions. This shows that the conclusions of this research are robust.

6 Heterogeneity analysis

According to the type of property rights of highly polluting enterprises, private enterprises and foreign-funded enterprises are classified as non-state-owned enterprises, and state-controlled enterprises and wholly state-owned enterprises at the central, provincial, county, and municipal levels are classified as state-owned enterprises. The regression test was conducted in groups, and the specific results are shown in Table 8. Regardless of the type of property rights, the effect of environmental regulation on green technology innovation in enterprises is obvious. Thus, hypothesis 3 is rejected. State-owned property rights enterprises with high pollution have lower tolerance for environmental regulation, are more sensitive to green technology innovation, adopt a more proactive approach in the face of environmental regulation, actively strengthen environmental protection investment, and invest in green technology innovation earlier in the product production process, and the "innovation compensation effect" of positive incentives occupies the mainstream earlier. Non-state-owned property rights enterprises, on the other hand, are relatively passive in responding to environmental regulations and

TABLE 8 Results of the impact of environmental regulation on green technology innovation of enterprises under different property rights.

Variable	The nature of state-owned property rights		Non-state-owned property rights	
	GTI	GTIE	GTI	GTIE
Er	0.224***(4.740)	0.403***(7.920)	0.179*** (4.220)	0.368***(8.140)
Er^2	−0.136*** (−6.600)	−0.208*** (−9.390)	−0.073*** (−3.090)	−0.151*** (−6.020)
Control variables	YES	YES	YES	YES
Time control	YES	YES	YES	YES
Individual control	YES	YES	YES	YES
R-sq	0.370	0.400	0.100	0.140
N	3,640	3,640	5,641	5,641

have a high degree of tolerance. The reason for this may be that the nature of state-owned property rights enterprise social responsibility is heavier, and it needs to be more proactive in responding to government environmental regulatory orders and, therefore, to green technology innovation.

7 Conclusion, recommendations, and future directions

7.1 Conclusion

This paper takes the data of enterprises in heavily polluting industries listed on A-shares from 2010 to 2020 as a research sample, studies the impact of environmental regulation on enterprises' green technology innovation, constructs a comprehensive index of environmental regulation, and uses enterprises' green patent applications as a proxy for enterprises' green technology innovation, using regression analysis and threshold effect testing. The method analyzes the impact of environmental regulation on enterprises' green technology innovation, the mediating effect of environmental protection investment, and the heterogeneity of enterprises with different property rights and uses the systematic GMM estimation method to control endogenous problems. The specific conclusions are as follows: (1) with the improvement of environmental regulation, the "U"-shaped relationship of first suppressing and then promoting enterprise green technology innovation exists; (2) environmental regulation has a single threshold effect on enterprise green technology innovation, and the threshold inflection point is 2.756. When environmental regulation is less than 2.756, environmental regulation has a suppressing effect on enterprise green technology innovation, and when environmental regulation is greater than 2.756, environmental regulation has a promoting effect on enterprise green technology innovation; (3) environmental protection investment has an intermediary effect in environmental regulation on enterprise green technology innovation, that is, changes in environmental regulation affect the choice of environmental protection investment by enterprises, and environmental protection investment affects enterprise green technology innovation; and (4) the degree of impact of environmental regulation on enterprise green technology innovation in different property rights enterprises is different, and the nature of state-owned property rights is more sensitive to environmental regulation and has a greater impact on enterprise green technology innovation.

7.2 Recommendations

Based on the aforestated conclusions, the following suggestions are made for environmental regulation and green innovation of heavily polluting enterprises:

(1) Formulating incentive-supporting policies for green technology innovation: Strengthening environmental protection is an important means to promote sustainable and high-quality economic development and transform the mode of economic development. Among them, enterprises must change their development thinking and improve the production of green products, and the key is the research and development of green technology innovation of enterprises. The government's flexible environmental regulatory incentives are crucial to strengthen the green technology innovation of enterprises. When the intensity of environmental regulation is low, in order to reduce passive environmental protection expenditure, such as fines by enterprises, we should start from the two aspects of financial incentives and talents, stimulate and promote the research and development of green technologies of enterprises, and pay attention to absorb and cultivate innovative talents, promote the transformation of green technology innovation, and promote the arrival of the "inflection point" as soon as possible.
(2) Improving the subsidy policy for environmental protection investment of enterprises: Environmental protection investment is an important way for enterprises to achieve green technology innovation, and in formulating environmental protection policies, we should pay attention to supporting environmental protection investment of enterprises and subsidies for environmental protection equipment. In

addition, in order to prevent enterprises from fraudulently obtaining subsidies through low-quality and high-volume innovation patents, they should divide innovation activities and classify subsidies according to the difficulty and value of innovation and research and development so as to truly promote the development of green high-tech innovation. Actively expanding financing channels for enterprises' environmental protection investment and reducing financing costs and financing risks help heavily polluting enterprises solve the dilemma of lack of cash flow for environmental protection investment and strongly support enterprises' green technology innovation.

(3) Improving the environmental awareness of enterprises themselves: State-owned property rights type of enterprises relatively take more social responsibility, are more sensitive to environmental regulations, and pay more attention to environmental protection investment. More enterprises should be guided to sort out the correct value orientation of environmental protection, encourage enterprises to take the initiative to disclose information related to environmental protection, and enhance their own awareness of social responsibility and a good environmental image in the minds of the public. Accelerating enterprise green innovation technology research and development will boost enterprises' transformation to green development. The green transformation of enterprises can not only promote sustainable economic development but also improve the core competitiveness of enterprises and effectively improve their business performance.

7.3 Shortcomings and future directions

Although this paper has conducted a detailed theoretical analysis and empirical research on environmental regulations and enterprises' green technological innovation, there are still some shortcomings that can be further studied in the future: First, this paper makes a comprehensive evaluation of environmental regulations but does not break down the different types of environmental regulations. Future research should consider the impact of different types of environmental regulations on green technology innovation to provide a theoretical basis for more precise policy implementation. Second, more industries are not considered, and this paper only considers highly polluting industries that are most sensitive to environmental regulations. Different industries have different sensitivities to environmental regulations and, therefore, have different degrees of influence on green innovation, and the heterogeneity of industries needs to be considered in future research. Thus, future research should focus on the impact of environmental regulations on green technology innovation in different industries.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

BY: data collection, writing, conceptualization, and methodology. QZ: editing, reviewing, and supervision. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Navigating the future: exploring technological advancements and emerging trends in the sustainable ornamental industry

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Technological advances have played a critical role in the production of flower crops, enabling farmers to maximize yields and reduce losses while also improving the quality of flowers. These advances have included the development of new breeding techniques, such as molecular marker-assisted breeding, and the use of modern technologies like high-throughput phenotyping to identify and select superior cultivars. In addition, precision farming techniques, such as the use of sensors and remote monitoring systems, have made it possible to closely monitor crop growth and optimize inputs like water and fertilizer, leading to higher yields and improved resource efficiency. Advancements in biotechnology have also resulted in the development of transgenic plants that are resistant to pests and diseases, reducing the need for chemical pesticides and improving plant health. Modern molecular genetic tools, particularly genome editing with CRISPR/Cas9 nucleases, are emerging in addition to conventional approaches of investigating these plants. Furthermore, the use of novel growing systems, such as hydroponics and vertical farming, has allowed for year-round flower production in controlled environments, mitigating the challenges associated with seasonal changes and climate variability. These innovations have also made it possible to produce high-quality flowers in urban areas, bringing fresh blooms closer to consumers. Overall, technological advances in flower crops have revolutionized the floriculture industry, enabling growers to produce high-quality flowers in a more sustainable and efficient manner. These advancements have not only improved the productivity and profitability of flower farming but have also contributed to the conservation of natural resources and the protection of the environment.

KEYWORDS

artificial intelligence, internet of things, robotics, soilless culture, vertical farming, flower industry, data analytics, image technology

1 Introduction

The cultivation of flowers has been intertwined with human civilization for centuries. Ancient cultures like the Egyptians, Greeks, and Romans were known to cultivate and use flowers for various purposes, including as offerings to their gods, for medicinal purposes, and to make fragrances and perfumes (Dafni et al., 2006). Flower production saw a seminal shift when colonial powers used Naval power along with railways to transport planting material across the continents thus bringing hitherto newer ornamental species and cultivars into gardens. As the demand for flowers increased over time, growers began to adopt new technologies to improve the quality and yield of their crops (Wani et al., 2018). The 20th century saw the advent of air and refrigerated transport and hence the ability to move flowers over long distances, particularly in the post-fifties which was the single most contributor to development of floriculture into a trans-continental and global enterprise. Flower production moved to areas around the equator that required less investment in energy in comparison to traditional production areas in northern latitudes. Newer flower types and cultivars were bred that withstood the rigours of long-distance transport, including improved post-harvest technologies and marketing that completed the value chain. Technologies have been rapidly developed and deployed to reduce the collective carbon footprint of the floriculture industry. In the post-2000s, flower industry has undergone the most rapid and paradigm shift in harnessing technologies that have emerged as the world ushered in the 4.0 industrial revolution (Hossen et al., 2020). Today, growers have access to cutting-edge technologies that have revolutionized flower production (Maraveas, 2023). As a result, the ability to handle big data in recent years has allowed the floriculture industry to make use of the most significant technological advances like genetic engineering (Cardoso and Vendrame, 2022; Khan et al., 2022) to create new flower varieties with improved characteristics, such as longer shelf-life, unique colors, and fragrance. By manipulating the plant's genetic code, breeders can develop flowers that are more resistant to pests and diseases, which reduces the need for harmful chemicals and makes the industry more sustainable (Huylenbroeck, and Bhattarai, 2022). AI and IoT have enabled the flower industry to reap the benefits of precision agriculture. This technology involves the use of sensors, drones, and GPS mapping to optimize crop inputs, reduce waste, and increase yields. By monitoring plant health and growth, growers can adjust irrigation, fertilization, and pest management practices more precisely, which reduces the overall environmental impact of flower production (Belal et al., 2021; Ferroukhi et al., 2023). Automation, robotics, and artificial intelligence (AI) have also played a significant role in reducing labor costs and increasing efficiency in flower cultivation. For example, automated planting and harvesting systems can perform tasks much faster and more accurately than manual labor, reducing the need for human workers (Jha et al., 2019). While these technological advances have greatly improved the quality and yield of flower crops and made the industry more sustainable, there are also potential drawbacks to consider. Genetic engineering raises questions about the safety of modified plants and their potential impact on the environment. Automation and use of artificial intelligence may lead to job losses, particularly in the global south where most of the production areas are currently located. Therefore, it is essential to explore the potential impact of these technological innovations on the environment, economy, and society and use them responsibly to promote sustainable and equitable flower production.

According to a report by the International Trade Centre, the global flower trade was valued at over USD 104 billion in 2019, with exports from developing countries accounting for a significant share of this value. However, the flower industry also faces challenges, including increasing competition, climate change, environmental degradation and gender equity. Technological innovations can help address some of these challenges, but they should be used responsibly and in conjunction with other sustainable practices such as organic farming, biodiversity conservation, and fair labor standards and health issues. In addition, technological advances should be accessible to all stakeholders, including small-scale farmers, and should not contribute to widening the existing economic and social disparities in the flower industry. By promoting sustainable and equitable flower production, we can ensure that this beautiful and culturally significant part of crop husbandry continues to thrive for generations to come. Technology has significantly impacted the floriculture industry, leading to significant advances in production, management, and sustainability. However, the looming challenge is to sustain and promote equity, inclusion and reduction of economic disparity by harnessing fourth industrial revolution in channelling its effects on advances in genetic engineering, climate control, carbon neutrality and making technologies available to all. Previous reviews on ornamental crops have primarily focused on a few technologies as evidenced by several available reviews (Rihn et al., 2022; Lea-Cox et al., 2013; Mahmud et al., 2023) whereas Rihn et al. (2022), on the other hand, examined factors linked to the inclination of the nursery industry to utilize automation and mechanization, and discussed the barriers to adoption for currently available technologies. This review article stands out as a comprehensive overview of available technologies for ornamental crop production. It discusses the potential benefits of using advanced technologies that are already employed in other crop industries and introduces the concept of virtual flowers, a new idea presented in this article. To the best of our knowledge, this is the first review article to delve so deeply into the significant technological advances for the ornamental industry, which have the potential to transform the floriculture industry.

The ornamental industry is continuously enhancing its production, distribution, and marketing processes by leveraging existing agricultural technologies, while also exploring new and emerging ones. Below are several technologies that are either currently being utilized or hold promising potential for adoption within the ornamental industry.

2 Biotechnology

Biotechnology has made significant advances in ornamental crops, such as flowers and decorative plants (Darqui et al., 2017). Tissue culture has been employed to produce a large number of identical plants within short period and efficiently, which can be useful for breeding and propagating new varieties of ornamental

TABLE 1 Some specific examples of various biotechnological interventions in improving targeted ornamental traits.

Gene	Plant transformed	Technology used	Source	Plant attributes	Reference
CHS	*Gentian*	Transgenic	Gentian	RNAi results in white flowers	Nishihara et al. (2006)
RCC2	Chrysanthemum	GM technology	Oryza sativa	Improved powdery mildew tolerance	Pourhosseini et al. (2013)
Rice chitinase (chill)	*Chrysanthemum*	Transgenic	Oryza sativa	Resistance to septoria leaf spot	Sen et al. (2013)
Rice chitinase 10 (RCH10)	*Lilium oriental*	GM technology	Oryza sativa	Resistance to Botrytis cineria	De Cáceres Gonzalez et al. (2015)
C3HC4H, 4CL, CCR, IRX	*Dendrobium officinale*	CRISPR	Not applicable	Altered lignocellulose biosynthesis pathway	Kui et al. (2017)
SGR	*Festuca arundinacea*	Genome Editing	Not applicable	Chlorophyll degradation	Sarmast, (2019)
GST1	Japanese Gentian (*Albireo*)	Genome Editing	Not applicable	Reduced anthocyanin in petals, white and pale blue flower	Tasaki et al. (2020)
flavonoid 3′-hydroxylase (F3′H)	*Euphorbia pulcherrima*	CRISPR-based Gene Editing	Not applicable	Flower color changed from vivid red to vivid reddish-orange	Nitarska et al. (2021)
DPL	*Petunia hybrid*	CRISPR-based Gene Editing	Not applicable	Vein associated anthocyanin pattern	Zhang et al. (2021a)

crops (Din et al., 2022). This technique can also be used to produce new varieties of plants with desirable traits. Using genetic engineering technology and transgenics, new varieties of ornamental crops with desirable traits, such as brighter colors, longer vase life, resistant to insect pests have been developed (Table 1) (Azadi et al., 2016; Boutigny et al., 2020). Marker-assisted breeding has been used to identify desirable traits in ornamental crops, such as improved color or longer vase life (Ahn et al., 2020; Chandler and Tribe, 2022; Suprasanna and Jain, 2022). This technique can be used to speed up the breeding process and create new varieties of ornamental crops more quickly. RNA interference has been used to silence specific genes in ornamental crops, leading to improved traits such as longer vase life or improved resistance to pests and diseases. Genome editing has been used to make precise edits to the DNA of ornamental crops, leading to improved traits (Table 1) (Sirohi et al., 2022; Ahmad et al., 2023; Jin et al., 2023). Overall, biotechnology has made significant advances in ornamental crops, leading to new varieties of plants with improved traits, increased resistance to pests and diseases, and more sustainable production practices (Din et al., 2021). The spread of the commercialization of GM ornamentals has been impeded by economic and regulatory constraints despite the positive scientific outlook for transgenic flowers. It is now time to deal with the legal challenges to the commercial distribution of GM plants, including flowers. Due to the costs and skills required for commercial development, the release of ornamental items will remain exceedingly challenging in the absence of an internationally suitable and authorised framework for regulation of GM crops. Reduced regulatory requirements for decorative plants and other non-food plants are needed to reduce this nuisance (Noman et al., 2017). By leveraging these advances, horticulturists can produce new varieties of ornamental crops that are more resilient, beautiful, and sustainable. In this review, we have made an effort to highlight recent advances and the need for attention in order to maximise the long-term sustainability of technology and society (Table 1).

3 Nanotechnology

Nanotechnology is a field of science that involves manipulating matter at the nanoscale level, which is typically between 1 and 100 nm in size. In the flower industry, nanotechnology is being explored for various applications, including improving flower quality, disease resistance, and shelf life. One application of nanotechnology in flowers is the use of nanoscale particles to improve the efficiency of fertilizers and pesticides. By attaching fertilizer or pesticide molecules to nanoparticles, growers can increase the efficiency of these products, reducing the amount needed and minimizing environmental impact. Nanoparticles can also be used to deliver nutrients and other compounds directly to plant cells, improving uptake and reducing waste. Another application of nanotechnology in flowers is the development of nanosensors for monitoring plant growth and health. Nanosensors can be designed to detect changes in temperature, humidity, nutrient levels, and other factors that affect plant growth. Nano biosensors have the potential to revolutionize agriculture by not only monitoring soil and plant health but also by predicting outbreaks of pests or diseases. By detecting changes in the biochemical makeup of plants or soil at a molecular level, nano biosensors can provide farmers with early warning signs of potential problems (Rai et al., 2022). This allows them to take preemptive measures to mitigate the impact of these issues, such as applying targeted treatments or adjusting their growing practices. This information can be used to optimize growing conditions and improve flower quality. In addition, nanotechnology can be used to develop materials with unique properties that are useful in the flower industry. For example, researchers are developing nanomaterials that can absorb and release water slowly, helping to maintain proper moisture levels

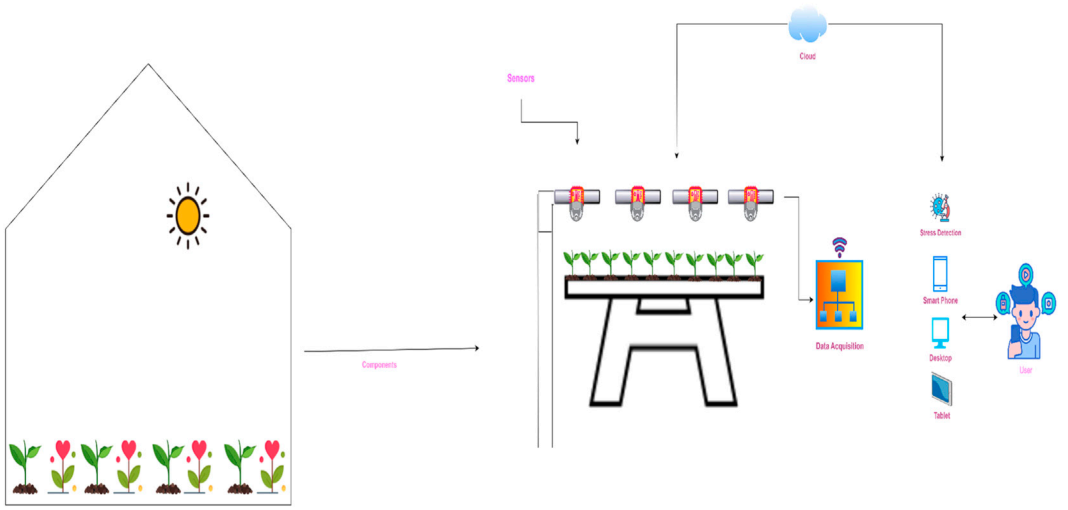

FIGURE 1
Conceptual design of smart greenhouse and individual overhead bench system.

in flower arrangements. Nanomaterials can also be used to develop coatings that improve the durability and longevity of flowers, reducing waste and improving the sustainability of the industry. Cut flowers have ornamental value and are commercially very important, but the flowers' shelf-life is very short (Solgi et al., 2009), due to higher microbial contamination (Lu et al., 2010a). The early wilting of the flowers is due to microbial and stem barrier infection that causes stem blockage which limits the uptake and transport of water, leading to water imbalances (Lü et al., 2010; Witte et al., 2014). Hence, it is important to overcome stem blockage by controlling microbial infections. Several reports have suggested that nano-silver has the potential to broaden the vase life of cut flowers (Li et al., 2012; Alekasir et al., 2017; Amingad et al., 2017). The most important nanoparticle, graphene oxide (GO) is a graphene-imitating carbon-based NPs containing enormous quantities of oxygenated groups with an extensive surface area that contributes a first-rate capability to transfer nourishment for sluggish-discharge fertilizers (Zhang et al., 2014; Rana et al., 2021). Overall, nanotechnology has the potential to revolutionize the flower industry by improving efficiency, reducing waste, and improving flower quality and sustainability. While many of these applications are still in the research phase, they offer exciting possibilities for the future of flower production and distribution.

4 Smart greenhouse technology

Greenhouse technology is widely used in horticulture to create an optimal growing environment for plants. Greenhouses allow growers to control the temperature, humidity, and other environmental factors to create an optimal growing environment for plants (Koukounaras, 2021). This can be particularly important for growing plants in regions with extreme climates or for producing crops out of season. Greenhouses can help to protect plants from pests and diseases by creating a barrier between the plants and the outside environment. This can help to reduce the need for pesticides and other chemical interventions (Messelink et al., 2021). Greenhouses can extend the growing season for plants by providing a sheltered environment that protects them from the elements. This can be particularly important for producing crops out of season or in regions with short growing seasons (Nassar and Ribeiro, 2020; Pereira et al., 2021). Greenhouses can help to conserve water by collecting and recycling irrigation water. This can be particularly important in regions with limited water resources or in areas with high water usage. Greenhouses can help to increase the productivity of horticultural crops by providing a controlled environment that promotes plant growth and reduces the risk of crop loss due to weather or pests. Greenhouses can help to maximize space utilization by allowing plants to be grown vertically or in tightly spaced rows (Stanghellini, 2013). This can help to increase the yield per unit area of land. Overall, greenhouse technology is a key tool in modern horticulture, allowing growers to produce high-quality crops year-round in a controlled environment. Keeping in view the sustainability there is an urgent need to upgrade or device smart greenhouses (Figure 1). Smart greenhouses use sensors and automation technology to monitor plant growth and create an optimal environment for flowers to flourish. This technology can increase crop yields, reduce waste, and improve the overall quality of the flowers. By leveraging the benefits of greenhouse technology, horticulturists can increase productivity, conserve resources, and produce crops that are healthier and more sustainable.

5 Post-harvest technology

Post-harvest technology in flowers has advanced significantly in recent years, with new technologies and techniques being developed to extend the vase life of cut flowers and improve their quality. Here are some of the key advances in post-harvest technology in flowers. Modified atmosphere packaging (MAP) involves storing cut flowers in an environment with controlled levels of oxygen, carbon dioxide, and humidity. This can help to extend the vase life of cut flowers by reducing respiration rates and slowing the growth of bacteria and fungi. Ethylene is a gas produced by plants that can cause flowers to wilt and decay. New technologies, such as ethylene-absorbing sachets and controlled atmosphere storage, can help to reduce the levels of ethylene around cut flowers, extending their vase life (Yang et al., 2021). Temperature is a critical factor in post-harvest flower care. New techniques, such as hydrocooling and forced-air cooling, can help to reduce the temperature of cut flowers quickly after harvest, reducing respiration rates and extending vase life (Rabiza-Świder et al., 2021). The quality of water used to hydrate cut flowers can affect their vase life. New techniques, such as reverse osmosis and ultraviolet sterilization, can help to improve the quality of water used in post-harvest flower care. New treatments, such as pulsing with sugar or plant hormones, can help to extend the vase life of cut flowers by promoting water uptake and reducing the growth of bacteria and fungi (Ichimura et al., 2007; Kazaz et al., 2019). Research and development in the floriculture industry are ongoing, and new chemicals are continually being developed to improve the vase life of cut flowers. Here are some examples of new chemicals that have shown promising results in recent studies: Nitric oxide (NO): NO is a natural signaling molecule that plays a role in regulating plant growth and development. Studies have shown that treating cut flowers with NO can delay senescence (the aging process) and increase vase life (Hussain et al., 2022). NO can also improve the quality of flowers by enhancing color, scent, and overall appearance. Polyamines are organic compounds found in all living cells, including plants. They are involved in various physiological processes, such as cell division, differentiation, and stress response. Recent studies have shown that treating cut flowers with polyamines, such as putrescine and spermidine, can improve their vase life by reducing senescence and preserving flower quality (Qu et al., 2020; Mazrou et al., 2022). Chitosan is a biodegradable polymer derived from chitin, which is found in the shells of crustaceans. It has antimicrobial and antifungal properties and has been shown to improve the vase life of cut flowers by reducing microbial growth and maintaining water balance (Ali et al., 2022). Essential oils: Essential oils are volatile compounds extracted from plants, and they have been used for centuries in various applications, including aromatherapy and medicine. Recent studies have shown that treating cut flowers with essential oils, such as lavender and rosemary, can improve their vase life by reducing microbial growth and enhancing flower quality (Teerarak et al., 2019; El-Sayed et al., 2021). Overall, advances in post-harvest technology in flowers are helping to improve the quality and longevity of cut flowers, reducing waste and improving the sustainability of the floral industry. By leveraging the latest technologies and techniques, horticulturists can produce high-quality flowers that retain their beauty and freshness for longer periods of time.

