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Exploring the influence of internet technology adoption on the technical efficiency of food production: insight from wheat farmers

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Digital technology plays a crucial role in advancing sustainable farming and ensuring food security, especially in developing countries. This study evaluates the impact of Internet technology usage on technical efficiency in crop productivity, using data from 600 wheat farmers in rural Pakistan. It addresses the imperative need to enhance agricultural practices within the context of sustainable food production. To achieve this, a matched sample of Internet users and non-users was formed through propensity score matching. The study employs the stochastic frontier method with sample selection adjustment, ensuring a robust evaluation of technical efficiency between these groups. The findings reveal a positive influence of Internet usage on efficiency, persisting even after mitigating self-selection bias from observed and unobserved factors. Internet users exhibit a technical efficiency score of 0.62, surpassing the 0.55 score of non-users. Quantile regression analysis exposes varying impacts of Internet usage on technical efficiency, with less efficient farmers experiencing substantial improvements. Widespread Internet adoption holds the potential to significantly enhance agricultural production for growers. The research underscores the role of promoting Internet utilization to stimulate growth and improve farming efficiency within the evolving digital economy. Policymakers are advised to promote the adoption of modern technology to enhance crop production and support economic growth.

KEYWORDS

sustainable food system, internet technology, technical efficiency, rural areas, Pakistan, propensity score matching

1 Introduction

Agricultural production in many countries, particularly in developing nations, is predominantly driven by intensive farming practices, marked by substantial input usage and consumption. This reliance on inputs leads to diminished technical efficiency (TE), which not only impedes the development of local agriculture and compromises food production and quality but also imposes significant pressure on the ecological environment (Fu and Zhu, 2023). Overusing chemical fertilizers and pesticides further exacerbates groundwater pollution, posing grave threats to drinking water and agricultural irrigation in countries such as Pakistan, Bangladesh (Huq et al., 2019), Iran (Ostad-Ali-Askari et al., 2017), and others. There is an urgent need to transition from inefficient to efficient agricultural practices to address these pressing environmental and agricultural challenges.

Enhancing agricultural productivity and efficiency is crucial for ensuring food security and lifting rural communities from poverty. However, many smallholder farmers in developing countries face significant barriers preventing them from reaping agricultural progress benefits. These obstacles include limited access to information about suppliers and markets, high transaction costs, a lack of farming expertise, and difficulty accessing credit (Fu and Zhu, 2023). Specifically, due to information disparities, smallholder farmers, especially those in rural areas, struggle to adopt technologies such as improved seeds, fertilizers, and pesticides or efficiently use available resources. Consequently, these growers experience low crop yields and incomes, undermining their livelihoods and hindering rural development (Khan et al., 2022). Therefore, reducing information gaps through modern technologies is essential to improving farm performance.

The integration of sustainable Internet technology (IT) can mitigate information asymmetry by facilitating the swift and cost-effective distribution of information. Past studies have shown that IT usage enhances farmers' accessibility to financial and agricultural services (Fu and Zhu, 2023), strengthens their connections to input and output markets, and amplifies their engagement in income-generating endeavors like off-farm employment and social media usage on their sustainable development (Kılıçaslan and Töngür, 2019; Dvorský et al., 2023; Valaskova et al., 2024). Many nations have adopted diverse sustainable Internet-driven programs to bolster farm productivity and foster rural advancement (Ankrah et al., 2023; Zheng and Ma, 2024). These initiatives encompass models like the "Internet-Agriculture-Finance" framework, online farmer field schools, and platforms for sustainable rural e-commerce (Zheng et al., 2021; Khan et al., 2022).

Many studies have delved into the effects of integrating computers, mobile phones, and IT, on-farm performance, and farmers' welfare (Kaila and Tarp, 2019; Leng et al., 2020). These investigations have tackled the issue of selectivity bias in technology adoption, employing a variety of methodologies, including propensity score matching (PSM), endogenous treatment regression (ETR) models, and instrumental variable (IV) approaches. For instance, Issahaku et al. (2018) utilized a PSM model and discovered that mobile phone usage significantly enhances agricultural productivity in Ghana. Similarly, Ma et al. (2020) employed an ETR model, revealing that Internet utilization notably boosts the income of households and expenditures in rural areas.

IT can influence the TE of crop production by shaping farmers' production strategies concerning the amalgamation and application of diverse inputs, such as fertilizers, pesticides, labor, and capital assets. TE denotes the ratio of observed output to the maximum achievable output given the existing inputs (Khan et al., 2022; Liu and Liu, 2023), reflecting the effectiveness with which various agricultural inputs are utilized. Existing literature indicates that the use of these modern technologies significantly impacts farmers' decisions regarding seed and fertilizer usage (Kaila and Tarp, 2019), and land expansion (Zheng et al., 2021). Based on our understanding, apart from the study by Mwalupaso et al. (2019) in Zambia, no prior research has investigated the influence of IT usage on the TE of crop production. Mwalupaso et al. (2019) analyzed the impact of IT usage via mobile phones on the TE of maize production in Zambia and found a significant improvement in farmers' TE. However, a limitation of the study is its failure to address the issue of unobserved selection bias in IT usage.

This study aims to evaluate the influence of IT usage on the TE of wheat crop production in Pakistan. This study analysis is grounded in survey data collected from 600 wheat farmers across the country. Our focus specifically on wheat production in Pakistan stems from several reasons. First, we adopt a more nuanced approach to IT adoption, concentrating solely on its role in accessing information to enhance wheat crop yields, in contrast to previous studies that relied on broader indicators like overall IT investment or ownership (Battese, 1997; Ramalho et al., 2010; Zheng et al., 2021). This focused approach establishes a direct link between farmers' IT usage and agricultural output. Second, despite the potential positive impacts of agricultural output on the economy and poverty alleviation (Ma et al., 2018; Khan et al., 2021; Zheng et al., 2021), there has been limited research in this domain, and our study aims to bridge this gap. Third, by employing QTE, policymakers can glean valuable insights into the varied impacts of IT on TE, which can inform the design of tailored and pragmatic solutions to address the specific requirements of diverse crop farmers. This research endeavors to ascertain whether IT utilization influences growers' decisions regarding input usage, consequently augmenting crop yield efficiency and technological effectiveness in rural Pakistan.

This article is structured into five sections. After the introduction, Section 2 reviews the literature background and presents the conceptual framework. Section 3 outlines the methodology employed. The research findings and discussions are presented in Section 4. Finally, Section 5 summarizes the conclusions and discusses policy implications, limitations, and future directions.

2 Literature background and conceptual framework

2.1 Literature background

Information and communication technology (ICT) has seen significant advancements in recent decades across various fields. Due to its potential to transform the economy and society, extensive research has been conducted to examine its impact on various aspects (Chandio et al., 2023). Early studies concentrated on production, economic growth, and poverty reduction, and ICT was considered part of the production function alongside land, capital, and labor (Chandio et al., 2023). Numerous studies indicate that ICT positively affects employment (Atasoy, 2013), family income, and labor mobility (Hartje and Hübler, 2017). Some scholars suggest that ICT may help reshape rural economies and narrow the global development gap (Ma et al., 2020). Research on ICT has expanded to encompass various topics, including gender gap reduction (Ojo et al., 2013), entrepreneurship promotion (Afutu-Kotey et al., 2017), and financial empowerment. ICT benefits these factors by enhancing the efficiency of information generation, transmission, and access, reducing search and transaction costs, and enabling more efficient production and management systems.

