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Consumer Acceptance of AI in E-Commerce: An Empirical Analysis Based on the Technology Acceptance Model (TAM)

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Abstract

In recent decades, AI has proved crucial to electronic business. Its rapid expansion has altered online shopping habits. In this study, we use the Technology Acceptance Model (TAM) to look at AI in the context of online shopping. We want to see how AI adoption can help businesses make more money, work smarter, and reach their goals in the digital market. E-commerce shoppers were polled online. Our data analysis using Partial Least Squares (PLS) Smart. The popular TAM was chosen to assess e-commerce AI technology acceptance. The study found that Subjective Norms and PEU positively affect Perceived Usefulness (PU) and attitudes towards usage. PU improves how people feel about using something and their plans to do so. However, the findings do not indicate a significant effect of trust on perceived usefulness or usage. The urge to deploy AI technology ultimately improved its application. This study enhances our theoretical and practical understanding of the TAM model in e-commerce. It helps entrepreneurs maximize AI use with the TAM model.

Keywords

TAM, Artificial Intelligence (AI), E-Commerce, Structural Equation Modeling (SEM), AI Adoption

1. Introduction

The shift to digitization in the global economy has occurred during the past three decades. Technology has replaced more antiquated methods of managing and running a company (Kraus et al., 2022; Khan et al., 2022). A significant portion of the market share was to be attained in order to gain a competitive advantage (Pizzo et al., 2022). Businesses have benefited greatly from the advancements in information technology and the internet (Yuan et al., 2021). With a mobile internet connection, consumers may shop online at any time, from any location, for a wide variety of brands and prices. To stay ahead of the competition, retailers took advantage of technology and opened up online shopfronts, commonly called e-commerce (Chen et al., 2002; Davies & Hughes, 2014). A relatively new kind of company, "e-commerce" conducts all of its activities online through the web and other forms of modern technology. Mishra and Mukherjee (2019) state that consumers have the option to compare brands and exchange products and services through online platforms. The advancements in this area have allowed businesses to proceed to the next level, utilizing smart technologies like AI (Sestino & De Mauro, 2022).

The use of artificial intelligence (AI) has expanded across numerous sectors of the economy and society (Lee, 2022). Online businesses are not immune to the impact that artificial intelligence is having on other sectors, such as healthcare, academia, banking, and advertising (Gams & Kolenik, 2021). Many view AI as a promising new avenue for online business. With its inclusion, new avenues for e-commerce growth have been revealed (Akpan et al., 2022). According to Song et al. (2019) citing Gartner, more than 80% of customer support jobs have been replaced by AI. Chat-bots are becoming increasingly popular, with 40% of customers regularly interacting with AI-powered chat-bots for both assistance and product purchases. According to Wang (2021), major e-commerce platforms such as Alibaba, Amazon, and Rakuten utilize AI to analyze customer feedback and provide product recommendations. E-commerce businesses benefit from AI applications in two ways: first, it simplifies data management, chat-bot customer service, sales prediction, and post-sale support for owners; and second, it provides customers with chat-bots that can converse with them, image recognition, and personalized recommendation systems (Lim, 2023).

Artificial intelligence is always evolving. The COVID-19 pandemic altered consumer habits significantly. Due to lockdowns, many people resorted to buying online. The rapid expansion of online trade was accelerated by the government's backing of this shift (Al Shamsi et al., 2022). In the years between 2020 and 2027, the artificial intelligence market is projected to grow at a CAGR of 34.9%, reaching a value of $6.76 billion, according to Acumen Research (Piccialli et al., 2021; Bondy, 2021). Between 2010 and 2020, 2399 publications were analysed in a biometric study by Al-Emran and Granić (2021). After making certain adjustments for specific courses, they discovered that the Technology Acceptance Model (TAM) remains a valuable tool. Additionally, Al-Nuaimi et al. (2022) praised TAM, stating that it serves as an excellent model for studies pertaining to online commerce.