6 Smart irrigation technology

Irrigation technology has been playing an essential role in flower crop production by providing the right amount of water to the plants, increasing crop yield, and optimizing the use of water resources. In general, irrigation technology in flower crops involves the application of water in the right amount and at the right time, using advanced systems and methods. One of the main advances in irrigation technology for flower crops is the use of drip irrigation systems. These systems provide water directly to the root zone of plants, minimizing water loss due to evaporation and runoff. They also allow for precise control of water application, reducing the risk of over- or under-watering. Another irrigation technology that has gained popularity in recent years is the use of soil moisture sensors. These sensors measure the moisture content in the soil and provide real-time data to growers, allowing them to adjust irrigation schedules and avoid water stress or over-watering. In addition, advanced irrigation controllers are now available that use weather data to adjust irrigation schedules automatically based on the local climate conditions, further optimizing water use. Finally, fertigation technology is also being used in flower crops, where fertilizers are injected into the irrigation system to provide nutrients directly to the roots. This approach ensures that the plants receive the necessary nutrients for healthy growth while minimizing fertilizer waste and runoff. Overall, irrigation technology has revolutionized flower crop production by providing precise control over water and nutrient application, resulting in increased yields, improved quality, and reduced water usage. Automation through an IoT system could be an effective approach to improve a conventional surface irrigation system operation. An automated surface irrigation system refers to its operation with timers, sensors or computers or mechanical appliances with minimal manual involvement (Figure 2). Many researchers have reported that automation in irrigation projects using an intelligent irrigation controller and wireless sensor network could save water up to 38% (Al-Ghobari, et al., 2013; Bowlekar et al., 2019). Automation is a smart technique to deal with the problem of high labor requirements and low water application efficiency of surface irrigation systems (Table 2). Many soil moisture sensors such as tensiometer, gypsum block, granular matrix sensor, time-domain reflectometer, dielectric probe are commercially available for soil moisture measurement and they could generally be used for manual or integrated with automatic irrigation control systems through an IoT system (Bowlekar et al., 2019; Hardie, 2020; Vera et al., 2021; Pramanik et al., 2022). The sensor senses the water advance front and gives a signal to cut-off the flow.

Smart irrigation systems using Internet of Things (IoT) technology have been successfully implemented for ornamental crop production. For example, Banda-Chávez et al. (2018) developed an IoT-based sensor network using an IoT platform and soil moisture sensors (YL-69) to automate the irrigation of ornamental plants (Figure 2). Beeson and Brooks (2006) also used an evapotranspiration (ETo) model-based smart irrigation system for wax-leaf privet, reducing water usage by 22.22% annually compared to traditional overhead irrigation methods. While there are limited studies on IoT-based automatic irrigation systems for the ornamental industry, the promising potential of this technology in other crop industries suggests it could benefit ornamental crop production. However, sensor-to-sensor variability and accurate sensor positioning are important factors that can affect efficacy. Determining the optimal number of sensors for a particular nursery environment depends on various factors such as the accuracy and repeatability of the sensors, variation among sensors, spatial variability of the nursery environment, and cost.

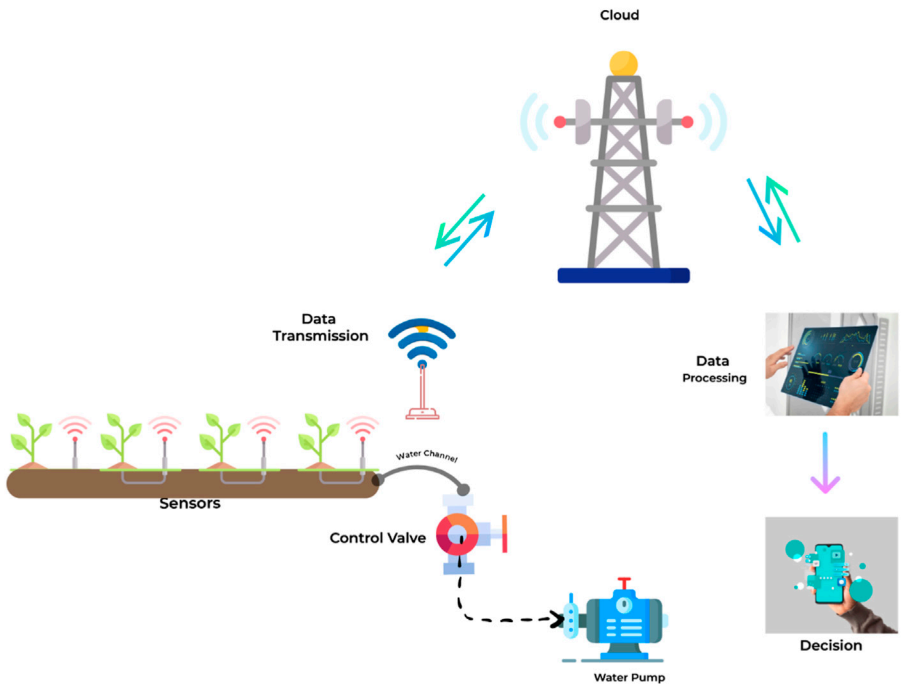

FIGURE 2
Conceptual design of smart irrigation system under protected/open cropping systems.

TABLE 2 Summary of reports smart irrigation system helping in conserving water efficiently.

Crop species	Sensor	% Water saving	Reference
Red Maple and Cherokee Princess	Matric potential and capacitance sensors (WSNs)	Not Reported	Lea-Cox et al. (2008)
Hydrangea	Capacitance-based (WSNs)	Not Reported	Coates et al. (2012)
Dogwood and Red Maple	Capacitance-based (WSNs)	34%–63%	Belayneh et al. (2013)
Ornamentals	Capacitance-based (WSNs)	20%–25%	Chappell et al. (2013)
Dogwood and Red Maple	Capacitance-based (WSNs)	62.9%	Lea-Cox and Belayneh (2013)
Hydrangea	Electrical conductivity (WSNs)	≥83%	Kim et al. (2014)
Ornamental plants	Capacitance-based (IoT)	Not Reported	Banda-Chávez et al. (2018)
Japanese Andromeda; Catawba Rosebay; Oakleaf Hydrangea; Mountain Laurel	Capacitance-based (WSNs)	50%	Wheeler et al. (2020)

7 Soilless technology

Limited resources, such as fertile soil and clean water, are already a reality in many parts of the world. Climate change further exacerbates the challenges of conventional farming practices, as the availability and quality of arable land become increasingly limited. Soilless cultivation, also known as hydroponics, is a method of growing plants without soil, using a nutrient-rich solution instead. By eliminating the need for soil, soilless cultivation systems can help conserve water and open up urban areas, such as residential rooftops, for food production in close proximity to consumers (Fussy and Papenbrock, 2022). The development of automation and computer technology, coupled with the greenhouse feature, has accelerated the adoption of soilless cultivation in many developed countries in recent years. Conventional farming practices typically rely on soil-bound methods, which can have a range of negative impacts on the environment, including high and inefficient water demand, large land requirements, fertilizer use, soil degradation, and loss of biodiversity. It is imperative to explore alternative approaches to food production, such as soilless cultivation, to address these challenges and ensure sustainable agricultural practices for the future (Killebrew and Wolff 2010; Walls 2006). In the flower industry, soilless

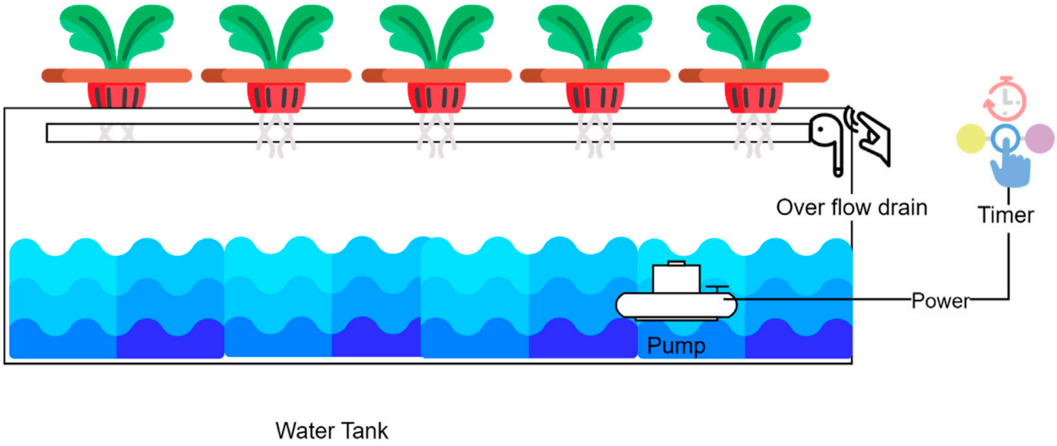

FIGURE 3
Conceptual design of smart Soilless culture system-NFT.

cultivation is gaining popularity due to its ability to improve crop yields, reduce water consumption, and minimize the use of pesticides and fertilizers (AlShrouf, 2017). One of the benefits of soilless cultivation in flowers is the ability to control growing conditions more precisely. By controlling the temperature, humidity, and nutrient levels of the growing solution, growers can optimize plant growth and flower quality (Zimmermann and Fischer, 2020). Soilless cultivation also eliminates the need for soil, which can reduce the risk of soil-borne diseases and pests (Savvas, 2002; Hussain et al., 2014). There are several methods of soilless cultivation that can be used in the flower industry (Kahraman and Akçal, 2018; Khalaj and Noroozharaf, 2020; Kromwijk and van Os, 2020). For example, one common method is to grow flowers in a nutrient-rich solution that is recirculated through a series of pipes or channels. This method is known as a recirculating hydroponic system. Another method is to grow flowers in a substrate, such as rockwool or coco coir, which is soaked in a nutrient-rich solution (Leiva et al., 2019; Kharrazi et al., 2020). This method is known as a substrate-based hydroponic system. Soilless cultivation can also be combined with other technologies to further improve flower production. For example, some growers use vertical farming techniques to maximize space utilization and improve growing conditions. Vertical farming involves growing plants in stacked layers, using artificial lighting and environmental controls to optimize plant growth. Overall, soilless cultivation has the potential to revolutionize the flower industry by improving crop yields, reducing water and fertilizer consumption, and minimizing the risk of pests and diseases. By using nutrient-rich solutions and advanced environmental controls, growers can produce high-quality flowers with less waste and environmental impact (Figure 3).

7.1 Aeroponics

Aeroponics is a modern agricultural technique that involves growing plants in an air or mist environment without soil. Instead of soil, plants are grown in a nutrient-rich solution that is misted onto the roots. Aeroponics is becoming increasingly popular in flower crop production because of its many advantages (Nir, 1982). One

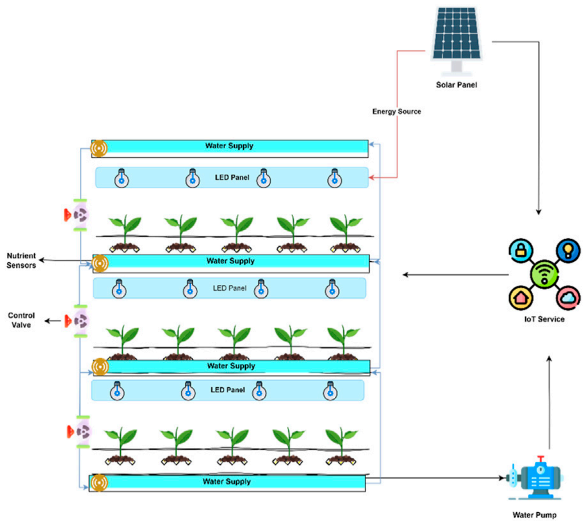

FIGURE 4
Conceptual design of smart vertical farming system.

advantage of aeroponics is that it allows for more efficient use of resources like water and nutrients. Because the nutrient solution is misted onto the roots, plants can absorb more of the nutrients and water than they would if they were grown in soil. This can lead to faster growth and higher yields. Another advantage of aeroponics is that it reduces the risk of disease and pests. Because plants are grown in a sterile environment, there is less chance of soil-borne diseases or pests affecting the crop. This can reduce the need for pesticides and other chemicals, making aeroponics a more sustainable and environmentally-friendly option. Aeroponics can also be used to grow flowers year-round, regardless of weather conditions. This makes it possible to produce flowers in areas where traditional outdoor growing methods may not be feasible. The performance of the system has been tested successfully (growing and rooting) with several plants, such as ornamental plants like carnation, croton,

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chrysanthemum, Eustoma geranium, euonymus, Ficus, philodendron, dracaena, dieffenbachia, Zantedeschia, etc (de Kreij and van der Hoeven, 1997; Christie and Nichols, 2004; Hayden, 2006; Fascella and Zizzo, 2007). In order to analyse plant root systems for a variety of studies, researchers need a practical growing system. An aeroponic system that was created by a French engineer and modified by members of the legume community, was detailed by Cai et al. (2023) and was initially intended for nodulating legume root systems. For researchers looking to better understand root growth and development, this approach offers various benefits. With this aeroponic device, researchers can grow hundreds of plants at once. Even though it is not a sterile system, it may be kept axenic in the lab with appropriate procedures. During plant growth, the nutritional medium can be changed based on the demands of the experiment. Overall, aeroponics is a promising technology for flower crop production, offering many benefits over traditional growing methods. However, it requires careful monitoring and management to ensure optimal plant growth and health.

7.2 Smart vertical farming

Vertical farming is a growing trend in the agriculture industry, and it is also being explored for flower production. Vertical farming in flowers involves growing plants in vertical layers, often in controlled environments, such as indoor facilities or greenhouses (Touliatos et al., 2016). Numerous countries including Korea, Japan, China, Germany, the United Arab Emirates, China, France, India, Sweden, Singapore, and the United States, have convened to discuss vertical farming. They have repeatedly endorsed the concept as integral to the long-term sustainability of their cities (Despommier, 2014). Vertical farming can provide several benefits to flower growers (Figure 4). Firstly, it allows for the efficient use of space, as plants can be stacked vertically, increasing the amount of production per unit area of land. Furthermore, indoor farming provides a low-impact system that can significantly reduce travel costs, as well as reduce GHG emissions, by cutting down on travel distances between distant farms and local markets (Astee, and Kishnani, 2010; Mukherji and Morales, 2010). Also, vertical farming could ignite local economies by providing much-needed “green collar” jobs to urban areas (Healy and Rosenberg, 2013; Mukherji and Morales, 2010). This is particularly advantageous in urban areas where land is limited and expensive. Secondly, vertical farming can offer precise control over growing conditions, such as temperature, humidity, light, and nutrient levels, ensuring consistent plant growth and reducing the risk of disease and pest infestations (Al-Kodmany, 2018). By using artificial lighting and hydroponic or aeroponic systems, vertical farms can provide optimal growing conditions for flowers, resulting in higher quality and more consistent blooms (Despommier, 2010; Eve, 2015; Levenston, 2017; Meinhold, 2017). Thirdly, vertical farming can reduce the need for pesticides and herbicides, as plants are grown in a controlled environment with fewer pests and diseases. This reduces the environmental impact of flower production and provides safer working conditions for growers. Finally, vertical farming can also reduce water usage, as hydroponic and aeroponic systems recycle water, reducing waste and conserving resources. While vertical farming in flowers is still in its early stages, it has the potential to transform flower production by providing a more sustainable, efficient, and cost-effective way to grow flowers. With further research and development, vertical farming could become a key method of flower production in the future.

8 Green roofs and walls

Green roofs and walls are becoming more popular in urban areas as a way to add green space and reduce the urban heat island effect. Advances in materials and installation techniques have made it easier and more cost-effective to install and maintain these features. Green roofs and walls are innovative and sustainable solutions to improve urban environments by incorporating vegetation into buildings. Green roofs are roofs that are covered with plants and vegetation, often including a layer of soil and a drainage system, to support the growth of vegetation. They can provide several benefits, including reducing urban heat island effects, improving stormwater management by retaining rainwater, and providing additional insulation to buildings to reduce energy consumption (Mayrand and Clergeau, 2018). They can also provide habitat for wildlife and improve air quality by filtering pollutants (Haaland and van den Bosch, 2015). Green walls, also known as living walls or vertical gardens, are similar to green roofs, but they are installed vertically on the side of buildings. They can be made up of a variety of plant species and can be used for both aesthetic and functional purposes. Green walls can also provide similar benefits to green roofs, such as improving air quality and reducing urban heat island effects. Both green roofs and walls require proper installation and maintenance to ensure their long-term viability. They can also provide unique opportunities for urban agriculture and rooftop gardens, creating additional benefits for local communities. Overall, green roofs and walls are sustainable solutions to improve urban environments and promote green infrastructure (Elmqvist et al., 2015).

Green roofs and walls can support a variety of vegetation, including flower crops. In fact, adding flower crops to green roofs and walls can increase their aesthetic value and provide additional benefits to the environment. Flower crops such as sedum, lavender, and wildflowers are often used in green roofs due to their hardiness and ability to withstand harsh weather conditions. They can also attract pollinators, such as bees and butterflies, which play an important role in the pollination of plants. When it comes to green walls, flower crops can be arranged in different patterns and designs to create beautiful living walls (Pétremand et al., 2017). For instance, a mix of flowering plants such as petunias, pansies, and geraniums can be used to create a colorful and vibrant wall. In addition to their aesthetic benefits, green roofs and walls with flower crops can also provide environmental benefits such as reducing urban heat island effects and improving air quality (Ode et al., 2023). They can also provide opportunities for urban agriculture, such as growing edible flowers and herbs (Li et al., 2016). However, it is important to note that green roofs and walls with flower crops require regular maintenance to ensure their health and viability. This includes proper irrigation, fertilization, and pest management. Overall, incorporating flower crops into green roofs and walls can be a sustainable and beautiful solution for urban environments.

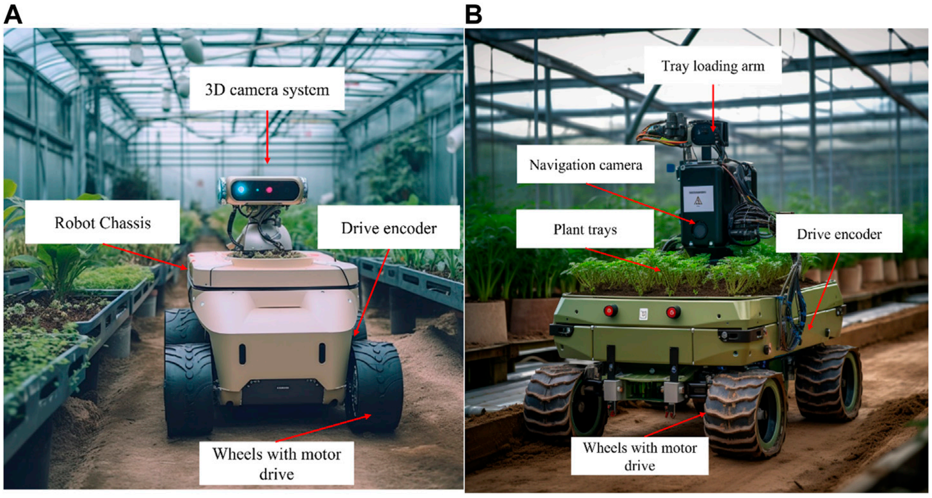

FIGURE 5
Conceptual design of robotic systems for performing various tasks in ornamental nurseries, **(A)** plant health monitoring, and **(B)** plant carrier platform with loading and unloading system.

9 Robotics

Robotics is a rapidly developing field that is also making strides in the floriculture industry. Despite the clear benefits of existing approaches to robotizing harvesting operations in gardens, the relationship between a robot's degree of autonomy and its ability to perform multiple agricultural tasks on a single platform has not been thoroughly investigated. Developing effective calculation methods will be crucial to unlocking the full potential of mobile robots by increasing their autonomy and expanding their functionality. At the same time, the issues of increasing the technical efficiency of solutions aimed at achieving a high level of robot autonomy require development. This can be achieved by applying intelligent approaches to the complex processing of data coming from a complex of information devices (Bechar et al., 2016; Grimstad, 2017) Robotics in flower crops involves the use of automated and autonomous systems to perform various tasks related to the cultivation, care, and harvesting of flower crops (Abarna and Selvakumar 2015). Robotic mowers, trimmers, and other automated maintenance equipment can now be used to maintain lawns and other outdoor spaces (Oliveira et al., 2021). In addition, the availability of a skilled workforce that accepts repetitive tasks in uncomfortable greenhouse conditions is decreasing rapidly, causing a reduced availability of workforce (Adegbola et al., 2019; Arad et al., 2020). Furthermore, the issue of labor shortage has become even more relevant during the current COVID-19 pandemic caused by the SARS-CoV-2 virus, which has limited international travel for migrant workers (Woo et al., 2020). These machines can work continuously and efficiently, reducing the need for manual labor and improving overall maintenance quality. One significant benefit of using robotics in flower crops is the potential for increased efficiency and productivity. Robots can work 24/7, perform tasks with precision and consistency, and work in harsh environments without risking the health and safety of human workers. Robots can be used to perform tasks such as planting, pruning, weeding, and harvesting (Sori et al., 2018; Uchida et al., 2019; Verbiest et al., 2020; Tarannum et al., 2021). For example, robots equipped with sensors, cameras, and other technology can navigate fields, identify flowers, and accurately harvest them with minimal damage to the plant. Some examples of flower harvest robots currently on the market include the Flower Robotics' "Ryden" and the "Harvest Croo" system, which is designed specifically for harvesting strawberries but could potentially be adapted for use with other types of flowers. QuickFlora is testing another robot 'FloraBot' to automate the flower arrangement process. FloraBot designs advanced technologies which enable customers to automate the handling and assembly of fresh flower arrangements something that was impossible in the past (www.flora.bot). Everything starts with a vision of how to increase efficiency, improve product quality and provide scalability when needed, using flower-friendly robotics. In simple terms, robots do things that have not been possible before in mass-production floral environments. We are able to automate the assembly of floral products and processes that were previously off-limits to automation. These robots can also monitor plant growth and detect any diseases or pests that could harm the crops, allowing for quicker response times to prevent the spread of disease and reduce the need for chemical treatments (Figure 5). Similar robots can be designed using a combination of computer vision and machine learning algorithms to recognize flower types and colors and arrange them into a desired pattern or design. The robots can be equipped with a specialized gripper that can pick up and handle delicate flowers without damaging them. Similarly, "Starship robots" are designed to transport food packages over short distances and have been successfully used to deliver flowers to customers (www.starship.xyz). They are operated by Starship Technologies, a company founded by two Skype co-founders, Ahti Heinla and Janus Friis.

An automated system for harvesting *Gerbera jamesonii* cut flowers grown in greenhouses has been developed using image processing (Kawollek, and Rath, 2008). The harvesting process uses an industrial robot with six axes and an additional linear axis, equipped with an end-effector using razor blades for cutting the flower stems. The whole harvesting system, including the robots, end-effectors, transport unit, and cameras, is calibrated online using special calibration algorithms. The system analyzes image data from eight different viewpoints to identify all flower stems in at least one of the positions, enabling stepwise harvesting, if necessary, in different positions of the plant. To ensure a collision-free process, a path-planning module is integrated, and an algorithm for flower stem tracking predicts the emerging of the stem in the following non-visible area. In harvesting experiments, 80% of all flower stems were harvested, with a decreasing rate of harvest with an increasing number of flower stems per plant. For plants with one or two flower stems, 98% of the flower stems were harvested, while for plants with five or more flower stems, 51% of all flower stems were harvested. Al-beeshi et al. (2015) designed a self-propelled robot, which can analyze soil moisture and monitor and adjust the water pump's condition in order to activate the soil watering function. A multi-task robotic work cell for greenhouse transplanting and seedlings has been developed by Han et al. (2018). The work cell mainly consists of two conveyors, a filling unit, a control system, and a transplanting system, which is made up of multi-grippers designed to automatically pick up and plant whole rows of seedlings. Several studies have been conducted on the development of robots that can perform various agricultural tasks with precision and accuracy. Chang et al. (2016) developed a low-cost planting robot that can navigate straight lines with great accuracy. The robot is equipped with a drilling mechanism that can dig up to 30 cm depth, and an ultrasonic sensor is used to detect the drilling depth. Gao et al. (2017) designed a prototype of a robot sprayer that can adjust the spray angle according to crop height, canopy shape, thickness, and plant density. The system uses magnetic sensors installed on the tracks to detect the canopy ridge. Wang et al. (2022) designed an intelligent and modular greenhouse seedling inspection robot that can acquire images of seedlings and environmental data during cultivation. The robot's environmental data collection module can accurately obtain data on the light intensity, temperature, humidity, and CO_2 concentration in the greenhouse. Masuzawa et al. (2017) developed a mobile robot capable of supporting flower harvesting by utilizing a simultaneous localization and mapping (SLAM) algorithm to map the environment. The robot has an RGB-D camera installed not only to measure the distance to objects but also to allow for person-following capability. The robot uses image-based person detection and tracking and trajectory generation for following movements to trace the person's trajectory as a guide to safe path planning. Ohi et al. (2018) utilized the same technology to develop a robot that can perform fully autonomous precision pollination of bramble plants in a greenhouse environment. The robot uses vision techniques to detect the position of flowers for pollination, and an RGB-D camera installed on the robotic arm enables precise short-range positioning. These advancements in robot technology show great potential for improving agricultural practices and increasing efficiency in various tasks, from planting and spraying to harvesting and pollination. While the use of robotics in flower crops is still in its early stages, it has the potential to significantly improve the efficiency, quality, and sustainability of flower production. However, the development and adoption of flower harvest robots face challenges such as cost, technical complexity, and the need for further refinement to ensure they can operate in diverse field environments. By leveraging robotics, floriculturists can maximize their yields, reduce labor costs, and minimize their environmental impact, leading to a more sustainable and profitable industry.