Several factors influencing agricultural productivity have been identified (Issahaku et al., 2018). Over the last two decades, a significant body of literature has emphasized the role of ICT. Lio and Liu (2006) initially demonstrated the role of ICT in enhancing agricultural output in 81 countries between 1995 and 2000. Subsequent research by various scholars supported these findings. Ogutu et al. (2014) showed that widespread ICT use improves production in small-scale agriculture by addressing information asymmetry. Internet connectivity significantly boosted food production in Vietnam (Kaila and Tarp, 2019), reducing poverty in rural areas (Twumasi et al., 2021). Another study in Pakistan found that mobile phone and Internet usage increased wheat growers' income, indicating improved marketing and sales efficiency that enhances crop profitability (Khan et al., 2022). Deng et al. (2019) also reported that Internet use enhances resource efficiency and lessens agricultural waste.

Extensive literature evidence supports the Internet's role in agricultural production, prompting investigations into its causes. These studies highlight increased human capital and information access as key factors. Access to technical agricultural information aids growers in diversifying crops, allocating land and inputs more efficiently (Leng et al., 2020), and expanding their land holdings (Hou et al., 2019), leading to higher productivity. Additionally, addressing challenges like knowledge asymmetry and adverse selection helps farmers make better decisions and exhibit more effective management. Enhancing farmer communication and providing learning opportunities can significantly bolster social capital and information literacy and ultimately influence farmer behavior toward the adoption of more productive agricultural practices. For instance, when farmers have access to Internet-based resources, they tend to exercise greater discernment in using chemical inputs such as fertilizers and pesticides. Additionally, IT platforms have the potential to broaden the social capital of households, fostering an environment conducive to the dissemination and application of production technology (Fu and Zhu, 2023). Similarly, Deng et al. (2022) indicated that Internet use influenced rural growers' perceptions of ecological contamination in China, suggesting that Internet access can be a valuable tool for promoting environmentally friendly agricultural expansion and mitigating environmental issues.

Furthermore, studies have examined the agriculture industry from various perspectives, analyzing the impact of technological advancements on the incomes of the agricultural sector and rural families. For instance, research suggests that using ICT could effectively reduce income inequality in rural areas (Deng et al., 2022). Moreover, Min et al. (2020), utilizing empirical data from 2008 to 2015, concluded that ICT plays a significant role in driving economic expansion and growth. The assumption that IT usage positively influences rural growers' well-being is supported by Ma et al. (2020). Nie et al. (2021) provide support for their conclusions. Existing literature commonly acknowledges the positive impact of technology on the agriculture industry. Technology holds promise for improving the economic feasibility of biochar in conventional agriculture while also fostering contributions to the circular economy (Maroušek et al., 2023). Based on the results, this research investigates the impacts of IT on wheat crop output. While some research has focused on different Pakistani crops, most have examined the long-term consequences of climate change. Research centered on crop production differs from ours in several fundamental ways. The most recent study by Lin et al. (2022) is comparable to ours regarding topic choice. Investigators look at the key elements that will boost agricultural output, but, in contrast to our findings, they place a greater emphasis on cooperative participation.

The findings of the study suggest that cooperative contributions positively impact the overall factor efficiency of small- and medium-sized businesses. Specifically, in Pakistan, a limited number of studies have explored the influence of IT usage on crop yield, particularly among those investigating the impact of ICT on the agricultural industry. The information collected in this regard will aid in understanding how the agricultural sector, facing pressure from both demand and supply due to population growth and climate change, may address this issue.

2.2 Conceptual framework

In the following section, we elaborate on key concepts within the productivity framework to clarify the potential pathways through which IT usage can impact the TE of farms. We begin with a simple representation of the production frontier, which signifies the maximum output attainable at each input level. Productivity is quantified by the ratio of aggregated output over aggregated input (Coelli, 1995). Consequently, farms situated on the frontier are deemed technically efficient, while those below are not, as a greater output can be achieved with the same input level, or inputs can be conserved without compromising the output level. Therefore, achieving elevated TE requires either increasing the output with the current inputs or reducing the inputs without compromising the prevailing output.

Internet technology could act as a factor influencing TE for several reasons. First, IT can assist farmers in making informed decisions and guide them toward adopting suitable farming methods. Crop and vegetable farmers in less developed countries face challenges such as a lack of education and experience, restricted access to inputs, and inferior agricultural extension services. By facilitating direct, fast, and global information and idea exchange between farmers and experts and addressing these issues (Hobbs, 1996; Bozoğlu and Ceyhan, 2007; Aker, 2008; Schmidt and Wagner, 2019; Quintana-García et al., 2021; Kang et al., 2023), ICT enhances the transmission of information. Producers may also gain greater access to advice and instruction from reliable professionals.

Second, IT promotes the availability of agricultural inputs with greater quality or cheaper cost and gives information on products and services (Zhu et al., 2021). Farmers may currently acquire the up-to-date market report and are no longer confined to the few options they had previously for keeping up with factor markets. Third, IT can assist rural families in distributing labor and capital more effectively by connecting them with suppliers and consumers and enabling communication (Zanello and Srinivasan, 2014; Hou et al., 2019). Farmers may identify market trends and quickly modify production methods to account for potential risks and losses when they have immediate access to market and pricing information related to agriculture.

3 Methodology

3.1 Description of the study area

Balochistan, the largest province in southwestern Pakistan, covers a vast area of 347,190 square kilometers. Despite being the least populous province, it constitutes 44% of the country's total land area. The agricultural sector in Balochistan holds significant economic potential (Shami et al., 2016; Abdullah and Ahmed, 2018). Many areas in the province are conducive to agricultural production, but the true potential has not been fully realized due to various challenges. Over 81% of farmers across the province express concerns about issues such as power and water shortages negatively impacting agriculture (Ashraf and Routray, 2013). Provinces serve as the highest administrative units in Pakistan, each with its provincial government. Districts operate as second-level administrative units within a province, while tehsils are sub-district administrative units within a district. Union councils (UCs) represent the smallest rural administrative units within a tehsil.

3.2 Data collection and study variables

3.2.1 Data collection

The current study, conducted from July 2022 to March 2023, focused on the Balochistan province in Pakistan. In total, 600 questionnaires were distributed to wheat farmers using multistage random sampling techniques to collect data. The objective was to ascertain the impact of IT usage on TE in wheat crop production efficiency. The study progressed through seven phases: Pakistan was chosen in the first phase, and Balochistan became the main study area in the second phase. In the third phase, study data were categorized into five districts based on the proportion of agricultural production. The fourth phase involved choosing ten tehsils from the five districts to administer a predetermined questionnaire. In the fifth phase, 20 UCs were nominated from the selected tehsils. The sixth phase randomly monitored 20 villages from these UCs, involving 600 farmers in the seventh phase (see Figures 1, 2).

