DOI: 10.52131/pjhss.2025.v13i4.3079

Pakistan Journal of Humanities and Social Sciences

Volume 13, Number 04, 2025, Pages 204-219
Journal Homepage:
https://journals.internationalrasd.org/index.php/pjhss

Consumer Purchase Intention in AI-Enabled Digital Commerce: An Extended UTAUT2 Perspective

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ARTICLE INFO

Article History:

Received:	October 09, 2025
Revised:	December 28, 2025
Accepted:	December 29, 2025
Available Online:	December 30, 2025

Keywords:
Artificial Intelligence
UTAUT2
Customer Satisfaction
Trust in AI
Behavioral Intention to Purchase

Funding:
This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ABSTRACT

Artificial intelligence has been a leading dimension in the sense of e-commerce, thus the need to describe how consumers create purchase intentions in conditions of AI. The objective of the current study is to identify the impact of primary technology acceptance beliefs on the behavioral intentions to purchase mediated by customer satisfaction and trust in AI, while disaggregating the moderating role of task complexity. The research is based on UTAUT2, which includes performance expectancy, effort expectancy, hedonic motivation and habit as the key antecedent variables. The data were collected through a structured questionnaire, which was applied to 377 British consumers and then analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM). The empirical evidence shows that performance expectancy, effort expectancy, hedonic motivation and habit have important positive impacts on customer satisfaction and trust in AI. In line with this, customer satisfaction and trust in AI have a significant positive effect on behavioral intention to purchase and thus serve as important mediating variables in the relationship between the beliefs about acceptance and purchase intention. The findings also indicate that customer satisfaction and behavioral intention to purchase, or trust in AI and behavioral intention to purchase are positively moderated by task complexity, indicating that these relationships are stronger when task complexity is high. Overall, this study augments the UTAUT2 framework by the incorporation of satisfaction, trust in AI, and task complexity and thereby offers a more complete explanation of consumer purchase intention in AI-mediated digital commerce and provides valuable information on scholarly investigation and practical implementation.

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1. Introduction

Artificial intelligence (AI) has become an inseparable part of modern e-commerce, causing a paradigm shift in the way consumers search, compare, and finally decide to buy a product. The adoption of AI-based functionalities (e.g., personalized recommendations, automated customer support, and intelligent decision aids) is increasingly being integrated into online and mobile retail settings to improve the efficiency of operations and customer experience. Considering the fast development of digital markets, a thorough insight into consumer behavioral intentions in AI-enhanced environments turns out to be an important issue among researchers and practitioners of the industry. Empirical evidence indicates that the desire to adopt and use technology is not based only on functional advantages, but also on experiential and psychological evaluation, which changes during communication with digital systems (Venkatesh, Thong, & Xu, 2012; Williams, Rana, & Dwivedi, 2015). In developed digital economies like the UK, where mobile internet connectivity and online shopping are very common, the adoption of AI is no longer new and post-adoption reviews are especially significant in influencing consumer reactions. UTAUT2 has been extensively used to justify consumer technology acceptance in various contexts, such as mobile commerce, fintech, electronic banking, and services involving artificial intelligence. The fundamental UTAUT2 variables, including performance expectancy (PE), effort expectancy (EE), hedonic motivation (HM), and habit, have always been reported to have an effect on the intention to behave based on the perception of usefulness, ease of use, enjoyment, and routinized behavior (Çalık, 2025; Hanif et al., 2021; Venkatesh, Thong, & Xu, 2012). The recent extensions of UTAUT2 into the field of AI further indicate that these predictors can be useful when consumers engage with intelligent systems, including chatbots and recommendation engines (Dixit, Choudhary, & Govil, 2025; Garcia de Blanes Sebastian, Sarmiento Guede, & Antonovica, 2022). However, the increase in the role of AI as a mediator of the purchasing decision-making process does not imply that behavioral intention shouldn't be driven by the acceptance beliefs but also by the evaluative judgments of consumers in terms of outcomes and system reliability.