10 Imaging technology

Imaging technology has become an important tool for the floriculture industry. Imaging technology in flower crops involves the use of advanced cameras and sensors to capture detailed images of plants, flowers, and their surrounding environments. These imaging techniques include visible imaging (machine vision), imaging spectroscopy (multispectral and hyperspectral remote sensing), thermal infrared imaging, fluorescence imaging, 3D imaging and tomographic imaging (MRT, PET and CT) (Li et al., 2014). These images are then analyzed using advanced algorithms and computer programs to provide insights into plant growth, development, and health. One of the primary applications of imaging technology in flower crops is for the detection and diagnosis of plant diseases and pests (Saleem et al., 2020). By capturing high-resolution images of plants and analyzing them using artificial intelligence and machine learning algorithms, floriculturists can quickly and accurately detect early signs of disease or pest infestations, allowing for timely intervention and treatment (Sasaki et al., 1999; Chaerle et al., 2007). Imaging technology can also be used to monitor plant growth and development, including factors such as leaf area, stem diameter, and flower size. This information can be used to optimize growth conditions, such as lighting, temperature, and irrigation, to maximize plant health and productivity (Nakarmi and Tang, 2012; Tilly et al., 2012; Longchamps et al., 2023).

Plant phenotyping robots are cutting-edge technology that allows for the high-throughput measurement of morphological, chemical, and physiological properties of a large number of plants. Multiple robotic systems have been developed for different phenotyping missions. Robotic phenotyping has the potential to efficiently monitor changes in plant traits over time, both in controlled environments and in the field (Atefi et al., 2021). Various studies have discussed the use of image-based techniques, including 2D and 3D reconstruction, to extract architectural traits such as inflorescence length and width, inflorescence volume (weight), grain shape and size, grain angle, number of grains, and number of flowers (Faroq et al., 2013; Crowell et al., 2014; Gage et al., 2017; Rudolph et al., 2019). To measure morphological traits in plant phenotyping, a robot equipped with LIDAR or a camera can automatically capture images or point cloud data from various angles of the inflorescence. Physiological traits are important indicators of stress or disease in plants. For example, the temperature of the spikes has been used to detect water stress in plants (Panozzo et al., 1999). A robotic arm equipped with a temperature sensor can potentially grasp the spike and insert the sensor into spikelets to record their temperature. In fruit quality assessment, various properties such as water content, sugar content, chlorophyll, carotenoid, soluble solids, acidity, and firmness need to be measured. Spectroscopy and spectral imagery are non-destructive and high-throughput methods that can be used to estimate these qualitative parameters (Atefi et al., 2021; Shao and He, 2008; Wu et al., 2008; Nishizawa et al., 2009; Penchaiya et al., 2009; Ecarnot et al., 2013; Guo et al., 2013; Dykes et al., 2014; Wang et al., 2015; Mancini et al., 2020). A robotic system can be utilized to monitor the dynamics of fruit attributes for hundreds of growing fruits per day. For instance, a portable spectrometer can be attached to the robot's end-effector. The robot can detect the fruit on the plant, grasp it, and gather its spectral data to infer its quality parameters. This approach offers a high-throughput and non-destructive method for fruit quality assessment, enabling efficient monitoring of fruit development over time. In addition, imaging technology can also be used to assess the quality of flowers, providing insights into factors such as color, shape, and size, which are important for marketability and consumer appeal (Prunet and Duncan, 2020). Overall, imaging technology is proving to be a valuable tool in the floriculture industry, providing floriculturists with the ability to detect and treat plant diseases, optimize growth conditions, and improve the quality of their products.

11 Computerized monitoring systems

Computerized monitoring systems in agriculture are technology-driven systems that use sensors and automated data collection to track and monitor various aspects of crop production. These systems can provide farmers with real-time data on soil moisture, temperature, weather patterns, and other environmental factors, allowing them to make more informed decisions about irrigation, fertilization, and other inputs. Computerized monitoring systems can also be used to detect and respond to potential problems, such as pest infestations or disease outbreaks before they have a chance to cause significant damage. Overall, computerized monitoring systems are helping to improve the efficiency and productivity of agricultural operations, while also reducing waste and environmental impact.

12 Data analytics

Data analytics is playing an increasingly important role in agriculture, helping farmers to make more informed decisions and improve crop yields. Here are some of the key areas of data analytics in agriculture: Predictive analytics: Predictive analytics uses data analysis techniques to make predictions about future outcomes, such as crop yields or weather patterns. This information can help farmers to make more informed decisions about planting, harvesting, and other aspects of agricultural production (Lassoued et al., 2021). Precision agriculture: Precision agriculture involves using data analytics to optimize crop production by tailoring inputs such as water, fertilizer, and pesticides to specific areas of a field (Griffin et al., 2018; Akhter et al., 2021). This approach can improve crop yields while reducing waste and environmental impact. Remote sensing: Remote sensing involves using satellites, drones, and other technologies to collect data on crop health, soil moisture, and other environmental factors. This data can be used to identify areas of a field that require additional inputs or interventions. Data visualization tools can be used to display data in an easy-to-understand format, helping farmers to identify trends and make informed decisions (Kumar et al., 2019a; 2019b). For example, farmers can use data visualization tools to track weather patterns, crop yields, and other key metrics. Supply chain analytics: Supply chain analytics can be used to optimize the distribution and delivery of agricultural products, reducing waste and improving efficiency. Overall, data analytics is transforming agriculture by providing farmers with real-time data on crop health, weather patterns, and other environmental factors. By leveraging the power of data, farmers can make more informed decisions about planting, harvesting, and other aspects of agricultural production, contributing to a more sustainable and secure food supply.

13 Internet of things (IoT)

The Internet of Things (IoT) is a new technology that allows devices to connect remotely to achieve smart farming (Patil and Kale, 2016). The IoT has begun to influence a vast range of industries, from health, trade, communications, energy and agriculture, to enhance efficiency and performance across all markets (Elijah and Rahman, 2018; Sisinni et al., 2018; Shi et al., 2019). The Internet of Things (IoT) is a network of connected devices and sensors that communicate and exchange data with each other. In the flower industry, IoT is being used to improve the efficiency of flower production and supply chain management. IoT sensors can be used to monitor environmental conditions such as temperature, humidity, and light levels, which are critical factors in flower growth and development. By collecting data on these factors, growers can optimize growing conditions to ensure the best quality and yield of flowers. For example, sensors can be used to adjust the temperature and humidity levels in a greenhouse to create the ideal environment for flower growth. IoT can also be used to monitor the health and growth of flowers. For instance, sensors can be placed on individual plants to measure their growth rate, nutrient uptake, and water consumption. This can help growers to identify any issues early on and take corrective measures before they become serious. The Internet of Things (IoT) technology enables the remote monitoring of plants and animals, retrieving information from mobile phones and other devices. Through the use of sensors and instruments, farmers can assess weather patterns and anticipate production levels. The IoT also plays a crucial role in water management, allowing for the monitoring and control of water flow, assessment of crops' water requirements, and optimization of water usage, like never before (Yong et al., 2018). With sensors and cloud connectivity through the gateway, the status of the water supply can be remotely monitored based on soil and plant needs (Mekala et al., 2017). The benefits of IoT technology extend to correcting nutrient deficiencies, pests, and diseases, as farmers cannot manually monitor every plant. This technology has ushered farmers into a new era of modern agriculture (Mittal and Singh, 2007). In addition, IoT can be

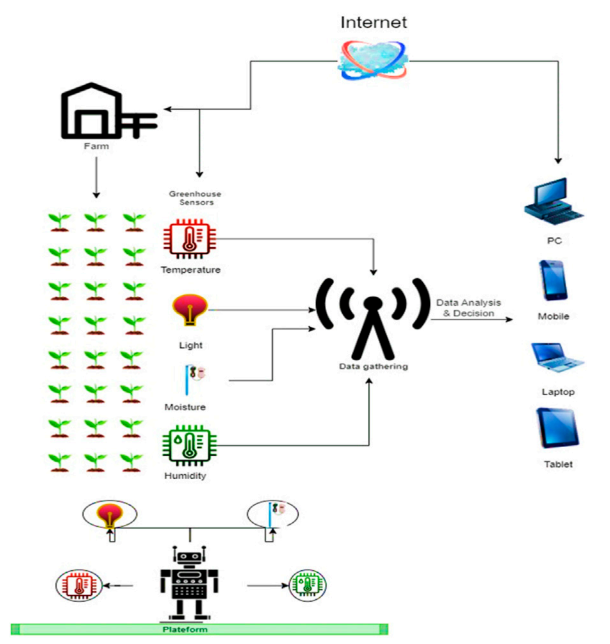

FIGURE 6
AI-based monitoring wireless sensor network and IoT concept.

used to improve supply chain management by providing real-time data on the location and condition of flowers during transportation. IoT sensors can track the temperature, humidity, and other conditions during shipping and alert growers and distributors if there are any deviations from the ideal conditions. Overall, IoT has the potential to improve the efficiency and quality of flower production and supply chain management. By using IoT sensors and devices, growers and distributors can optimize growing conditions, reduce waste, and ensure the best quality and freshness of flowers for consumers.

14 Artificial intelligence (AI)

Artificial intelligence (AI) is a broad term that refers to the ability of machines to perform tasks that typically require human intelligence, such as learning, problem-solving, and decision-making. In the flower industry, AI is being used to improve flower production and quality, as well as to optimize supply chain management. One application of AI in flowers is to analyze and interpret data from sensors and cameras to optimize growing conditions. AI algorithms can be used to analyze large datasets of environmental and plant growth data to identify patterns and make predictions about the optimal conditions for growing different types of flowers (Figure 6). For example, AI algorithms can help growers optimize the amount of water, fertilizer, and light that flowers receive, which can improve yield and quality (Song and He, 2007; Eli-Chukwu, 2019; Vincent et al., 2019). Another application of AI in flowers is to improve disease detection and prevention (Adedoja et al., 2019). AI algorithms can be trained to recognize the symptoms of different plant diseases and to detect them early on. This can help growers take corrective measures before the disease spreads and affects the entire crop. AI can also be used to develop predictive models for disease outbreaks based on environmental and weather data. In addition, AI can be used to optimize supply chain management by analyzing data from sensors and cameras to monitor the condition and location of flowers during transportation (Figures 5, 6). AI algorithms can predict the best routes and transportation methods for delivering flowers while minimizing waste and reducing costs (Wang et al., 2017). Overall, AI has the potential to improve the efficiency, quality, and sustainability of flower production and supply chain management. By analyzing data and making predictions (Talaviya et al., 2020), AI can help growers optimize growing conditions, detect and prevent diseases, and improve supply chain logistics for delivering high-quality flowers to consumers.

15 Machine learning (ML)

Machine learning is a type of artificial intelligence that enables computers to learn from data and improve their performance over time without being explicitly programmed. In the flower industry, machine learning is being used to improve flower production and quality, as well as to optimize supply chain management. One application of machine learning in flowers is to analyze and interpret data from sensors and cameras to optimize growing conditions (Benos et al., 2021). Machine learning algorithms can be used to analyze large datasets of environmental and plant growth data to identify patterns and make predictions about the optimal conditions for growing different types of flowers. For example, machine learning algorithms can help growers optimize the amount of water, fertilizer, and light that flowers receive, which can improve yield and quality (Sun et al., 2019; Virnodkar et al., 2020). Another application of machine learning in flowers is to improve disease detection and prevention. Machine learning algorithms can be trained to recognize the symptoms of different plant diseases and to detect them early on. This can help growers take corrective measures before the disease spreads and affects the entire crop. Machine learning can also be used to develop predictive models for disease outbreaks based on environmental and weather data. In addition, machine learning can be used to optimize supply chain management by analyzing data from sensors and cameras to monitor the condition and location of flowers during transportation (Liakos et al., 2018; Zhang J. et al, 2021). Machine learning algorithms can predict the best routes and transportation methods for delivering flowers while minimizing waste and reducing costs.

The integration of IoT, AI, and machine learning has significant potential to revolutionize flower production and supply chain management (Figure 7). IoT sensors and devices can help growers and distributors optimize growing conditions and reduce waste, while AI and machine learning can help them make data-driven decisions to improve efficiency, quality, and sustainability. For instance, the use of IoT sensors can monitor factors such as soil moisture, temperature, and light levels, helping growers create the ideal growing conditions for each flower variety. This can lead to increased yields, reduced water usage, and lower energy costs. Additionally, IoT devices can monitor the flowers' post-harvest conditions, ensuring they are stored and transported at optimal temperatures to maintain their quality and freshness. The use of AI and machine learning can further enhance flower production and

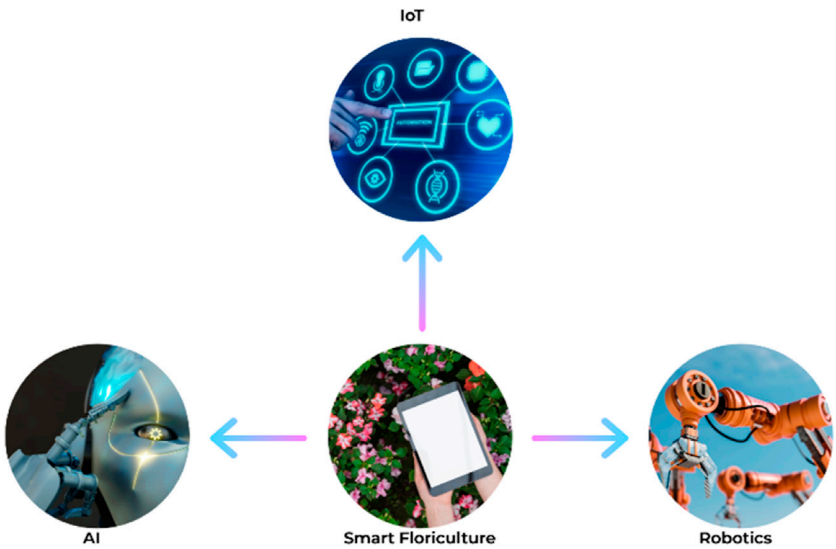

FIGURE 7
The Future of Ornamental industry: Unleashing the Potential of integrated IoT, AI, and Robotics.

supply chain management. By analyzing vast amounts of data, AI can help growers make informed decisions on when to harvest their crops, reducing waste and increasing efficiency. AI can also predict and detect diseases early, allowing growers to take preventive measures and reduce the need for harmful pesticides. Furthermore, machine learning can help growers optimize their logistics and supply chain management, ensuring that flowers reach consumers quickly and efficiently. By analyzing historical data on demand and supply, machine learning can help growers forecast demand accurately, reducing overproduction and minimizing waste. In conclusion, the integration of IoT, AI, and machine learning can help flower growers and distributors to create a more efficient, sustainable, and high-quality supply chain. By leveraging these technologies, they can reduce waste, improve growing conditions, and deliver fresher, higher-quality flowers to consumers. This not only benefits the flower industry but also helps promote sustainability and environmental protection.

16 Radio frequency identification (RFID tags)

RFID (Radio Frequency Identification) technology is an automated identification system that uses radio waves to transfer data between a tag attached to an object and a reader. A Radio Frequency Identification (RFID) tag functions as a barcode that can hold information (Kumar and Srivastava, 2014). There are two main types of RFID tags: active and passive, with a variety of shapes and forms available for different applications (Fernandez, 2014). Passive tags can be made from paper, plastic, or vinyl (Want, 2006) and are designed to withstand continuous exposure to the elements, including water, heat, dirt, and chemicals, making them suitable for outdoor nursery production environments. Each RFID label has a unique identification code and can be encoded with important production information such as genus, species, cultivar, and planting dates. Passive RFID labels are relatively inexpensive, and as adoption increases, costs are expected to decrease due to economies of scale. These labels are read using a specific UHF radio frequency with an RFID interrogator. One of the advantages of RFID in agricultural operations is that it does not require a clean label, unlike barcodes which can be obscured by dirt or damage (Ruiz-Garcia and Lunadei, 2011). RFID tags have been used for tagging and tracking animals and plants, health monitoring (Wang et al., 2006), identifying and tracking livestock, and monitoring irrigation system management (Floyd 2015; Deng et al. 2020).

In the flower industry, RFID technology is used for tracking and tracing flowers from the field to the store, providing greater transparency and efficiency in the supply chain (Ampatzidis et al., 2009; Jones et al., 2005; Verdouw et al., 2013). One application of RFID in flowers is the tracking of individual flower stems from the time they are harvested to the time they are sold. Each stem can be tagged with an RFID tag, which contains information about the grower, variety, and other key details. As the flowers move through the supply chain, RFID readers can be used to track their location and monitor temperature and humidity levels, ensuring that the flowers are properly handled and stored (Luvisi et al., 2010). RFID tags are also used to monitor temperature and humidity during transport, ensuring that the flowers are kept in optimal conditions (Dose et al., 2021). RFID technology can also be used to improve inventory management and reduce waste in the flower industry. By tracking the movement of flowers in real-time, retailers can better manage their inventory levels, reducing the risk of overstocking or stockouts. This can help to reduce waste by ensuring that flowers are sold before they spoil or lose their freshness.

Another application of RFID in flowers is the ability to provide consumers with information about the flowers they are purchasing. By scanning the RFID tag with a smartphone or other device, consumers can access information about the flower's origin, growing conditions, and other details. This can help to build trust between consumers and growers and promote greater sustainability and transparency in the industry. Overall, RFID technology offers numerous benefits for the flower industry,

TABLE 3 Some specific examples of effects of LEDs on some ornamental species.

S. No	Crop	Effects of LEDs on crop	Reference
1.	*Chrysanthemum morifolium*	The study showed that short-day plants have their long night interrupted most effectively by a moderate-to-high R:FR ratio of 0.66, and that flowering is not regulated by FR light alone. In all species, stem length increased quadratically with the increase in R:FR ratio during the night interruption, peaking at a ratio of 0.66.	Craig and Runkle (2013)
2.	*Antirrhinum majus*	The study found that decreasing the R:FR ratio led to a linear increase in plant height and total leaf area, while keeping R constant and increasing FR resulted in a linear increase in shoot dry weight. However, substituting R with FR radiation caused a linear decrease in shoot dry weight per unit leaf area.	Park and Runkle (2016)
3.	*Petunia hybrida*	Night interruption with green light in short-day conditions promoted flowering in petunia	Park et al. (2017)
4.	*Helianthus annuus*	The study found that light sources have varying effects on phyllosphere-associated fungi and bacteria. Fungi are directly influenced by the physical properties of the light source, while bacteria are indirectly affected through modifications in the plant environment caused by the different light sources.	Alsanius et al. (2017)
5.	*Lilium* and *Dahlia*	The study found that while dahlia 'Karma Serena' flowered earliest without supplemental light, plants grown under light treatments had greater height, width, and shoot weight. The use of gibberellic acid had significant effects on the growth and flowering measurements for both dahlia 'Karma Serena' and Asiatic lily 'Yellow Cocotte'.	Mills-Ibibofori et al. (2019)
6.	*Antirrhinum majus*	stem elongation, lengths of the inflorescences, and increased the size and number of florets. Extended vase life.	Xiang et al. (2020)
7.	*Rosa hybrida*	The study determined that an optimal balance of light for maximizing plant quality (size, number of flowers, branching) and minimizing powdery mildew infestation can be achieved by using a relatively high proportion of red light (49%–67%) in combination with blue (13%–16%) and green-yellow fractions (10%–15%) of visible light at a PPFD of 200 _mol m-2 s-1 for 18 h, and at an R:FR ratio ranging from 2.1 to 11.3.	Matysiak (2021)
8	*Gerbera jamesonii*	The study found that LED light did not disturb the endogenous phytohormone balance and was more effective in mitigating the stress experienced by *in vitro* grown plants compared to fluorescent lamps. The red LED was the most effective in reducing stress. Red and red:blue light lowered tissue auxin levels, while blue LED light lowered the shoot multiplication rate and height but induced the highest content of gibberellins at the last stage of the culture.	Cioc et al. (2022)
9	*Brassavola nodosa*	The study found that LED-3 with a lower intensity of 80 _mol m^{-2} s^{-1} PPFD resulted in the best plant performance *in vitro*, while LED-2 with a higher intensity of 1015 _mol m^{-2} s^{-1} PPFD showed the best plant performance *ex vitro*.	Vendrame et al. (2022)
10.	*Petunia × hybrida* '	The study found that gradually increasing the percentage of blue light led to the maximum dry weight of shoot, shoot length, and leaf area. On the other hand, a gradual decrease in blue percentage led to maximum leaf number, root dry weight, and root length. The modification of the R:B ratio during the seedling stage also resulted in a reduction of electricity consumption, leading to higher efficiencies.	Rashidi et al. (2023)

including improved supply chain efficiency, better inventory management, and greater transparency for consumers. As RFID technology continues to evolve, its use in the flower industry will likely become even more widespread and impactful.

17 LED (Light Emitting Diode)

LED (Light Emitting Diode) technology is revolutionizing the way flowers are grown by providing a more efficient and customizable light source for plants (Al Murad et al., 2021). LEDs are more energy-efficient than traditional light sources, and they can be tuned to specific wavelengths that optimize plant growth and flowering. One application of LEDs in flower cultivation is in the production of cut flowers. By using LEDs to provide the optimal light spectrum for flower growth, growers can achieve faster growth, increased flower size, and improved color and fragrance. This can help to increase yield and quality while reducing production costs, as LEDs use less energy than traditional lighting methods (Table 3). Another application of LEDs in flowers is in the production of potted plants and indoor flowers (Mills-Ibibofori, et al., 2019; Kang et al., 2019). LEDs can be used to provide a specific light spectrum that promotes healthy growth, even in low-light environments. This can be particularly useful in urban areas or areas with limited access to natural light, where plants may struggle to thrive without artificial lighting. In addition, LEDs can be used to control the timing and quality of flower blooms (Paradiso and Proietti, 2022). By adjusting the light spectrum and duration, growers can induce flowers to bloom at specific times of the year or in response to certain environmental cues. This can be particularly useful for the production of holiday flowers, such as Cyclamen, chrysanthemums, poinsettias, gerberas, petunias, Easter lilies (Heo et al., 2003; Higuchi et al., 2012; Park et al., 2016; Mills-Ibibofori, et al., 2019). However, in general, studies investigating the effects of LED light on flower crops typically vary in terms of the specific flower species (Mills-Ibibofori et al., 2019) being studied, the type and intensity of the LED light used, the duration and timing of the light treatments, and the specific growth or developmental parameters being measured (Craig and Runkle, 2013; Park and Runkle, 2016; Matysiak, 2021; Vendrame et al., 2022). These studies often aim to optimize plant growth and development, increase yield, improve flower quality and color, or reduce disease incidence (Cioc et al., 2022; Rashidi et al., 2023). Results can vary widely depending on these factors, and further research is needed to better understand the effects of LED lighting on flower crops under different growing conditions. Overall, LEDs offer numerous benefits for the flower industry, including improved growth and flowering, reduced energy costs, and greater control over bloom timing and quality. As LED technology continues to evolve, it is likely that its use in the flower industry will become even more widespread and impactful.

18 Virtual flowers

Virtual flowers refer to computer-generated images or animations of flowers that are created using software programs and displayed on electronic devices such as computers, smartphones, or virtual reality headsets. Virtual flowers can be used in a variety of ways, including as digital decorations for websites or social media posts, as 3D models for gaming or animation, and as virtual bouquets or gifts. Virtual flower gardens can also be created for educational or entertainment purposes, allowing users to explore and learn about different types of flowers in a virtual environment. One advantage of virtual flowers is that they can be created and shared easily and quickly, without the need for physical flowers or transportation. This can be particularly useful for events or occasions where flowers may be difficult to obtain or transport, such as in remote or urban areas. Virtual flowers also offer the opportunity for greater customization and personalization than traditional flowers. Users can choose from a wide range of flower types, colors, and arrangements to create a unique and personalized gift or message. Virtual flowers can also be easily modified or updated, allowing for changes in color or arrangement to suit different preferences or occasions. Overall, virtual flowers offer a fun and creative way to enjoy the beauty of flowers in a digital environment. While they cannot replace the physical experience of receiving or giving real flowers, they offer a unique and convenient alternative for those who may not have access to physical flowers or who want to explore the creative possibilities of digital technology.

19 Advances in landscaping technology

Advances in landscaping technology have led to the development of new tools and techniques that make it easier and more efficient to design, install, and maintain outdoor spaces. 3D modeling software is widely used in the landscaping industry for designing and planning outdoor spaces. Here are some of the top 3D modeling software used for landscaping:

SketchUp: SketchUp is a user-friendly 3D modeling software that allows designers to create detailed 3D models of landscapes, buildings, and other outdoor spaces. It features a large library of 3D models, allowing designers to add plants, trees, furniture, and other elements to their design.

AutoCAD: AutoCAD is a powerful software that is widely used in the architecture, engineering, and construction industry. It allows designers to create 2D and 3D models of landscapes, buildings, and other outdoor spaces. AutoCAD also features advanced tools for creating accurate measurements, annotations, and other design elements.

Lumion: Lumion is a 3D visualization software that is widely used in the landscaping industry. It allows designers to create stunning 3D renderings of landscapes, buildings, and other outdoor spaces. Lumion features a large library of 3D models, textures, and materials, allowing designers to create realistic and visually appealing designs (Figure 8).

Vectorworks: Vectorworks is a powerful 3D modeling software that is widely used in the landscaping industry. It features advanced tools for creating detailed 2D and 3D models of landscapes, buildings, and other outdoor spaces. Vectorworks also features advanced tools for creating accurate measurements, annotations, and other design elements.