This study gathered data from wheat farmers using interviews and questionnaires. Recognizing the complexity of the questionnaire supplemented the process with in-depth interviews for a thorough understanding. To enhance reliability, we pre-tested the questionnaire before the main data collection phase. The survey questionnaire encompassed a wide array of information, including the socioeconomic profiles of the farmers, IT usage, and other relevant variables pertinent to the study objectives. Subsequently, the collected data underwent meticulous editing and coding procedures using Stata 14 software. This rigorous process aimed to ensure the accuracy, validity, uniformity, consistency, and completeness of the dataset, thus laying a robust foundation for subsequent analysis and interpretation.

The representative sample size stated above was obtained using a sample size calculation formula developed by Yamane (1973), which is considered best for a homogeneous population. The formula and the number of representative samples obtained using the Equation 1 is given by:

$$n = \frac{N}{1 + N\left(e^2\right)} \rightarrow n = \frac{24{,}100}{1 + 24{,}100\left(0.05\right)^2} \rightarrow \frac{24{,}100}{61.25} = 600 \qquad (1)$$

where n is the required sample size; N = size of the population or total number of rural households living in the study areas; and e = precision level, which is assumed to be 5%, as standard.

3.2.2 Study variables

The variables considered in the current research investigations are displayed in Table 1. The treatment variables for IT use (indicating whether respondents use IT to find information related to crop production) are utilized to categorize farmers into treatment groups of IT users (IT) and the control group of IT non-users (NIT). Output consists of farmers' crop sales income. Input variables refer to factors used in production. Labor measures the costs of household labor and hired labor. Households facing labor shortages may need to hire extra workers for labor-intensive crop cultivation tasks. This study efficiency assessment considers both paid and unpaid labor costs, following FAO (Lys and Cachia, 2016) methodologies. We calculate labor expenses using the formula [number of unpaid laborers * working days * daily wage]. To determine wages, we apply the principle of opportunity cost, considering the potential earnings in alternative paid employment. Recognizing lower rates of off-farm employment among experienced crop cultivators (Poon and Weersink, 2011), the current study utilizes the average regional wage for crop farming as a proxy for opportunity costs. Land denotes the total size of crop production (in hectares).

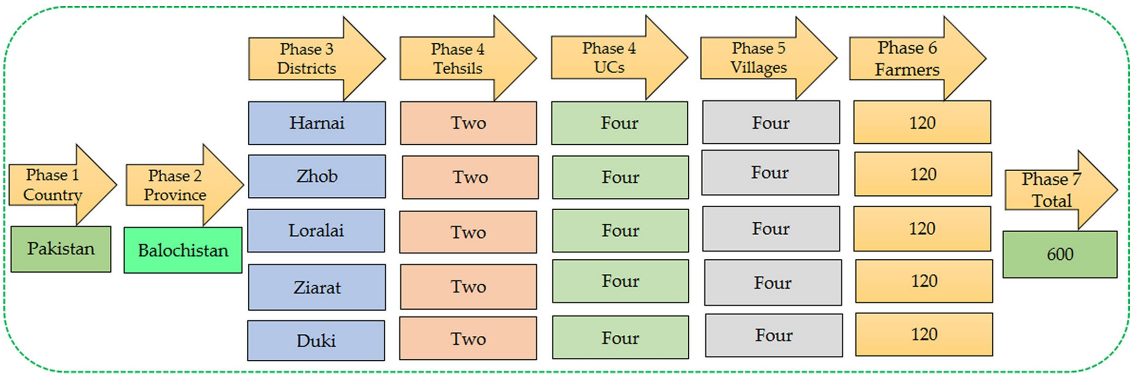

FIGURE 1
Distribution of sample.

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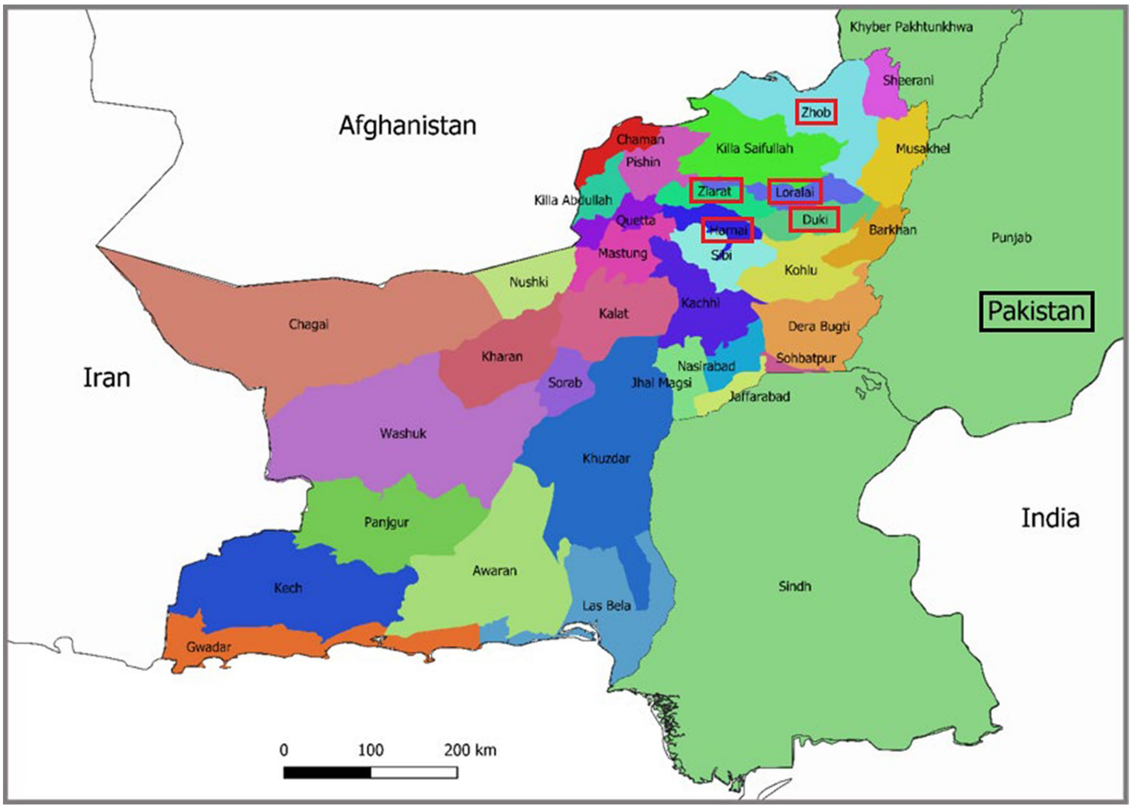

FIGURE 2
Map of Pakistan showing its study districts.