Customer satisfaction has become a central post-adoption measure in digital commerce studies. It represents a total evaluation of consumer attitudes towards service performance, which includes the aspects of efficiency of delivery, quality of service, and interactive experience. Previous empirical studies have suggested that satisfaction is the primary factor in the creation of repurchase intention, word-of-mouth diffusion, and long-term usage of digital platforms (Kalinić et al., 2019; Subramanian et al., 2014; Vidosavljević, Marinković, & Marić, 2025). Subjective satisfaction in the framework of an AI-based purchasing experience is a critical determinant of user experience: is intelligent functionality being useful to the purchasing cycle beyond being a standard of automation? Empirical studies based on the UTAUT2 theory have assumed that satisfaction as a mediator variable exists between technology-related cognitions of users and resultant behavioral consequences, especially in mobile and online commerce contexts (Ferreira Barbosa et al., 2021; Ibrahim, Hua, & Harun, 2025). This implies that satisfaction is a key mediator between perceptions of technology and purchase intention. Besides customer satisfaction, trust in artificial intelligence has emerged as a decisive indicator of consumer behavior in intelligent systems. Artificial intelligence is typically applied as a decision agent, according to AI-based platforms, which selects products, propose solutions, and resolves problems. In this aspect, consumers will need to develop confidence in the reliability, competence, and goodwill of AI systems. As empirical research confirms, AI trust is a valuable variable that leads to acceptance, intention to use, and purchase behavior, particularly in regards to algorithmic suggestions and automated decision making (Malhotra & Ramalingam, 2023; Zhang et al., 2025). The issue of trust is particularly appropriate to the context of AI-assisted purchasing because customers may feel uncertain, uninformed, or less influential about the outcomes of the decisions. Addition of trust in UTAUT2-based frameworks has therefore been strongly proposed in current AI adoption frameworks (Masrek, Baharuddin, & Syam, 2025; Plohl & Čuš Babič, 2024).

The complexity of the task is another factor that predetermines consumer dependency on artificial intelligence systems. Task complexity is the extent to which tasks are cognitively challenging and involve a problem solving and a judgment. The more complicated the purchase decision, the more likely the consumers develop a tendency to use the assistance of external sources, including AI-based tools, to make the process easier and reduce uncertainty (Morgeson & Humphrey, 2006). The empirical evidence shows that the role of trust and satisfaction in usage and purchase intentions increase with the complexity of tasks in the situation of AI-aided services (de Matos, Laurentino, & Veiga, 2025; Song & Lin, 2023; Xu et al., 2020). Task complexity is another moderating variable that has received minimal consideration as a relevant variable in UTAUT2-based purchasing model, particularly in consumer-centric artificial intelligence scenarios. The study contributes to the research literature in that it integrates UTAUT2 with the concept of customer satisfaction and belief in artificial intelligence (AI) to explicate behavioral intentions to buy in a UK environment. The study discusses the desperate need to know how intelligent systems can affect consumer decision-making within existing digital markets through the online and mobile environment of purchase, which is AI-enabled. The scope of the research includes performance expectancy (PE), effort expectancy (EE), hedonic motivation (HM), and habit as the main predictors; customer satisfaction and trust in AI as the parallel mediators; and task complexity as the moderating variable. The research is strategically grounded on purchase intention and not actual consumer behavior, thus enabling a narrow exploration of intention development in AI-assisted situations. It is assumed that the expected results will provide practical information to online merchants and platform developers who want to enhance satisfaction, develop trust, and maximize AI capabilities when it comes to complex consumer activities.

Despite the extensive use of UTAUT2 to explain the technology adoption and usage intentions in antecedent literature, the literature lacks a thorough, comprehensive evaluation of the effectiveness of the acceptance beliefs in predicting purchase intentions through both customer satisfaction and trust in AI. Numerous studies predict satisfaction, but do not model AI trust explicitly, whereas some studies predict trust separately, and not across predictors of core UTAUT2. In addition, the moderating role of task complexity in influencing the relationship between satisfaction and intention, and trust and intention is under-researched in consumer purchasing situations, especially in highly developed digital markets like the UK. This methodology limits our knowledge of the circumstances in which satisfaction or trust has stronger influence in AI-assisted decision-making. To address this gap, the current research suggests a complex model, which concurrently examines dual mediation in the context of customer satisfaction and trust in AI, yet considers task complexity as a boundary condition. In this way, the study contributes to the theory by demonstrating how UTAUT2 can be generalized to a more situational model that explains the intention to purchase in AI-based online shopping.

2. Literature Review

2.1. UTAUT2 and Acceptance of AI-Enabled Purchasing Technologies

The UTAUT2 theory is a very useful theory in explaining how consumers adopt digital and intelligent technology. UTAUT2 was established by Venkatesh, Thong and Xu (2012) as a continuation of UTAUT by including consumer-specific measures, i.e. hedonic motivation and habit, that are especially applicable in experience-based and voluntary settings, such as online shopping. The theory assumes that performance expectancy, effort expectancy, hedonic motivation, and habit determine how people develop behavioral intentions due to the impact they have on how individuals perceive value, usability, enjoyment, and routinization. There is a large amount of empirical evidence that UTAUT2 can explain in mobile commerce, fintech, e-banking, and AI-based services (Çalışkan, Yayla, & Pamukçu, 2023; Cao, 2024; Hanif et al., 2021; Tak & Panwar, 2017). Performance expectancy in the context of AI-enabled purchasing environments indicates the extent to which consumers think that AI functionalities enhance the quality of decisions, efficiency, and purchasing.

