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How a Successful Implementation and Sustainable Growth of e-Commerce can be Achieved in Developing Countries; a Pathway Towards Green Economy

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Apart from the goal of the digital world and other benefits of e-commerce, it becomes the need of time during this COVID-19 pandemic. Successful implementation and sustainable growth of e-commerce in developing countries is a challenge. The goal of the digital world without the implementation and sustainable growth of e-commerce in developing countries is incomplete. Based on UTAUT theory, we have developed an integrated model to study the developing countries' consumers' adoption intentions towards e-commerce. We collected a valid useable sample of 796 respondents from a developing country, applied the SEM-ANN two-step hybrid approach to testing the proposed hypothesis, and ranked the antecedents according to their importance. Results revealed that Trust in e-commerce, Perceived risk of using e-commerce, Ease of use in e-commerce, Curiosity about e-commerce, Facilitating Conditions, and Awareness of e-commerce benefits influence the adoption intentions of developing countries' consumers. Sensitivity analysis results revealed that Ease of use in e-commerce platforms and awareness of e-commerce benefits are the two most crucial factors behind the adoption intentions in developing countries. The study's findings help authorities adopt sustainable e-commerce, multinational companies effectively market their goods online, and academics better understand how inhabitants of developing nations perceive e-commerce.

Keywords: e-commerce, developing countries, sustainable growth, adoption intention, curiosity, awareness of e-commerce, SEM-ANN, Pakistan

INTRODUCTION

We are on the verge of a technological revolution due to COVID-19, which has the potential to reshape the way people connect and go about organizing their daily activities. Increased globalization and commercialization are occurring as people and machines become more interconnected through the internet.

The COVID-19 pandemic changed the course of human lives; the term social distancing emerged in human lives to secure healthy lives and avoid infection and spread of COVID-19. Apart from many other benefits of e-commerce, E-commerce is an alternative to traditional means of shopping and a blessing in avoiding the spread of COVID-19. Traditional buying channels require personal interaction, and the chances of COVID-19 spread can be increased. Hence there is essential to implement e-commerce globally to facilitate a common consumer and open new horizons for small and big businesses.

E-commerce has several benefits over traditional shopping channels, such as 1) everything in one place, 2) saving time and money, 3) simplicity and comfort, 4) a wide range of selection and facilities to compare, 5) maintain a healthy lifestyle (COVID-19 context) (Khurana, 2019).

Online shopping is more popular among millennials than among baby boomers. Millennials, defined as those between the ages of 25 and 34, are the largest demographic of online shoppers. 38.4% of US online buyers are under 35 years old. Only 14.4% of internet shoppers in the United States are 65 years old or older (Law, 2021).

The majority of the studies on e-commerce adoption emphasize companies' adoption of e-commerce and facilitate the e-commerce models of B2B (full), B2C (partial), and C2B (partial) and ignore the potential end-user who is an integral part of the successful model of e-commerce. Specifically, C2C (in full capacity), B2C (partial), and C2B (partial), because if end users will not adopt e-commerce, the full goal of a digital word is unachievable. Hence, motivating the end user to adopt e-commerce is the most important factor behind the goal of the digital world. But to motivate end-users to adopt e-commerce, first, we need to learn how various factors influence consumers' intention to adopt e-commerce.

Recent studies focus on the adoption of e-commerce in logistics sector companies (Juliet Orji et al, 2022), economic outcomes of e-commerce adoption (Li et al, 2021), retail adoption of e-commerce (Fuller et al., 2022).

Researchers claim that e-commerce is a rapidly developing market that draws a large number of entrepreneurs; it has a lower survival rate than other industries (Cuellar-Fernández et al, 2021). User agreements for e-commerce are seldom reviewed but are virtually approved by users (Chakraborty et al, 2022). Unfriendly provisions adversely impact customer satisfaction in terms of service (ToS), but the company's survival is increased. Second, companies with a larger market share select more consumer-friendly phrases. Third, the severity of ToS plays a role in the relationship between market share and business performance (Chakraborty et al., 2022). It can create mistrust between consumers and sellers, and end-users may hesitate to adopt e-commerce or quit it.

Researchers also examine the interaction of pandemic response plans with other facilitators of e-commerce adoption in the logistics industry and their influence on business performance. They found facilitating strategies and grouped them into technical-related, pandemic response-related, firm-level-related, and institution-related (Juliet Orji et al., 2022). Still ignored the end-users of e-commerce.

Researchers also revealed that people's demands and values might drive e-commerce adoption; e-compatibility with people's digital abilities and infrastructure is crucial; exposure to dangerous material has been experimentally established as an impediment (Ariansyah et al, 2021). This study is based on the net gain maximization framework/standard utility. They did not study the factors such as social influence, trust factor between seller and buyer, ease of use, or awareness of e-commerce because 72% of their sample were non-adopter of e-commerce (never experienced or had no knowledge about e-commerce). Researchers have also examined the differences between products in people's acceptance of E-commerce. Still, they have overlooked the motivational factors for end-users that lead to the adoption of e-commerce (Liu and Wei, 2003).

Researchers also studied the outcomes of e-commerce use and its impact on family earnings in china but ignored to study the factors that motivate an individual to adopt it. The possible reason might be an established infrastructure of e-commerce in China. They found e-commerce adoption has a considerable impact on family income, with e-commerce adopters earning much more money than non-adopters. While e-commerce adoption has had a big and detrimental influence on wages, it has had little effect on transfers. Using additional data, researchers found that the income consequences of e-commerce adoption vary depending on geographic region and household-level factors (Li et al., 2021). Researchers also found that the success of online merchants is impacted by the deployment of e-commerce capabilities at the appropriate time (Fuller et al., 2022). Lastly, we have explored through a literature review that the effect of gender as a moderator is rarely studied in e-commerce adoption. We believe it should be considered for a sustainable implementation of e-commerce as researchers claim that consumer psyche differs with gender. Furthermore, limitations of previous studies, such as "Individuals' m-commerce activities were black-boxed. Their perspectives may alter" (Ashraf et al., 2021), also motivates us to study the subject.

After a careful investigation of past literature, we have figured out that the researchers have rarely studied the e-commerce adoption factors in developing countries, which have a major portion of the world population. A developing country is one in which the quality of life, industrial development, and economic as well as other aspects of the country's development stays at or below average. Around 6.62 billion people live in 152 nations classified as "developing" by the International Monetary Fund (IMF), 85.22% of the world's population; this is a significant number (Worlddata, 2021).

As e-commerce expands globally, economic giants are looking towards the digital world and bigger markets for their products. So it has become necessary to study how different factors influence developing countries' users to adopt e-commerce. It will help policymakers and global firms to make plans to implement e-commerce globally and make a dream come true of a sustainable digital world. We have proposed the following study questions based on the above-mentioned research gap.

RQ1. How do different e-commerce related factors influence the adoption intentions of e-commerce of end-users in developing countries?

RQ2. What are the most significant predictors (importance-wise) behind the e-commerce adoption in developing countries?

Based on UTAUT, we have proposed an integrated model to answer these research questions. The study is one of the first to study users' intention to adopt e-commerce in developing countries. We have selected Pakistan as our study area (selection detail is in the section research context). We have obtained data from five cities in Pakistan and analyzed the dataset using a hybrid SEM-ANN model to test the proposed hypothesis and ranked the understudy factors based on their normalized importance (SEM = RQ1, ANN = RQ2). Study results revealed that Trust in e-commerce, Curiosity about e-commerce, Ease of use in e-commerce platforms, Facilitating conditions to operate e-commerce and awareness of e-commerce benefits positively influence users' e-commerce adoption intention, whereas perceived risk negatively influences the intention. Social factors behind adopting e-commerce are the only factor that was found insignificant in our study. Sensitivity analysis based on ANN revealed that Ease of use and Awareness of e-commerce benefits are the most influential factors behind the adoption of e-commerce in developing countries. Social influence, perceived risk, and trust factors are the least influential factors behind the adoption intentions of users in developing countries. Study results are beneficial for policymakers to make plans to achieve a sustainable e-commerce implementation, for multinational firms to introduce their products through e-commerce successfully, and for academics to understand the behaviour of developing countries' residents towards e-commerce.