Fertilizer and pesticide expenditures are included. Regarding determinants of IT use, previous studies have identified household characteristics, local conditions, and geographic attributes (Pick et al., 2015; Issahaku et al., 2018; Mwalupaso et al., 2019). The current study used different variables such as the householder's gender, age, education, experience, certificate (professional farmer certificate), family burden ratio (the number of family members without income divided by those with income), market (distance to market), government (distance to government administration), cooperative membership, IT training, information literacy (Appendix 1 for the variable definition), social capital (frequency and quality of social contacts); [Appendix 2: this variable was adapted from Fu and Zhu (2023)], and five locational dummy variables (districts) as relevant covariates.

3.3 Empirical methods

To investigate the impact of IT on TE, we employ a multi-step approach designed to progressively mitigate potential bias arising from both observable and unobservable factors. Initially, we present SF model results on the original (unmatched) sample, recognizing potential selection bias. Subsequently, PSM is utilized to construct a balanced sample of IT users and non-users, addressing bias related to observed characteristics. Then, Greene's (2010) sample selection model is applied to the matched sample to rectify potential bias stemming from unobserved factors. We then compare TE scores of IT users and non-users resulting from different combinations of these correction procedures, with the most reliable outcomes derived from the sample selection SF model on the matched sample. Finally, QTE can be calculated using observed data, effectively correcting for selection bias by comparing quantiles of the outcome distribution among individuals with varying treatment values. This analytical approach facilitates an understanding of whether the influence of IT varies depending on the efficiency level within the agricultural sector.

3.3.1 Stochastic frontier (SF) method: technical estimation

Technical efficiency measures an individual's capacity to maximize outcomes from specified inputs, and its assessment can employ various methodologies, such as the SF method and the data envelopment analysis model. The SF method is considered a parametric approach that incorporates symmetric variables to address statistical noise and one-sided factors to account for inefficiencies, rendering it less susceptible to measuring errors (Førsund et al., 1980; Bauer, 1990; Batiese, 1992; Bitsch, 2005). SF accurately measures efficiency but relies on specific assumptions, making it sensitive to deviations and outliers in data, which can affect its precision. Despite these limitations, SF remains a valuable tool for assessing TE in diverse economic settings. The fundamental structure of Equation 2 is outlined as follows.

$$Y_i = f\left(X_i;\beta\right) * \exp\left(V_i - U_i\right) \quad (2)$$

TABLE 1 Variables and descriptive statistics for IT users and IT non-users.

Variables name	Description of variables	IT users		IT non-users		Diff.
		Mean	SD	Mean	SD	
Treatment variables						
IT usage	1 = if farmers use IT for crop yield information; 0 otherwise	0.53	0.50	0.47	0.50	0.06
Outcome variables						
Output	Wheat sales revenue 2022 (PKR)	15.07	−14.55	11.25	−10.04	3.82***
Input variables						
Labor	Household labor costs (PKR)	6.20	−4.43	6.14	−4.36	0.06
Fertilizer	Fertilizer cost (PKR)	1.85	−1.95	1.80	−1.60	00.5
Pesticide	Pesticide cost (PKR)	0.55	−0.71	0.43	−0.53	0.12***
Farm size	Farm size under wheat cultivation (ha)	4.80	5.55	3.50	4.85	1.30*
Control variables						
Age	Farmer age (years)	48.90	8.93	53.17	8.10	−4.27***
Gender	Gender of respondent	0.99	0.12	0.93	0.20	0.06***
Education	Farmers' education (years)	8.50	2.49	7.21	2.90	1.29***
Experience	Farming experience (years)	22.30	9.93	21.90	11.69	0.40
Certificate	1 = if farmer has official professional certificate; 0 otherwise	0.10	00.28	0.05	0.21	0.05**
Tractor	1 = if farmer has own tractor; 0 otherwise	0.55	0.49	0.44	0.49	0.11***
Cooperative	1 = if farmer membership of cooperative; 0 otherwise	0.10	0.28	0.07	0.21	0.03***
Market	Distance from farmhouse to a local market (km)	3.02	4.01	2.93	2.90	0.09
Ratio	Dependency ratio between usually not in the workforce and usually in the workforce	0.90	0.73	0.69	0.60	0.21***
Government	Distance from family farm to local government (km)	6.10	8.45	4.66	2.90	1.44***
Training	1 = if the farmer receives IT-related training; 0 otherwise	0.10	0.20	0.07	0.18	0.03***
Information literacy	Capacity to obtain and use information (**Appendix 1**)	53.56	4.90	50.80	5.27	3.24***
Social capital	Quality and frequency of social contacts (**Appendix 2**)	41.34	6.88	39.30	5.93	2.04***
IV: certificate	The proportion of certificate holders in the village area	0.04	0.02	0.02	0.03	0.02***
IV: Cooperatives	Are cooperatives in the study area?	0.045	0.39	0.38	0.30	0.15***

*, **, and *** indicate the significance levels (10, 5, and 1%, respectively) for the mean difference (t-test) between users (IT) and non-users of Internet technology (NIT).

where β is the parameters vector to be assessed. Y_i is the production of i^{th} individual. The group of X_i is an independent input variable. $V_i \sim iid\left(0,\sigma_v^2\right)$ signifies omitted variables, function from error, and dimension error term, and $U_i \sim iid\left(0,\sigma_u^2\right)$ represents a non-negative ran variable capturing the inadequacy influence.

In the existing study, we employ a translog "transcendental-logarithmic" SF method as a flexible, Equation 3 functional structure by processes of production that approximate the productivity technology as follows:

$$lnY_i = \beta_0 + \sum_{j=1}^{J}\beta jinX_{il} + \frac{1}{2}\sum_{J=1}^{J}\sum_{m=1}^{M}\beta jmln\left(X_{ij}\right)\ln\left(X_{im}\right) + v_i - u_i \quad (3)$$

TE is referred to as the ratio of the experiential output of SF outcome Equation 4 and could be computed as follows (Jondrow et al., 1982; Batiese, 1992):

$$TE_i = \frac{Y_i}{f\left(X_i;\beta\right) * \exp\left(V_i\right)} = \exp\left(-U_i\right) \quad (4)$$

3.3.2 Propensity score matching (PSM): observed bias correction

The existing investigation aims to determine the average impact of IT on the TE of agricultural families. Simply comparing TE scores between IT utilizers and non-utilizers groups without accounting for variations in the initial situations of the two grower groups cannot accurately replicate the influence of IT. In 1974, Rubin introduced a counterfactual paradigm called the Rubin causal model (RCM) (Rubin, 1974). Cook et al. (2002) define the counterfactual as the likely outcome or condition of events that would occur if a particular factor, such as IT, did not exist. The primary concern is understanding how the TE of crop growers might have changed if they had not utilized IT. Although such a scenario has never been observed, the PSM method, proposed by Rosenbaum and Rubin (1983), is employed to generate a control cluster with the same identified attributes as the treatment cluster, yielding a counterfactual result. Based on the RCM, this study categorizes sample households into a treatment group of Internet technology (IT) users and a control group of non-Internet technology (NIT) users. We utilize *i* to represent the individual grower and D_i to specify whether or not grower *i* uses IT.