Research indicates that the perceived usefulness continues to be a major motivator of positive ratings in AI-based systems, such as recommendation systems and virtual assistants (Dixit, Choudhary, & Govil, 2025; García de Blanes Sebastián et al., 2024; Kalinić et al., 2019). It is also important that effort expectancy, the perceived ease of interaction, should be gauged since AI systems that seem challenging to grasp or manage can decrease consumer confidence and interest (Mahfuz & Khanam, 2016; Tarhini et al., 2016). Hedonic motivation focuses on intrinsic good fun and has been reported to be a driving force in mobile and AI-based services where interactive and customized options are found to benefit the user experience (Ferreira Barbosa et al., 2021; Jung & Cha, 2022). Habit indicates the patterns of repeated and automatic use, and over time, it makes consumers more dependent on digital platforms (Setiyani, Natalia, & Liswadi, 2023; Susilowati, Rianto, & Wijaya, 2021). Although these constructs are traditionally directly related to behavioral intention in UTAUT2, recent research asserts that in sophisticated AI environments, the acceptance beliefs directly influence the evaluative reactions, including satisfaction and trust, before converting them into purchase intention (Plohl & Čuš Babič, 2024; Williams, Rana, & Dwivedi, 2015). Based on UTAUT2, this paper hypothesizes that the concept of acceptance beliefs impacts customer satisfaction and AI trust. According to the above discussion, the following hypothesis are formulated;

H1: PE has positive effect on CS.
H2: EE has positive effect on CS.
H3: HM has positive effect on CS.

H4: HBT has positive effect on CS.
H5: PE has positive effect on TAI.
H6: EE has a positive effect on TAI.
H7: HM positively effect on TAI.
H8: HBT has positive effect on TAI.

2.2. Customer Satisfaction

Customer satisfaction is a general cognitive and effective post-use assessment of service performance. The concept of satisfaction in digital commerce studies is based on Expectation-Confirmation Theory whereby individuals make comparison between pre-use expectations and actual performance outcomes where they make satisfaction judgment's that inform future intentions (Cody-Allen & Kishore, 2006). In online shopping, satisfaction reflects the image of efficiency in delivery, responsiveness in services, quality of products and experience. It is empirically shown that satisfied consumers show better purchase intentions and purchase continuity (Kalinić et al., 2019; Subramanian et al., 2014; Sun, 2024). In AI-based buying, satisfaction is more complicated since consumers do not only assess the results of the services but also the quality of the assistance of AI on the way of making a decision. Research involving the combination of UTAUT2 and satisfaction has shown that performance expectancy and effort expectancy increase satisfaction through the confirming of functional expectations, whereas hedonic motivation increases affective reactions to digital platforms (Ferreira Barbosa et al., 2021; Ibrahim, Hua, & Harun, 2025; Isnaini & Tulasmi, 2024). Repeated interactions also increase satisfaction by diminishing cognitive effort and uncertainty (Tamilmani, Rana, & Dwivedi, 2018; Venkatesh, Thong, & Xu, 2012; Vidosavljević, Marinković, & Marić, 2025) .

In theoretical perspective, satisfaction provides a psychological linkage between technology beliefs and the behavioral outcomes. Instead of directly affecting purchase intention, UTAUT2 beliefs affect satisfaction which becomes the immediate antecedent of intention(Dler M Ahmed, Z Azhar, & Aram J Mohammad, 2024; Dler Mousa Ahmed, Zubir Azhar, & Aram Jawhar Mohammad, 2024). This facilitating function has been aided in the mobile commerce, e-wallets, and services with the help of AI (Kalinić et al., 2019; Pawaskar & Nattuvathuckal, 2024; Sipos, 2025). In this regard, customer satisfaction is supposed to clarify the way acceptance beliefs can be converted to behavioral intention to buy under AI-enabled settings. According to the above discussion the following hypotheses are developed:

H9: CS has a positive impact on the probability of PB.
H13 CS mediates the relationship between PE and PI.
H14: CS mediates the relationship between EE and PI.
H15: CS mediates the relationship between HM and PI.
H16CS mediates the relationship between HBT and PI.