THEORETICAL BACKGROUND

Using the Unified Theory of Acceptance and Use of Technology (UTAUT), we developed an extended model to explain better user behaviour and the influences on their e-commerce adoption intentions. After studying and comparing existing theories, a theory of adoption (UTAUT) was created and empirically tested (Venkatesh et al, 2003) to explain users' behaviour toward technology adoption. Researchers have used UTAUT to evaluate consumers' behaviour to adopt 5G (Mustafa et al., 2022e), psyche to buy smartwatches (Mustafa et al., 2022b), e-commerce system adoption (Hwang, 2010), consumers purchase intentions (Chen et al., 2021; Javed et al, 2021), social e-commerce adoption (Mamonov and Benbunan-Fich, 2017), consumer satisfaction in m-commerce (Kalinić et al, 2021), Predicting m-commerce adoption determinants (Chong, 2013a), wearable payment (Lee et al, 2020), word of mouth and satisfaction in mobile commerce services (Kalinić et al, 2020), mobile financial service (Yan et al, 2021) etc. We have integrated factors such as Trust, Perceived risk, Curiosity, and Awareness of e-commerce benefits to exclusively study the adoption intentions of e-commerce in developing countries (Detail literature is discussed in the following section). We have also studied the moderation effect of gender, which was originally incorporated in UTAUT2, an extended version of UTAUT (Venkatesh et al, 2012). The reason behind not exclusively considering the UTAUT2 is that factors such as hedonic motivation, satisfaction, and habit are concerned about the post-adoption behaviour of technology that leads to its continuous use. After considering the relvant literature and theories we have incorporated new factors in UTAUT and proposed the following model to study e-commerce adoption intention in developing countries (**Figure 1**).

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Social Influence

Individuals' perceptions of others' ideas about the appropriateness of utilizing a specific technology or service or doing an action are examples of subjective norms. An individual's societal influence to accept or reject a technology is social influence (Mustafa and Wen, 2022). Studies have found it a significant predictor; it does not influence an individual's decision in some circumstances. In the acceptability of mobile payments, perceived simplicity of use and perceived utility are essential factors to consider (Işık et al., 2021; Liébana-Cabanillas et al, 2018). In a recent study on 5G adoption, researchers discovered that Social factors play a critical role in 5G adoption (Mustafa and Wen, 2022). Subjective Norms significantly influence customer satisfaction in the context of mobile purchasing, as has been shown (Isik et al., 2021; San-Martín et al., 2016). Researchers have also revealed that consumers' willingness to use m-commerce is strongly influenced by social factors (Yadav et al, 2016) and willingness to adopt the IoT (Yan et al., 2022).

On the contrary, researchers argue that, In mobile commerce, consumer happiness is not favourably influenced by Social Influence (SI) (Kalinić et al., 2021). Studies also found that SI does not significantly affect customers' contentment with mobile commerce and their readiness to promote it to others (Kalinić et al., 2020). The following hypothesis is proposed in light of the fact that customers' success in adopting new technology or m-commerce relies heavily on social influence.

H1. Social influence positively influences the adoption intention of e-commerce in developing countries users.

Trust

Marketing studies in the last several decades have focused on the importance of trust in a corporate relationship and how it affects the longevity of that collaboration. Trustworthiness and security are two of the most common ways in which writers have tackled this issue, despite the fact that it is difficult to define trust (Kalinić et al., 2021). Trust in online purchases is based on the assurance that firms will keep their commitments and responsibilities without manipulating or deceiving the buyer party (Kalinić et al., 2021). Trust may also be described as a behavioural trait as "the predisposition of one party to be vulnerable to the actions of the other party based on the expectation that the other party will perform a particular action important to him or her, regardless of the ability to monitor or control the other"

(Mayer et al, 1995) that is a predisposition to follow a certain course of action. When customers trust service providers, they often expect their satisfaction level to rise, leading to increased loyalty over time (Marinao-Artigas and Barajas-Portas, 2020). Attitude, user pleasure, behavioural intention, and loyalty were shown to be strongly associated with trust in (Sarkar et al, 2020) meta-analysis of the antecedents and outcomes of trust in m-commerce. Recent studies revealed that customer happiness in mobile commerce is positively influenced by their trust in the merchant (Kalinić et al., 2021) and brand trust positively influence purchase intention (Tian et al, 2022). A considerable antecedent of contentment in mobile banking services and apps (Poromatikul et al, 2020), as well as smartphone apps in fashion sales, has also been documented (Aguilar-Illescas et al, 2020; Awan et al., 2022). We believe that people from developing countries have low income and seriously concerned about the online payment, they mighty hesitate to adopt e-commerce because they do not have a habit to pay online. Hence, if consumers have mistrust in e-payment and online purchase they may hesitate to use e-commerce. Based on the importance of e-commerce and other factors involved in online transactions we hapothise the following

H2. Trust of a consumer in e-commerce will positively influence e-commerce adoption in developing countries.

Perceived Risk

A study has revealed that the risk barrier in mobile social commerce is the second most critical factor preventing consumers from using social commerce (Hew et al, 2019). Researchers define risk as to the uncertainty and possible negative effects of a business transaction (Işık, 2013; Kalinic et al, 2019; Ali et al., 2021). Customer perception of risk is defined as consumers' belief that they may be exposed to personal information leaks and money losses while using mobile payments (Kalinic et al., 2019). (Park and John, 2010) identified two primary forms of perceived risk. 1) Consumers' risky behaviour results from internet businesses' efforts to profit from the convenience of online buying. Customers' consideration of online time, a pleasant mood, and a perception of the value of products/services are often factors in product risks. It is hard to regulate the transaction; thus, financial and security risks are associated with online buying. 2) Environmental risk results from emotional and impulsive considerations when participating in purchase activity. A negative correlation between user behaviour and perceived risk has been shown in recent research on mobile payments (Kalinic et al., 2019). Another study in Indonesia figured out that e-commerce platform usage and perceived risk have no relation among generation Z. They claim that generation Z does not think risk factors can negatively affect or be a barrier to e-commerce adoption (Lestari, 2019). Researchers have also related the perceived risk with income level. They argue that Malaysian people are less likely to use e-commerce platforms because they see internet purchasing as riskier (Man Hong et al., 2017). Because online transactions are fraught with danger, it is

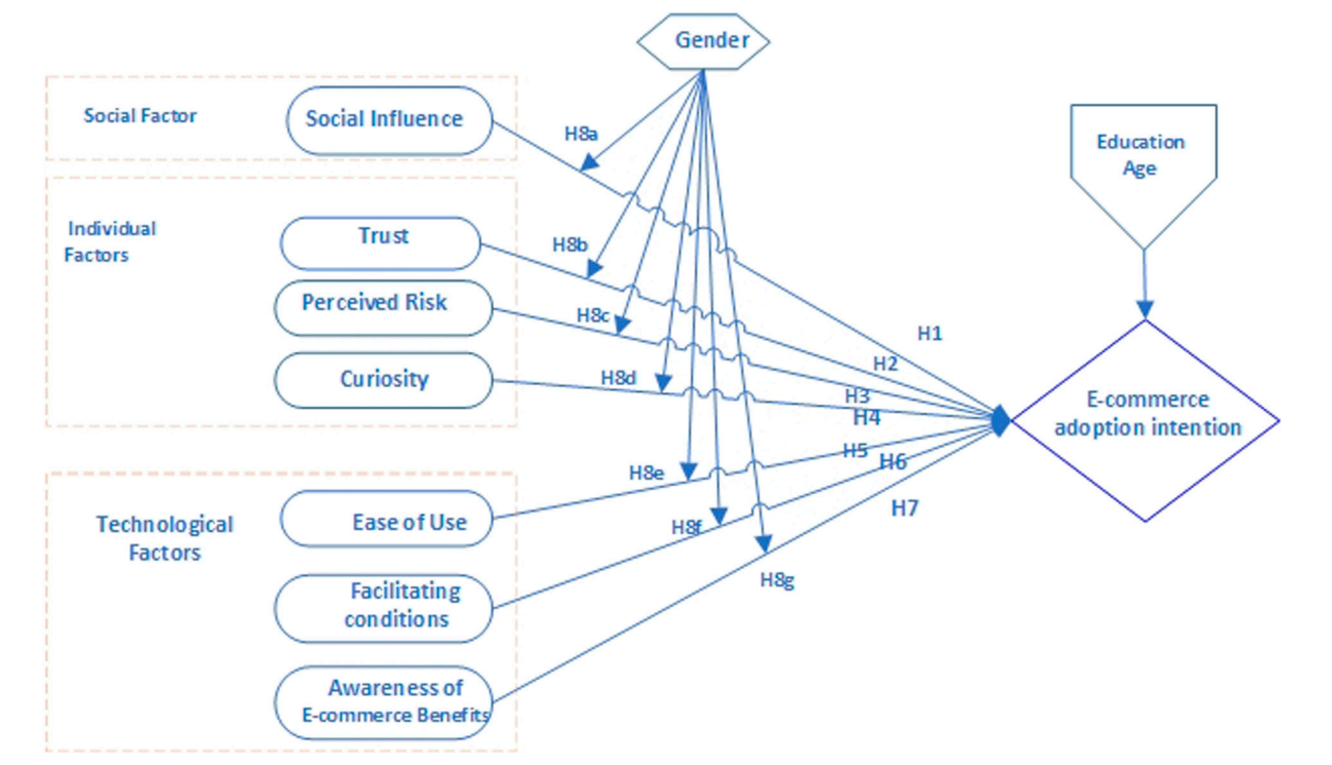

FIGURE 1 | Conceptual framework.

critical that those making decisions take consumer behaviour into account when making a decision (Lestari, 2019). With this dissussion on prior literature we hypothesie that

H3. Perceived risk negatively influences the adoption of e-commerce in developing countries.