In the next stage, probit regression is utilized to evaluate a farmer's propensity score (P-score), described as the conditional probability (z_i), predicting an individual's adoption of IT based on the observed attributes z_i. The covariates the current study chose to match IT users and non-users included households' sex, education, age, experience, certificate, government distance, market distance, household burden rate, cooperative membership, training, social capital, information literacy, and position variables. Moreover, the PSM is assessed as follows in Equation 5:

$$p\left(Z_i\right) \equiv p\left(D_i = 1 \mid Z = Z_i\right) \quad (5)$$

Each IT utilizer is paired with a comparable non-utilizer based on the intended P-score. We explore various matching algorithms to assess the effectiveness of reducing selection bias. This research evaluates the implementation of radius, kernel matching, and nearest neighbor techniques, revealing that all three methods yield similar results regarding bias reduction. The optimal results are achieved through Gaussian kernel matching, showcasing a balanced trade-off between matching quality and sample size.

In Equation 6, we use the standardized bias "S" to assess whether the distribution of pertinent variables is balanced between the treatment and control group following matching. There should not be any substantial variations between the variables once the propensity score has been conditioned. The formula for S is as follows:

$$S = \mid z_{IT} - z_{NIT} \mid / \sqrt{S_{z,\ IT}^2 - S_{z,\ NIT}^2 / 2} \quad (6)$$

where $z_{IT}, z_{NIT}, S_{z,\ IT}^2$, and $S_{z,\ NIT}^2$ denote the mean and variance of the covariate for each group. Usually, the standardized bias should not be greater than 10% (Rosenbaum and Rubin, 1983).

3.3.3 Corrected selection stochastic frontier (SF) model: addressing unobserved bias

The corrected selection SF model aims to mitigate unobserved bias, particularly self-selection bias, by leveraging the PSM technique. The assumption of unconfoundedness underpins PSM, asserting that all factors influencing both acceptance choices and outcome variables are adequately accounted for. Failure to consider the association between unobservable elements impacting outcomes and those influencing the selection method can lead to biased and inconsistent estimators with traditional regression procedures (Greene, 2010; Lai, 2015; Bravo-Ureta et al., 2021; Vrachioli et al., 2021). Consequently, the selection bias stemming from unobservable variables is rectified using the selection-corrected SF model.

The SF method with sample selection comprises three key formulas.

(i) Selection Equation:

The selection equation, denoted as D_i, captures the likelihood of adopting IT to access crop production information. Here, h_i represents a vector of individual factors influencing farmers' choices, y denotes the corresponding coefficients, and e_i represents the normalized error term. The outcome variable D_i is binary, taking a value of 1 if $D_i > 0$ (indicating adoption of IT) and 0 otherwise in Equation 7.

$$D_i = h_{iy} + e_i, \text{with } D_i = \begin{cases} 1, \text{ if } D_i > 0 \\ 0, \text{ otherwise} \end{cases} \quad (7)$$

(ii) Frontier Equation:

The frontier equation calculates the outcome variable Y_i based on the selected production technology set. It accounts for two probable sets of production technologies, represented by vectors $\beta^1 and\ \beta^2$. These technologies are influenced by the variables v_{1i}, u_{1i}, v_{2i}, & u_{2i} v_{1i}. $f\left(X_i;\beta^1\right)$ and $f\left(X_i;\beta^2\right)$ represent the production functions corresponding to the selected technologies. When $D_i = 1$, the outcome is determined by β^1, and when $D_i = 0$, it is determined by β^2. The variables vi, v_{1i}, and v_{2i} represent the symmetric errors associated with the frontier Equation 8.

$$Y_i = \begin{cases} f, \left(X_i; \beta^1 \right) * \exp\left(v_i - u_{1i} \right), if\ D_i = 1 \\ f\left(X_i; \beta^2 \right) * \exp\left(v_{2i} - u_{2i} \right), if\ D_i = 0, \end{cases} \quad (8)$$

(iii) Symmetrical Errors in Corrected Selection SF Model

The equation presented represents the distribution of three symmetrical errors in the corrected selection SF model. These errors denoted as e_i, v_{1i}, and v_{2i} which are crucial in understanding and addressing biases in the model. They are constrained to be uncorrelated with the explanatory variable vectors and are treated as a set of bivariate normal random vectors to compute the likelihood function for Eqs 7 and 8.

The equation is as follows:

$$\begin{pmatrix} e_i \\ v_{1i} \\ v_{2i} \end{pmatrix} \sim \left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_1 \sigma_{v1} & \rho_2 \sigma_{v2} \\ \rho_1 \sigma_{v1} & \sigma_{v1}^2 & \rho_{12} \sigma_{v1} \sigma_{v2} \\ \rho_2 \sigma_{v2} & \rho_{12} \sigma_{v1} \sigma_{v2} & \sigma_{v2}^2 \end{pmatrix} \right) \quad (9)$$

where ρ_1, ρ_2, and ρ_{12} represent correlation coefficients between errors, with ρ_1 and ρ_2 indicating correlations between ei and v_{1i} and v_{2i}, respectively. ρ_{12} signifies the correlation between v_{1i} and v_{2i}. The parameters σ_{v1}^2 and σ_{v2}^2 denote variances of v_{1i} and v_{2i}, reflecting their variability. The covariance σv_{12} and σv_2 illustrates how changes in one error relate to changes in the other, indicating their joint variability (Eq. 9). Understanding these parameters is crucial for accurate modeling and interpretation of error behavior.

A two-step technique is employed to calculate this equation system (Greene, 2010; Lai, 2015). First, the selection equation (Eq. 7) is estimated using the probit model to determine likelihood estimators ρ_1 and ρ_2. Then, using these estimators, the frontier model (Eq. 8) is measured. The latent components v_{1i} or v_{2i} influencing Y_i are connected to unobservable feature e_i that affects the selection method, provided that either ρ_1 or ρ_2 is non-zero. In the absence of non-zero values for ρ_1 or ρ_2, the endogenous self-selection bias arising from unobserved variables can be feasibly neglected.

3.3.4 Quantile treatment effect (QTE)

The equation represents the computation of the QTE. $QTE\tau$ denotes the QTE at a specific quantile level, denoted by τ. However, Q^{τ}_{IT} represents the quantile of the outcome distribution for individuals who received the treatment (IT stands for "With Treatment"). Q^{τ}_{NIT} represents the quantile of the outcome distribution for individuals who did not receive the treatment (NIT stands for "No Treatment") (Eq. 10).

$$QTE\tau = Q\tau IT - Q\tau NIT \quad (10)$$

4 Results and discussion

4.1 Descriptive statistics

Table 1 presents the means and standard deviations for both the combined treatment (IT users) and control (IT non-users) groups. The IT group includes 310 observations, while the NIT group comprises 290. On average, household heads in the IT group are approximately 48 years old, compared to 53 years old in the NIT group. This age difference aligns with research indicating that older individuals are less likely to innovate and utilize the Internet for entertainment (Nguyen et al., 2023). Additionally, Internet users tend to have higher levels of education, possibly due to lower-educated individuals lacking IT skills or facing difficulties with comprehensive texts (Močnik and Širec, 2010). Penard et al. (2015) also demonstrate that younger and better educated individuals are more inclined to the Internet. Regarding gender, approximately 84% of households in the IT group are male-headed, which is approximately 5% higher than in the NIT group. Moreover, farmers affiliated with cooperatives are more likely to use the Internet, possibly because growers find it easier to understand and utilize modern technologies. Furthermore, farmers with greater farming experience are more inclined to adopt IT. These findings collectively emphasize the need for targeted interventions and support mechanisms to promote the widespread adoption of digital tools in agriculture, ultimately fostering enhanced TE and productivity in food production.