Blender: Blender is a free and open-source 3D modeling software that is widely used in the landscaping industry. It features a large community of users and developers, allowing designers to access a large library of 3D models, textures, and materials. Blender also features advanced tools for creating animations and visual effects, making it an ideal tool for creating animated walkthroughs of outdoor spaces. Overall, 3D modeling software is an essential tool for landscape designers, architects, and other professionals in the landscaping industry. It allows them to create detailed and accurate models of outdoor spaces, reducing the risk of errors and misunderstandings.

20 Drone mapping

Drones equipped with cameras and sensors can be used to create detailed maps of landscapes, Drone mapping is becoming an increasingly popular technology in the floriculture and landscaping industries. It involves using drones equipped with cameras to capture high-resolution aerial images of a landscape, allowing designers to analyze topography, vegetation, and other factors that can affect the design and maintenance of outdoor spaces which can then be used to create detailed maps, 3D models, and other visualizations (Kleinschroth et al., 2022). Here are some of the ways that drone mapping is being used in floriculture and landscaping: Site surveys: Drones can be used to quickly and accurately survey a landscape, allowing designers and landscapers to gather detailed information about the topography, vegetation, and other features of the site. Plant health monitoring: Drones equipped with specialized cameras can be used to monitor the health of plants in a greenhouse or outdoor growing environment (Pantos et al., 2023). This can help growers detect issues such as nutrient deficiencies, water stress, and pest infestations before they become more serious problems (Attada and Katta, 2019). Irrigation management: Drones can be used to monitor irrigation systems and detect issues such as leaks, clogs, and other problems that can waste water and damage plants. Design visualization: Drones can be used to capture high-resolution aerial images of a landscape, which can then be used to create detailed 3D models and other visualizations (Figure 9). This can help designers and clients

FIGURE 8
Lumion-based 3D visualization model prepared for a landscaping plan.

FIGURE 9
Conceptualization of drone mapping and imaging for ornamental nurseries.

better understand the layout, features, and potential of a site. Precision application of inputs: Drones equipped with spraying equipment can be used to apply fertilizers, pesticides, and other inputs to crops and landscaping areas with greater precision than traditional ground-based methods (Hassler and Baysal-Gurel, 2019). This can reduce waste, improve efficiency, and reduce the risk of damage to non-target areas. Overall, drone mapping is a powerful tool for floriculture and landscaping professionals, providing a detailed and accurate view of a landscape from above. It can help improve efficiency, reduce waste, and improve the health and productivity of plants and other vegetation.

21 Sustainable materials

There is a growing trend towards using sustainable and environmentally-friendly materials in landscaping, such as recycled materials, native plants, pot making, floral arrangement making, and permeable paving (Darras, 2020).

These materials can reduce environmental impact and provide long-term cost savings. Overall, advances in landscaping technology are making it easier and more efficient to design, install, and maintain outdoor spaces. These technologies are helping to create more sustainable and enjoyable landscapes that can benefit both people and the environment.

22 Blockchain technology

Blockchain technology is a secure and decentralized database system that has been adopted in various industries, including agriculture. In the flower industry, blockchain technology is being explored as a means to improve supply chain management, traceability, and transparency. Blockchain technology can provide a secure and transparent record of every transaction along the flower supply chain, from the grower to the retailer. This can help to increase consumer trust by ensuring that the flowers are grown and distributed sustainably and ethically. By using blockchain technology, consumers can verify the origin, quality, and freshness of flowers, and can be confident that they are purchasing a genuine product. In addition, blockchain technology can help to reduce the risk of fraud, counterfeiting, and mislabeling in the flower industry. It can provide a secure and tamper-proof record of every step in the supply chain, which can help to identify any irregularities or inconsistencies. This can help to reduce waste, increase efficiency, and save costs. Furthermore, blockchain technology can also provide benefits to flower growers by improving payment systems and reducing transaction costs. By using blockchain-based payment systems, growers can receive payment faster, without the need for intermediaries such as banks or payment processors. Overall, blockchain technology has the potential to transform the flower industry by improving transparency, traceability, and efficiency throughout the supply chain. With further adoption and development, blockchain technology could become a key tool in ensuring the sustainability, quality, and authenticity of flowers for consumers around the world.

23 E-commerce platforms

E-commerce platforms allow for online sales of flowers and plants, making it easier for customers to purchase and receive products. Here are some global e-commerce platforms for flowers:

Interflora: A global flower delivery service that operates in over 140 countries, providing same-day and next-day flower delivery options.

Florist.com: A global online flower delivery service that offers a wide range of floral arrangements and gift options for various occasions.

Flower Chimp: An online florist that operates in several Southeast Asian countries, including Malaysia, Singapore, and the Philippines.

FloraQueen: A global flower delivery service that operates in over 100 countries, providing fresh flower arrangements for various occasions.

Bloom & Wild: An online flower delivery service that operates in several European countries, including the United Kingdom, Germany, and France.

Euroflorist: An online flower delivery service that operates in several European countries, including Sweden, the Netherlands, and Germany.

Avas Flowers: An online flower delivery service that operates in the United States and provides same-day delivery options for many areas.

JustFlowers.com: An online flower delivery service that operates in the United States of and provides same-day delivery options for many areas.

FlowerAdvisor: An online florist that operates in several countries across Asia, including Indonesia, Singapore, and Malaysia.

daFlores: A global flower delivery service that operates in over 180 countries, providing fresh flower arrangements for various occasions.

To address existing challenges and promote sustainable large-scale production of ornamental plants, innovative solutions are being developed (Cardoso and Vendrame, 2022). One such project, FloraGuard (Lavorgna et al., 2020), aims to combat the illegal online market of endangered plants by tracking, providing information, strengthening legislation, and exploring strategies. This initiative seeks to reduce the over-collection and commercialization of threatened or endangered plants that are unlawfully extracted from their natural habitats.

24 Conclusion and future prospectus

The flower industry has experienced noteworthy benefits due to the ongoing advancement of technology, including enhanced efficacy in production procedures, superior flower quality, and increased profitability. As the floral sector experiences further development and expansion, the imperative for sustainable and ethical methodologies becomes increasingly pressing. The overuse of pesticides and fertilisers in flower cultivation is a significant ecological issue that can result in detrimental consequences for the environment and the wellbeing of labourers engaged in the production process. The implementation of precision agriculture methodologies, which entail the utilisation of sensors and data analytics, can potentially mitigate the excessive application of chemicals by furnishing precise insights regarding soil quality, pest invasions, and crop nourishment necessities. In addition, the adoption of biodegradable packaging materials and the integration of energy-efficient systems within the flower production sector can substantially mitigate the industry's carbon emissions. The attainment of this objective can be realised by embracing sustainable energy alternatives, such as solar or wind energy, and integrating circular economy tenets, which involve the recycling or repurposing of waste materials. One additional ethical issue prevalent in the flower industry pertains to the potential exploitation of labour in developing nations, which serve as the primary location for flower cultivation. In order to tackle this matter, it is possible to implement fair trade practises and certifications, which can guarantee that labourers are remunerated equitably, provided with secure working environments, and granted access to educational and healthcare resources. Moreover, the utilisation of technology can facilitate the advancement of social and economic growth within regional communities by creating novel employment prospects and fostering entrepreneurial activities. The utilisation of e-commerce platforms has the potential to establish a direct connection between consumers and small-scale flower growers, thereby obviating the requirement for intermediaries and augmenting the profit margins of the growers. To conclude, the flower industry must prioritise sustainability, ethical practices, and social responsibility in the development and implementation of novel technologies. By endorsing these principles, the floral industry can sustain its growth and satisfy the increasing need for aesthetically pleasing and significant flowers, all while making a positive impact on both the environment and society.

Author contributions

Author MAW and AD wrote the intial draft, conceived the idea, prepared figures, ITN, TR, RAL, and ZAB helped in collecting data and literature, JMA-K, SMJ, and MM helped in the language editing and funding accIquisition. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Understanding the relationship between technological innovation and environmental sustainability under the silver lining of education

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Information and communication technology has gradually become one of the most important pillars of the economy. In addition to economic growth, environmental pollution is a product of information and communication technologies (ICTs) as well. However, whether and how ICTs may affect these systems is unclear. Based on a more comprehensive measurement of ICTs, the current study has investigated the impact of ICTs, education, and economic performance on environmental sustainability from 2000 to 2019 across 93 countries categorized as low-income, middle-income, and high-income. Contrary to preceding studies, this research has used advanced econometric techniques to counter heterogeneities and dependencies in the data and, thus, has produced more trustworthy and efficient results. The finding obtained from the Bias-corrected method of the moment's estimator and Driscoll and Kraal's standard error techniques are consistent. According to the results, ICTs have a heterogenous effect on environmental sustainability across low-, middle- and high-income countries. Further results have revealed that education plays a significant role in maintaining environmental sustainability across middle—and high-income groups but does not seem to do so for lower—income groups. Environmental education for all should be part of the policy measures to tackle climate change across all income groups.

KEYWORDS

information and communication technologies, education, environmental, middle income countries, high income countries, low income countries

1 Introduction

The largest yearly climate change conference in the world is the Conference of the Parties (COP). International organizations like the COP are promoting the Sustainable Development Goals (SDGs) to help with climate change adaptation. About 200 nations signed the Climate Pact at COP26 to lower carbon emissions worldwide. Money was the main issue of discourse during COP 26. According to developing nations, the shift to using more renewable energy and less nonrenewable energy should be facilitated by acquiring funding and transferable technologies. (Xu et al., 2020). At least $100 billion will be committed over the following year as a direct result of COP 26 to help developing countries achieve a net-zero environmental footprint. The Paris Agreement aims to keep global warming to 1.5°C between 2020 and 2025 by cutting emissions. The United Nations (hereafter UN) COP26 2021 conference on climate change provides an urgent and meaningful commitment and provides a better opportunity for world leaders to take action to limit global temperature to 1.5°C above preindustrial levels by 2050. This reversal of climate change requires a concerted effort by everyone, including researchers in information technology and related fields, to develop a robust and comprehensive research agenda (Dwivedi et al., 2022). ICTs and their development have provided a vast means for information transmission in the form of internet, telephony and media (Zhou and Li, 2022).

Nowadays, countries are facing environmental challenges, including climate change, energy efficiency improvement, proper waste management, the quality of water, and scarcity. Climate change is a universally recognized fact that affects humans, businesses, industry, and the environment in various forms (Dwivedi et al., 2022). This resulted in changing patterns of global weather, with frequent hurricane incidence, drought and mounting temperatures triggering habitats to vanish and altering ecosystems. Recently, fast-growing global society, development, and economy have brought serious environmental issues, including air pollution, the greenhouse effect, and ecosystem degradation. The significance of ICT will rebuild society and affect society for tomorrow. ICTs are essential for industrialization and eventually affect economic performance and the environment. ICTs also contribute directly and indirectly to the economic, social, and environmental dimensions of the Sustainable Development Goals (hereafter SDGs). ICTs provide the basis for monitoring climate change, mitigating and adapting its impacts, and supporting the transition to a green and circular economy. Nevertheless, in the productive role of ICTs in improving economic performance, future environmental impacts of ICTs, including the role of satellites, mobile phones, or the Internet are ignored. All of these have an important role to play in tackling the major challenges of climate change and sustainable development. Simultaneously, since the 1980s, the growing use of ICT has encouraged economic output and influence the ecological environment to a certain degree, which has this attract the scientific community to take a keen interest in evaluating the environmental impact of ICT, which has grown considerably (Wang and Xu, 2021).

Technology plays a dominant role in the promotion of intelligent development of environmental governance and innovative applications in the field of environmental protection (Wu et al., 2021a; 2021b). For the achievement of Sustainable Development Goals (SDGs), governments have dedicated themselves to promoting policies towards a sustainable environment (N'dri et al., 2021). However, sustainability through ICTs is a complex matter (Chien et al., 2021), and its environmental impact is still not clear, despite the critical role of ICT in combating climate change challenges the digital era (Zhou et al., 2019). The complex nature of ICT is similar in both developed and developing countries. In view of the exact futuristic role of ICT is not known, and how today's decision will set the direction of sustainable development is unknown. For better life standards, the inclusion of ICT should be tailored towards encouraging human rights, privacy, and security (Zhou and Li, 2022). So based on the aforementioned discussion, this study examines the role of ICTs in environmental sustainability, considering the role of education and digital trade across the globe.

The additional feature of this empirical work is as follow: first, this empirical inquiry examines the information technology-environmental sustainability relationship for 93 countries from 2005 to 2019. In this study, countries are categorized as low-income, middle-and high-income to capture the difference in environmental impact of ICT across income region. We employ a more detailed measure of ICTs by developing an index. Although available literature mainly focused on either internet use or mobile phone descriptions. We focus on three ICT services: mobile phone, fixed broadband subscription, and internet use provides better insight into policy making for improving environmental quality.

Second, this study introduces a newly developed technique of bias-corrected moment estimator that have been ignored in earlier studies and that are robust for heteroskedastic errors, higher-order autoregressive models and cross-sectional dependence. Henceforth, this paper has proposed more efficient and unbiased findings than previous studies in the ongoing literature. The robust findings of this paper provide a guideline for policymaker to make more accurate recommendations.

Third, we examine the importance of ICTs in the environment across various income groups in different countries. From a policy perspective, it is very important to examine what happens across different income groups. To overlook distributional heterogeneity during empirical analysis may generate counterfeit regression findings and, subsequently inappropriate policy suggestions. From what we know from the literature, none of the papers examined the relationship between ICTs and carbon emissions across different income groups in countries, considering education and digital trade. To summarize, such a holistic methodological assessment is lacking so far in the literature. So, the estimation results of this paper provide direction to world economies in designing better policies to tackle climate change issues.

Our study is divided into four primary portions for the remainder of it. The research gives an overview of related studies on the topic in Section 2. In Section 3, the information on the data and techniques used in this study is detailed. The detailed analysis and explanation of the projected results are covered in Section 4. Section 5 of the report concludes with conclusions and suggestions for future policy.

2 Literature review

2.1 Theoretical underpinning

The closely related literature that lends support for this area comes from production theory. An eminent economist, Robert Solow, once pointed out the productivity paradox of the US economy to explain why productivity stagnated regardless of having powerful computing abilities. Since the early debate on the productivity paradox, the role of ICTs in promoting economic growth and increasing productivity has been well acknowledged. In addition to improving productivity (Ollo-López and Aramendía-Muneta, 2012), ICTs substantially decrease emissions by supporting to building smart cities, electric grids, transportation systems, and efficient business processes. It also plays an important role in optimizing production processes and increasing carbon productivity as an input to production systems (Dedrick et al., 2010). Watson et al. (2010) believe that transformation is an important component of ICTs that can help build an environmentally sustainable society. In theory, the production perspective of ICT, such as the production of ICT equipment and instruments, energy use, and recycling of electronic waste, is responsible for enhancing CO_2 emissions. On the contrary, ICT reduces CO_2 emissions at the global level by promoting smart city projects, efficient transportation systems, smart grids, and energy-saving gains (Añón Higón et al., 2017). The impact of ICT is obvious on society and technology has brought us to the edge of a new social and cultural era of transition. The importance of ICT and advancement in technology is undeniable, but the debate on the environmental impact of ICT is still growing gradually. The notion that ICT is an important determinant of economic growth and productivity has been well acknowledged. Thus, complementing the popular environment's Kuznets curves, where an inverse relation is often expected between economic growth and environmental sustainability in the long run. To conclude, production theory and the environmental Kuznets curve hypothesis provide the foundation for this study.

2.2 ICT's and environmental Kuznets curve (EKC) studies

Empirical work regarding the ICT-pollution nexus has been widespread and continues to grow. Anyway, studies belong to individual countries, groups of countries, and cross-regional studies, and the data span covered has varied. Similarly, different measures have been used for both ICTs and the environment. Apart from this, these studies have employed various estimation tools. The studies on the evidence are summarized below in this section. Several studies have investigated the ICT-emissions nexus controlling the model for various indicators. Among those, Sahoo et al. (2021) considered financial development; Haldar and Sethi, (2022) renewable energy, innovation and trade; Evans and Mesgan (2022) governance and regulation; Danish, (2019) trade and foreign direct investment (hereafter FDI); Liu et al. (2021) corruption; Caglar et al. (2021) and Charfeddine and Kahia. (2021) renewable energy consumption; Chatti and Tariq, (2022) smart urbanization; Chatti. (2021) freight transport; Magazzino et al. (2021a) electricity consumption; Altinoz et al. (2021) total factor productivity and Ulucak and DanishKhan. (2020) globalization in ICTs and carbon emissions nexus. However, in the first strand, studies related to the impact of ICTs on carbon dioxide (hereafter CO_2) emissions within the environmental Kuznets Curve (hereafter EKC) are discussed. For instance, Chien et al. (2021) used the Methods of Moments-Quantile Regression (hereafter MMQR) method for testing the EKC hypothesis for BRICS countries. The empirical findings have recommended the beneficial role of ICT in improving environmental quality, along with the confirmation of the presence of the EKC hypothesis. A similar conclusion has been drawn by Sahoo et al. (2021) during an insight for India; Danish. (2019) for Belt and Road Initiative (hereafter BRI) countries; Danish et al. (2019) for high income, middle-income and lower income countries; Danish et al. (2018) for emerging countries; Park et al. (2018) for European Union (hereafter EU) countries; and Haldar and Sethi. (2022) for 16 emerging countries. Evans and Mesgan (2022) approved the EKC hypothesis in 31 African countries during ICT-trade and environment nexus in terms of the significance of the moderating role of governance and regulation. Añón Higón et al. (2017) estimated non-linear relationship between ICT and CO_2 emissions with the validation of the EKC hypothesis for developing and developed countries. Liu et al. (2021) investigate the effect of ICTs and corruption on CO_2 emissions within the EKC hypothesis. The empirical estimation suggests that both ICTs and corruption increase CO_2 emissions. The EKC is relevant to the significance of ICT and corruption in Asian countries.

Hypothesis 1: Whether or not EKC exists in the significance of ICT's.

2.3 ICT's and environmental degradation

In the second aspect, studies related to the linear and non-linear relationship between ICT and CO_2 emissions with various additional variables have been reviewed. These studies are divided into two groups. One group of studies has recommended the beneficial role of ICT in reducing carbon emissions. In this regard, Usman et al. (2021) conducted a symmetric and asymmetric analysis of ICT on CO_2 emissions for selected Asian countries. The number of countries where ICT disturbs the emission of CO_2 has not changed much in linear and non-linear models. However, the asymmetric impacts of ICT on CO_2 emissions intensified and were perceived in more than half of the sample countries. Following a non-linear model, Ben Lahouel et al. (2021) showed that ICT could boost economic growth and mitigate climate change. N'dri et al. (2021) identified the long run relationship between ICT and CO_2 emissions for 58 developing countries through a pooled mean group autoregressive distributive lag (hereafter PMG-ARDL) estimator. The empirical analysis clarifies that ICT usage reduces carbon emissions in low-income developing countries, whereas an insignificant relationship was found for high-income developing countries. In line with this, Khan et al. (2020) documented the beneficial role of ICT in carbon emissions reduction for a panel of 91 countries.

Another group of studies has concluded that ICT has an adverse impact on environmental quality. Asongu et al. (2018) studied whether ICT penetration decrease CO_2 emissions in sub-Saharan African countries. From the generalized method of moments (hereafter GMM), the conclusion is drawn that there is no linear relationship between ICTs and CO_2 emissions. Besides, the non-linear relationship between internet penetration and CO_2 emissions is positive and significant, whereas increasing mobile phone penetration alone decreased CO_2 emissions. Besides, Avom et al. (2020) studied the impact of various channels of ICT on CO_2 emissions in 21 sub-Saharan African countries. Both internet and mobile penetration have a linear and non-linear impact on CO_2 emissions, and these indicators of ICTs worsen environmental quality. Alataş (2021) employed various mean group estimators to investigate the impact of ICT on carbon emission in the context of globalization for 93 countries. The findings have provided evidence

TABLE 1 Summary of descriptive statistic.

Descriptive statistic															
	Low-income countries					Middle income countries					High income countries				
Variables	Obs.	Mean	Std.Dev.	Min		Obs	Mean	Std.Dev.	Min	Max	Obs	Mean	Std.Dev.	Min	Max
Ln CO_2	300	−0.1849	0.9277	−1.9828	1.9037	435	1.0795	0.7635	−1.8428	2.7112	645	2.1443	0.5887	0.4895	3.7962
Ln gdp	300	3.2633	0.2412	2.8404	3.9607	435	3.7692	0.2289	2.9629	4.1782	645	3.3408	0.2538	3.9329	5.0508
Ln tech.	300	−0.2166	0.9881	−4.1106	1.4370	435	0.1494	0.9817	−2.8441	2.5749	645	0.1246	2.2726	15.4681	25.5109
Ln edu	300	1.0374	0.0868	0.7558	1.1789	435	2.5972	0.1060	2.3608	2.8735	645	4.4866	0.1677	2.8443	3.9249
Ln dgt.	300	0.7931	0.3613	0.1707	1.9707	435	0.9271	0.3738	0.0358	1.9107	645	20.1946	0.9550	−2.0877	2.5134
Correlation matrix															
	Ln CO2	Ln gdp	Ln tech.	Ln edu	Ln dgt	Ln CO2	Ln gdp	Ln tech.	Ln edu	Ln dgt	Ln CO2	Ln gdp	Ln tech.	Ln edu	Ln dgt
Ln CO_2	1					1.000					1				
Ln gdp	0.7536	1				0.6284	1.000				0.3927	1			
Ln tech.	0.6371	0.3917	1			0.5385	0.3592	1.000			0.0578	0.0303	1		
Ln edu	0.5871	0.6315	0.3670	1		0.3189	0.4678	0.5123	1.000		−0.3363	0.1906	0.1680	1	
Ln dgt.	0.3146	0.2877	0.4618	0.2689	1	0.3828	0.6392	0.5263	0.2015	1.000	−0.1115	−0.0291	0.2378	0.237	1

TABLE 2 Bias-corrected method of moments estimator.

Regressors	Low-income countries			Middle income countries			High income countries		
	Coeff. [*p*-value]	Coeff. [*p*-value]	Coeff. [*p*-value]	Coeff. [*p*-value]	Coeff. [*p*-value]	Coeff. [*p*-value]	Coeff. [*p*-value]	Coeff. [*p*-value]	Coeff. [*p*-value]
Ln gdp	−5.096 ^{a} [0.003]	−4.963 ^{a} [0.004]	−5.189 ^{a} [0.006	5.358 ^{a} [0.001]	5.512 ^{a} [0.000]	4.974 ^{a} [0.002]	1.243 ^{a} [0.000]	1.237 ^{a} [0.000]	1.229 ^{a} [0.000]
Ln gdp^2	0.635 ^{b} [0.012]	0.594 ^{b} [0.015]	0.617 ^{b} [0.023]	−0.678 ^{a} [0.001]	−0.699 ^{a} [0.000]	−0.623 ^{a} [0.000]	−.0248 ^{b} [0.039]	−0.024 ^{b} [0.038]	−0.024 ^{a} [0.000]
Ln tech.	−0.025 [0.993]	−0.003 [0.899]	−0.011 [0.585]	−0.012 [0.460]	−0.016 [0.309]	−0.010 [0.547]	−.0514 ^{b} [0.016]	−0.052 ^{b} [0.030]	−0.053 ^{b} [0.029]
Ln dgt.	--	0.0253 ^{b} [0.025]	0.093 ^{b} [0.011]	--	−0.036 [0.269	−0.042 [0.223]	--	.0052 [0.772]	0.006 [0.727]
Ln Edu.	--		0.485^{c} [0.097]	--	--	−0.393 ^{c} [0.054]	--	--	−0.056 ^{b} [0.023]
Constant	9.941 [0.001]		9.864 [0.002]	−10.340 [0.004]	−10.597 [0.001]	−9.219 [0.001]	0.7536 [0.005]	0.750 [0.005	0.743 [0.005]
Number of groups	20	20	20	29	29	29	43	43	43
No. of observation	240	240	240	406	406	406	559	559	559

Note: a for 1%, b for 5% and c for 10% significance level. The square bracelets cover probability values.

that ICT is one of the driving factors that contribute to CO_2 emissions. However, globalization positively contributes to carbon mitigation. The similar result for ICT and CO_2 emissions is corroborated by Charfeddine and Kahia (2021) in the significance of renewable energy consumption for the Middle East and North Africa (hereafter MENA) region. The findings were further verified by Chatti (2021) and Chatti and Tariq (2022) for 42 countries and developing and developed countries, including freight transport and smart urbanization in the ICT-CO_2 emissions nexus, respectively. However, Awad (2022) determined as insignificant relationship between ICT services and CO_2 emissions for 47 sub-Saharan African countries.

Thirdly, some papers have considered ecological footprints for measuring environmental sustainability while investigating the ICT-environment relationship. Among those, Kahouli et al. (2022) documented the impact of ICT, green energy, and total factor productivity on the ecological footprint in the Kingdom of Saudi Arabia. The empirical investigation indicates that ICT is helpful in reducing ecological footprints. In another study, Caglar et al. (2021) concluded the positive role of ICT in abating environmental deterioration in world's top 10 polluted footprint countries. Kazemzadeh et al. (2022) highlighted the ICT impacts on ecological footprint for in the emerging countries. The result of the study is interesting since ICT does not influence ecological footprints. Özpolat (2021) probed the link between internet use and ecological footprints for a group of seven (hereafter G-7) countries employing Augmented Mean Group (AMG) panel data estimation method. According to the study's results internet use negatively impact environmental degradation. However, Huang et al. (2022) estimated the dynamic relationship between ICT, renewable energy, economic complexity and ecological footprint by comparing of the E−7 (developing) and G-7 (developed) countries. According to the empirical findings, ICT increases pollution in E−7 countries and decrease ecological footprint in G-7 countries.