Curiosity

Curiosity is defined as "a desire for information in the absence of extrinsic reward" (Pekrun and Linnenbrink-Garcia, 2014). In simple words, it refers to the state of human desire where they search for the unknown and try to find the hidden and unexplored things that fascinate them. According to recent research, curiosity fuels our activities, and our lack of knowledge about these factors contributes significantly to our want to learn more (Dahabiyeh et al, 2021). According to another research, "mystery" also plays a role in people's desire to learn and their feeling of engagement in doing so (Hill et al, 2016). It has also been shown that Curiosity plays an important role in shaping our behavioural intentions (Dahabiyeh et al., 2021). Researchers have also revealed that Curiosity significantly invokes consumers to adopt 5G technology (Mustafa and Wen, 2022). (Hill et al, 2016) claims that actively interested customers are more likely to report greater buy motivation levels than those in a neutral or post-curious mindset. With this discussion and previous findings, we conclude that e-commerce is new to the consumers of developing countries, and Curiosity may play a significant role in its adoption. Hence we hypothesize that

H4. Curiosity about e-commerce will influence consumers from developing countries to adopt e-commerce.

Ease of Use

Ease of use is the degree to which a user feels that e-commerce involves little effort and has no or little complexities. A recent study has explored that as much as technology is easy to use, people tend to adopt it and use it (Mustafa et al, 2021). Even though many people in developing countries are comfortable utilizing mobile devices like smartphones, still e-commerce apps may be a novel concept. That's particularly true now when the number of mobile commerce apps and functionalities is growing fast. New and inexperienced mobile users may find it challenging to utilize features such as making financial transactions. App developers confront making their e-commerce apps as easy to use as possible, yet this may need sacrificing features and functionality to do so (Chong, 2013b). Ease of use has been studied in several studies and found to be a significant factor behind technology adoption such as mobile banking (Malaquias and Hwang, 2019; Sharma et al, 2020), wearable payments (Lee et al., 2020), mobile payment acceptance (Liébana-Cabanillas et al., 2018), mobile commerce services (Kalinić et al., 2020). But some studies have also shown that ease of use has no impact on the m-commerce use of Serbian people (Liébana-Cabanillas et al, 2017) and m-commerce adoption in India (Yadav et al., 2016). We believe that consumers in developing countries may have difficulties adopting e-commerce because of low literacy rates, insecure banking systems, and unawareness of online payment. Their engagement and use of platforms such as e-commerce will highly depend on their ease of use. Hence we hypothesize

H5. Ease of use in e-commerce platforms will influence consumers to adopt it in developing countries.

Facilitating Conditions

Facilitating conditions refer to the technical infrastructure and associated resources/devices to complete online shopping (Venkatesh et al., 2003). Describe facilitating conditions as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system." It is helpful to mould consumers' behaviour to adopt or reject a new technology (Mustafa and Wen, 2022). However, researchers in the past claim that facilitating conditions are the least important for Chinese consumers to adopt m-commerce (Chong, 2013a). Facilitating conditions found significant to adopting mobile banking (Malaquias and Hwang, 2019; Sharma et al., 2020), wearable payments (Lee et al., 2020), and mobile payment (Liébana-Cabanillas et al., 2018; Rehman et al, 2022). Let's particularly talk about the developing countries. There are still many localities where the basic required infrastructure is not well established, and consumers may lack facilitating conditions to carry on e-transactions. Hence we believe that facilitating conditions is one of the basic requirements for e-commerce. It will play a vital role in successfully accepting or rejecting e-commerce in developing countries. We hypothesis that

H6. Facilitating conditions required to use e-commerce will influence consumers' e-commerce adoption in developing countries.

Awareness of e-Commerce Benefits

Awareness refers to the knowledge/recognition of benefits and costs/sacrifices made by an individual who adopts or rejects technology. Researchers have rarely investigated this factor in consumers' e-commerce adoption intention. In the past, researchers found that many people have never heard of online banking, which is an excellent example of e-commerce. This lack of information is a major deterrent to clients using online banking. According to his findings from a survey of 500 Australian clients, most of them were unaware of the advantages of internet banking (Sathye, 1999). This can also be true in the current scenario of developing countries, as e-banking or the use of digital currency is quite a new thing for developing nations. According to research by (Howcroft et al, 2002), the difficulty in implementing e-commerce due to a lack of familiarity with online banking services was confirmed. We believe that if consumers are aware of the benefits that e-commerce can render, their intentions to adopt e-commerce will be much higher than those who know nothing or little about the benefits of e-commerce. Hence awareness of e-commerce benefits can play a vital role in adopting e-commerce, as explored in the 5G adoption (Mustafa and Wen, 2022) and farmers' awareness about climate change (Ahmad et al., 2021; Sohail MT et al., 2022; Sohail et al, 2022). Based on this, we hypothesize that

H7. Awareness of e-commerce benefits will influence users of developing countries to adopt e-commerce.

Gender as Moderator

Male and female perception of certain factors is different from each other. The human psyche towards purchasing is different for both genders. A recent study in Indonesia revealed that men are more likely to make online purchases than women to be young, married, educated, and self-employed. They are also more likely to do so if they can readily get logistical assistance and financial support, and they are better at utilizing technology and have not been exposed to dangerous material (Ariansyah et al., 2021). The use of technology can boost individual productivity, but the outcome depends on how people react to accepting a particular technology (Lestari, 2019; Işık et al, 2020). Female students' interest and desire to assess items and services are stimulated by personal innovation. It is common for women to thoroughly study a product before making a choice, saying that they have no intention of adopting it. If they are unsatisfied with the product, such as e-commerce, they will stop using it (Lestari, 2019). Male students' evaluation of e-commerce platforms is motivated by their conviction in their ability to perform well, a concept known as "self-efficacy." Higher levels of self-efficacy and good feelings about an online shopping platform increase male students' desire to use it. Whereas confidence in completing a task does not drive female students to assess items and services, a greater degree of confidence motivates them to use an e-commerce platform (Lestari, 2019). Researchers also found that the online contribution pattern of male and female users is also different for both genders (Mustafa et al., 2022d; Mustafa and Wen, 2022). Another study revealed that the female group is more influenced by social conventions, whereas the male group is more influenced by pleasure to adopt e-commerce (Hwang, 2010). Another study measures the moderation effect of gender in mobile payment adoption. Results revealed that trust is a strong predictor of customer satisfaction in mobile payments for female consumers but not male consumers (Hossain, 2019). With this discussion, we believe there will be a difference in the influence of e-commerce adoption factors for both genders. Hence we hypothesize that

H8. Gender will moderate the relationship between Social influence (8a), Trust (8b), Perceived risk (8c), Curiosity (8d), Ease of use (8e), Facilitation conditions (8f), and awareness of e-commerce benefits (8g) and Behavioural intention to adopt e-commerce.