4.2 Stochastic frontier model results: unmatched samples

The results of the selection-corrected SF and conventional SF models are presented in Table 2 for both the IT users and non-users groups, utilizing the entire samples. One exhibits statistical significance at the 1 % level, indicating the need to consider the SF method with corrective selection. The conventional SF model is also refuted by the likelihood ratio (LR) tests conducted under both regimes. The first-order constants can be interpreted as outcome elasticities computed at the sample mean by categorizing all variables based on their geometric values before calculation. This interpretation holds because all variables are segmented using their geometric means, as estimated previously (Orea, 2002). IT users display an output elasticity of 0.30, signifying that a 1% increase in fertilizer usage will result in a 0.3% boost in output. For growers utilizing IT, land has the most significant impact on agricultural output, with an output elasticity of 0.48, as per findings from earlier research on vegetable productivity in Sri Lanka (Padmajani et al., 2014). Reduced yields in vegetable cultivation may be attributed to growers using excessive amounts of chemicals to mitigate the risk of crop loss due to illness and pests. In the case of IT non-users, land size has the largest elasticity (0.30), while fertilizer and other inputs contribute approximately 0.26 and 0.23, respectively, to production. Compared to labor, pesticides exhibit a lower production elasticity of 0.1%. Our estimates align with previous investigations (Dong et al., 2019).

The cumulative fractional productivity elasticities for the IT user and non-user groups sum to approximately 1, indicating a consistently sized regression that remains robust to the subsequent results (Shrestha et al., 2016). Standard TE scores for the unmatched are presented in Table 3 for both the conventional and selection-corrected SF approaches. In the conventional SF model, IT users exhibit an average TE score of 0.62, while the non-users group has a score of 0.57. The selection-corrected SF method is anticipated to yield slightly higher TE scores. When measuring unobservable bias, the TE value for the non-users group increases by 0.03, whereas it only increases by 0.01 for IT users. The assessment of unobserved bias reveals that the

TABLE 2 Stochastic frontier model evaluations: unmatched samples.

Variables name	Conventional SF				Selection-corrected SF			
	IT users				IT non-users			
	IT users		IT non-users		IT users		IT non-users	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
Labor	0.538***	0.054	0.071	0.053	0.076	0.054	0.090	0.067
Land	0.280***	0.047	0.363***	0.069	0.488***	0.071	0.305***	0.084
Fertilizer	−0.067*	0.035	0.228***	0.042	0.296***	0.061	0.255***	0.056
Pesticide	0.199***	0.050	0.093**	0.037	−0.069	0.043	0.111**	0.050
Harnai	0.352***	0.119	0.203	0.124	0.350***	0.133	0.278*	0.154
Zhob	0.204*	0.119	0.362***	0.124	0.354***	0.120	0.385***	0.143
Loralai	0.395***	0.120	0.073	0.119	0.242*	0.132	0.159	0.120
Ziarat	0.357***	0.116	0.429***	0.125	0.374***	0.133	0.467***	0.139
Duki	0.268***	0.104	0.013	0.129	0.320**	0.128	0.015	0.143
Constant	0.059	0.048	0.482***	0.107	0.352**	0.153	0.277	0.169
P	0.653***	0.114	0.043	0.045	−0.475***	0.179	0.341	0.227
σ u	0.380***	0.061	0.800***	0.070	0.616***	0.126	0.734	0.120
σ v	−316.947	−312.301	0.325***	0.043	0.416***	0.061	0.420***	0.067
Loglikelihood	−315.850		−310.202		−410.450		−415.637	
N	310		290		310		290	

Significance levels are denoted as ***, **, and * representing 1, 5, and 10%, respectively.

TABLE 3 TE: Unmatched and matched sample.

Types	U (M)	IT non-users		IT users		Diff.
		M	SD	M	SD	
Conventional SF	U (M)	0.575 (0.572)	0.178 (0.182)	0.61 6(0.629)	0.155 (0.144)	0.042*** (0.058***)
Selection-corrected SF	U (M)	0.597 (0.573)	0.150 (0.174)	0.611 (0.623)	0.145 (0.135)	0.033*** (0.070)
ESR	U (M)	0.590 (0.585)	0.182 (0.188)	0.648 (0.568)	0.143 (0.135)	0.058*** (0.073)

Significance levels are denoted as ***, representing 1%. U indicates “Unmatched” and M in parenthesis indicates the matched.

two-group frontier TE values in the selection-corrected SF demonstrate a positive effect of utilizing IT on crop producers’ TE.

4.3 Outcomes of propensity score matching

This study used PSM to decrease the observed bias between IT users and non-users. After calculating *P*-scores and matching, Table 4 shows that the standardized biases of variables greatly decrease after matching, with all absolute values lowered to less than 10%, demonstrating the success of the matching procedure. To verify the trustworthiness of matching, we must analyze the covariate balance between IT and non-IT groups. Table 4 shows how the unmatched sample fails to attain a covariate balance. However, following matching, standardized bias is significantly decreased, with absolute levels. Furthermore, the *t*-test findings fail to reject the null hypothesis that there are no systematic distributional differences between the two groups, confirming the efficacy of the matching procedure.

The Probit model marginal effects and constants in Table 5 elucidate how various factors impact growers’ decisions to use IT for information gathering. Gender exerts a strong and favorable influence on IT use, suggesting that male growers are more inclined to use IT for information gathering than their female counterparts. Conversely, the age of respondents has a substantial and adverse effect on the choice to utilize IT, indicating that older growers are less likely to adopt IT, consistent with the belief that senior farmers may possess lower IT abilities. Despite the general trend, experienced farmers, while more knowledgeable about technology adoption, are also more likely to employ IT for agriculture-related information (Okello et al., 2012; Paustian and Theuvsen, 2017). Family members residing near government facilities or with access to IT-related training in town exhibit a greater motivation to adopt IT, as they tend to be more open to positive initiatives to improve farming and assist producers (Kiiza and Pederson, 2012). Furthermore, participation in agricultural cooperatives, which often promote IT adoption and disseminate information through IT channels, increases the likelihood of IT utilization (Abdul-Rahaman and Abdulai, 2018). As highlighted in earlier research (Aker, 2011), a higher information literacy score is crucial for IT adoption and optimizing available resources. In particular, cooperative membership and certificate ownership can influence TE, potentially biasing the outcome. To address this issue of

TABLE 4 Assessing propensity score matching quality using *t*-test: unmatched (U) and matched (M).