Following COVID-19, when online shopping became increasingly popular, AI became an integral part of e-commerce (Sakaguchi & Aoki, 2022). E-commerce firms are continuously seeking solutions that benefit their clients and their business (Akıl & Ungan, 2022). While few studies have examined AI's role in online shopping, the vast majority have focused on the technological or business systems that AI impacts (Grewal et al., 2021; Liu, 2022). But there is a lack of data on consumers' perceptions of AI in e-commerce, the ways in which AI streamlines their buying processes, and the features of AI that are most valued by them (Cheng et al., 2022). That void is filled by this study, which examines consumer AI usage and offers recommendations for improving e-commerce platforms.

2. Literature Review

2.1. E-Commerce

E-commerce denotes the utilisation of the internet and modern communication technologies for the exchange of information essential for the completion of commercial processes (Song et al., 2019). Numerous e-commerce business models exist; organisations must select one based on their objectives, with the primary emphasis of these models centring on network technology (Paliwal et al., 2022). According to Nikiforova (2022), electronic technology is utilized to execute business operations such as marketing, logistics, payment processing, and distribution, as well as to develop customer relationship management in e-commerce. Electronic Data Interchange (EDI), intranet, internet, databases, email, and web development technologies serve as the primary foundations of e-commerce (Song et al., 2019). Chalmers et al. (2021) argue that e-commerce is a key revolutionary indicator of scientific, technical, and cultural advancement. The shift in various commercial activities due to e-commerce and changes in consumer behavior toward e-commerce have significantly contributed to global economic development (Har et al., 2022; Zulfiqar & Shahzeb, 2022).

Consumers can purchase anything without going anywhere in just two or three steps with the help of e-commerce (Mohamad et al., 2022). Many e-commerce platforms, such as Amazon, Flipkart, Myntra, and eBay, utilize information and communication technology to operate and manage their businesses online. Nowadays, businesses are shifting from physical locations to e-commerce due to the rapid development of online commerce, which offers numerous advantages to both clients and companies. Therefore, organizations must choose appropriate and sustainable technologies that support corporate growth, provide a competitive advantage, and ensure customer satisfaction.

2.2. AI in E-Commerce

In the current business environment, Artificial Intelligence (AI) and e-commerce are closely linked (Isaac et al., 2018; Oana et al., 2017). AI provides valuable support to consumers in online business, enabling them to make smart decisions. The increasing use of technology and its revolutionary contributions have driven commerce enterprises while also developing electronic platforms that engage clients effectively (Ibrahim et al., 2015; Johnson, 2022).

Artificial Intelligence (AI) significantly influences e-commerce and enhances business process efficiency. It improves customer interactions with online businesses through digital means. When an e-commerce business integrates AI into its website, it can attract more customers, increase sales, and improve productivity and efficiency. Additionally, intelligent search, automation, voice assistants, personalization, and remarketing are key advancements in e-commerce (Asling, 2022; Khan et al., 2022).

Online businesses use voice commerce and virtual assistant chatbots 24/7 to handle various customer inquiries with the help of artificial intelligence (AI). This provides a convenient and efficient way for individual customers to inquire about products and services (Frontczak, 2021). According to Clymer (2019), intelligent search provides a competitive advantage to the e-commerce sector through AI. It allows individual customers to perform faceted searches, autocomplete, navigation, auto product suggestions, and access recent search history, offering a customized product search experience. Additionally, it acquires behavioral and voice data from the search history. AI can recommend products, services, and relevant promotions according to customers' preferences, based on their recent history, browsing patterns, and purchase records (Sahin, 2022).