METHODOLOGY

Pakistan and e-Commerce/Research Context

Pakistan is one of the developing countries and one of the greatest untapped marketplaces for e-commerce globally; Pakistan has a population of around 220 million and a variety of financial inclusion options. E-commerce in Pakistan is growing at a faster rate than any other sector and has the capacity to become its economy's driving force (RLTSquare, 2020). E-Commerce revenue in Pakistan reached US $6 billion in 2021, making it the 37th biggest market in the world (ecommerceDB, 2022). Pakistan has long sought to turn its economic and commercial operations into a lively and technologically sophisticated country, thanks to the emergence of an IT industry, an expanding population, and an increasing number of smartphones and internet users. It is possible that e-commerce may help a less developed nation, such as Pakistan, go a long way toward socioeconomic and technical advancement in a short time (RLTSquare, 2020). Olx.com.pk, Daraz.pk, PakWheels.com, Zameen.com, Kaymu.pk, and Shophive.com are popular e-commerce platforms in Pakistan. According to the recently published dataset by the Pakistan telecommunication authority (PTA), there are 193 million cellular subscribers, and 113 million has 3g/4g subscription (PTA, 2022). These incredible statistics make Pakistan one of the best places to test our model. Hence we have picked Pakistan as a study location to check the e-commerce adoption intention in the developing countries.

Data Collection

We have used a validated construct from previous studies to collect a dataset. Detailed measurement items of the construct used to capture the sample response are presented in **Supplementary Material** We have slightly changed the wording of measurement items to fit our study best and collect the response accurately. Two academics approved the modified version of the construct to carry on the study. We have conducted a pilot study before finally going into an in-depth survey. For this purpose, thirty household and twenty master's level students were selected to test the finalized questionnaire's readability and response time. Participants of the pilot study and the initial results of the pilot study provided favourable indications to carry on further investigation (Kost and de Rosa, 2018). The pilot study respondents were not included in the final sample to avoid biases.

We have picked an online survey method to collect data and avoid human mismanagement in data handling. We have divided our population into five clusters (Lahore, Karachi, Islamabad/ Rawalpindi, Peshawar, and Faisalabad) based on the literacy level, population condensation, and other facilities required for e-commerce. In these clusters, we have applied a Systematic sampling technique and picked every 10th consumer who visited the supermarkets to shop. This is one of the best ways to collect the response from a heterogeneous population (Sekaran, 2019). We have used google forms to administrate the survey and collection of responses. Respondents were requested to provide their cell numbers to avoid multiple attempts, data cleaning purposes, and to collect follow-up responses. The survey lasted for 2 weeks, between the second and third week of March 2022.

Each respondent has explained the purpose of the study, and their consent was obtained before collecting their information and response. We have used a seven-point Likert scale to measure the response, with "1 representing strongly disagree and 7 as strongly agree." Researchers explained that seven points Likert scale is more precise and easy to administer and is considered better than higher-order alternative scales (Finstad, 2010). A total of 1,200 questionnaires were distributed in 5 clusters, with 240 in each cluster. 796 valid responses were collected, with an overall response rate of 66.33%. The sample size is much more than the threshold level of ten times per construct item to carry on statistical analysis (Hair et al, 2020).

Demographics of Respondents

We have collected the age, gender, education, occupation, residential status, etc., of each respondent so that we can have a better outlook of our study sample and its characteristics. The detail of the demographic characteristics of our total sample (796) is presented in **Table 1**.

Common Method Bias

A common method bias (CMB) may lead to the incorrect relationship among variables, as most data was collected at a specific time and from a single source CMB can be a potential threat to the robustness of findings (Podsakoff et al, 2012). We performed several procedural checks and statistical tests to avoid CMB throughout the design and analysis phases in response to recommendations (Podsakoff et al., 2012). Throughout the design process of our survey building, we paid significant attention. Scales that were not only simple and clear but also recognizable were used. We made it obvious to respondents that there were no right or wrong answers and that they may answer questions as genuinely as possible as part of the data collection process. During the analysis phase, we began with an exploratory factor analysis based on Harman's single-factor test (Podsakoff et al., 2012). Harman's single-factor analysis showed that only 32.01% of the total variation could be explained by a single component, far less than the 50% threshold value. We also tested for CMB by conducting a follow-up survey 3 weeks later after doing the first survey. We choose one proxy item for each component to shorten the second survey's original questionnaire (Ashraf et al., 2021; Işık et al., 2022). Both the first and subsequent items were strongly associated with supportive results. Researchers have also suggested that if the value of VIF or full collinearity is less than 3.3, the data does not pose CMB problems (Kock, 2015) **Table 2**. We can claim that CMB is not a serious threat in our study based on these results.

PLS-SEM

We used PLS-SEM since it is highly recommended for studies that aim to predict and explore the dependent variables in order to explain the utmost amount of variation possible. As a result, the optimum method for making predictions is PLS-SEM (Roldán and Sánchez-Franco, 2012; Zhongjun et al, 2022). It can also concurrently handle the structural (inner) and measurement (outer) models. It is possible to get more precise findings with a small sample size using the PLS-SEM. As a result, PLS-SEM appears to be the best method for this study. Recent studies have shown a surge in interest in using the PLS-SEM approach because of its potential advantages in Management science (Mustafa et al., 2021; Mustafa and Wen, 2022).

As part of the PLS path modelling process, the constructs' measurements are tested in two ways to guarantee that they are accurate and reliable: 1) "The measurement model evaluation shows the reliability and validity of the outer mode," and 2) the structural model assessment identifies the inner model or connection among the latent components (Hair et al., 2020).

Multivariate Assumptions

Mustafa and Wen (2022) state that prior to doing any multivariate tests, it is necessary to assess the multivariate

TABLE 1 | Demographic characteristics.

Characteristics	Range	Frequency	Percentage (%)
Gender	Male	428	53.8
	Female	368	46.2
Age	18–25 Years	196	24.6
	26–35 Years	265	33.3
	36–45 Years	254	31.9
	> 45 Years	81	10.2
Education	High school or less	124	15.6
	Bachelor	307	38.6
	Master	339	42.6
	Doctorate	26	3.3
Occupation	Student	123	15.4
	Govt. employee	289	36.3
	Private company employee	179	22.5
	Businessman/women/other	205	25.8
Residential status	Lahore	170	21.4
	Karachi	169	21.2
	Islamabad/Rawalpindi	162	20.3
	Faisalabad	166	20.8
	Peshawar	129	16.3
E-commerce user	Yes	672	84.4
	No	124	15.6

assumptions of multicollinearity, linearity and homoscedasticity. During the survey's data collection, we assured respondents' privacy and made it clear that there was no right or wrong response. We followed earlier researchers and assessed whether the data distribution was normal using the Kolmogorov-Smirnov (K-S) test; however, it was found not (Mustafa and Wen, 2022).**Supplementary Material** confirms the non-linear and linear interactions between independent and dependent constructs in terms of linearity. Finally, the variance inflation factor (VIF) scores were examined to determine whether the model had collinearity problems. According to (Hair et al., 2020), VIF values less than five indicate that the gathered data does not include any issues about collinearity. According to the findings of this research, all indicators have VIF scores that are less than five in magnitude. Hence, no collinearity problem with the study dataset confirms the model's robustness.

Finally, by following earlier studies, we construct a scatter plot of the regression standardized predicted value, and the residual value shows that the data supports this assumption (Mustafa et al., 2021; Mustafa and Wen, 2022). Supplementary material contains the loadings and cross-loadings of the indicators.

Measurement Model

According to (Hair Jr et al, 2016), a measuring model's reliability is dependent on its discriminant and convergent validity. The instrument's reliability was evaluated using indicator loadings and Cronbach's Alpha (α). Using convergent validity, the constructs' indicators were assessed for their ability to measure the research variables correctly. AVE is used to express the overall variation in the indicators, whereas CR indicates the variables' reliability **Table 2**. Elements with factor loadings of at least 0.6 have been included in the model (Hair Jr et al., 2016) (**Figure 2**). Assessed values of "α" are considerably higher than the threshold value of 0.7, composite reliability (CR) for all variables is above 0.7, and average variance extracted (AVE) is also found to be significantly higher than 0.50, a recommended value by experts (**Table 2**). These results indicate the reliability of the construct used in the study (Hair Jr et al., 2016).

Finally, before moving to the next step, we have applied the Fornell-Larcker criterion to determine the discriminant validity of the instrument. A robust discriminant validity has been established. **Table 3** represents the results of the Fornell-Larcker criterion.

Structural Model Assessment

Structural model evaluation is the next step in the PLS-SEM evaluation process. Evaluating predictive relevance,

TABLE 2 | Reliability and validity analysis.