2.3. Trust in AI

The concept of trust in AI has become one of the key constructs in the explanation of user behavior on intelligent systems. According to the Trust Theory, people are more eager to trust those systems which they view as reliable, competent, and consistent with their interests. Consumers are often relying on algorithmic promotions, chatbot robots, and decision support systems in AI-enabled buying, which adds uncertainty and the sense of being deprived of control (Ho & Cheung, 2024; Zhang et al., 2025). Reliability on AI thus forms a condition to believe AI-created products and act on them. In the empirical research, it is always found that trust in AI has a positive impact on adoption intention, usage behavior, and purchase decisions. Garcia de Blanes Sebastian, Sarmiento Guede and Antonovica (2022) showed that trust is a significant indicator of AI virtual assistant intention to use, whereas Malhotra and Ramalingam (2023) revealed that trust positively affects purchase intentions in AI-mediated shopping contexts. Research also shows that UTAUT2 beliefs determine trust; confidence in the competence of AI is provided by the perception of usefulness and ease of use, and emotional comfort and dependence are established by pleasant and habitual interaction (Ganesa, John, & Mane, 2020; Nahtan et al., 2025; Popa et al., 2025). The socio-technical theory also states that trust in AI comes into existence when there are interactions between the technological capabilities and human perceptions. Users will gain confidence and trust that will minimize perceived risk and enable delegation of decisions Kim, Lee and Kang (2025); Song and Lin (2023) when AI systems provide useful and correct results on a consistent basis. In turn, trust in AI serves as a mediating variable that bridges the relationship between the acceptance beliefs and the behavioral intention in AI-assisted purchasing. Accordingly, the following hypotheses are proposed:

H10: TAI has positive effect on BIP
H17: TAI mediates the relationship between PE and BIP.
H18: TAI mediates the relationship between EE and BIP.
H19: TAI mediates the relationship between HM and BIP.
H20: TAI mediates the relationship between HBT and BIP.

2.4. Task Complexity

Task complexity can be interpreted as the extent to which the tasks require mental effort, judgment and problem solving (Morgeson & Humphrey, 2006). Task Technology Fit Theory claims that technology can work more effectively when its capabilities are more in line with the demands of tasks. The complexity of tasks in purchasing with AI depends on the product and choice; complex purchases can be based on information overload, uncertainty, and increased perceived risk(Ragmoun, 2024; Ragmoun & Ben-Salha, 2024). The empirical evidence shows that the more complicated a task is, the greater the reliance on AI assistance and, thereby, satisfaction and trust. Xu et al. (2020) argued that the impact of trust on usage intention in AI customer service is reinforced by task complexity, whereas Song and Lin (2023) revealed that users are more ready to leave the decision-making to AI under complicated conditions. de Matos, Laurentino and Veiga (2025) also emphasized that the nature of tasks determines the ways in which consumers perceive AI-mediated interaction and results. In the current research, task complexity should enhance customer satisfaction, AI-based trust, and behavioral intention to purchase associations. In case of complex tasks, the satisfied consumers and those who trust AI systems are more inclined to base their decisions on AI recommendations and make a purchase. At this point, therefore, task complexity is a boundary condition and not a direct predictor.

Based on Task-Technology Fit Theory, the following hypotheses are proposed:
H11: TC positively moderates the relationship between CS and BIP.
H12: TC positively moderates the relationship between TAI and BIP.

2.5. Research Gap

Despite the existence of significant empirical studies on the UTAUT2 theory, customer satisfaction, and trust in artificial intelligence, there is no single integrative framework that can explain the behavioral intention to purchase with dual mechanisms of mediation and at the same time explain task-related boundary conditions. The current research tends to consider satisfaction and trust as discrete constructs or to evaluate acceptance beliefs as the direct predictors of intention without a methodical elucidation of the psychological processes involved. In addition, the moderating effect of the complexity of tasks is not yet sufficiently developed in consumer-focused AI purchasing studies, specifically in well-established digital conditions, thus limiting a holistic view of how and when the acceptance beliefs are converted to purchase intention in AI-based conditions. To fill this gap, this paper integrates UTAUT2, Expectation-Confirmation Theory, Trust Theory, and Task-Technology Fit Theory to provide a comprehensive explanatory framework of consumer behavioral intention to purchase in AI-assisted online trade.