Automation in online business operations is only possible due to AI involvement in e-commerce. E-commerce companies provide 24/7 customer support, reduce operational costs, and save time and effort. With AI in e-commerce, new products are promoted automatically, increasing sales through various channels. It also offers discounts to potential customers and detects high-risk transactions (Special Guest Contributor, 2021). By employing AI in e-commerce, online businesses can identify target customers based on their behavioral patterns and purchase history (Lau, 2022). Advancements in e-commerce are increasing over time due to the continuous development of AI technologies, enhancing efficiency and effectiveness in online business operations. AI is involved in various aspects of e-commerce, such as marketing strategies, product development, identifying potential customers, and maintaining strong customer relationships.

3. Conceptual Framework and Hypothesis

There are various Technology Acceptance Models (TAMs), such as the Theory of Planned Behavior (Fishbein & Ajzen, 1975), the Technology Acceptance Model (Ajzen, 1985), the Innovation Diffusion Theory (Davis, 1986), the Unified Theory of Acceptance and Use of Technology (Parasuraman, 2000), the Technology Readiness Index (Rajagopal, 2002), and the Theory of Reasoned Action (Sánchez-Prieto et al., 2017). According to Venkatesh (2000), although each model has distinct characteristics and behaves differently, they all help clarify the acceptance and rejection of technology by information technology users.

Even though various advanced technology acceptance models have been developed by different scholars, Davis's model remains the most prevalent for technology acceptance, as illustrated in **Figure 1**. It has been widely recognized by both academic and industry scholars (Taherdoost, 2018; Venkatesh et al., 2003). One key reason for adopting the TAM model is its primary focus on an individual's capacity to adopt technology, whereas the UTAUT model primarily focuses on technology adoption at the organizational level (Rondán-Cataluña et al., 2015). This study finds that, based on consumer judgment, the TAM model is superior in technology acceptance. Therefore, the study employs the TAM model to measure AI adoption among e-commerce consumers.

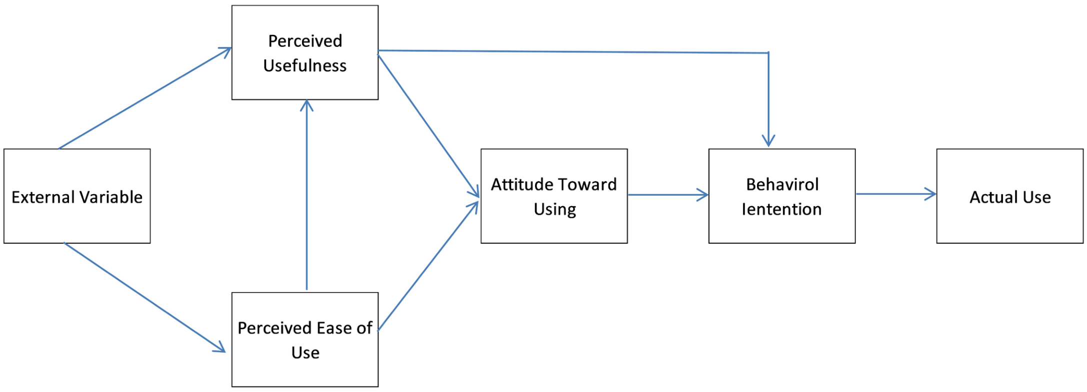

Figure 1. Conceptual framework.

The Technology Acceptance Model (TAM) includes external factors, Perceived Usefulness (PU), Perceived Ease of Use (PEU), attitude, Behavioral Intention to Use (BI), and Actual Use (AU). As per TAM, external conditions have a direct effect on PU and PEU, which are key components of cognitive belief. PEU has a direct impact on both PU and attitude, whereas PU influences attitude and BI, ultimately determining AU. Table 1 presents a summary of advanced empirical studies that provide strong support for the UTAUT model.

Table 1. Studies support to hypothesis.