Constructs	Items	Loadings	T Statistics	VIF	α	CR	AVE
Awareness of e-commerce benefits	AEC1	0.750***	34.040	1.503	0.785	0.861	0.607
	AEC2	0.757***	30.280	1.504			
	AEC3	0.809***	51.980	1.673			
	AEC4	0.799***	58.320	1.550			
Behavioural intention	BI1	0.892***	78.530	2.260	0.882	0.927	0.808
	BI2	0.908***	115.07	2.685			
	BI3	0.898***	83.740	2.532			
Curiosity	CUR1	0.922***	174.60	2.730	0.951	0.965	0.872
	CUR2	0.936***	208.67	2.626			
	CUR3	0.924***	174.09	2.567			
	CUR4	0.954***	273.51	2.458			
Ease of use	EOU1	0.860***	67.930	2.641	0.899	0.926	0.716
	EOU2	0.878***	77.610	2.935			
	EOU3	0.864***	64.220	2.808			
	EOU4	0.896***	113.41	2.187			
	EOU5	0.721***	33.250	1.608			
Facilitating condition	FC1	0.784***	37.300	2.093	0.781	0.857	0.601
	FC2	0.730***	27.280	1.927			
	FC3	0.755***	30.330	1.485			
	FC4	0.826***	65.870	1.665			
Perceived risk	PR1	0.834***	46.370	1.795	0.842	0.904	0.759
	PR2	0.881***	64.030	2.195			
	PR3	0.899***	82.530	2.143			
Social influence	SI1	0.895***	119.79	2.980	0.928	0.949	0.823
	SI2	0.918***	135.79	2.638			
	SI3	0.916***	156.84	2.418			
	SI4	0.899***	116.84	2.301			
Trust	TR1	0.870***	45.500	2.356	0.863	0.906	0.707
	TR2	0.875***	41.430	2.519			
	TR3	0.828***	23.570	2.293			
	TR4	0.787***	21.930	1.832			

*Notes: α >0.7; CR > 0.7; AVE > 0.5; VIF < 5. ***Significant at p < 0.001.*

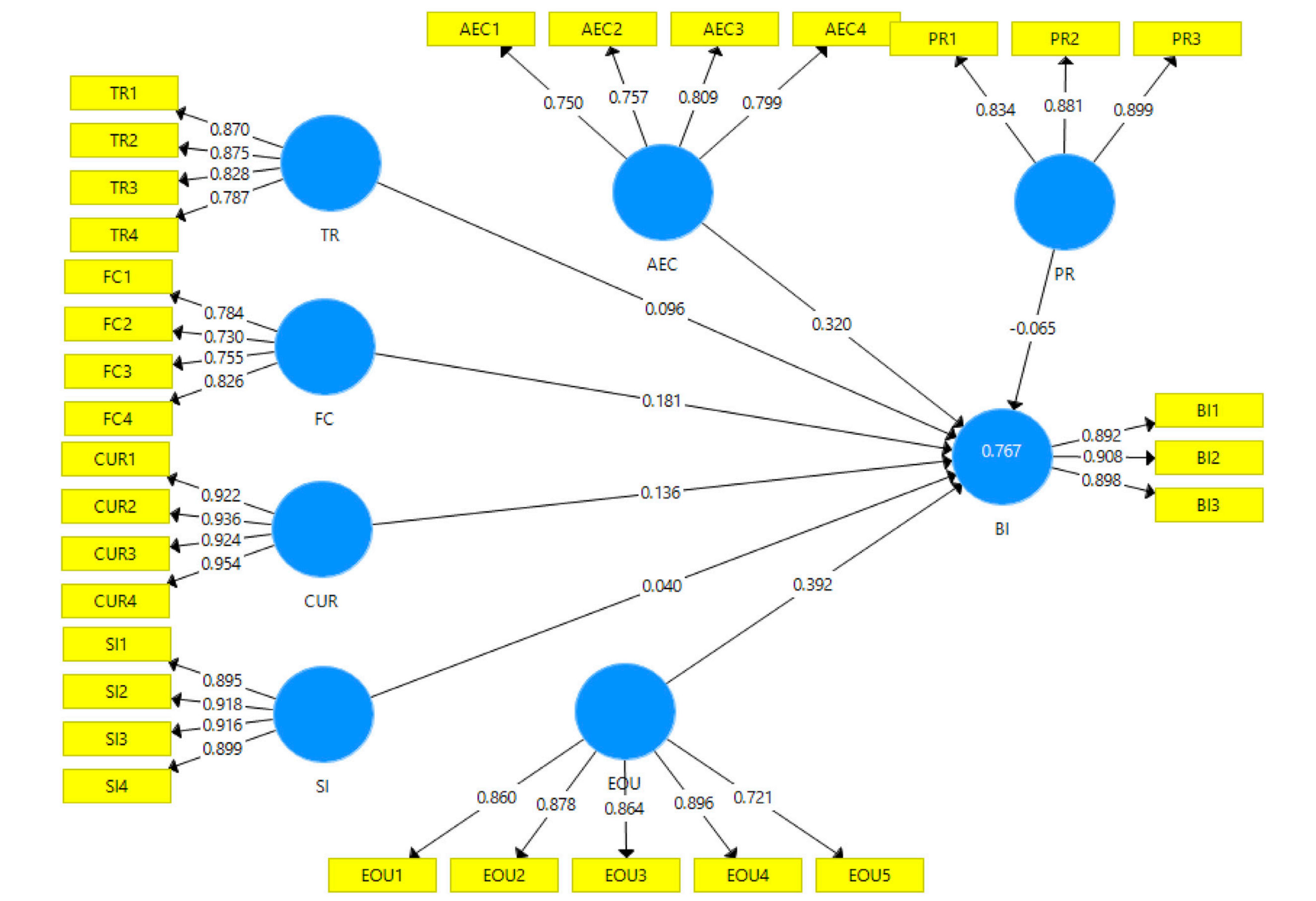

FIGURE 2 | Measurement model.

TABLE 3 | Discriminant validity (Fornell-Larcker Criterion).

	Mean	Std.dev	AEC	BI	CUR	EOU	FC	PR	SI	TR
AEC	4.63	1.4	0.779							
BI	4.94	1.43	0.725	0.899						
CUR	5.15	1.41	0.462	0.597	0.934					
EOU	4.87	1.33	0.649	0.817	0.609	0.846				
FC	4.52	1.33	0.559	0.717	0.451	0.757	0.775			
PR	4.91	1.36	0.436	0.56	0.753	0.645	0.496	0.871		
SI	5.31	1.21	0.357	0.51	0.692	0.525	0.451	0.627	0.907	
TR	4.31	0.94	0.011	0.206	0.136	0.186	0.128	0.152	0.147	0.841

Note: EOU, ease of use; PR, Perceived risk; TR, Trust; CUR, Curiosity; SI, Social Influence; AEC, Awareness of e-commerce benefits; FC, Facilitating conditions.

multicollinearity, the empirical significance of path coefficients and confidence level are all part of evaluating the structural path model (Hair et al., 2020). The outcomes of this research were analyzed and interpreted in accordance with a set of basic guidelines (Hair Jr et al., 2016). The R^2 value of the first model (**Table 4**) for direct effect analysis on e-commerce adoption intention is 0.76 (Q^2 = 0.61), whereas the same for Model 2 (**Table 5**), examining the moderation effect of gender, is 0.88 (Q^2 = 0.607). It indicates that 76% and 88% variance is explained in both the models by implied constructs, respectively. Q^2 score greater than 0.01 means that the model has a high degree of predictive accuracy (Mustafa and Wen, 2022).

To examine the proposed hypothesis, we have run two models. Model 1 (**Figure 3**) assesses the direct effect proposed in our model (H1-H7), and Model 2 examines the moderation effect of gender (H8). We run a bootstrapping of resampling 5,000 for each model. Results of Model 1 indicate that AEC ($\beta = 0.321$; $p < 0.001$), CUR ($\beta = 0.137$; $p < 0.001$), EOU ($\beta = 0.392$; $p < 0.001$), FC ($\beta = 0.181$; $p < 0.001$), TR ($\beta = 0.096$; $p < 0.001$) positively influence e-commerce adoption intentions, whereas PR

TABLE 4 | Model 1 (Direct path analysis).