Hypothesis 2: ICTs has significant either positive or negative impact on the environmental sustainability.

2.4 Information technology, education and CO_2 emissions studies

Only a few studies in the literature have included education as a determinant of carbon emissions in the ICT and CO_2 emissions model. Likewise, Shobande and Asongu. (2022) discussed the critical role of ICT and education in the environment, and the empirical findings infer that both information technology and education play prominent role in promoting environmental sustainability. For South Asian economies Zafar et al. (2022a) captured the effect of ICT and education on environmental quality. Panel data estimation tools recommended the positive role of both ICT and education in CO_2 emissions. The similar negative role of education in environmental quality is found by 22 top remittance-receiving countries. Zhang et al. (2022) unveiled the role of education in the environmental impact of ICT in developing countries. According to the study's findings, ICT increases environmental quality, but interestingly, education has a detrimental effect on the environment. Apart from this, Zaman et al. (2021) and Liu

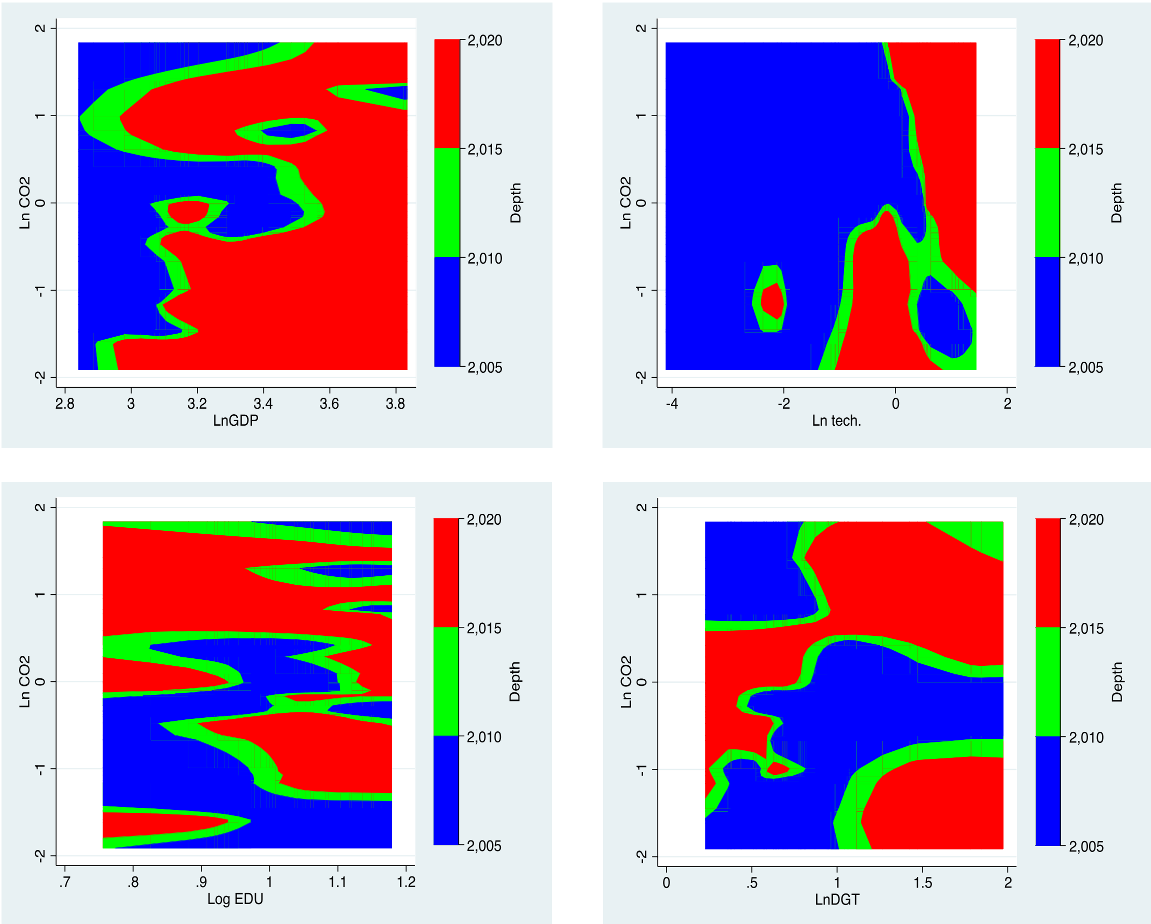

FIGURE 1
Shows the impact of explanatory variables on CO_2 emissions for low-income countries.

et al. (2022) concluded that education helps reduce carbon emissions in China. Sarwar et al. (2021) analyze that environmental quality can be improved through better education standards across 179 countries, and a similar argument was developed by Mehmood (2021) for G-11 countries.

Hypothesis 3: Education helps in improving environmental sustainability.

2.5 Literature gap

From the evaluation of earlier studies, the role of ICT in environmental degradation is unknown, and the future role of ICT in environmental degradation is unknown. Despite the larger number of studies that have investigated the impact of ICT on environmental quality, we found some deficiencies in the earlier studies. First the results are misleading because of result differences, so the conclusion and recommendations are deceptive. Second, measurement of ICT services is based on two proxies: mobile phone penetration and/or internet penetration. So, the misleading results might be due to ICTs measurement and/or the empirical methodologies employed in earlier studies. To gain a better understanding of the role of technology in the environment, this inquiry focuses on the role of technology, education, and digital trade in the environment across various income groups of countries. This paper considers a more comprehensive measure of information technology and recently developed econometric tools for empirical analysis such as Bias-corrected method of moments estimator by Breitung et al. (2021).

3 Materials and methods

3.1 Model formulation

The widespread use of mobile phones, the internet, and other ICT applications has encouraged substantial investments in ICT assets. The concept of smart cities, smart grid transportation systems, and the achievement of energy-savings globally are expected due to huge ICT investment, and these can help in energy efficiency improvement. For example, shifting from paper books to electronic books and electronic paper, tele-conferencing instead of traveling,

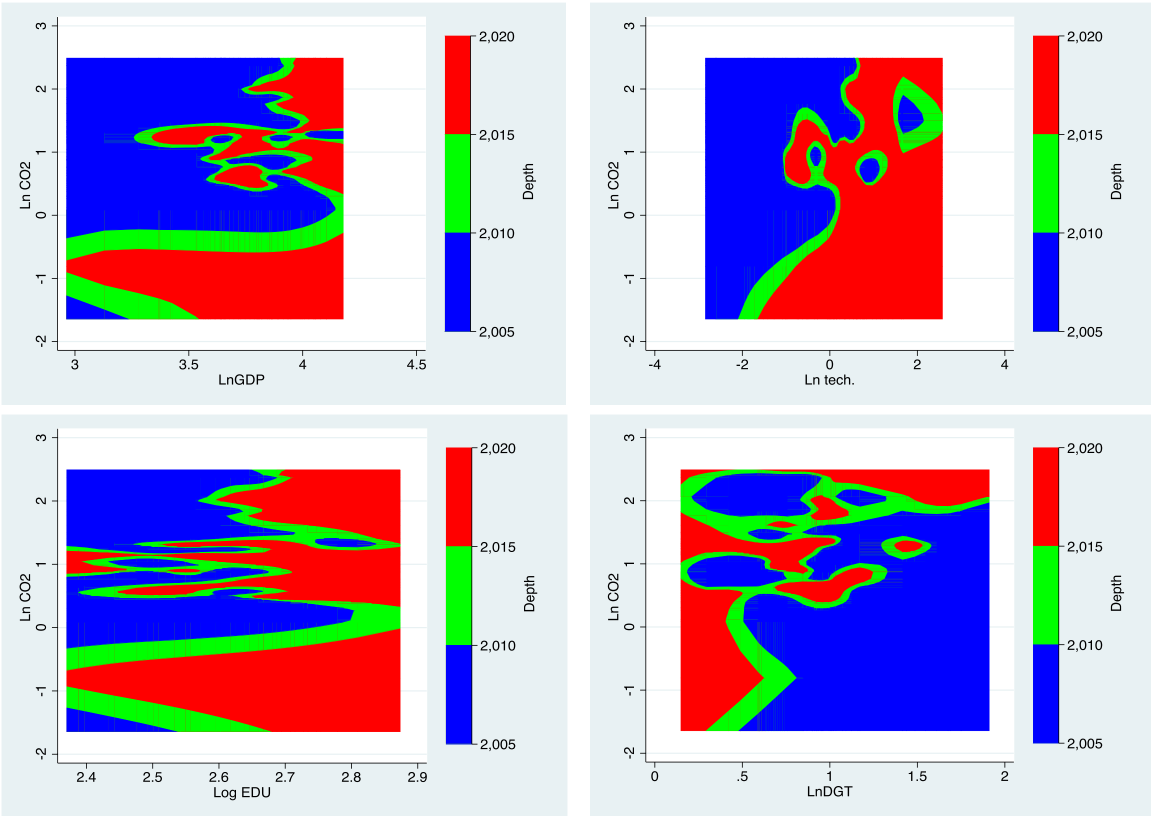

FIGURE 2
Shows the impact of explanatory variables on CO_2 emissions for Middle-income countries.

working from home rather than at the workplace, online food services, and online shopping all become possible only due to ICT advancement. All these activities have limited outdoor activities, so ultimately energy consumption will decline. Another aspect of ICT advancement is that energy saving has become easier in some areas of life, which exceeds ICT-induced surplus energy use in other areas. Likewise, smaller ICT devices, including laptops, smartphones, and others, are energy efficient. It can be assumed that the world is benefiting from the technology spillover effect because of meaningful technological development over the past 3 decades. To interpret this ICT use, the quality of the environment and the environmental implication of ICT become significant. To this end, the ICT-pollution nexus for the study is investigated with the EKC framework, which is expressed as:

$$Ln\,(CO)_{2it} = \alpha_0 + Ln\,\beta_1\,(Tech)_{it} + Ln\,\beta_2\,(GDP)_{it} + Ln\,\beta_3\,(GDP)^2_{it} + Ln\,\beta_4\,(dgt)_{it} + +Ln\,\beta_5\,(Edu)_{it} + \varepsilon_{it} \tag{1}$$

Where CO_2 emissions mean carbon dioxide emissions as a proxy for environmental sustainability, technology refers to information and communications technologies, *DT* is digital trade, *GDP* means gross domestic product as a measure of economic performance, and *EDU* indicates education for "*i*" cross-section and time period of "*t*". If the co-efficient values of β_1 greater than zero and β_2 less than zero are directed toward the existence of the *EKC hypothesis*. Motivation of control variables in the model is determined by the perception of their impact on CO_2 emissions, as mentioned in the literature. Recently, education has been observed to be the key driving force behind environmental quality. Climate change is influenced directly by inhabitants' lifestyles and the lives of individuals, so education is important to raise awareness among citizens and should be a significant part of the policy drive. With this in mind, "education for the future" aims to provide youth and children with climate awareness so that policy analysts can use their creativity, benefit from their willingness to learn and energy to develop sustainable solutions, particularly through ICT technology (World Economic Forum, 2021). Education is expected to have a positive effect on environmental quality by lowering CO_2 emissions.

3.2 Econometric methods

For panel data, empirically implausible dynamic models are widely used. Since the work of Anderson and Hsiao (1981) for short panel data with large samples and short periods GMM estimators have been broadly used for linear dynamic panel data model estimation. But the GMM method by Eakin et al. (1988) and Arellano and Bond (1991) suffers from the weak-

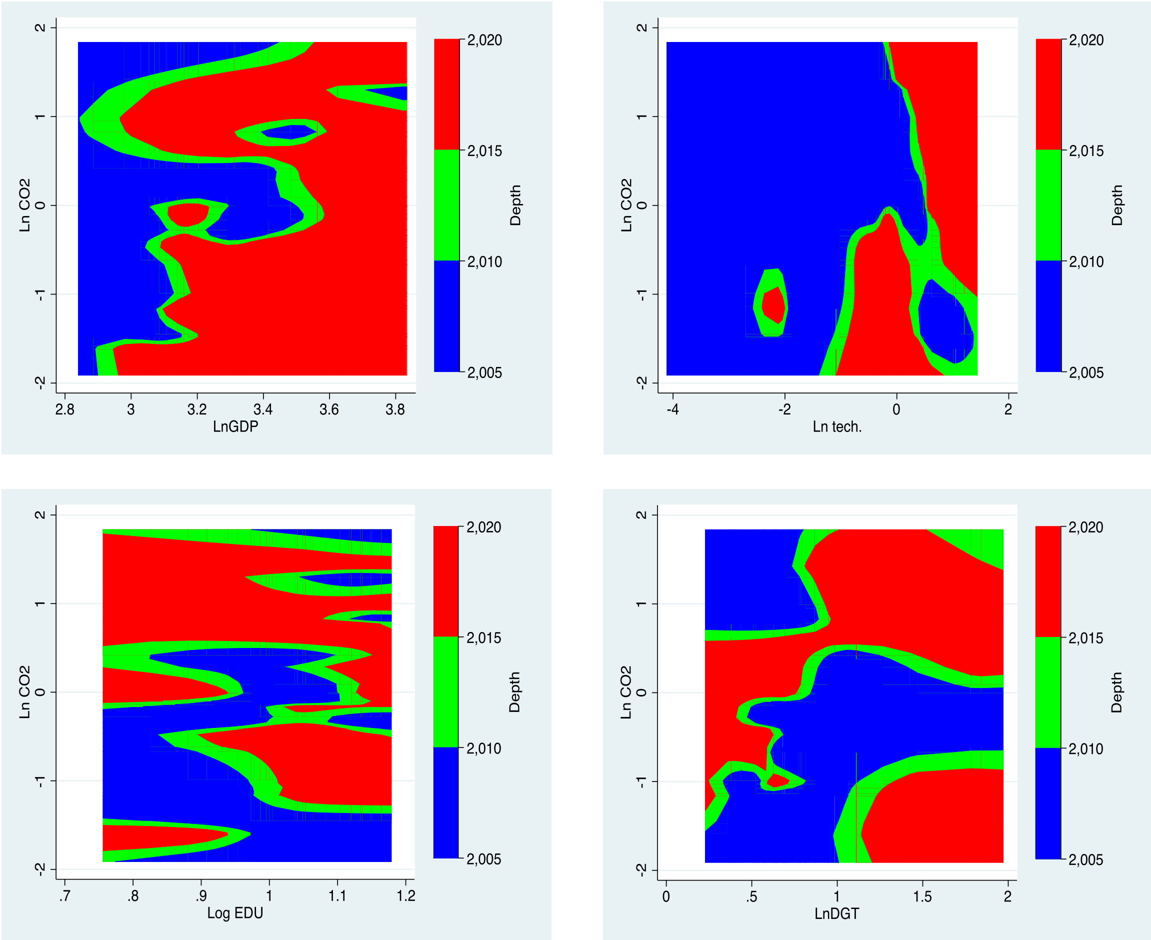

FIGURE 3
Shows the impact of explanatory variables on CO_2 emissions for Middle-income countries.

instruments issue in the case of the strong persistency of the data, as verified by (Blundell and Bond, 1998). As an alternative, they developed the so-called system GMM method, which mitigates the problem for models in levels with first-differenced instruments. Nowadays, the system GMM method is widely used but Bun and Windmeijer, (2010) disclosed that dynamic GMM suffers from the issue of weak instruments when the variance of the individual-specific effects is larger than that of the idiosyncratic errors. On this note, Breitung et al. (2021) proposed a newly developed technique. Recently the bias-corrected method of moment (BCMM) method overtakes prevalent GMM approach with regard to efficiency and accurately sized tests. This technique can adjust both fixed-effects and random-effects heteroskedastic errors in higher- order autoregressive models as well. If cross sectional dependance is present in the data and there is moderate persistence, the Breitung et al. (2021) estimator appears robust. The BCMM test is free from the assumption of preliminary standards of the dynamic process, and a preliminary estimator is not necessary. With regard to model specification, employing the Breitung et al. (2021) estimator tolerates additional control variables in large numbers and handles an equitably dynamic adjustment process in the independent variables, too.

3.3 Data

This study's sample covered 93 countries from 2005 to 2019. The selection of countries and the time were based on the availability of data. Panel data allow academics to model dissimilarities in behavior within groups more efficiently and flexibly. The ICT index is based on three the ICT services: mobile cellular subscriptions (per 100 people), fixed broadband subscriptions (per 100 people), and individuals using the internet (per 100 people). For construction of the ICT index, we have used the principal component analysis (PCA) technique for three ICT services[1]. Digital trade is calculated as the amount of sum of the exports and imports of ICT goods and services. Education is measured through the education index, defined as the average mean years of schooling (of adults) and anticipated years of schooling (of children). Economic performance is calculated through *per capita* GDP (constant 2015 US dollar), and its square was also integrated to validate the EKC hypothesis.

1 The PCA analysis results are not shown in the paper due to space constraints, but they can be provided upon request.

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TABLE 3 Results of DK-Regression method with fixed effect for low-, middle- and high-income countries.

Regressors	Low-income countries			Middle income countries			High income countries		
	Coeff. [*p*-value]	Coeff. [*p*-value]	Coeff. [*p*-value]	Coeff. [*p*-value]	Coeff. [*p*-value]	Coeff. [*p*-value]	Coeff. [*p*-value]	Coeff. [*p*-value]	Coeff. [*p*-value]
Ln gdp	−0.661^{c} [0.076]	−0.857^{b} [0.036]	−0.966^{a} [0.034]	21.506^{a} [0.000]	21.375^{a} [0.000]	20.984^{a} [0.000]	13.042^{a} [0.000]	10.455^{a} [0.000]	10.109^{a} [0.000]
Ln gdp^2	0.091^{c} [0.098]	0.119^{b} [0.048]	0.134^{c} [0.045]	−2.712^{a} [0.000]	−2.688^{a} [0.000]	−2.603^{a} [0.000]	−1.498^{a} [0.000]	−1.186^{a} [0.000]	−1.135^{a} [0.000]
Ln tech.	0.007 [0.180]	0.004 [0.594]	0.003 [0.608]	0.220^{a} [0.000]	0.235^{a} [0.000]	0.267^{a} [0.000]	−0.094^{a} [0.004]	−.0827^{b} [0.013]	−0.028^{b} [0.026]
Ln dgt.	--	0.026 [0.122]	0.026 [0.114]	--	−0.099 [0.177]	−0.160^{b} [0.040]	--	0.202^{c} [0.051]	0.185^{c} [0.065]
Ln edu	--	--	0.052 [0.109]	--	--	−0.878^{a} [0.001]	--	--	−1.420 [0.002]
Constant	1.2029^{c} [0.055]	1.5185^{b} [0.026]	1.6648^{b} [0.025]	−41.344^{a} [0.000]	−41.100^{a} [0.000]	−38.500^{a} [0.000]	−26.083^{a} [0.000]	−20.996^{a} [0.000]	−18.746^{a} [0.000]
R-squared	0.021	0.032	0.034	0.54	0.53	0.53		0.195	0.233
F-value	6.72	7.04	5.69	1,542.82	1,535.25	3,540.38		103.16	161.58
Prob > F	0.0056	0.0030	0.0054	0.000	[0.000]	0.000		0.000	0.0000
Number of groups	20	20	20	29	29	29	43	43	43
No. of observation	280	280	280	435	435	435	860	860	860

Note: a for 1%, b for 5% and c for 10% significance level. The square bracelets cover probability values.

Various sources were accessed to collect the data for the variables of the study. Data on the GDP *per capita* and three measures for the ICT index and digital trade were gathered from the database of the World Bank (http://data.worldbank.org). Data about the education index is borrowed from the Human Development Data Center (http://hdr.undp.org/en/data). It is beneficial to conduct a preliminary analysis of variables before exploring the relationship between them. The outcome of descriptive statistics and the correlation matrix are shown in Table 1.

4 Results and discussion

This paper estimated the empirical model (Eq. 1) through the bias-corrected method of moment estimators. The reported results in Table 2 suggest the impact of economic performance (Ln GDP) and its square (LnGDP^2) on carbon emissions is negative and positive for low-income countries. The negative-positive impact of GDP denied the existence of the EKC curve in low-income countries. Against this, for the impact of economic performance, positive and negative coefficients of GDP are observed for middle- and high-income countries. The positive-negative effect of GDP infers that middle- and high-income countries confirm the EKC hypothesis. So, results found a U-shape in low-income countries and an inverted U-shape relationship for middle- and high-income countries, corresponding to economic performance and CO_2 emissions. Likewise, ICT has positive and significant impact on environmental degradation in low-income countries. For middle income countries, ICT has an insignificant relationship with carbon emissions, and finally information technology averts environmental pollution in high-income countries. Another variable that reveals a negative relationship with carbon emissions across low-income, middle- and high-income groups is education. Further results show that digital trade increases carbon emissions in low-income countries but decreases them in middle- and high-income countries. The graphical representation of the impact of explanatory variables on CO_2 emissions for low-income, middle-income, and high-income countries is shown in Figure 1, Figure 2 and Figure 3 respectively.

5 Discussion

According to the results (Table 3), economic performance led to environmental pollution in low-income countries. The negative-positive relationship between economic performance and its square recommends a U-shaped relationship for the EKC curve. From an economic point of view, as economy of low-income countries are in their developing stages, as the economies grow, consumption of goods and services increase, which causes a rise in energy demand and CO_2 emissions. The negative role of economic performance in environmental pollution in the ICT-growth-emissions model can be associated with earlier work that estimated the same results. For instance, Lin and Zhou (2021) estimated a U-shaped relationship between economic performance and environmental conditions in Chinese provinces. Contrary to this, economic performance is a driver for environmental sustainability, as well as reflected in the results that better economic performance lowers carbon emissions once the economy reaches it optimum level. The positive and negative coefficients of economic performance validated the inverted U-shaped relationship and directed toward the EKC curve in middle- and high-income countries. For an economic perspective, this finding is corroborated by the fact that environmentally cognizant customers are willing to control energy use through the purchasing of energy-efficient appliances, electric vehicles, or trains instead of a short-distance flight (Herweg and Schmidt, 2022). So, this indicates a trade-off between higher economic performance and environmental quality. This result is supported by Sahoo et al. (2021), Chien et al. (2022), and others, as discussed in this paper earlier in the literature review.

ICT is the sole factor in carbon emissions under investigation in the study. The heterogeneous effect of ICTs on carbon emissions is observed across different income regions. In low- and middle-income countries, ICT has an insignificant relationship with carbon emissions as compared to high-income countries, where ICT is beneficial for the environment. These results could be due to the delay in the development of technology in low- and middle-income groups. The same conclusion is drawn by Amri et al. (2019). On the other hand, information technology is beneficial for the environment by helping in carbon emission reduction in high-income countries. Technology advancement is fruitful for pollution mitigation in high-income countries since these economics have shifted to e-paper, tele-conference, e-commerce, and online shopping. These activities improve energy efficiency through the avoidance of dirty fuel (oil, gas, and coal) consumption. High-income countries also mitigate pollution through proper waste management, particularly electronic waste. The results similar to us drawn by Ben Lahouel et al. (2021) for Tunisia and concluded that information technology help in pollution reduction through boosting economic growth. N'dri et al. (2021) identified long ICT usage reduces carbon emissions in low-income developing countries, whereas no relationship exists high-income developing countries. In line with this, Khan et al. (2020) documented the beneficial role of ICT in carbon emissions reduction for panel of 91 countries. Similar results is found by (Nwani et al., 2022) for Africa; (Faisal et al., 2020); for fast-emerging economies; (Ulucak and DanishKhan, 2020); for BRICS countries; (Zhao et al., 2022); for emerging Asian economies. Likewise, (Danish et al., 2019), found that ICT help to form inverted U-shape hypothesis of EKC curve for Belt and Road countries. Contrary to this, (Magazzino et al., 2021b; 2021a), found increasing effect of ICT on pollution European Union and OECD countries. Similar argument developed by (Danish et al., 2018) for emerging economies. Charfeddine and Kahia (2021) argued that ICT affect environmental quality by increasing CO_2 emissions in Middle East and North Africa region. The heterogenous effect of ICT on CO_2 emissions is found by Dehghan Shabani and Shahnazi. (2019) and Danish et al. (2019) for various sectors and different regions respectively. But a cross-regional comparison of countries on an income basis divulges that ICT promotes environmental sustainability in high-income countries and middle-income while low-income economies show the *vice versa*.