Variables name	Unmatched (matched)	Mean			Reduct	
		Treated	Control	% bias	Bias	*p*-value
Age	U (M)	49.173 (49.350)	54.710 (50.125)	−67.3 (−9.4)	(86)	−9.28*** (−1.23)
Gender	U (M)	0.985 (0.984)	0.951 (0.987)	19.1 (−1.9)	(90.2)	2.66*** (−0.38)
Schooling	U (M)	8.627 (8.578)	7.832 (8.617)	30.4 (−1.5)	(95.1)	4.21*** (−0.22)
Experience	U (M)	21.015 (20.939)	20.333 (21.392)	6.7 (−4.4)	(33.6)	0.92 (−0.61)
Certificate	U (M)	0.079 (0.077)	0.041 (0.061)	16.1 (6.6)	(59)	2.21** (0.84)
Government	U (M)	8.105 (6.712)	5.650 (6.323)	35.2 (5.6)	(84.2)	4.79*** (1.19)
Ratio	U (M)	0.867 (0.853)	0.631 (0.851)	35.9 (0.3)	(99.2)	4.94*** (0.04)
Cooperative	U (M)	0.137 (0.138)	0.057 (0.140)	27.3 (−0.5)	(98.1)	3.75*** (−0.06)
Training	U (M)	0.198 (0.202)	0.127 (0.208)	19.2 (−1.8)	(90.6)	2.64*** (−0.23)
Market	U (M)	2.007 (2.015)	1.923 (2.013)	2.6 (0.1)	(98)	0.36 (0.01)
Social capital	U (M)	42.447 (42.249)	40.417 (42.114)	30.3 (2)	(93.3)	4.18*** (0.27)
Information literacy	U (M)	55.645 (55.390)	51.092 (54.972)	74.9 (6.9)	(90.8)	10.34*** (1.02)
Harnai	U (M)	0.114 (0.119)	0.146 (0.110)	−9.5 (2.9)	(70)	−1.32 (0.41)
Zhob	U (M)	0.216 (0.220)	0.287 (0.200)	−16.5 (4.7)	(71.5)	−2.28** (0.69)
Loralai	U (M)	0.147 (0.154)	0.146 (0.156)	0.2 (−0.5)	(−119.3)	0.03 (−0.07)
Ziarat	U (M)	0.284 (0.263)	0.211 (0.275)	16.9 (−2.8)	(83.6)	2.33** (−0.37)
Duki	U (M)	0.152 (0.157)	0.119 (0.181)	9.6 (−7.1)	(26.5)	1.33 (−0.89)

Significance levels are denoted as ***, **, and * representing 1, 5, and 10%, respectively.

TABLE 5 Probit model marginal effects: matched and un-matched samples.

Variables name	Un-matched				Matched			
	Coeffi.		Marginal effect		Coeffi.		Marginal effect	
	M	S.E.	M	S.E.	M	S.E.	M	S.E.
Age	−0.052***	0.008	−0.015***	0.002	−0.051***	0.008	−0.016***	0.003
Gender	0.687**	0.324	0.201**	0.095	0.673**	0.322	0.207**	0.020
Schooling	−0.006	0.022	0.001	0.006	−0.007	0.022	−0.002	0.008
Experience	0.028***	0.006	0.008***	0.002	0.028***	0.007	0.009***	0.002
Certificate	1.173	0.728	0.348	0.215	1.073	0.774	0.330	0.237
Government	0.051***	0.014	0.015***	0.004	0.049***	0.015	0.015***	0.004
Cooperative	1.087**	0.465	0.323**	0.137	0.971**	0.476	0.299**	0.145
Training	0.339**	0.157	0.101**	0.046	0.322**	0.157	0.098**	0.049
Market	0.013	0.022	0.004	0.006	0.012	0.021	0.005	0.008
Social capital	0.000	0.008	0.000	0.003	0.001	0.009	0.000	0.004
Information literacy	0.070***	0.010	0.021***	0.003	0.071	0.010	0.022***	0.003
Harnai	−0.072	0.237	−0.021	0.070	−0.098	0.234	−0.030	0.072
Zhob	−0.189	0.226	−0.055	0.067	−0.211	0.226	−0.065	0.069
Loralai	−0.073	0.210	−0.021	0.062	−0.077	0.208	−0.024	0.065
Ziarat	0.542**	0.233	0.161**	0.069	0.466**	0.228	0.143**	0.070
Duki	0.128	0.212	0.038	0.063	0.129	0.207	0.040	0.065
Residual cooperative	−0.549**	0.265	−0.163**	0.078	−0.462*	0.270	−0.142*	0.083
Constant	−3.021***	0.785			−3.027***	0.780		
Loglikelihood	−398.515				−399.593			

Significance levels are denoted as ***, **, and * representing 1, 5, and 10%, respectively.

endogeneity, Wooldridge's (2015) two-stage control function model is employed. The coefficients of the generalized residuals for the certificate and cooperative variables, presented in Table 4 as predictions from the initial phase of the control function, indicate that cooperation and certification are indeed endogenous in the IT selection model, with both associated coefficients being statistically significant.

4.4 Stochastic frontier model findings: a matched samples

The parameter estimate findings for the selection-corrected SF and conventional methods for the matched samples are presented in Table 6. The returns to scale and output elasticities of both models do not differ significantly from the unsampled dataset. The results from the selection-corrected SF method indicate that the coefficient of the sample selection bias variable ρ_1 for the IT group is statistically different from zero, consistent with a random sample. The current research, which examines traditional SF for IT users, once again highlights questions related to selection bias. The significant value of ρ_2, indicating a selection bias of IT non-users in SF, is unsupported by any empirical evidence.

According to the findings in Table 3, IT users had average TE values after matching 0.61 in conventional SF and 0.62 in selection-adjusted SF, respectively, compared to 0.55 for IT non-users in both indicators. In the matched sample, our analysis reveals that the TE variance among the IT users' and non-users' groups is larger than in the mismatched group, increasing from 0.03 to 0.07. Consequently, if selection bias induced by both apparent and unobserved factors is disregarded, the mean TE variance between users and non-users may be understated. This result aligns with research conducted in past studies. There are a few factors to consider regarding the TE mean score. First, existing results are consistent with recent studies (Dong et al., 2019; Liang et al., 2019), with an average value of approximately 0.062. However, compared with neighboring countries' crop growers globally, including Vietnam, where growers had an average productivity value of 0.74 (Nguyen et al., 2021, 2023), or India, where the score is 0.77 (Murthy et al., 2009), Pakistani crop growers seem to have inferior TE values. One probable explanation for this disparity is Pakistan's land tenure structure, which may not be as favorable to efficient crop-growing techniques as in other nations. Farmers' capacity to make investments in land resources and increase TE is constrained by land utilization or transfer limitations.