	Beta	Std. Dev	T-Value
Statistical paths			
AEC—> BI	0.321***	0.031	10.442
CUR—> BI	0.137***	0.029	4.69
EOU—> BI	0.392***	0.04	9.884
FC—> BI	0.181***	0.033	5.481
PR—> BI	−0.065***	0.027	2.447
SI—> BI	0.04^{NS}	0.026	1.551
TR—> BI	0.096***	0.019	5.035
Control variables			
Age- > UB	−0.011^{NS}	0.051	0.341
Education- > UB	0.051^{NS}	0.024	0.425
R^2	0.767		
Adjusted R^2	0.765		
Q^2	0.61		
NFI	0.98		
SRMR	0.055		

****Significant at p < 0.001. **Significant at p < 0.05, NS: Not Supported.*

($\beta = -0.065$; $p < 0.015$) negatively influence (**Table 4**). Social influence is the only predictor that does not affect users' e-commerce adoption intentions. It confirms the H2-H9, but H1 is not supported.

Moderating Effect Analysis

In the second model, we have added the interaction terms and checked the moderation effect of gender on direct relationships. The second model's direct effect results hold out and serve as the robustness of model 1 results. Results in **Table 5** indicate that gender positively moderates the relationship between AEC, EOU, TR, and BI, but it negatively moderates the relationship between PR and BI. These findings supports the H8 (b, c, g, and e) but rule out H8 (a, d, and f).

The control variable of education level and age in both models was insignificant.

Artificial Neural Networks Analysis

We have carried out a two-step analysis in this study to rank the antecedents according to their normalized importance and confirm our results' robustness. Researchers claim that ANN has the upper hand over other variance-based techniques such as SEM, Multiple Linear Regression, Multiple Discriminant Analysis, and Binary Logistics Regression in prediction because of its deep learning and predictive accuracy (Kalinić et al., 2021; Mustafa et al., 2021). Multivariate assumptions like linearity and normality are not required in ANN. Furthermore, no particular data type is required, and it may be expanded to new datasets without disrupting its balance; it can also address the challenges originating from insufficient data (Kalinić et al., 2021; Mustafa et al., 2021), and it is robust for noise and outliers (Kalinić et al., 2021; Mustafa et al., 2021). Researchers suggest that when the dataset has a non-linear relationship between endogenous and exogenous variables and data is not normally distributed, it is better to carry on two-step SEM-ANN modelling for robust results (Kalinić et al., 2021; Mustafa et al., 2021).

Complex interactions between inputs and outputs may be modelled using ANNs, a frequently used artificial intelligence technology. ANNs are intelligent, resilient, and particularly efficient at modelling these relationships (Kalinić et al., 2021; Mustafa et al., 2022a). Numerous ANN models can be broadly divided into four categories, i.e., multilayer perceptron networks, feedforward neural networks, recurrent networks, and radial basis function networks. A multilayer perceptron (MLP) is a popular choice for technology adoption studies because of its many benefits (Kalinić et al., 2021).

1. The robustness of MLP neural networks in the face of imbalanced datasets is shown.
2. It can change weight coefficients and build an input-output mapping to learn.
3. Non-linear connections may be modelled with MLP neural networks since it is also non-linear.
4. Without the user's involvement, MLP is able to adapt to any situation.

In light of this aspect, we decided to use a feedforward back-propagation multilayer perceptron as a foundation ANN model for the investigation. We have adopted sigmoid as an activation function; two hidden layers and a number of hidden neurons were allowed to be selected by software following earlier research automatically (**Figure 4**). We have used 90% of the data for training and 10% for testing to obtain comprehensive results (Kalinić et al., 2021; Mustafa et al., 2021). 10-fold cross-validation process has been used to prevent over-fitting concerns.

Root means square error (RMSE) values predict the predictive power of ANN; in this study, these values are marginal and far below the threshold level of 1. It means our model has high

TABLE 5 | Model 2 (Moderation analysis).

	Beta	Std. Dev	T-Value
Statistical paths			
AEC—> BI	0.316***	0.029	10.755
CUR—> BI	0.159***	0.032	5.014
EOU—> BI	0.392***	0.04	9.682
FC—> BI	0.179***	0.032	5.538
PR—> BI	−0.071***	0.028	2.555
SI—> BI	0.024^{NS}	0.026	0.908
TR—> BI	0.088***	0.019	4.655
AEC * GEN	0.024***	0.037	2.501
EOU * GEN	0.005**	0.038	1.961
FC * GEN	−0.032^{NS}	0.038	0.845
PR * GEN	−0.058**	0.053	1.999
SI * GEN	0.045^{NS}	0.03	1.494
TR * GEN	0.013***	0.03	3.449
CUR * GEN	−0.048^{NS}	0.035	1.387
Control Variables			
Age	−0.006^{NS}	0.047	0.334
Education	0.007^{NS}	0.034	0.427
R^2		0.889	
Adjusted R^2		0.863	
Q^2		0.607	
NFI		0.96	
SRMR		0.065	

****Significant at* p *< 0.001. **Significant at* p *< 0.05, NS: Not Supported.*

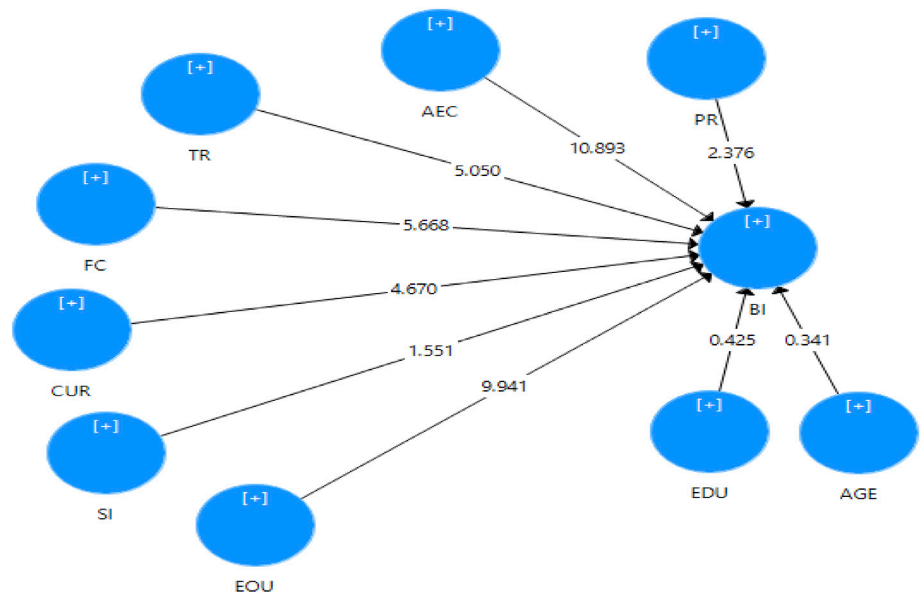

FIGURE 3 | Path model (M1).

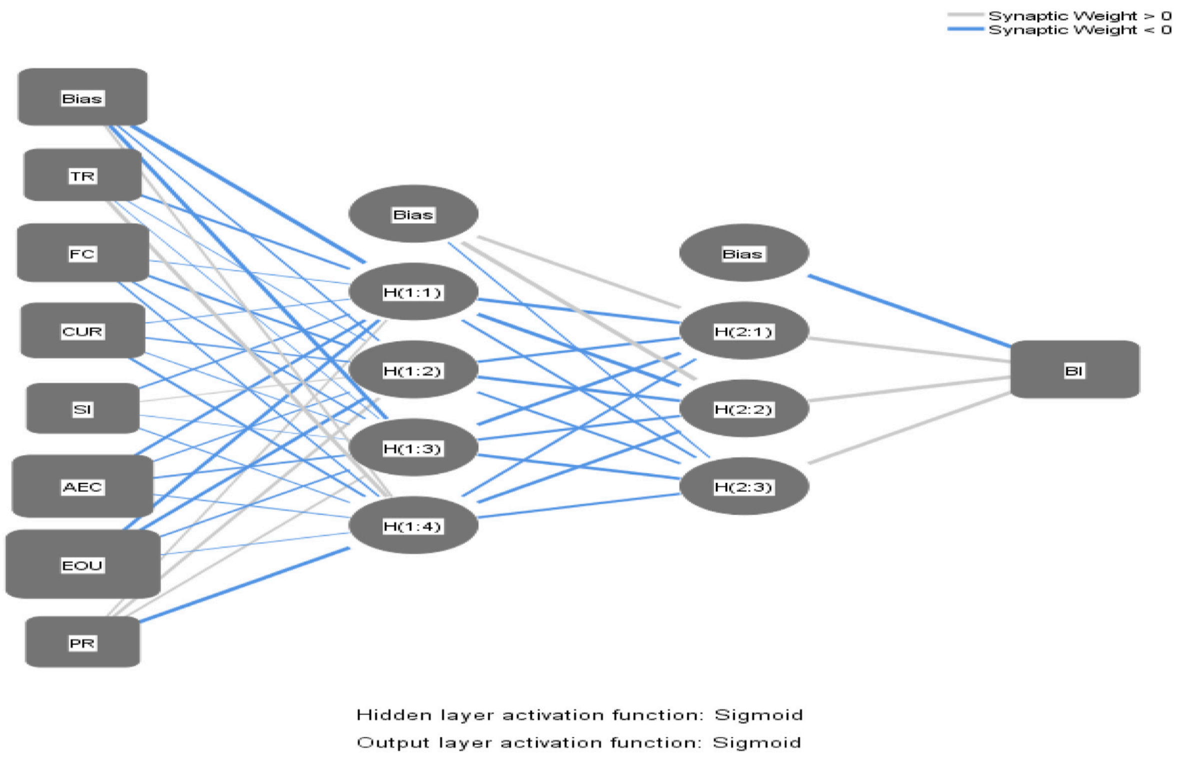

FIGURE 4 | ANN model for BI.