Authors	Study Focus	Support to Hypothesis
To & Trinh (2021)	Mobile wallet adoption in Vietnam	Perceived ease of use positively impacts perceived usefulness.
Elkaseh et al. (2016)	Social media in e-learning (Libya)	
Ibrahim et al. (2014)	Telecom services and consumer behavior (Pakistan)	
Ali (2021)	Purchase intentions in second-hand car market (Iraq)	
Samuel & Thompson (2021)	Myths and societal beliefs	
Haenlein et al. (2020)	Influencer marketing strategies	
Huang et al. (2022)	University students' internet use for learning	
Kanchanatanee et al. (2014)	E-marketing adoption	Perceived ease of use positively impacts attitude towards use.
Ramayah & Ignatius (2005)	Online shopping intention	
Harrigan et al. (2021)	Trust and online purchase intention	
Chocarro et al. (2021)	Chatbots in education	
Wang et al. (2020)	Ride-sharing service adoption	
Tandon et al. (2016)	Online shopping satisfaction (India)	
Chao (2019)	Mobile learning adoption	

Continued

Majumder et al. (2022)	Online reviews and consumer perception	Perceived usefulness has a positive impact on attitude towards use.
Prasetyo et al. (2020)	COVID-19 prevention measures	
Tandon et al. (2017)	Customer satisfaction in online shopping	
Ha (2020)	Perceived risk in online shopping	
Han et al. (2021)	Eco-friendly tourism behavior	Perceived usefulness has a positive impact on behavioral intention to use.
Almahamid et al. (2010)	E-government adoption	
Pantano (2020)	Retail service evaluation via facial expressions	
Fjelland (2020)	Artificial intelligence limitations	
Wang & Chen (2022)	Brand nostalgia and consumer preference	
Albukhitan (2020)	Digital transformation in manufacturing	
Park (2009)	E-learning adoption among university students	Attitude towards use positively impacts behavioral intention to use.
Yeo et al. (2017)	Online food delivery services adoption	
Cao et al. (2021)	AI adoption in decision-making	
Eichorn & Donnan (2021)	Speech disfluencies in children	
Sufiawati et al. (2021)	Dentists' knowledge on HIV/AIDS	
Trip et al. (2019)	Radicalization and extremism	
Schönegger & Wagner (2019)	Ethics in academia	
Trip et al. (2019)	Radicalization and extremism	Behavioral intention to use has a positive impact on actual use.
Vărzaru et al. (2021)	Mobile technology adoption in e-commerce	
Mailizar et al. (2021)	Teachers' e-learning adoption	
He et al. (2021)	Green purchasing behavior	
Mahmud et al. (2021)	Corporate social responsibility and COVID-19	

The TAM model considers two key external variables when exploring AI in e-commerce: subjective norms and trust. These variables directly influence perceived usefulness and perceived ease of use. Subjective norms emerge from an individual's social relationships, such as influences from family, friends, instructors, mentors, or other admired figures (Legrisa et al., 2003; Santos & Liguori, 2020). Subjective norms refer to the social pressure that influences an individual's decision to use a product or service. People often follow these norms to justify their decisions in alignment with societal expectations (Trafimow & Finlay, 1996). According to Teo (2009), individuals do not adopt products or services solely for their inherent benefits but are also influenced by those they admire and respect. This is why companies frequently hire celebrities to promote their products or services (Singh & Banerjee, 2018). Consumers are more likely to use products or services that they find impressive or aspirational (Den Hartog et al., 2020).

Trust refers to a confident belief in the reliability, dependability, and capability of an individual, organization, or entity (Irshad et al., 2022). Humans are a combination of cognitive and emotional elements; therefore, trust develops based on shared experiences that shape cognitive perceptions in the human brain (Yuan &

Dennis, 2019; Gunasekera et al., 2021). The decision to use a product or service depends on an individual's level of trust in that product or service (Rachmawati et al., 2019). Human decision-making is influenced by both trust and emotions (Sætra, 2019; Castelo et al., 2019). These two external variables, subjective norms and trust, are included in the TAM model because they significantly influence an individual's perceived usefulness (PU) and perceived ease of use (PEU).