Another core variable of the study is education, and the results show that education does contribute to pollution in low-income countries, but it reduces pollution in middle- and high-income countries. Conclusively highly educated citizens use more ICT software and services. Date advocates that ICT dominance is subordinate in countries with low ratios of education. Our findings proposed that education could help raise awareness among citizens regarding climate change mitigation and global warming impacts on pollution by providing a foundation for science, technology and innovation. Likewise, mobile phones and the internet are better sources for connectivity among people, which contributes to pollution mitigation and endorses sustainability. Access to newer and broader ICT coverage helps in carbon monitoring and the sharing of knowledge (Shobande and Asongu, 2022). Education enables citizens to change the behavior and attitudes by understanding the climate change on this planet. Education motivates people to adopt a sustainable lifestyle and grow their skills in managing climate change. IT and IoT require a profound educational transformation to enhance teaching and learning about environmental sustainability. In the context of climate change, teaching required an interdisciplinary and cross-disciplinary approach to integrate different perspectives. Information regarding the impact of climate change impact be part of the syllabus. Information technology use would be a useful approach for interactive activities that benefit students by allowing them to know and learn about climate change awareness. Along with information technology, students should be learning how to measure carbon emissions along with the practical application of the same. At the graduate and undergraduate level, students should provide opportunities to learn about attaining environment sustainability; for example, environmental-related projects would be a much better option for handling climate change problems using IT and IoT technologies (Dwivedi et al., 2022). The negative role of education is causing pollution is associated with Zhang et al. (2022) and Zafar et al. (2022b) who found education contributes to carbon emissions in developing countries, but they failed to provide any logical reason. However, Shobande and Asongu (2022) and Liu et al. (2022) claim *vice versa* for the role of education in carbon emissions. The same evidence is found by Zaman et al. (2021) for China.

6 Conclusion and policy measures

6.1 Findings

In the 1980s, ICT advancement and the progressively noticeable environmental crisis, a rising global interest in evaluating the environmental impact of ICTs through econometric tools was observed. Based on production theory and EKC hypotheses, this paper contributes to the literature by assessing the empirical association between CO_2 emissions, economic performance, ICT, education, and digital trade across low-, middle-, and high-income countries. In terms of empirical evidence, this paper relies on the BCMM and DK-regression estimators for panel data from 93 countries from 2005 to 2019. Several important findings are observed: 1) an inverted U-shaped relationship between economic performance and environmental quality is observed across middle- and high-income countries, but reserved findings are obtained for low-income countries. 2) The heterogenous effect of ICTs on CO_2 emissions is concluded. 3) Education is found to be a key driver for carbon emission mitigation.

6.2 Policy recommendation

The findings of the study have important policy implications. In low-income countries where ICT is detrimental to the environment, it does not make sense to stop adopting ICT, but to promote a clean, green, low-carbon, and sustainable ICT industry and encourage ICT equipment favorable to environmental quality. Governments in these low-income countries should devise policies associated with the development of green ICTs to achieve the status of a low-carbon economy. Production of carbon intensive ICT products should be restricted through consolidating of environmental measures. Along with this, policymakers should develop an effective system for monitoring ICT equipment processes that are energy and carbon intensive, and it is urged the government in lower and higher-income countries take to measures to limit the inefficient use of ICT equipment. Also, data centers with high energy consumption need to be regulated by taking appropriate measures and setting targets for their power consumption by engaging more stakeholders. Further, governments should support research on green ICT and innovative ICT technologies such as green mobile communication fifth generation (5G) technology and allocate funds for its promotion through direct investment or public-private partnerships that would benefit in controlling emissions. Likewise, the government can establish research centers to study ICT energy efficiency with the help of private companies or universities. Financial institutions need to ease the process of credit availability for environmentally friendly ICT projects and companies that manufacture equipment for green ICT and innovative technologies. It was concluded from the results that education is playing a great role in reducing pollution, so governments in low- and middle-income countries should teach about environment education and include environment as a special subject in the syllabus. Apart from this, the curriculum should encourage the young generation to be made aware of how mobile and the internet can be used for philanthropic purposes, business purposes and to improve the quality of the environment.

6.3 Limitations of the study

The study has some important limitations. Various ICT measures have been used in the study; however, the ICT measure can be extended by including social media, and future studies study should focus on the potential role of social media in pollution mitigation across the globe. Further, future studies in this direction can focus on the role of ICTs in waste management, which contribute to reducing pollution and leading a country toward a circular economy. This study only goes up to 2019, so future researchers can investigate newer drivers of CO2 emissions with extended data from recent years. Furthermore, ICT-related CO2 emissions should be investigated further in other sectors of the economy, including the agriculture sector, the industrial sector, and the services sector.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

KI and YW conceived and designed the manuscript, Danish analyzed the data, and SK wrote the literature review. NM and WS proofread the manuscript. NL contributed to the final version of the manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2023.1235376/full#supplementary-material

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Assessing the factors of economic and environmental inefficiency of sunflower production in Pakistan: an epsilon-based measure model

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Considering the growing pressure of the edible oil imports bill on Pakistan's national accounts, the significance of sunflower cultivation is gaining more attention to meet the domestic edible oil demand. Given the declining area for sunflower production, this study explored the factors of economic and environmental inefficiencies affecting sunflower growers in Pakistan. The study adopted the epsilon-based measure (EBM) model at the first stage and the Tobit truncated regression model at the second stage to precisely estimate the economic and environmental inefficiencies in the data collected from 240 sunflower growers. Results found that out of 240, 69.9% of the sunflower growers are economically inefficient, while the average environmental inefficiency of sunflower growers is 56.3%. The findings further revealed that farmers' age, cultivated land, and market distance are the driving factors of farmers' economic and environmental inefficiencies. However, formal education, farming experience, and access to agricultural extension services decreased the farmer's inefficiencies. Based on the present study's findings, diverse policy options are presented to address the problem of contraction of the area under sunflower production.

KEYWORDS

epsilon-based measure, influencing factors, economic inefficiency, environmental inefficiency, sunflower production

1 Introduction

Edible oil is an essential part of food in Pakistan, and to meet the increasing demand for edible oil, the country is forced to import it from the international market (Khan et al., 2021). Consequently, Pakistan pays a significant portion of its foreign exchange reserves to purchase edible oil due to the inadequate indigenous production of oil seeds (Raza et al., 2023). Therefore, improving the local oil seed crop production is imperative to save foreign exchange and address the country's bleak economic situation. Being a non-traditional oil seed, sunflower is considered superior to other oil seed crops due to its high oil content and natural compatibility with the agronomic environment of Pakistan (Javed et al., 2003). Thus, the expansion of sunflower cultivation can reduce the edible oil demand and supply gap in Pakistan. Moreover, keeping in view of the sunflower crop's pervasive forward and backward linkages, it possesses a prominent status in rural development. Accordingly, sunflower production growth has the potential for rural development and assures the country's economic growth. Although large-scale sunflower cultivation was introduced in the early 1970s, the area under sunflower production remained inconsistent due to various socioeconomic factors. Therefore, it is crucial to assess the factors that affect the economic and environmental inefficiencies of sunflower production systems.

Agriculture is the second largest source of nitrogen emissions after the fossil fuel industry (Kholod et al., 2020). The greenhouse gas (GHG) emission reductions associated with agricultural production caused by fertilizer applications and soil nitrous oxides are gaining significant attention from scholars across the globe (Asgharipour et al., 2016; Yue et al., 2017; Elahi et al., 2019; Lamb et al., 2021). Agriculture in Pakistan is vulnerable to climate change because of GHG emissions (Waseem et al., 2022). Therefore, sunflower cultivation is an effective technique to produce oil seeds with low GHG emissions compared to other crops (Figure 1).

Many scholars studied sunflower cultivation in Pakistan because of the importance of sunflower production. For instance, Javed et al. (2003) studied factors affecting sunflower production in Pakistan. Tabassum et al. (2020) summarized the adoption of a hybrid sunflower program in Pakistan. Shah et al. (2013) found the potential of sunflower production to increase indigenous edible oil production. Nasim et al. (2016) assessed the impact of climate change on sunflower production and its adoption in Pakistan. However, these studies have few limitations. First, the economic and environmental inefficiencies of sunflower growers were not determined. Second, and perhaps most importantly, previous literature did not consider the influencing factors of economic and environmental inefficiencies of sunflower growers to assess the constraints in sunflower production. Therefore, to fill the gap in the existing studies, it is imperative to find the factors contributing to economic and environmental inefficiencies in sunflower production in Pakistan.

The four features of the present study that contribute to existing literature are as follows: first, considering the fluctuating area under sunflower cultivation, the primary aim of the present research is to estimate economic and environmental inefficiencies of sunflower growers. The second contribution of the present study is to explore the factors contributing to economic and environmental inefficiencies in sunflower production and evaluate the main hindrances to sunflower cultivation. Adoption of a more sophisticated approach known as the epsilon-based measure (EBM) model to precisely measure the economic and environmental inefficiencies of sunflower growers is the third contribution. Fourth, after precisely calculating the farmer's inefficiencies, the current study also adopted a second-stage regression analysis by applying the Tobit truncated regression model to evaluate the factors contributing to economic and environmental inefficiencies in sunflower production. The present study also suggests viable policy options to address Pakistan's shrinking area under sunflower production.

The remainder of this article is structured as follows: Section 2 briefly presents the relevant literature to explain the research gap and discusses the significance of the selected models. Section 3 explains the selected mathematical and econometric models, along with data and variables. Section 4 is designated for the results and discussion, followed by conclusion and policy recommendation in Section 5.

2 Literature review

Sunflower, with its comparatively low greenhouse gas emissions, high drought tolerance, and high edible oil content, is one of the most important crops to tackle the problem of food security and environmentally friendly agriculture. Therefore, considering the importance of the sunflower crop to the livelihood of millions of people around the globe, agriculture economists have carried out several research studies in different parts of the world, keeping in view different research objectives. For instance, Towo and Mugisha (2013) explored the sunflower growers' technological adoption in Uganda. Based on the qualitative and quantitative data, author revealed that male sunflower growers were more proactive in adopting advanced sunflower technologies compared to female farmers in the northern parts of Uganda. Similarly, Oguz and

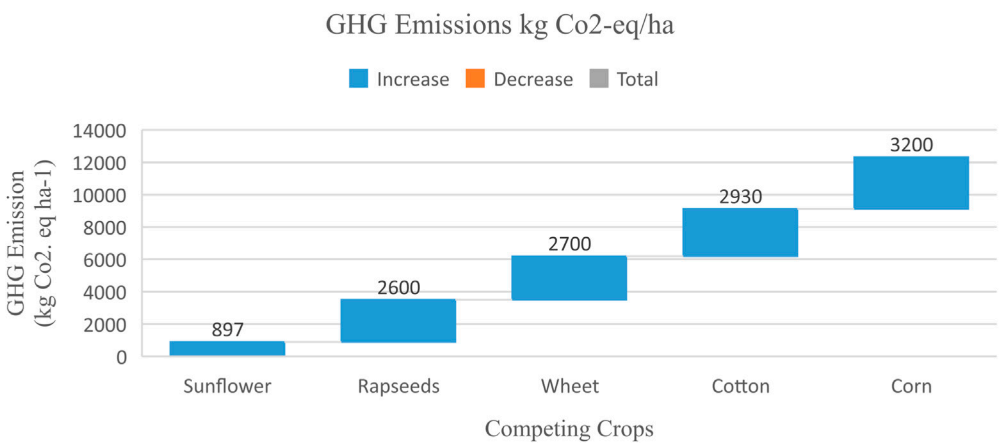

FIGURE 1
GHG emissions from competing crops.

Yener Ogur (2022) evaluated the production and energy efficiency of sunflower cultivation in Turkey and found that only one-third of the sunflower enterprises involved in the sunflower business were found to be energy-efficient in the production process, while two-thirds of the respondents were found to be energy-inefficient. The author suggested that improving the energy efficiency of the sunflower farmers would have a positive impact on economic efficiency. In another study, Mousavi Avval et al. (2011) explored the energy efficiency of sunflower enterprises and found that sunflower production can be more energy-efficient with the adoption of hybrid seeds and advanced sowing techniques. Similarly, other researchers studied the efficiency of sunflower production in different regions of the world; for example, Unakıtan and Aydın (2018) compared the economic and energy efficiency of sunflower and wheat growers in Turkey. Vorobyov et al. (2021) estimated the economic and ecological efficiencies of sunflower production in Russia. Kondratyuk (2015) calculated the production efficiency of sunflower growers considering the area under sunflower cultivation and soil fertilization. Kuts and Makarchuk (2021) estimated the economic viability of sunflower seeds in Ukraine.

Historically, the cultivation of the sunflower crop in Pakistan followed inconsistent adoption behavior due to a lack of quality seeds, fertilizers, financial hindrances, and, most importantly, a lack of cultivation information. Therefore, to suggest suitable policies, few studies have been carried out in Pakistan, keeping in mind the specific research objectives. For example, Joyo et al. (2016) carried out a research study in Sindh Province of Pakistan and evaluated the economic analysis of sunflower production and found that a large number of sunflower growers in the research zone do not have appropriate knowledge of recommended sunflower seed and variety. Shah et al. (2013) carried out a study to suggest policies to improve the production of sunflower and increase the area under sunflower cultivation in Dera Ghazi Khan (D. G. Khan) District of Punjab Province of Pakistan. The author found that approximately 80% of the farmers were sowing imported hybrid seeds, which were expensive, and it was suggested that the government introduces locally produced varieties that should be genetically modified according to the local environment and be economical. Awais et al. (2018) estimated the impact of climate change on sunflower adoption technologies in Pakistan. The findings of the research suggest that earlier and denser plantation of sunflowers can reduce the risk of production losses. Moreover, the study also suggested that as the sunflower crop is drought-resistant, skipping the second irrigation may lead to an increase in production per acre in the research zone. Sethar (2015) carried out research in Sindh Province of Pakistan to explore the comparative economic analysis of hybrid and conventional sunflower production. Although there are plenty of studies that have been carried out in different parts of the world, including Pakistan (Mandal et al., 2015; Singh et al., 2019; Abbas et al., 2021; Mushtaq et al., 2021; Wu and Ding, 2021), these studies have limitations. For example, the studies previously cited did not estimate the economic and environmental efficiency of sunflower production. Moreover, to the best of our knowledge, none of the studies explored the influencing factors of economic and technical inefficiencies in sunflower production in Punjab Province of Pakistan. Therefore, considering the area under sunflower cultivation, it was imperative to estimate the economic and environmental efficiencies, considering the GHG emissions in the analysis. Moreover, influencing factors of economic and environmental inefficiencies in sunflower production in Pakistan were explored using the epsilon-based measure model and the Tobit regression model.

There are two categories of economic and environmental efficiency calculations: single factor and total factor. The single-factor method is simpler, considering a single input with one desired output, and this technique is commonly used in various studies. However, it has a disadvantage as it does not consider the substitution effect among other inputs. As a result, the results obtained through this method may be spurious and biased. Therefore, to address these notable estimation limitations, Hu and Wang (2006) introduced the concept of total-factor efficiency. In contrast to single-factor efficiency estimations, the total-factor approach is a more refined and accurate method as it considers all inputs and outputs, including substitution effects, resulting in a comprehensive analysis of economic and environmental efficiencies. While the single-factor approach has its usefulness in certain situations, the total-factor approach is generally considered a more reliable method for economic and environmental efficiency estimation. Moreover, the total-factor energy efficiency can be determined using a parametric model, such as stochastic frontier analysis, or a non-parametric model, such as data envelopment analysis (DEA). The DEA model is a preferred method as it does not require any assumptions before analyzing the data, making it widely applicable in efficiency measurement across various fields (Wei et al., 2020; Mushtaq et al., 2021).

However, it is noteworthy that the traditional DEA models are prone to underestimating undesirable outputs, which can lead to biased and inconsistent results (Abbas et al., 2020). They operate under the assumption that all inputs, including both desirable and undesirable outputs, should be minimized to maximize overall efficiency. To ensure accurate economic and environmental efficiency measurements, Abbas et al. (2022a) recommended minimizing inputs while maximizing desirable outputs and simultaneously reducing undesirable outputs. In addition to that, the traditional DEA models employ radial or non-radial models, and their calculations may not always be entirely reliable due to the loss of critical information. The EBM model proposed by Tone and Tsutsui (2010) has emerged as a promising approach for measuring environmental efficiency. Unlike traditional methods that assume a fixed radial or non-radial direction for measuring efficiency, the EBM model allows for the possibility of measuring efficiency in both directions simultaneously. This feature provides a more flexible and accurate method of estimating environmental efficiency, which is particularly important in cases where the production process is complex and multifaceted. The EBM model has emerged as a promising approach for measuring environmental efficiency, and its benefits have been demonstrated in several recent studies. For example, Mushtaq et al. (2022) and Yang et al. (2018) adopted the EBM model to assess environmental efficiency in different fields. Thus, keeping in view the aforementioned advantages of the EBM model application, the study aims to provide a more accurate and comprehensive assessment of energy efficiency in the selected context.

Furthermore, the present study also explores the influencing factors of environmental and economic inefficiencies in sunflower production in Punjab Province of Pakistan. Although different types of mathematical or econometric models can be applied to explore

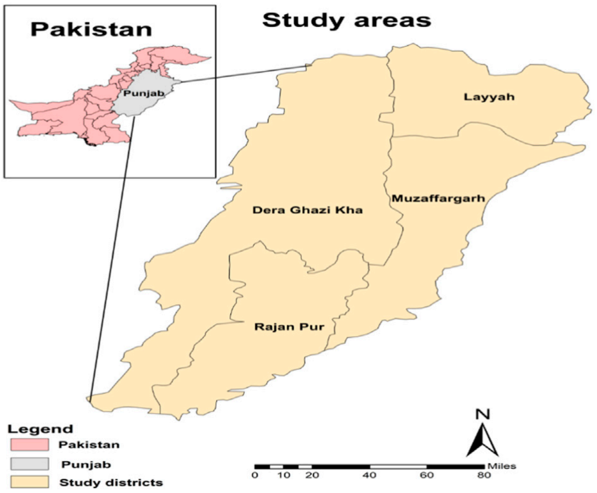

FIGURE 2
Sunflower's sampling selection zone.

the influencing factors of economic and environmental inefficiencies in sunflower production in Pakistan, it is noteworthy that the environmental and economic efficiency scores lie between 0 and 1, which makes them limited dependent variables. Therefore, adopting simple OLS, Cobb–Douglas model, or other models may lead to spurious outcomes. However, from the present literature, it is evident that the Tobit models can be more reliable in the case of the limited nature of the dependent variable to explore the factors of economic and environmental inefficiencies. Many studies applied the Tobit model to explore the factors of efficiencies or inefficiencies in different fields in different regions of the world. For instance, Wei et al. (2020) applied the Tobit model to explore factors influencing efficiencies in cotton production in Pakistan. In another study, the Tobit regression was applied to explore the factors contributing to coal consumption inefficiencies in the energy-intensive industries of China. Similarly, Liu and Lin (2018) and Ma et al. (2018) also applied the Tobit regression model to evaluate the influencing factors of efficiency in China. Thus, based on the nature of the dependent variable and the advantages of the Tobit regression model, the present study will also apply the Tobit regression model to explore the factors contributing to economic and environmental inefficiencies in sunflower production in Pakistan.

From the aforementioned discussion, it is concluded that the present research on sunflower production is very limited to Pakistan, and none of the studies estimated the economic and environmental efficiencies in Pakistan; moreover, no study was found to explore the factors contributing to the economic and environmental inefficiencies of sunflower growers. Therefore, to overcome the limitations in the existing literature, the present study, at its first stage, will estimate the economic and environmental inefficiencies in sunflower production using a more sophisticated epsilon-based measure model. Furthermore, the study is unique in that it explores the factors of economic and environmental inefficiencies applying the Tobit regression model to suggest precise policy options to help policymakers and farmers increase sunflower cultivation to meet growing edible oil demand at local levels.

3 Materials and methods

3.1 Research zone

Sunflower cultivation is a source of livelihood for many people, from cultivation to the production of edible oil. Although the sunflower crop is cultivated across different climate zones in Pakistan, southern parts, mainly Sindh and South Punjab, are considered more suitable for the sunflower crop. Therefore, considering the area under sunflower cultivation, the present study was carried out in the four sunflower-producing districts of South Punjab: D. G. Khan, Layyah, Muzaffargarh, and Rajanpur. Figure 2 depicts the research zone for sample selection.

3.2 Sampling technique

The multistage random sampling technique was applied to collect the primary data from 240 farmers cultivating sunflowers. In the first step, Punjab Province was selected, considering the area under sunflower cultivation. In the second step, using the random sampling technique, Layyah, Muzaffargarh, Rajanpur, and D. G. Khan districts were selected from Punjab Province. In the following step, one tehsil from each district was randomly selected, e.g., Tehsil Dera Ghazi Khan, from D. G. Khan District; Tehsil Lal Esan represented Layyah District; and Tehsil Kot Addu and Rajanpur represented Muzaffargarh and Rajanpur districts, respectively. Later, we selected three union councils from each selected tehsil, and one village from each selected tehsil was randomly selected. In the third step, 18–22 sunflower growers were chosen from the selected villages of each union council from these districts, depending on the respondents' availability. Prior to full-scale data collection, a pretest survey was also conducted to test the instrument's compatibility and the selected region's scope. Table 1 presents a brief summary of the sample selection zone.

3.3 Epsilon-based measure model

The EBM method, derived from DEA, was adopted to assess the environmental and economic efficiency of sunflower growers in Pakistan. DEA is a renowned, non-parametric method that measures the decision-making units' (DMU's)efficiency (Mushtaq et al., 2021). Additionally, by drawing a production frontier between inputs and outputs to assess the effectiveness of numerous inputs and outputs, DEA does not necessitate presumptions (Singh et al., 2019). However, the standard DEA model has a common shortcoming: it cannot precisely evaluate environmental efficiency when there is more than one decision-making unit on the production frontier, which may impair the integrity of the empirical findings (Mushtaq et al., 2022).

Therefore, to address the limitations in the basic DEA methods, the current study employed the input-oriented epsilon-based measure method to estimate the environmental and economic efficiency of sunflower growers in Pakistan. The EBM model is preferred over slacked-based models and CCR, as this model equally deals with radial and non-radial models. Moreover, the EBM model also considers the radial ratio of the besieged inputs compared to the

TABLE 1 Layout of random sample selection of sunflower farmers.

Province	District	Tehsil	Union council	Village	Sample	Total sample
Punjab	D. G. Khan	D. G. Khan	Wadore	1	20	240
			Samina	2	19	
			Nawan	3	21	
	Layyah	Karor Lal Esan	Chak # 98/ML	1	20	
			Chak # 90/ML	2	22	
			Samtia	3	18	
	Muzaffargarh	Kot Addu	Sanawan	1	19	
			Chak # 547/TDA	2	19	
			Budh	3	22	
	Rajanpur	Rajanpur	Piroo Wala	1	22	
			Jahanpur	2	18	
			Noorpur	3	20	

*Authors' own tabulations.

actual inputs in addition to the non-radial slacks with other inputs in the sample (Liu et al., 2017). Equation 1 represents the transition from radial to non-radial as a result of input variance.

$$\delta^* = min\, \vartheta_{\vartheta,\rho,S} - \epsilon_X \sum_{k=1}^{m} \frac{v_k^- s_k^-}{x_{k0}} Subject\, to \begin{cases} \sum_{i=1}^{n} X_i\, \rho_i + S^- = \delta X_0, \\ \sum_{i=1}^{n} Y_i\, \rho_i \geq Y_0, \\ S^- \geq 0, \\ \rho_i \geq 0, \end{cases} \tag{1}$$

where δ represents the radial efficiency value of DEA contact return to scale of the decision-making unit 0 given in subscript. v_k and s_k^- represent the weight and the slack vector of the kth non-radial input, respectively. The parameter determines the dispersion of inputs ϵ_X. ρ_k indicates the weight vector and range of the efficiency value between 0 and 1. The decision-making unit is considered efficient if the obtained efficiency score equals one. This implies that DMU lies on the production frontier, while DMU is considered inefficient if the efficiency score is less than one. Furthermore, the EBM input orientation can be mathematically expressed, as shown in Eq. 2, if $x_k = \vartheta x_{k0} - S_k^-$.

$$\delta^* = mini_{\vartheta,x,\rho,S} (1 - \epsilon_X)\vartheta + \epsilon_X \sum_{k=1}^{m} \frac{v_k^- s_k^-}{x_{k0}} Subject\, to \begin{cases} x_k - \sum_{i=1}^{n} X_i\, \rho_i = 0, \\ \sum_{i=1}^{n} Y_i\, \rho_i \geq Y_0, \\ S^- \geq 0, \\ \rho_i \geq 0. \end{cases} \tag{2}$$

3.4 Tobit truncated regression analysis

The sunflower growers' economic and environmental inefficiency scores are influenced not only by the weight of inputs applied and obtained outputs but also by external factors. Therefore, many researchers applied regression in the second stage of the analysis to find the inefficiency factors in different fields. For instance, Wei et al. (2020) applied Tobit regression in the second stage, to assess and explore the factors affecting the production efficiency of cotton growers. Abbas et al. (2022a) used the Cobb–Douglas production function in the second stage to find the factors affecting the production efficiency of cash and grain crops. Bonfiglio et al. (2017) measured the efficiency of arable farms and applied regression in the second stage to evaluate the influencing factors for efficiency. Therefore, following the existing literature, the present study also conducted a second-stage regression analysis to find the influencing factors of economic and environmental inefficiencies of the sunflower growers in Pakistan.

The present study took the inefficiency score gained through the EBM model as the dependent variable that lies between 0 and 1, making the dependent variable the limited variable. Tobin (1956) introduced the Tobit regression model to address the limited value problem of the dependent variable. Ma et al. (2018) believed that the use of tailed regression may lead to inconsistent and biased estimations. Thus, to overcome the limitations of these models, the present study used Tobit truncated regression analysis to find the factors contributing to economic and environmental inefficiencies of sunflower growers in Pakistan. The Tobit regression model can be mathematically expressed as given in Eq. 3:

$$Y = \begin{cases} Y^* = \alpha + \beta X + \epsilon & Y^* > 0, \\ 0, & Y^* \leq 0, \end{cases} \tag{3}$$

where X represents the vector of the independent variable. Inefficiency score is a dependent variable indicated by the symbol Y. While α and β represent intercept and regression parameters, respectively, ϵ is an error term, such that $\varepsilon \sim N(0, \sigma^2)$.