predictive power and is accurate in prediction (Kalinić et al., 2021; Mustafa et al., 2021). Furthermore, to assess the efficacy of the ANN models, we calculated a goodness-of-fit coefficient equivalent to the R^2 in the regression models based on a given approach (**Figure 5**) (Kalinić et al., 2021; Mustafa et al., 2022c). **Table 6** shows the accuracy of the ANN model's predictions.

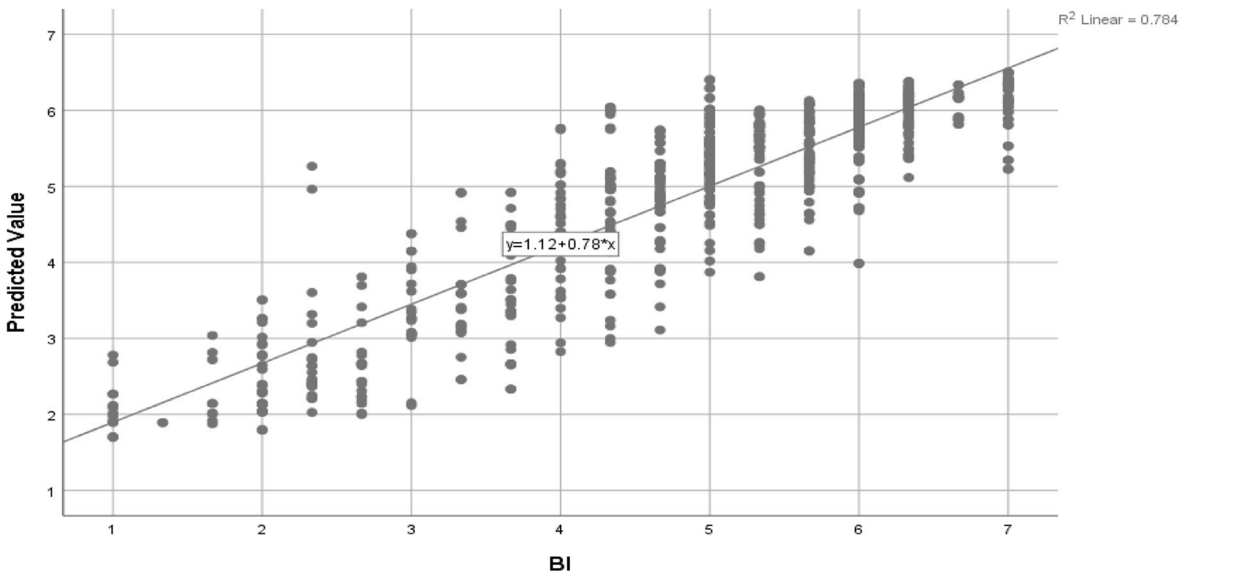

FIGURE 5 | Regression standard residuals.

Sensitivity Analysis

Finally, a sensitivity analysis was conducted using the ANN model, and the results are shown in **Table 7**. The hidden layer of the neural model's non-zero synaptic weights verified the relevance of the inputs. The root means square error (RMSE) results for the training and testing sets are shown for all 10 runs (**Table 6**). The model output varies significantly with changes in each input's value, which is used to calculate its "relative importance." With the help of these results, we have calculated the normalized importance of each variable by calculating the ratio with respect to the highest average value. Sensitivity analysis results are presented in **Table 7**.

TABLE 6 | RMSE values for training and testing.

Training			Testing			Total sample
N	SSE	RMSE	N	SSE	RMSE	
719	4.819	0.082	77	0.379	0.070	796
708	4.826	0.083	88	0.651	0.086	796
697	4.295	0.079	99	0.781	0.089	796
712	5.600	0.089	84	0.612	0.085	796
714	4.513	0.080	82	0.370	0.067	796
714	4.855	0.083	82	0.576	0.084	796
713	4.828	0.082	83	0.618	0.087	796
713	4.869	0.083	83	0.494	0.077	796
709	4.375	0.079	87	0.446	0.072	796
720	5.284	0.086	76	0.537	0.084	796
Mean	4.826	0.082	Mean	0.546	0.080	
Std Dev	0.393	0.003	Std Dev	0.128	0.008	

1. R^2 = 1-RMSE/S^2, where S^2 is the variance of the test data's desired output.
2. N, number of samples; RMSE, root mean square of errors.
3. Ease of use; perceived risk; trust; curiosity; social influence; awareness of e-commerce benefits,; facilitating conditions serve as the input neurons.
4. Behavioural intention served as the output neuron.

Ease of use influences e-commerce adoption, followed by an awareness of e-commerce benefits, facilitation conditions, and Curiosity. Trust, perceived risk and social influence are the least influential factors behind e-commerce adoption intentions.

DISCUSSION

This study aims to explore the potentially influential factors behind e-commerce adoption in developing countries so that a sustainable e-commerce implementation goal can be achieved and a dream of the digital world come true. For this reason, based on UTAUT, we have proposed an integrated model and selected a developing country to test our proposed model. We have used a dual-stage SEM-ANN model to test the hypothesis and rank the understudy factors according to their normalized importance.

H1 to H7 unveils a direct effect of variables, while H8 presents the moderating effect of gender on e-commerce adoption (RQ1). We have observed that social influence (H1) does not affect the developing countries' consumers to adopt e-commerce, and they look for other reasons to consider e-commerce platforms. A possible reason behind this can be that e-commerce is new, and people have a habit of using traditional means of shopping; furthermore, the courier/delivery infrastructure is not well established, so people are not using it frequently and less talk about the use of e-commerce to shop when the people do not publicly consider about e-commerce it is hard to influence by society. Our findings are consistent with the previous studies (Kalinić et al., 2021) but contradict (Kao and André L'Huillier, 2022). Trust (H2) positively influence consumers toward e-commerce adoption. Trust evolve over time. Consumers interact with the sellers and value the after-sale services, which eventually build trust in the system, seller, and consumer.

TABLE 7 | Sensititvity analysis.

Neural network	EOU	AEC	FC	CUR	TR	PR	SI
NN-1	1.000	0.730	0.549	0.406	0.273	0.209	0.182
NN-2	1.000	0.571	0.372	0.434	0.211	0.188	0.111
NN-3	1.000	0.828	0.762	0.609	0.255	0.180	0.049
NN-4	0.805	1.000	0.412	0.735	0.348	0.174	0.073
NN-5	1.000	0.647	0.405	0.352	0.279	0.211	0.092
NN-6	1.000	0.653	0.388	0.376	0.213	0.257	0.159
NN-7	1.000	0.694	0.448	0.495	0.284	0.261	0.220
NN-8	1.000	0.777	0.460	0.469	0.309	0.107	0.065
NN-9	1.000	0.685	0.454	0.344	0.347	0.188	0.157
NN-10	1.000	0.969	0.626	0.298	0.223	0.164	0.183
Average importance	0.980	0.756	0.488	0.452	0.274	0.194	0.129
Normalized importance	100%	77.0%	49.7%	46.0%	27.9%	19.7%	13.1%

Note: EOU, ease of use; PR, perceived risk; TR, trust; CUR, curiosity; SI, social influence; AEC, awareness of e-commerce benefits; FC, facilitating conditions.