A strong relationship exists between customers' online shopping attitudes and their perceptions of compatibility, safety, usefulness, and ease of use (Castelo et al., 2019). Consumer perception is a key motivator for online shopping behavior and self-efficacy. Therefore, perceived usefulness and perceived ease of use play a significant role in motivating consumers' repurchase intentions (Vijayasarathy, 2004). Some criticism has been highlighted questioning the applicability of the Technology Acceptance Model (TAM) to evaluate attitudes towards artificial intelligence (Gefen et al., 2003). These authors assert that online businesses integrate AI into their websites, leaving users with little alternative but to engage in online buying at those stores. Consequently, standard TAM may not evaluate sentiments towards AI. Customers have the option to utilise innovative technology, such as purchasing through an AI-driven online store (Schepman & Rodway, 2020; Persson et al., 2021).

4. Methodology

This study employed a quantitative, cross-sectional research design to empirically test the Technology Acceptance Model (TAM) using survey data. A structured questionnaire was developed by adopting validated measurement scales from prior TAM literature, with all constructs measured on a five-point Likert scale. Data were collected from technology users through a convenience sampling approach, ensuring that respondents had prior experience with the technology under investigation. The sample size satisfied the minimum requirements for Partial Least Squares Structural Equation Modeling (PLS-SEM). Reliability and validity of the measurement model were assessed using Cronbach's alpha, composite reliability, average variance extracted (AVE), and the heterotrait-monotrait (HTMT) ratio. Structural relationships among constructs were examined using PLS-SEM with bootstrapping to test the proposed hypotheses. Ethical considerations were observed by ensuring voluntary participation, anonymity, and confidentiality of respondents.

4.1. Descriptive Results

This section reports the initial descriptive statistics like reliability and validity of the observed variables used in the SEM analysis. These results provide a preliminary understanding of the data distribution prior to testing the measurement and structural models.

4.2. Measurement Model

This study tested adopted scale for measurement of TAM model using the survey questionnaire and the measurement results are very much suitable for the testing of reliability and the validity of the survey scale. Table 2 reports the reliability and validity statistics of the study variables. The results of the reliability for external variables (Crobach's alpha = 0.816, CR = 0.876), perceived ease of use (Crobach's alpha = 0.872, CR = 0.922) and perceived usefulness (Crobach's alpha = 0.757, CR = 0.861), attitude (Crobach's alpha = 0.860, CR = 0.922) and behavioral intention (Crobach's alpha = 0.916, CR = 0.941) and the dependent variable actual use (Crobach's alpha = 0.894, CR = 0.926). TAM model all variables verified the internal consistency by Crobach's alpha and composite reliability (CR) threshold 0.7. Secondly the study results verified convergent validity by applying Average Variance Extracted (AVE) score well above the threshold of AVE > 0.5.

Table 2. Reliability & validity scores.

Variable	Items	Loadings	Cronbach's Alpha	CR	AVE
External Variable **(EV) (Subjective Norma and trust)**	EV1	0.720	0.816	0.876	0.640
	EV2	0.780			
	EV3	0.877			
	EV4	0.831			
Perceived Ease of Use **(PEU)**	PEU1	Delete	0.872	0.922	0.797
	PEU2	0.843			
	PEU3	0.912			
	PEU4	0.922			
Perceived Usefulness **(PU)**	PU1	0.831	0.757	0.861	0.673
	PU2	0.841			
	PU3	0.789			
Attitude **(AT)**	AT1	Delete	0.860	0.922	0.705
	AT2	0.793			
	AT3	0.843			
	AT4	0.860			
	AT5	0.861			
Behavioral Intention **(BI)**	BI1	0.897	0.916	0.941	0.799
	BI2	0.886			
	BI3	0.904			
	BI4	Delete			
	BI5	0.889			
Actual Use **(AU)**	AU1	0.910	0.894	0.926	0.759
	AU2	0.772			
	AU3	0.916			
	AU4	0.880			

Heterotrait-monotrait (HTMT) ratio of correlations for discriminant validity examination. Here the results of measurement modeling confirms discriminant validity as all of the scores are well below the criteria of 0.85 in Table 3.