TABLE 2 Descriptive statistics of the variables used in the EBM model.

Variable	Unit	Mean	Maximum	Minimum	Standard deviation
Economic output	kg	2,124.25	2,272.42	1,976.29	148.07
GHG emissions	kg eq. CO_2	897.60	961.78	799.50	81.73
Seed	kg	5.69	2.50	1.50	2.19
Human workers	Hours	30.00	35.00	29.00	3.21
Machine hours	Hours	12.35	6.00	3.50	4.56
Irrigations	No.	6.00	9.00	4.00	2.52
Fertilizers	kg	197.60	210.00	60.00	83.25
Insect/pest chemicals	Liters	9.78	11.25	2.50	4.69
Costs and revenue					
Revenue	PKR	34,519.63	369,240.63	321,147.13	1,102.83
Land rent	PKR	88,920.00	98,800.00	83,980.00	2,258.23
Labor wages	PKR	11,090.00	13,575.00	9,550.00	2,030.90
Land preparation	PKR	18,500.00	20,550.00	14,800.00	2,914.19
Seed cost	PKR	10,000.00	15,000.00	7,500.00	2,108.35
Irrigation charges	PKR	12,356.00	15,648.00	7,410.00	4,146.58
Cost of fertilizers	PKR	15,500.00	20,000.00	0.00	2,104.53
Cost of chemicals	PKR	4,250.00	6,900.00	800.00	145.68

*Authors own tabulations.

4 Results and discussions

4.1 Descriptive statistics of the variables used in the EBM model

Table 2 presents a description of the input and output variables to evaluate the economic and environmental inefficiencies of the sunflower growers in Pakistan. The current paper considered six variables as inputs: seed rate, human workers, machine hours, fertilizers, number of irrigations, and pest/insect control chemicals. On the other hand, two variables were taken as outputs: economic output in the form of farm yield and greenhouse gas emissions, which were taken as undesirable outputs to assess the environmental efficiency of the sunflower farmers.

The greenhouse gas emissions reported in Table 2 are calculated using the mean inputs used for sunflower production. The GHG emission in sunflower production was 897.35 kg CO_2 ha^{-1}. Furthermore, Table 3 shows that nitrogen fertilizer contributed most to GHG emissions with a share of 70%, followed by potassium and fuel with 25% and 15% for sunflower production, respectively.

4.2 Economic and environmental inefficiencies in sunflower production

Table 4 shows the results obtained through the epsilon-based measure model, as presented in the second chapter of this study. The findings in Table 4 depict that, on average, 69.9% of sunflower farmers are economically inefficient, and these farmers can become efficient with similar technology and without compromising the economic output. Moreover, findings also revealed that only 8.75% of the farmers are economically less than 1% inefficient, while approximately 36% are more than 50% economically inefficient. The economic inefficiency of the sunflower growers causes a negative impact on the expansion of sunflower production in the region. Therefore, it is indispensable to find the factors contributing to economic inefficiency to address the problem of sunflower cultivation growth.

Furthermore, the results in Table 4 indicate that the average environmental inefficiency of sunflower growers is 56.3%, which reveals that most sunflower growers are highly environmentally inefficient. Moreover, 42 percent of the sunflower growers have less than 50% efficiency. The findings also revealed that only 6.25% of farmers in the sample were less than 10% inefficient, indicating that a farmer's environmental inefficiency can be reduced without compromising the economic output. Thus, it is important to find the factors contributing to environmental and economic inefficiencies in sunflower production to attract farmers to grow sunflowers in Pakistan. The findings in Table 4 are comparable with the results of the study conducted by Yousefi et al. (2017), who estimated the economic efficiency of sunflower growers in Iran.

4.3 Factors contributing to economic and environmental inefficiencies in sunflower production

Keeping in view the high average economic and environmental inefficiency scores of the sunflower growers, it

TABLE 3 GHG calculation for sunflower production.

Input	Average input (ha^{-1})	GHG emission ($Unit^{-1}$)	GHG emissions equivalents (kg CO_2 ha^{-1})
Nitrogen fertilizer (N) (kg)	120	5.27	632.4
Potassium (K) (kg)	39.5	0.57	22.51
Phosphorus (P) (kg)	37.5	0.572	21.45
Seeds (Kg)	5.69	2.025	11.52
Chemical pesticides (L)	9.7	7.7	74.69
Fuels (L)	439	0.307	134.77
Total			897.35

Authors own tabulations.

TABLE 4 Economic and environmental inefficiencies in sunflower production.

Efficiency range	Economic inefficiency		Environmental inefficiency	
	N	%	N	%
EI ≤ 0.1	21	8.75	15	6.25
0.1 < EI ≤ 0.2	24	10.00	19	7.92
0.2 < EI ≤ 0.3	63	26.25	59	24.58
0.3 < EI ≤ 0.4	42	17.50	47	19.58
0.4 < EI ≤ 0.5	59	24.58	61	25.42
EI > 0.5	31	12.92	39	16.25
Mean	69.9		56.3	
Total	240	100	240	100

EI, economic and environmental inefficiencies.

is vital to find the influencing factors of economic and environmental inefficiencies of the sunflower growers in Pakistan. Thus, at the second stage, the present study applied the Tobit regression model, as discussed previously, to find the influencing factors of economic and environmental inefficiencies in sunflower production. The results in Table 5 revealed that formal education, experience, labor productivity, farm machinery, and access to extension services had helped the farmer reduce economic and environmental inefficiencies. On the other hand, the area of cultivated land, farmer age, and market distance had accelerated the economic and environmental inefficiencies of the sunflower growers. The findings suggested that labor productivity had a regression coefficient of −0.035, which implies that 3.5% of the economic inefficiency of the sunflower growers can be reduced by improving 1% of the labor productivity. Furthermore, the formal education coefficient for environmental inefficiency is −0.15, which suggests that 1 year of additional formal education leads to a 15% decrease in environmental inefficiency. Therefore, it is important to improve labor productivity by providing technical education and strengthening sunflower cultivation skills. The results in Table 5 are in line with the findings of the study by Jariko et al. (2011), who found that areas under sunflower cultivation and formal education significantly caused an impact on sunflower production in Sindh Province of Pakistan. Javed et al. (2003) also suggested that proper formal education and skills increased sunflower production in Pakistan.

The findings of the study revealed that most sunflower farmers were economically and environmentally inefficient in their production, which has a negative impact on the expansion of sunflower cultivation in the region. The study also identified the factors contributing to economic and environmental inefficiencies among sunflower growers. The economic inefficiency of sunflower growers can be attributed to several factors, including the excessive use of fertilizers, human labor, and pest/insect control chemicals. These findings are consistent with the literature, as previous studies have also reported that farmers tend to overuse fertilizers and pesticides, resulting in increased production costs and decreased economic efficiency (Singh et al., 2019; Abbas et al., 2020; Mushtaq et al., 2021; Vorobyov et al., 2021). Similarly, the environmental inefficiency of sunflower growers can be attributed to high greenhouse gas emissions, particularly from nitrogen fertilizers. This finding is

TABLE 5 Influencing factors of economic and environmental inefficiencies in sunflower production.

variable	Unit	Economic inefficiency		Environmental inefficiency	
		Coefficient	SD	Coefficient	SD*
Cultivated land	Hectors	0.00081***	0.00061	0.00438***	0.04534
Farmer's age	Years	0.00138**	−0.00815	0.03805**	0.00947
Formal education	Years	−0.00042***	0.00057	−0.15903***	−0.41457
Sunflower-growing experience	Years	−0.00069*	0.00784	−0.09125**	0.00549
Labor productivity	No.	−0.03571**	0.04874	−0.00744***	0.02501
Farm machines	Yes/No	−0.04819	0.00018	0.20189***	0.00815
Access to extension services	Yes/No	−0.00189***	0.00915	−0.07315	0.04935
Credit accessibility	Yes/No	−0.00538***	0.20214	0.05481***	0.07691
Market distance	km	0.0058**	0.00453	0.00069***	0.28913

*, **, and *** represent the level of significance of parameters at 10%, 5%, and 1%, respectively. SD, standard deviation.

consistent with other studies that have reported nitrogen fertilizers being one of the major sources of greenhouse gas emissions in agriculture (Mohammadi et al., 2014; Vetter et al., 2017; Yue et al., 2017; Abbas et al., 2022b). The study found that improving economic and environmental efficiencies among sunflower growers requires the adoption of best practices, such as optimal use of inputs, improved crop management techniques, and reducing the use of chemical fertilizers and pesticides. These findings are consistent with the literature on sustainable agriculture, which emphasizes the importance of adopting best practices to improve economic and environmental performance in agriculture (Elahi et al., 2018; Pellegrini and Fernández, 2018; Singh et al., 2019; Wu and Ding, 2021). In conclusion, the study highlights the economic and environmental inefficiencies of sunflower growers in Pakistan. The findings stress the need for interventions to address these inefficiencies, including policy measures to promote sustainable agricultural practices, technology transfer and training, and access to finance and extension services. The factors identified in this study can serve as a basis for policymakers to design effective interventions to promote sustainable sunflower production in Pakistan.

5 Conclusion and policy implications

Based on the aforementioned findings, it is concluded that sunflower production attains a significant status in bridging the gap between edible oil demand and supply in Pakistan. However, it was important to find the causes of stagnant growth in the area under sunflower production for 40 years after its introduction. Therefore, the present study evaluated the factors contributing to economic and environmental inefficiencies of sunflower growers. In the second stage, we applied a well-designed regression model to find the factors contributing to farmers' inefficiencies in Pakistan.

The study's findings revealed that most of the farmers were economically inefficient and that most of the sunflower growers were operating well below the production frontier. Furthermore, more than 60% of the farmers were less than 50% economically efficient. Moreover, the present study also estimated the environmental inefficiency of the sunflower growers in the region. The result indicated that the farmers' environmental inefficiency score was even worse than the economic inefficiency score. Based on these findings, identifying the influencing factors of these inefficiencies became indispensable; thus, the study applied the Tobit truncated regression model.

Furthermore, inefficiency was increased due to inadequate access to extension services, and many farmers were unfamiliar with sunflower cultivation's production technology. The farmers were unaware of suitable seed varieties for their fields. In addition, sunflower growers were not well informed of the recommended dosage of chemical fertilizers for sunflower cultivation. Therefore, the poor availability of agricultural extension services was one of the main factors contributing to the farmers' economic inefficiencies in the study region. Furthermore, lack of formal education, cultivated land, and farmer's age contributed to the economic and environmental inefficiencies. However, improved labor productivity and advanced farm machinery decreased farmers' inefficiency scores. Thus, based on these findings, this study suggests improving the extension services in the region. The agriculture extension department should introduce special services, including sunflower production technology training, to address the growers' low economic and environmental inefficiencies.

Although the present study suggests feasible policy options to address the inefficiencies in sunflower production, it did not consider the other related crops cultivated in the study area to assess the comparative economic analysis. Therefore, evaluation of the economic trade of sunflower with wheat and maize in South Punjab, Pakistan, is on our agenda for future work.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

All authors contributed significantly to the preparation of this manuscript. Conceptualization, methodology, software, validation, formal analysis, investigation, and writing—original draft preparation, AA and ZM; resources, AA; writing—review and editing, KY, CZ, and AI; supervision, CZ. All authors contributed to the article and approved the submitted version.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The impact of SO_2 emissions trading scheme on pollution abatement and labor market for industrial enterprises in China

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To cope with the emissions permit trading program, industrial firms have to change production decisions, which may affect their pollution discharge, labor demand, and workers' wage earnings. Using a time-varying difference-in-differences framework together with robustness checks, this research explores the impacts of the SO_2 emissions trading scheme (SETS) on SO_2 emissions, employment, and wages of industrial firms in China. It was noted that the program resulted in a remarkable decline not only in SO_2 emissions but also in labor demands and wages. The mechanism analyses further show that emissions reduction is mainly driven by fossil energy input decrease rather than by desulfurization technology. The negative effects of employment and wages are driven by the negative output effect and insufficient technology rather than by the environmental substitute effect. Our findings contribute to the improvement of the market-oriented environmental permit trading program and development of regulated firms in developing countries.

KEYWORDS

SO_2 emissions trading scheme, pollution abatement, labor demand, wage, industry

1 Introduction

Since the reform and opening up in 1978, the economy of China has advanced a lot. However, long-run growth has brought serious environmental challenges. According to the Environmental Performance Index report (Wolf et al., 2022), China's environmental performance is ranked 120th in 180 countries; its air quality has become the second worst, which makes pollution abatement a top priority of the society. The Chinese government has executed a variety of policies and regulations for environmental conservation. However, environmental protection is tied to economic short-run growth cuts (Chen et al., 2018). For example, China used to mainly rely on mandatory measures to curb environmental pollution, which discouraged the enthusiasm of economic entities for production (Tu and Shen, 2014). Thus, it has long been a critical issue for China on how economic growth can be kept in balance with environmental protection. A tradable permit scheme based on the price principle gets the government's good graces owing to being less costly. However, even if the tradable program is less costly, it might still impose production costs, especially labor costs, on regulated firms due to the reallocation of inputs and outputs (Curtis, 2018). China's economic growth rate has slowed down, given that there are many workers who migrate from rural to urban areas, there is a large amount of low-skilled employment in manufacturing, and keeping a stable employment is an important concern for policymakers (Liu et al., 2017).

Particularly, to reduce SO_2 emissions, China has initiated the SO_2 emissions trading scheme (SETS) in 2002. As a market-based instrument, the SETS is mainly aimed at industrial enterprises. Does it take effect in emissions reduction? In the meanwhile, does this policy affect labor markets of industrial firms? How does it influence these? We used the matched firm-level data from the Annual Survey of Industrial Firms (ASIF) and the Environmental Survey and Reporting (ESR) to estimate the impact of the SETS on emissions, employment, and wages of industrial enterprises in China. The result indicates that the SETS reduces employment and wages, while decreasing emissions due to decreasing coal inputs, negative output effects, and insufficient technology. The key contribution of this study is that we took wages into consideration to explore the full effects of the SETS on industrial enterprises' labor markets in China and clarified the impact mechanism of the policy, which broadens the existing literature and is crucial for improving the policy system and promoting China's sustainable development.

2 Literature review

Generally speaking, environmental regulations are divided into administrative measures and market-oriented policy instruments. Mandatory environmental governance measures are argued as being not conducive to reducing emissions reduction costs, while market-oriented emissions trading schemes are more effective than mandatory tools due to lower pollution abatement costs (Montgomery, 1972). Some research have examined the effects of administrative policies on environmental quality and pollution emissions (Fan et al., 2019; Chen et al., 2022), health and mortality (Greenstone and Hanna, 2014; Ye and Tao, 2023), employment and productivity (He et al., 2020; Liu et al., 2021), and abatement costs and the related economic outcomes (Walker, 2013; Cai et al., 2016). Some studies have also explored the effects of market-oriented tools, and most of the works emphasize on the influences of environmental tax/subsidies (Franco and Marin, 2017; Shouraki et al., 2018) or the impacts of tradable permit schemes, such as the carbon emissions trading scheme (Wang et al., 2016; Lin and Jia, 2019; Peng et al., 2023), NO_x emissions trading scheme (Farrell et al., 1999; Linn, 2008; Deschênes, 2017), and SO_2 emissions trading scheme (Färe et al., 2013; 2014). These studies have examined environmental efficiency and abatement costs (Zhang and Zhang, 2019; Zhu et al., 2020) and innovation and technology (Borghesi et al., 2015; Ren et al., 2022). No matter the mandatory measures or the tradable environmental schemes, most evidence indicate to environmental improvement that has been brought about by technical progress or has come at the expense of economic costs, especially costs that are related to the labor market.

In terms of technical progress, according to Van der Linde and Porter (1995), appropriate regulations on the environment can activate technological innovation in the long run. The supporters state that technological innovation can partially or fully offset the costs of regulation and achieve a win–win scenario between the environment and economy (Calel and Dechezleprêtre, 2016). But opponents argue that environmental regulations may increase production costs and hinder firms' technology upgrades (Gray, 1987; Levinsohn and Petrin, 2003). Other researchers consider that the impact is uncertain (Testa et al., 2011). In terms of economic costs, the inefficiency or economic losses of the farming and transport sector have been examined (Abbas et al., 2022; Abbas et al., 2023). Particularly, the variations from the labor market such as enterprises' employment and workers' income caused by environmental regulations have been the most concerning issues. Implementation of the environmental policy may increase production and abatement costs, limit the production scale, and decrease the labor demand of enterprises (Abbas et al., 2022). Meanwhile, an increase in costs will be passed on to product prices, resulting in lower market demand, lower corporate profits, and lower wages. However, firms can use tradable permits of emissions as a competitive element to raise production scales and profits of enterprises and increase labor demand and wages. The economic performance is called the output effect (Berman and Bui, 2001; Morgenstern et al., 2002). Considering the effect of substitution, if pollution management activities of firms occur at the production process, it will lead firms to shrink production, transfer costs to product price, and cut down workforce and wages of enterprises. If firms implement the end-of-pipe treatment, the operation and maintenance of pollution abatement equipment may require the enhancement of labor, but abatement costs from the end-of-pipe treatment will also pass on to the product price and result in decrease of wages (Sheriff et al., 2019). Some works have argued that environmental regulations could reduce jobs or wages (Walker, 2011; Gray et al., 2014), while other scholars have an opposite view (Martin et al., 2015; Yamazaki, 2017). For example, Anger and Oberndorfer (2008) found that the EU ETS did not have a significant impact on the employment of regulated firms. Curtis (2018) argued that the NO_x trading scheme decreased employment and earnings in the manufacturing sector, while Ren et al. (2020) considered that China's SETS significantly increases the labor demand of regulated firms based on listed enterprise data. This implies that the overall impact of environmental management on firms' wages and on employment still remains unclear and thus requires clarification of this question.

This work adds to relevant research outcomes in two aspects. Firstly, we provide comprehensive evidence on the impacts of the SETS on emissions, labor demand, and wages of industrial firms in a developing economy. Although a few studies have concentrated on the SETS, they have either explored Chinese regional outcomes (Hou et al., 2020), only examined a certain aspect (e.g., production or innovation) in China (Tang et al., 2020), or focused on developed countries (Carlson et al., 2000; Benkovic and Kruger, 2001). Actually, Ren et al. (2020) have examined the impact of China's SETS on employment of mining and manufacturing industries based on listed enterprises data, but the sample size of these data is not comprehensive. Moreover, estimating an employment effect alone could not capture the full effects of the labor markets. To bridge the abovementioned gaps, we gathered and matched an abundance of firm-level data by combining the ASIF with the ESR; we took wages into consideration and employed a framework of time-varying difference-in-differences (DID) identification to estimate the impact of the SETS on emissions, employment, and wages. We found that the SETS is effective if it could motivate the regulated firms to improve production and pollution discharge technology. Secondly, new empirical proof drawn from the leading developing nation is offered in the research for a debate on the environmental regulation and variation of the labor market. This study is a pioneering one to look into the SETS' impacts on wages in the largest developing economy.

3 Policy background

The SO_2 emissions trading scheme is of two stages. The first stage is the exploration phase (2001–2006). In 2001, Taiyuan promulgated the first local policy document on the SETS in China. Furthermore, SETS pilots were formally launched in 2002. Two business entity, three municipalities, and four provinces (China Huaneng Group, Liuzhou, Shanghai, Tianjin, Jiangsu, Shandong, Henan, and Shanxi) were selected as SETS pilot entities or regions. This scheme had expanded to 727 cities and firms by 2002. Four provinces and three municipalities in the SETS have traded 25,000 tons of SO_2 emissions by 2004, with a transaction volume exceeding 20 million yuan. In 2007, SETS began entering the second stage, namely, the intensification phase. The MEP (Ministry of Environmental Protection) extended pilots, another seven provinces that included Shanxi, Chongqing, Inner Mongolia, Zhejiang, Hebei, Hunan, and Hubei have been approved as regions of the SETS. The pilot regions comprises a diversity of geographical regions at different economic development levels, which, according to the statistics by the China Statistical Yearbook published in 2008, accounts for 56.1% of industrial SO_2 emissions in 2007. This scheme mainly involves the steel, cement, glass, chemical, mining, and other industries. For the initial allocation of emissions trading, the MEP caps the total emissions, and each province is allocated certain quotas based on its real emissions in a base year. The participant firms have to purchase initial emissions permits from the local MEP, and the allowances must not exceed the quantities meeting the environmental assessment standard. The benchmark price for SO_2 emissions trading is set by the local government, and the transaction price is decided by market competition subsequently. The firms are required to apply their emissions allowances to the production process and could not exceed the allowed permits; otherwise, it becomes punishable by the MEP by means of fines, prohibition of emissions, or cancellation of business licenses.

4 Estimation strategy and data

4.1 Estimation strategy

The pilots in the SETS are selected with little interference of the local governments by the central government, thus this policy is largely a quasi-natural experiment which allows us to estimate the effects of the SETS on firms' emissions and economic performances using the DD strategy. Specifically, the regression equation is

$$\ln Y_{it} = \partial_0 + \partial_1 treat_i \cdot post_t + \partial_s X_{it} + \varphi_i + \tau_{rt} + \gamma_{jt} + \varepsilon_{it}. \quad (1)$$

In formula (1), $\ln Y_{it}$ represents the outcomes of our concerns (logarithm of SO_2 emissions, employment, and wages) in i firms at t years (j indexes industries). $treat_i$ equals 1 if provinces, cities, or enterprises are designated as SETS pilots (China Huaneng Group, Liuzhou, Shanghai, Tianjin, Chongqing, Hebei, Jiangsu, Shandong, Zhejiang, Shaanxi, Henan, Shanxi, Hubei, Inner Mongolia, and Hunan) and 0 if otherwise. $post_t$ is an indicator variable that equals 1 if the year is after the start of the SETS. The program began in one business entity, three municipalities, and four provinces in 2002 and for another seven provinces in 2007. For the seven pilots that began in 2002, $post_t$ is equal to 1 for 2002 and the years that follow. With regard to the all other provinces, $post_t$ is equal to 1 for 2007 and the years that follow. X_{it} controls firms' ages. φ_i is the fixed effect of firms, which captures all of the firms' time-invariant differences. The variables τ_{rt} and γ_{jt} represent a set of region–year and industry–year fixed effects for the control of non-parametric aggregate time trend and common year-specific shocks for each region and industry. Specially, the regions include seven parts (northeast, east, north, central, south, southwest, and northwest), which are divided based on their geographic location. ε_{it} represents the error. On the level of city, standard errors are collected for the treatment of serial correlations and for the handling of heteroskedasticity.

4.2 Data and variables

Data used for empirical research are gathered and matched from two corporate data sets: one is the Environmental Survey and Reporting and the other is the Annual Survey of Industrial Firms. We also used official statistical publications, which consist of the city-level China City Statistical Yearbook and the China Statistical Yearbook. We finally constructed a data set incorporating each firm's environmental conditions and financial situation, city, and province, covering the time period from 1998 to 2007. In order to get the real output value and wage levels, we also used the producer and consumer price index data from the China City Statistical Yearbook and from the China Statistical Yearbook to deflate nominal outputs and wages. Furthermore, we discard the observed data that evidently go against accounting rules, for instance, the case of current depreciation exceeding the cumulative depreciation and the case of fixed assets (or net fixed assets) exceeding the total assets. In Table 1, we present, in detail, the definitions of the variables and summaries of the results. In Table 1, the amount of industrial SO_2 emissions for each firm is approximately 80,000 kg on average; the annual number of employees is 380.7 persons on average, and the annual total payable wages are 4,391 thousand CNY on average. The minimum operating profit of every enterprise is negative. Table 1 demonstrates that every variable exhibits great variations.

The estimates of this research rely on the identification assumption that the firms arranged for the SETS and the non-SETS have common trends in SO_2 emissions, employment, and wages before implementing the policy. To verify the validity of the identifying strategy, the method of event study by Jacobson et al. (1993) is adopted to check on the identification assumption. Figure 1 presents the coefficients for the time trend of SO_2 emissions, employment, and wages between the SETS and non-SETS firms with a 95% confidence interval. The result shows that all the

TABLE 1 Variable definition and summary statistics.

Variable		Definition	Mean	SD	Min	Max	Obs
Outcome variables	SO_2	Total industrial SO_2 emissions (kg)	80,000	360,000	0	6.300e+07	173,263
	Worker	Annual average number of employees (person)	380.7	451.9	10	26,000	189,434
	Wage	Total payable wages (10^3 yuan)	4,391	6,665	0.985	270,000	189,434
Control variables	Age	Firm age (year)	15.50	14.11	1	69	189,449
Mechanism variables	lntfp	Total factor productivity (logarithm)	2.78	0.995	0.103	5.367	189,449
	rd	Research and development expenditure (10^3 yuan)	316.7	3,668	0	630,000	87,155
	zjz	Industrial added value (10^3 yuan)	22,000	38,000	−49,000	7.400e+06	165,650
	Output	Industrial output value (10^3 yuan)	80,000	140,000	0	1.500e+07	189,433
	opprofit	Operating profit (10^3 yuan)	3,238	13,000	−520,000	1.500e+06	189,434
	fqzlsss	Number of waste gas treatment facilities (sets)	2.298	5.432	0	640	164,967
	tlsss	Number of desulfurization facilities (sets)	0.257	1.091	0	68	35,615
	mtxfzl	Industrial coal consumption (tons)	9,599	46,000	0	4.000e+06	129,136
	Fuel coal	Fuel coal consumption (tons)	3,659	18,000	0	4.000e+06	166,155
	SO_2 removal	Sulfur dioxide removal (kg)	47,000	790,000	0	8.600e+07	145,439
	tlnl	Desulfurization capacity of the desulfurization facility (kg/h)	63.60	2,964	0	500,000	35,615

Note: Data are compiled based on the years 1998–2007 from the ASIF.