Consumers in developing countries value the relationship between seller and buyer; hence if online businesses successfully win the trust of developing countries' consumers, it is easy to influence them to use e-commerce platforms. As researchers have explored that in developing countries, consumers have low income, and they are much concerned about losing their money in online transactions (Man Hong et al., 2017), so if consumers have trust in e-commerce, they will use it; otherwise, they will stop using it. Our findings are consistent with (Sarkar et al., 2020), who conducted a meta-analysis on mobile commerce. Perceived risk (H3) negatively affects the adoption intention in developing countries. Consumers in developing countries are risk-averse and prefer a clean transaction and fair business when money is involved. A risk factor in e-commerce is considered one of the significant barriers. Our findings align with (Kalinic et al., 2019) but contradict (Lestari, 2019), who claim risk factor does not affect gen-z users. Curiosity (H4) also positively influences e-commerce adoption. Consumers in developing countries found curious about e-commerce and its operations. Our findings revealed that Curiosity about e-commerce could lead to the test use of e-commerce; after this, if consumers have a good experience, they may use it again and, over time, become permanent users of e-commerce. We suggest e-commerce platforms and online sellers pay exclusive attention to trust-building with consumers so that they rely on it and be permanent users. Our findings are consistent (Hill et al., 2016; Mustafa and Wen, 2022). Ease of use (H5) put a positive insight into e-commerce adoption. People use technologies that are easy to use and easy to handle. Our findings suggest e-commerce app developers make it user friendly so new users easily cope with it and feel convenient using e-commerce applications. Our findings are consistent with (Kalinić et al., 2020; Mustafa and Wen, 2022) but contradict (Yadav et al., 2016; Liébana-Cabanillas et al., 2017). Facilitating conditions (H6) also positively influence user intention toward e-commerce adoption. Our findings suggest developing countries need to develop a good infrastructure to support e-commerce. Provide internet facilities and e-banking or other digital modes of payments; they also need to encourage people to use digital payments and safeguard their concerns. It contradicts the earlier research findings in china (Chong, 2013a) and supports (Sharma et al., 2020) findings in Fiji. Lastly, awareness of e-commerce benefits (H7) is positively associated with consumers' adoption intentions in developing countries. Consumers who are aware of the e-commerce benefits are more inclined to use e-commerce than those who have less knowledge. Our study findings suggest informing general consumers about e-commerce use benefits and motivating them to start using e-commerce platforms.

Gender's moderating effect (H8) is also established in four relationships, i.e., gender moderates the effect of trust (H8b), perceived risk (H8c), ease of use (H8e), and awareness of e-commerce benefits (H8g) on e-commerce adoption intentions in developing countries. Findings revealed that females' perception of the trust, perceived risk, ease of use, and awareness of e-commerce strongly moderate the e-commerce adoption intention in developing countries. It explains the adoption psyche of females that they value these factors more than their opposite gender. At the same time, social influence (H8a), Curiosity (H8d), and facilitating conditions (H8f) are not significantly moderated by gender in our study. Male was found to be less influential compared to females in the scenarios mentioned above. These findings contradict (Ariansyah et al., 2021), where males are more influential toward e-commerce adoption or (Lestari, 2019), who said males are more influential by self-efficacy in e-commerce adoption and support (Hossain, 2019) who claim that females moderates the relationship between trust and m-payment or (Lestari, 2019) who argue that females do more through comparison of product and technologies before adopting. Findings also contradict earlier studies when authors claim that females are more socially influenced in technology adoption and males look for enjoyment in e-commerce adoption (Hwang, 2010).

Finally, to answer RQ2, we used ANN. We ranked the predictors according to their normalized importance. The study revealed that ease of use with normalized importance of 100% is the most influential factor behind adoption that straight contradicts the earlier findings (Yadav et al., 2016), followed by an awareness of e-commerce benefits newly integrated variables in the study of e-commerce adoption intentions with normalized importance of 77%. These are followed by facilitating conditions (49.7%) and Curiosity (46%). Whereas trust (27.9%), perceived risk (19.7%), and social influence (13.1%) are found to be the least influential for developing countries' consumers. We suggest e-commerce platform developers and service providers keep these factors in mind when implementing e-commerce in developing countries to achieve sustainable growth in the e-commerce business.

Theoretical Implications

Our study findings render some valuable implications in the available literature on e-commerce, especially in the context of developing countries. Firstly our findings improve the understanding of e-commerce adopters in developing countries and add a valuable contribution to the findings of prior studies (Hwang, 2010; Yadav et al., 2016; Liébana-Cabanillas et al., 2017; Mamonov and Benbunan-Fich, 2017; Lestari, 2019; Lin et al, 2019; Kalinić et al., 2020; Ashraf et al., 2021; Cuellar-Fernández et al., 2021) that was conducted in different countries and measure different variables.

Secondly, we have integrated Curiosity and Awareness of e-commerce benefits as antecedents of e-commerce adoption and empirically tested them in the proposed model of e-commerce adoption that can be used in future studies as a base model.

Thirdly, we have added the moderation effect of gender in the available literature on e-commerce adoption so that a better understanding of gender differences can be attained, which will eventually be helpful in the sustainable growth of e-commerce.

Fourthly, we have ranked e-commerce adoption factors in developing countries using sensitivity analysis and figured out that awareness of e-commerce benefits is the second most important predictor behind e-commerce adoption in developing countries. Furthermore, we also suggest using ANN analysis to understand human psychological related factors better as it can dig down deep into the data and provide a better understanding of the phenomenon.

Lastly, we have provided a new insight to UTAUT by adding new variables to understand technology adoption behaviour. We have empirically proved that technology adoption models must add curiosity and awareness factors to assess human behaviour towards its adoption and use.

Practical Implications

This study's results present immense practical implications for managers of e-commerce sites, policymakers, and multinational organizations. Based on the study findings, we have also presented some valuable suggestions to attain a sustainable implementation and growth of e-commerce in developing countries.

Starting with customer Trust building on e-commerce and perceived risk, as e-commerce involves online money transactions. In developing countries, the income level is low, and people are not advanced in using e-payments. They are also afraid of online scammers. We suggest developing countries' Governments pass strict rules against cyber crimes and secure e-payment and online transactions. They can also initiate an insurance system for online transactions to minimize the risk factor. Governments and policymakers need to ensure that people feel secure in spending online. Once the Trust in e-payments is established, consumers will frequently use e-commerce platforms because they will not fear online scams or money loss (Chakraborty et al., 2022).

In addition, e-commerce implementation and sustainable growth require a good infrastructure of facilitating conditions. Generally speaking, internet, courier service to make timely delivery, strong and secure banking system, particularly e-banking system or other moods of online payments needs to improve. This will add value to the use of e-commerce sites as we have found that ease of use and facilitating conditions influence the consumers' intentions to adopt e-commerce.

We also suggest e-commerce application/web developers introduce interfaces that are more user-friendly. Complex interface and lengthy buying process may lead to less use of e-commerce platforms (Fuller et al., 2022).

Lastly, we recommend conducting workshops and e-commerce awareness seminars to let people know more about e-commerce because we have figured out that Curiosity and Awareness of e-commerce positively influence adoption intention.

Financial institutions need to educate people about the e-payment methods and their use and educate people about the security of digital payments. We also recommend that advertising agencies produce commercials that can motivate a common person to use e-commerce and educate them about the benefits of e-commerce.

Limitations

Apart from several theoretical and practical implications, this study has some limitations that need to address here and can be used in future research directions. Firstly, we measured the adoption intention of e-commerce in general and overlooked the particular e-commerce platform characteristics such as Amazon, Olx, Daraz.pk, Taobao, Alibaba, etc., These site features can also influence the customers. Secondly, we consider the age and education as two demographic factors as a control variable and found them insignificant. Still, we believe that these demographic characteristics can influence the adoption intention as younger and old consumers perceive and behave differently, and so do the educated and illiterate. Thirdly we took our sample from Pakistan, and the e-commerce infrastructure is comparatively better than many neighbouring countries such as Yemen and Afghanistan or several African countries. Hence we believe that infrastructure facilities can play a great role and have the potential to change the perception of residents.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://docs.google.com/spreadsheets/d/1fayivac_U_AtJZnqbZ0RgDYecqTY-q2q/edit?usp=sharing&ouid=104056982942615139504&rtpof=true&sd=true.

ETHICS STATEMENT

Ethics review and approval/written informed consent was not required as per local legislation and institutional requirements.

AUTHOR CONTRIBUTIONS

SM: conceptualization, methodology, software, writing—original draft. TH and YQ: review the final draft, edit, visualization, and handle the data flow and manage it. SK and RS: investigation, and data collection.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.940659/full#supplementary-material

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