Table 3 Discriminant validity (HTMT).

Variables	AT	AU	BI	EV	PEU	PU
AT						
AU	0.225					
BI	0.259	0.810				
EV	0.530	0.074	0.098			
PEU	0.390	0.465	0.490	0.092		
PU	0.542	0.557	0.577	0.202	0.8234	

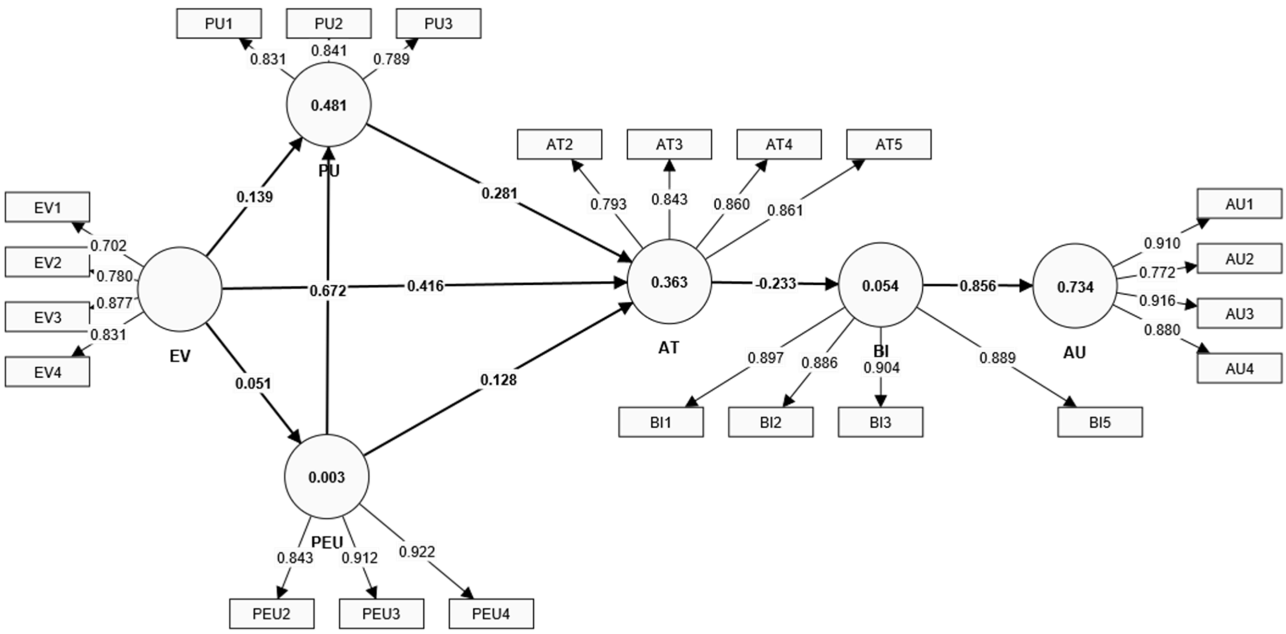

Figure 2. The structural model.