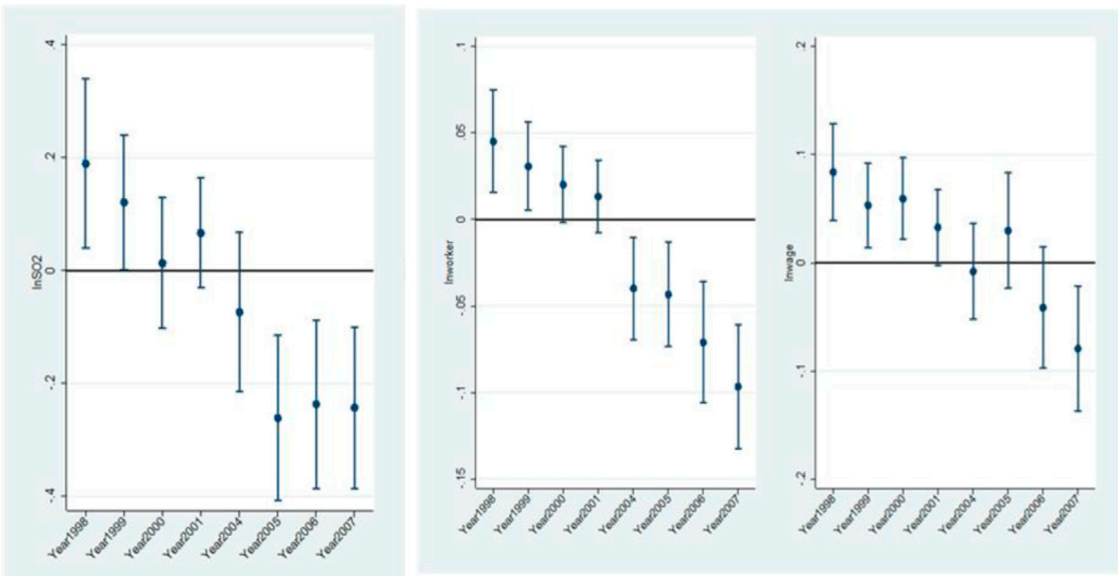

FIGURE 1
Parallel trend test for firm-level SO_2 emissions, employment, and wages. Note: The figure illustrates the time trends of industrial SO_2 emissions between the SETS and that of non-SETS firms. The omitted time category is 2002. In particular, the year 2003 is omitted owing to the lack of data. The estimation includes fixed effects of firms, region–year, and industry–year. Standard errors are clustered at the city–year level.

estimates in SO_2 emissions were positive before the policy was enacted, but the coefficients dropped to negative and were statistically significant after the adoption of the treatment, indicating that SETS and non-SETS firms have common trends in SO_2 emissions before policy intervention. In addition, the differences in the number of workers were significantly positive prior to the treatment, but after the treatment in 2002, these differences declined to become negative, and this situation persisted with an increasing magnitude. The estimates for wages were positive before implementing the SETS and despite some fluctuations, the coefficients became negative since 2004, suggesting certain lagging impacts that the change in policies

TABLE 2 Effects of the SETS on emissions, employment, and wages of industrial firms.

	(1)	(2)	(3)	(4)	(5)	(6)
	lnSO_2	lnSO_2	lnworker	lnworker	lnwage	lnwage
Treat × post	−0.087***	−0.100***	−0.015*	−0.023***	−0.025*	−0.030**
	(0.031)	(0.036)	(0.008)	(0.009)	(0.013)	(0.013)
Age	0.000**	0.000	0.000	0.000	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_Cons	9.927***	9.931***	5.481***	5.483***	7.755***	7.756***
	(0.010)	(0.011)	(0.003)	(0.003)	(0.005)	(0.005)
Firm fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y		Y		Y	
Region–year fixed effects		Y		Y		Y
Industry–year fixed effects		Y		Y		Y
N	130,458	130,435	169,074	169,057	169,074	169,057
R^2	0.820	0.823	0.927	0.928	0.895	0.897

Note: The values in parentheses are standard errors; *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors in parentheses are clustered at the city–year level.

exerted on the wages of enterprises. The results indicate that SETS and non-SETS firms have common trends in SO_2 emissions, employment, and wages, which provide an identifying basis.

5 Major results

5.1 Baseline estimates

Table 2 presents the baseline results. The estimates for SO_2 emissions are in given in Column (1), which includes the control variable and fixed effects of firms and years. SO_2 emissions dropped more evidently in SETS firms than in non-SETS firms after the policy was put into effect. Column (2) incorporates the control variable and fixed effects of firms, further adding the region–year and industry–year fixed effects to keep common year-specific shocks across regions and industries in check. The result shows that the SETS proves to have a remarkable negative influence on SO_2 emissions of designated firms. Our estimate in Table 2 indicates a 10% decrease of SO_2 emissions in designated firms when compared to non-SETS firms.

Columns (3)–(4) in Table 2 report the results of the SETS effects on firm employment. The SETS firms undergo a labor demand decline in comparison with the non-SETS firms. Column (5) presents a simple DD estimation for workers' wages with fixed effects in terms of firms and years. We find an evidently negative interaction. The estimation of Column (6) also shows a significantly negative interaction with increasing magnitude when including the control variable, fixed effects of firms, region–year, and industry–year, suggesting that the SETS has a significant negative effect on workers' wages of firms. Workers and wages of regulated firms had declined, respectively, by 2.3% and 3% due to the SETS policy.

5.2 Robustness checks

5.2.1 Exclusion of confounding effect from the SO_2 Two Control Zones

The central government proposed an SO_2 emissions reduction program in 1998, which was designed to build regional control zones that suffered the most SO_2 emissions and acid rains, i.e., the SO_2 Two Control Zones (TCZ). This policy was intended to lessen SO_2 emissions, hence a possible concern is that the results of our estimation may be influenced by the TCZ policy. To address this problem, we added the variable TCZ_T to control the impact of the TCZ policy, where the variable equals 1 if a city is categorized into the pilot group in TCZ in year T and later; otherwise, it equals 0. As proved by the results in Table 3, the SO_2 emissions, employment, and wage effects are continuously significantly negative, which implies that there is no evident influence resulting from the TCZ policy.

5.2.2 A placebo test with randomization of the treatment

With the intention to avoid the potential interference of omitted variables in the estimation results, 14 provinces are randomly selected from a total of 30 sampled provinces, and we assign the SETS status $treat^{false}$ to enterprises in the 14 selected provinces. In a similar way, the timing of adoption of the new evaluation-based shock $post^{false}$ to firms is generated randomly, and then we constructed a new regressor $t^{false} \times post^{false}$, with the equation being reexamined. For the purpose of removing potential rare events' contamination so as to strengthen the test reliability, the random assignment is performed as many as 500 times. The distributions of the estimated coefficients in terms of SO_2 emissions, workers, and wages are plotted in Figure 2. We find that all distributions are narrowly approximated to 0, and the

TABLE 3 Impacts of the SETS on industrial firms (exclusion of the effect from the TCZ policy).

	(1)	(2)	(3)	(4)	(5)	(6)
	lnSO_2	lnSO_2	lnworker	lnworker	lnwage	lnwage
Treat × post	−0.087***	−0.100***	−0.015*	−0.024***	−0.025*	−0.030**
	(0.031)	(0.036)	(0.008)	(0.009)	(0.013)	(0.013)
TCZ_T	0.057	−0.001	0.059**	0.075***	0.114**	0.126**
	(0.098)	(0.094)	(0.030)	(0.029)	(0.052)	(0.053)
Age	0.000**	0.000	0.000	0.000	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_Cons	9.886***	9.931***	5.437***	5.427***	7.670***	7.662***
	(0.072)	(0.069)	(0.022)	(0.022)	(0.039)	(0.040)
Firm fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y		Y		Y	
Region–year fixed effects		Y		Y		Y
Industry–year fixed effects		Y		Y		Y
N	130,458	130,435	169,074	169,057	169,074	169,057
R^2	0.820	0.823	0.927	0.928	0.895	0.897

Note: The values in parentheses are standard errors; *, **, and *** indicate the statistical significance at 10%, 5%, and 1% levels, respectively. TCZ refers to the Two Control Zones policy. Standard errors in parentheses are clustered at the city–year level.

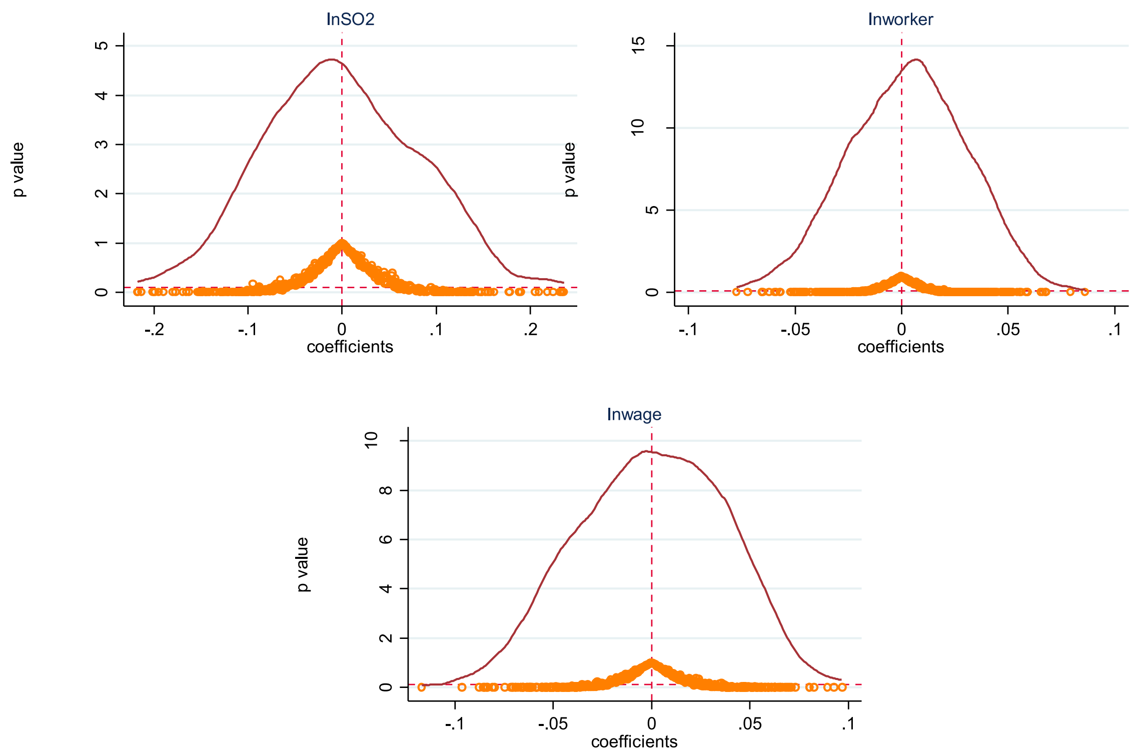

FIGURE 2
Placebo test. Note: The orange curve plots the kernel density distribution of the estimates, while the orange dots are associated with the *p*-values. The horizontal red dashed line indicates that the *p*-value is equal to 0.1.

TABLE 4 Effects of the SETS on industrial enterprises (by ownership).

	(1)	(2)	(3)	(4)	(5)	(6)
	State-owned firms			Non-state–owned firms		
	lnSO$_2$	lnworker	lnwage	lnSO$_2$	lnworker	lnwage
Treat × post	−0.080	−0.015	−0.016	−0.109***	−0.028***	−0.035**
	(0.061)	(0.013)	(0.018)	(0.039)	(0.010)	(0.014)
Age	0.000	0.000***	0.000***	0.000	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_Cons	10.167***	6.112***	8.155***	9.892***	5.374***	7.689***
	(0.012)	(0.003)	(0.003)	(0.012)	(0.003)	(0.005)
Firm fixed effects	Y	Y	Y	Y	Y	Y
Region–year fixed effects	Y	Y	Y	Y	Y	Y
Industry–year fixed effects	Y	Y	Y	Y	Y	Y
N	19,258	23,562	23,562	107,735	141,293	141,293
R^2	0.844	0.949	0.930	0.827	0.924	0.895

Note: The values in parentheses are standard errors; *, **, and *** indicate the statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors in parentheses are clustered at the city–year level.

TABLE 5 Effects of the SETS on industrial enterprises (by technology types).

	(1)	(2)	(3)	(4)	(5)	(6)
	High-technology firms			Low-technology firms		
	lnSO$_2$	lnworker	lnwage	lnSO$_2$	lnworker	lnwage
Treat × post	−0.060	−0.025	−0.032	−0.091**	−0.023**	−0.031**
	(0.054)	(0.017)	(0.021)	(0.038)	(0.009)	(0.014)
Age	−0.000	0.001	0.001	0.000	0.000*	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_Cons	9.181***	5.420***	7.830***	10.011***	5.492***	7.749***
	(0.019)	(0.009)	(0.011)	(0.011)	(0.003)	(0.005)
Firm fixed effects	Y	Y	Y	Y	Y	Y
Region–year fixed effects	Y	Y	Y	Y	Y	Y
Industry–year fixed effects	Y	Y	Y	Y	Y	Y
N	12,123	17,209	17,209	117,564	150,796	150,796
R^2	0.815	0.947	0.924	0.823	0.928	0.896

Note: The values in parentheses are standard errors; *, **, and *** indicate the statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors in parentheses are clustered at the city–year level.

p-values of the majority of estimates exceed 0.1, implying that the estimation equation is not mis-specified and the results are robust.

5.3 Heterogeneity analysis

An interesting question is that whether the effect of the SETS on SO_2 emissions, labor, and wages of firms varies by ownership, size, and technology, which gives us an insight into the way that firms of different sorts shoulder the burden of environmental regulations. As shown by the results in terms of firm ownership in Table 4, it is the private firms that primarily contribute to emissions reduction and bear the loss of employment and wages, while state-owned enterprises (SOEs) are not significantly impacted by the SETS in terms of their SO_2 emissions, workers, and wages, indicating that SOEs are controlled or invested in by the central or local

TABLE 6 Influence channel of SO_2 emissions reduction.

	(1)	(2)	(3)	(4)
	lnmtxfzl	lnfuelcoal	SO_2r	lntlnl
Treat × post	−0.042***	−0.043*	0.008	0.071
	(0.015)	(0.022)	(0.008)	(0.180)
Age	0.002***	0.000	0.000	−0.009
	(0.001)	(0.000)	(0.000)	(0.013)
_Cons	7.713***	7.223***	0.131***	2.882***
	(0.010)	(0.006)	(0.002)	(0.264)
Firm fixed effects	Y	Y	Y	Y
Region–year fixed effects	Y	Y	Y	Y
Industry–year fixed effects	Y	Y	Y	Y
N	89,054	104,579	104,271	2,620
R^2	0.929	0.878	0.656	0.838

Note: The values in parentheses are standard errors; *, **, and *** indicate the statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors in parentheses are clustered at the city–year level.

government. Compared with private firms, they can get more preferential policies and financial subsidies, therefore SOEs face less stringent enforcement of the SETS.

In addition, we explore the heterogeneity by technology types. According to the National Bureau of Statistics, we classify the industry into high- and low-technology industries. High-tech industries consist of computer manufacturing, pharmaceutical manufacturing, aviation and aerospace, electronics and telecommunication, information chemicals, and medical equipment. Other industries are low-tech industries. As shown by the results in Table 5, the SETS significantly reduces SO_2 emissions, employment, and wages of low-technology industry firms but has no significant impact on those of high-technology industry enterprises. The reason for this result may be because low-technology firms are typically labor intensive and energy intensive, their production technology and operating performance are relatively lagged, and they are more sensitive to the policy shock.

5.4 Mechanism analysis

5.4.1 Mechanism analysis of SO_2 emissions

Fossil fuels are the main contributors of ambient pollution in the process of manufacturing. In general, the more the fossil fuels such as coal are consumed, the greater the emissions such as SO_2 emissions. Meanwhile, the "end-of-pipe" treatment skills like desulfurization capacity may also affect the emissions of flue gas, and the desulfurization capacity can be seen as the pollution treatment technology. Emissions abatement is derived from energy reduction or technological advancement. To this end, we use the total industrial coal consumption and fuel coal consumption as the proxy of fossil energy. In addition, the removal rate of SO_2 at the firm level is estimated with the proportion of the total quantity of removed SO_2 over the sum of removed SO_2 and emitted SO_2. We collect desulfurization capacity data of firm-level desulfurization facilities and use the data and firm-level SO_2 removal rate as the proxy of pollution treatment technology. We explore the effects of the SETS on fossil energy and SO_2 treatment technique to clarify the channel of SO_2 emissions abatement. As implied by the estimates in Table 6, a significantly negative coefficient in coal and fuel consumption is seen, but there are no significant impacts on SO_2 desulfurization capacity and technology. These results suggest that a reduction in SO_2 emissions is derived from a decrease of fossil energy input rather than an improvement in desulfurization technology.

5.4.2 Mechanism analysis of employment and wages

The output effect generally means that the environmental regulation stimulates a firm to raise production scales, output values, and profits by improving technological innovation or firm competitiveness, resulting in an increase of the firm's workers and wages; otherwise, it means the opposite. The substitute effect implies that pollution control activities in the production process or "end-of-pipe" treatment shrink the firm's production scale and outputs, or the operation and maintenance of pollution abatement facilities may require more labor, leading to a decrease or an increase of workers and wages. Following this theory, we select the total industrial output value, the operating profit, and the industrial added value to be proxies of the output effects. The installation of flue gas treatment facilities and desulfurization units are used as proxies of the substitute effects. Furthermore, the total factor productivity (TFP) and R&D expenditures of industrial enterprises are employed as proxies of technology and innovation. Economic performances of firms are influenced by the output effects or substitute effects and are derived from technology. As indicated by the results shown in Table 7, the coefficients are significantly negative in aspects of industrial outputs and profits, but the results are not significant in the substitute effect of pollution treatment. Specifically, the SETS significantly reduced the total industrial

TABLE 7 Influence channel of employment and wages.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	lnzjz	lnoutput	lnopprofit	fqzlsss	tlsss	lntfp	lnrd
Treat × post	−0.027*	−0.054***	−0.133***	−0.013	0.008	0.010	0.122*
	(0.015)	(0.015)	(0.036)	(0.067)	(0.030)	(0.014)	(0.072)
Age	0.000***	0.000*	0.000	0.000	−0.003*	0.000	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.004)
_Cons	9.323***	10.578***	7.176***	2.391***	0.328***	2.767***	5.890***
	(0.005)	(0.005)	(0.012)	(0.018)	(0.037)	(0.004)	(0.088)
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y
Region–year fixed effects	Y	Y	Y	Y	Y	Y	Y
Industry–year fixed effects	Y	Y	Y	Y	Y	Y	Y
N	144,638	168,501	113,636	147,311	24,480	169,043	8,576
R^2	0.872	0.883	0.780	0.756	0.777	0.826	0.836

Note: The TFP value was estimated by using the Olley and Pakes (1996) approach. The values in parentheses are standard errors; *, **, and *** indicate the statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors in parentheses are clustered at the city–year level.

output value, industrial added value, and operating profits of the regulated enterprises in the pilots, but the decreasing extent of the total industrial output and industrial added value is smaller (0.054 and 0.027, respectively), while the decline extent of the operating profits is greater (0.133). This indicates that the relative contribution of the operating profits decline driving a lower labor performance that is larger than the output reduction. Although the policy has a significant positive effect on R&D expenditures of regulated firms, its impact on the TFP is not significant. This indicates that the program promotes regulated firms to jack up expenditures of research and development, but the R&D-based technology transformation of firms is insufficient, which is why the policy exerts a significant negative influence on the outputs of regulated enterprises. Therefore, the decline of the SETS on the employment and wages of enterprises in pilots mainly derives from the negative output effect and inadequate technological progress.

6 Analysis of economic costs

This study presents an economic cost analysis of the SETS, namely, the trade-offs between SO_2 emissions and labor market performances. The result shows that the SETS reduced the logarithm of SO_2 emissions by 0.1. Given that the control mean levels of SO_2 emissions are 17.436 tons, the estimation result indicates that the policy led to a decrease in SO_2 emissions by $17.436 \times 0.1 = 1.7436$. For employment, the policy led to an average decline in employees by 2.3 percentage points. The average number of workers in the sample period is 380.728 persons. Therefore, the result means a loss in employment ($380.728 \times 0.023 = 8.757$), which suggests that one ton of reduction in industrial SO_2 emissions would result in five persons' unemployment ($8.757/1.7436 = 5.022$). For wages, the policy resulted in an average decrease in wages by 3 percentage points. The average wage levels during our sample period are $4{,}391.53 \times 10^3$ Chinese Yuan (CNY). We deflate all firm-level wage values using the provincial consumer price index of each year and take the year 1998 as the baseline. Therefore, a 3% reduction in wages means a loss of 131.746 thousand CNY ($4{,}391.53 \times 10^3 \times 0.03 = 131.746 \times 10^3$). In other words, one ton of reduction in industrial SO_2 emissions would be at the cost of nearly 76 thousand CNY wages ($131.746 \times 10^3/1.7436 = 75.561 \times 10^3$).

7 Conclusion

This work examines how the SO_2 emissions trading scheme influences SO_2 emissions, employment, and wages of industrial enterprises in China. Through research, it is noted that the emissions trading program evidently reduces SO_2 emissions, employment, and wages of firms with environmental regulations. After a series of robustness checks, the results were found to be consistent. The heterogeneity analyses show that emissions reduction, the loss of employment, and wages from the SETS are mainly derived from private firms, large firms, and low-technology firms. Furthermore, the mechanism analyses indicate that firm-level SO_2 emissions reduction is driven by fossil energy input decrease rather than by desulfurization technology. The negative effects of firm-level employment and wages are driven by the negative output effect and insufficient innovations rather than by the environmental substitute effect.

This study has several policy implications. Firstly, the industrial enterprises should accelerate technological innovations, especially clean production technology and pollution treatment technology. This can help firms improve production and productivity and reduce input and pollution. Secondly, the government should unceasingly consummate the market mechanism of the SO_2 emissions trading program, bring full play into the competitiveness of enterprises, stimulate firm technology innovations, and expand market share to raise employment and income of workers. Finally, supporting policies can be put forward by policymakers so as to avoid potential negative effects of the SETS on employment and wages of firms. For example, appropriate financial support or subsidies should be given to the firms with good environmental performance, or reemployment training should be targeted at the laid-off workers.

This study also has some limitations. Our sample period is a little short because of the lack of data. Moreover, due to the lack of data on the specific types of workers, we only estimated the overall employment effect of the SETS on workers. Future research could concentrate on the effects of the policy on staff groups such as male staff and female staff and skilled staff and unskilled staff. In addition, the study can also be expanded to other environmental permit trading programs such as the energy use permit trading scheme.

Data availability statement

The data analyzed in this study are subject to the following licenses/restrictions: need to apply for use. Requests to access these data sets should be directed to the Annual Survey of Industrial Firms and the Environmental Survey and Reporting.

Author contributions

WZ: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Methodology, Writing–original draft, Writing–review and editing. PZ: Conceptualization, Methodology, Resources, Supervision, Writing–review and editing. XN: Conceptualization, Supervision, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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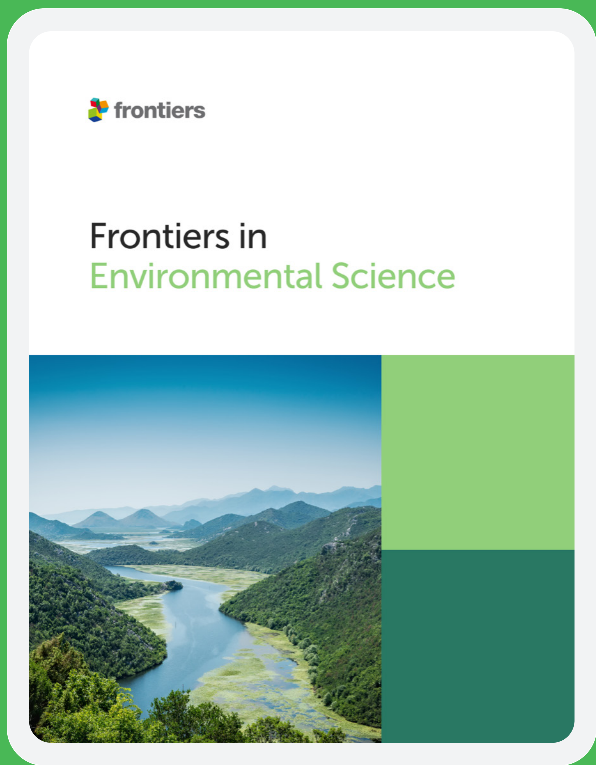

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