Second, crop growers often have fewer effective scores than other crop producers in Pakistan. For instance, the TE values for fruit growers and crop farms were determined to be 0.83 and 0.9, respectively. One of the causes of this mismatch is the labor-intensive nature of farming operations, which includes activities such as hand weeding, several harvests, and various insect management (Stringer et al., 2009). Additionally, compared to certain other crops, vegetables are more sensitive to environmental conditions such as temperature variations, water availability, and soil health (Tripathi et al., 2016). Furthermore, the progress of farmers' TE may be hampered by a lack of institutional and socioeconomic assistance, including cooperative help and extension services (Hongyun et al., 2020; Zheng et al., 2021). These outcomes imply a requirement for more empirical research as the efficiency impacts can be country or crop-specific. It is also important to keep in mind that the efficiency score amount can be impacted by various productivity evaluation techniques and variable settings (Madau, 2012, 2015).

TABLE 6 Stochastic frontier model findings: matched sample.

Variables names	Conventional SF				Selection-correction SF			
	IT-users		IT-non-users		IT-users		IT-non-users	
	M	S.E.	M	S.E.	M	S.E.	M	S.E.
Labor	0.076	0.049	0.093*	0.053	0.086	0.056	0.115*	0.067
Land	7.412***	0.055	0.371***	0.070	0.469***	0.072	0.329***	0.086
Fertilizer	0.294***	0.048	0.224***	0.042	0.306***	0.062	0.236***	0.055
Pesticide	−0.060*	0.036	0.107***	0.038	−0.063	0.045	0.124**	0.051
Harnai	0.367***	0.127	0.228*	0.122	0.370***	0.135	0.280*	0.153
Zhob	0.368***	0.121	0.355***	0.121	0.367***	0.122	0.368***	0.142
Loralai	0.260**	0.123	0.099	0.117	0.290**	0.136	0.172	0.124
Ziarat	0.410***	0.123	0.427***	0.122	0.387***	0.135	0.442***	0.137
Duki	0.313***	0.121	−0.011	0.126	0.291**	0.131	−0.020	0.138
Constant	0.277**	0.107	0.461***	0.106	0.310*	0.153	0.326**	0.155
ρ					−0.430**	0.190	0.349	0.275
σu	0.618***	0.139	0.820***	0.066	0.581***	0.143	0.821***	0.093
σv	0.397***	0.071	0.304***	0.042	0.430***	0.064	0.359***	0.066
Loglikelihood	−303.130		−303.363		−499.624		−506.804	
N	310		290		310		290	

Significance levels are denoted as ***, **, and *, representing 1, 5, and 10%, respectively.

4.5 Quantile treatment effects of it usage on TE

Understanding the diverse impact of IT on TE is crucial for developing effective agricultural development strategies. To achieve this, we utilize the residualized quantile regression (RQR) model as suggested (Nascimento et al., 2019; Borgen et al., 2021; Korkmaz et al., 2021), providing a flexible method to assess treatment effects across the distribution of results. In the existing study, the RQR model is calculated in two steps. First, to decompose the variation in the treatment variable into two different mechanisms, one that can be described through the examined control variable and one that is orthogonal to a control variable the treatment variable (IT) is adjusted for the control variable using ordinary least squares. The residualized treatment variable is regressed in the second phase using the minimal absolute deviation approach. Finally, QTE can be calculated using observed data while correcting for selection bias by comparing quantiles (τ) of the outcome distribution for individuals with different treatment values of equation QTE.

The outcomes in Table 7 shed light on this investigation. Apart from the 90th quantile, coefficients demonstrate a positive and statistically significant correlation between IT usage and TE, mirroring our prior findings. In particular, there is a marginal uptick in the coefficient for IT treatment from the 10th to the 25th percentile. The most substantial impact manifests at the 25th percentile, showcasing a coefficient of 0.116, suggesting that IT adoption notably enhances farm efficiency at lower distribution quantiles (Zheng et al., 2021). These results imply that embracing IT offers more significant advantages to farms initially operating at lower efficiency levels, as they possess greater potential for enhancement. Conversely, at the 90th percentile, the effect is statistically insignificant, hinting that IT utilization holds less sway over the most efficient farms. This may be attributed to their already optimized production processes, possibly extensively leveraging other information channels.

5 Conclusion and policy implications

5.1 Conclusion

Enhancing the TE of agricultural production remains a pressing concern in Pakistan, reflecting challenges encountered by numerous developing nations. A recent study delves into this issue by drawing insights from a sample of 600 farmers in rural Pakistan, aiming to discern the impact of IT utilization on the TE of crop production. The study employs the SF and PSM models to mitigate biases stemming from observed and unobserved factors. The research findings underscore that, when accounting for these biases, the disparity in TE between IT users and non-users holds both financial and scientific significance. This suggests that integrating IT into wheat crop production can yield positive outcomes for rural areas. Further exploration through the QTE method reveals a nuanced relationship between IT adoption and TE. The most pronounced effects are observed among the least efficient farmhouses, gradually diminishing in significance toward the median and ultimately becoming non-significant for farmhouses achieving maximum yield. This nuanced perspective highlights the varying impacts of IT on TE across different efficiency levels in the context of wheat crop production in rural areas.

TABLE 7 Quantile treatment effects of IT usage on TE.

Level of quantile	Coeff. (S.E.)
10th	0.095*** (0.028)
25th	0.116*** (0.028)
50th	0.080*** (0.020)
75th	0.045*** (0.010)
90th	0.001 (0.010)

5.2 Policy implications

The findings of the study have some important policy implications. First, emphasizing the positive impact of IT usage on crop production efficiency underscores the need for policymakers to invest in rural IT infrastructure and reduce access costs to promote technology adoption in rural areas. Second, tailored policies promoting emerging technologies should consider the diverse characteristics of smallholder farmers, with efforts to enhance access to information through various channels, including traditional agricultural services, farmers' organizations, and digital platforms. Third, policymakers can establish technical training centers to provide advisory services, improve rural education opportunities, and facilitate technology adoption among farmers. Finally, while IT adoption is crucial, policymakers should diversify support mechanisms by collaborating with financial institutions, research bodies, cooperatives, and agricultural enterprises to offer financial, technological, and production support.

5.3 Limitations and future research directions

This study has some limitations. First, its focus only on wheat production may restrict the applicability of findings to other crops due to differences in agricultural extension services. Second, the small sample size limited to one province may compromise the representativeness of the results. Finally, using cross-sectional data prevents exploration of the dynamic impact of IT usage on TE over time. Future research should aim to address the limitations of the study. First, expanding the scope of crops studied will provide a more comprehensive understanding of the impact of IT on agriculture beyond wheat production. Second, increasing the sample size and considering multiple provinces can enhance the representativeness and generalizability of the results. Finally, utilizing longitudinal or panel data analysis techniques can facilitate the exploration of the dynamic effects of IT usage on TE.

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.

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 [patients/participants OR patients/participants legal guardian/next of kin] was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

BA: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. ZZ: Writing – review & editing, Visualization, Supervision, Resources, Project administration, Investigation, Funding acquisition. XJ: Writing – review & editing, Supervision, Project administration, Conceptualization. HG: Writing – review & editing, Visualization, Validation, Project administration, Methodology, Investigation, Funding acquisition. NK: Writing – review & editing, Writing – original draft. YY: Supervision, Writing – review & 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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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2024.1385935/full#supplementary-material

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