The study is empirical in nature for the testing of hypotheses by the techniques of statistical model via PLS-SEM structural model for the technology acceptance model (TAM). The structural equation modeling results, including path coefficients and significance levels, are reported in Table 4. The study findings are very much supportive as the results indicated that external variables ($\beta = 0.051$, $p > 0.05$; $\beta = 0.139$, $p < 0.05$; $\beta = 0.416$, $p < 0.05$) influencing ease of use and perceived usefulness and attitude respectively H1 rejection, while acceptance of H2 and H3. Perceived ease of use ($\beta = 0.672$, $p < 0.05$) influencing and perceived usefulness H4. Coming to the next set of hypotheses H5 & H6, there came acceptance of significant influence of ease of use ($\beta = 0.128$, $p < 0.05$) and perceived usefulness ($\beta = 0.281$, $p < 0.05$) on attitude. The researcher also tested the influence of TAM attribute that is the attitude ($\beta = 0.233$, $p < 0.05$) influencing behavioral intention accepting H7. Finally the study results tested the influence of the behavioral intention on the actual use of the technology (β = 0.856, $p < 0.05$) and supportive of H8. The structural relationships and hypothesis testing results are illustrated in Figure 2.

Table 4. Structural equation modeling results.

	Coefficient β	Standard deviation (STDEV)	t-statistics	*p*-values
AT - > BI	0.233	0.061	3.837	0.000
BI - > AU	0.856	0.019	44.609	0.000
EV - > AT	0.416	0.049	8.482	0.000
EV - > PEU	0.151	0.058	2.876	0.031
EV - > PU	0.139	0.042	3.337	0.001
PEU - > AT	0.128	0.051	2.501	0.012
PEU - > PU	0.672	0.032	21.012	0.000
PU - > AT	0.281	0.069	4.073	0.000

5. Conclusion

Researchers in this study found those users' attitudes, trust, simplicity of use, and usefulness all significantly impacted their behavioral intention when it came to artificial intelligence (AI) on e-commerce sites. It emphasizes that for AI technologies to be usable, they need to be well-designed and easy to use. The lack of trust in AI-powered apps is a major reason why they aren't used more frequently. Particularly in the wake of the COVID-19 pandemic, artificial intelligence (AI) improves online shopping by providing tailored recommendations and decreasing search time. In order to boost consumer happiness and loyalty, it is crucial to personalize their trips. Entrepreneurs and digital marketers developing e-commerce platforms powered by artificial intelligence can benefit from the research by developing more effective business tactics. By integrating AI and e-commerce, this study differs from others that have solely examined TAM. This provides scholars and practitioners with a better knowledge while also filling a gap in the theory. Due to the increasing number of internet users in Pakistan, the findings are applicable to both developing and developed nations.

The structural equation modeling results provide important insights into the strength and significance of key relationships in the model. Notably, behavioral intention exhibits a very strong and significant influence on actual use (β = 0.856), indicating that users' intentions are highly predictive of their real usage behavior in AI-enabled e-commerce platforms. This finding emphasizes the central role of intention formation in translating positive perceptions into actual adoption. In contrast, the path from external variables to perceived ease of use was found to be non-significant, leading to the rejection of H1. This suggests that perceived ease of use is driven more by system design and functional characteristics rather than by external contextual factors. These path-specific results enhance the explanatory power of the model and provide clearer theoretical and practical implications for AI-based e-commerce adoption.

Additionally, the results show that businesses can grow by retaining clients through trust-building and regular good service delivery. This is because loyal customers are more likely to return and recommend the service to others. Companies may win people over by being forthright in their communications, providing trustworthy platforms, and discussing their security measures. The findings suggest that e-commerce managers can enhance AI feature adoption by leveraging subjective norms through social influence strategies. Specifically, highlighting peer usage, customer testimonials, influencer endorsements, and "most-used AI features" labels can create social pressure and positive normative beliefs, thereby strengthening users' attitudes and behavioral intentions toward AI-enabled services. Managers should also integrate social proof into marketing communications to normalize AI usage and accelerate adoption.

However, the study has its limitations, such as its reliance on a large number of variables and its narrow geographic focus. Researchers in the future should look into other fields using qualitative or longitudinal methodologies to find out more and see if there is a correlation. To further understand consumer behavior in AI-driven digital spaces, it is prudent to examine actual purchase patterns rather than merely intentions.

Conflicts of Interest

The authors declare no conflict of interests.

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