3. Theoretical Framework

The theoretical framework of the proposed study is based on the UTAUT2 theory, which describes the adoption of technology among consumers based on performance expectancy, effort expectancy, hedonic motivation, and habit (Venkatesh, Thong, & Xu, 2012). The constructs can be considered as driving forces as online purchasing, supported by artificial intelligence, is a voluntary, consumer-focused process where both functional and experiential beliefs influence user verdicts. In order to explain how these acceptance beliefs and purchase-related consequences are related to each other, the framework incorporates Expectation-Confirmation Theory, which argues that users make satisfaction assessments through comparison of expected and actual performance, thereby affecting future behavioral intention (Cody-Allen & Kishore, 2006; Subramanian et al., 2014). Considering the growing importance of algorithmic decision support in digital commerce, the Trust Theory is used to identify the range of trust among users in the context of reliability, competence, and goodwill of AI systems, which, in turn, assumes the existence of trust in AI as an evaluative process that can be performed simultaneously and affects purchase intentions (Ho & Cheung, 2024; Zhang et al., 2025). The framework also makes use of the Task Technology Fit Theory to explain the moderating effect of task difficulty arguing that the effect of satisfaction and trust on behavioral intention is enhanced when artificial-intelligence capabilities are aligned with challenging decision tasks (Morgeson & Humphrey, 2006; Xu et al., 2020). The suggested framework provides an all-encompassing explanation of how the technology-acceptance beliefs impact the behavioral intention to purchase depending on the level of satisfaction and trust in AI based on different levels of task complexity, through the incorporation of these supplementary theoretical lenses.

4. Data and Methodology

The study is placed in the framework of the United Kingdom, which is among the most developed and progressive digital trading environments in the world. The UK can be described as having a high internet penetration rate, a large number of smartphone users, and the prevalence of artificial intelligence in online shopping platforms, such as recommendation engines, chatbots, and automated customer services. These attributes make the UK an appropriate location to research AI-enabled buying behavior because consumers have high exposure levels to digital technology and use AI-based systems frequently. According to prior studies, mature digital markets also provide a proper environment to test extended UTAUT2 constructs as the development of behavioral intention in these cases is mainly affected by evaluative processes like satisfaction and trust, but not by the underlying adoption issues (Kalinić et al., 2019; Plohl & Čuš Babič, 2024; Venkatesh, Thong, & Xu, 2012). Furthermore, the United Kingdom has a strong institutional stability and consumer protection, thus reducing noise in the contexts and providing a clearer view of theoretical relationships, which further increases the generalizability and rigor of the results in comparison to the new or less digitally developed economies.

This study used a quantitative, cross-sectional research design, which implemented a self-administered questionnaire a method that is widely recognized as an appropriate instrument to test theory-based models of behavior in the context of technology adoption (Hair, 2014; Williams, Rana, & Dwivedi, 2015). The target audience was UK consumers who actively use AI-based and mobile internet-based online shopping. The non-probability purposive sampling technique was chosen due to the necessity of the study to involve respondents directly exposed to AI-supported purchasing systems. This method of sampling is typical of UTAUT2 and AI adoption studies in which a particular user experience is a precondition of meaningful responses (García de Blanes Sebastián et al., 2024; Hanif et al., 2021). The questionnaire was shared over the internet via online sources, such as consumer panels and social networks, and it was open to those customers who were more conversant with AI-powered online purchases. 1,000 questionnaires were disseminated among which 377 respondents returned their forms, which were usable and hence the response rate of 37.7 was achieved. The response rate is regarded as acceptable and matches the previous online surveys-based research in the field of digital commerce and AI studies (Cao, 2024; Dixit, Choudhary, & Govil, 2025). The responses were filtered in completeness and consistency prior to inclusion in the final dataset. The final sample with 377 respondents shows a heterogenous consumer profile that is aligned with the study objectives. The respondents were a balanced sample with respect to gender, age, and education levels with most of the respondents falling in the economically active age bracket and reported that they frequently used online purchasing sites. The dominance of respondents in terms of frequent use of AI-supported capabilities, such as personalized suggestions and automated help, confirms the relevance of the sample to the research setting. The inclusion of demographic variables will make the patterns of behavioral intention easier to interpret and is a best practice in consumer technology research (Marinković, Đorđević, & Kalinić, 2019; Venkatesh, Thong, & Xu, 2012).

The validity of all constructs was measured through scale-validated multi-item scales based on the previous research, thus providing content validity and reliability. The items were modified and used to measure performance expectancy, effort expectancy, hedonic motivation and habit (Venkatesh, Thong, & Xu, 2012). The customer satisfaction items were adapted from Subramanian et al. (2014) whereas trust in AI was measured from (Zhang et al., 2025). Task complexity items were adopted from Morgeson and Humphrey (2006). Behavioral intention to purchase was adapted from (Xu et al., 2019). All the items were measured using a five-point Likert scale, with the lowest score being strongly disagree (1) and the highest score being strongly agree (2). The questionnaire was pre-tested to be clear and contextually relevant.

4.1. Data analysis technique

The data was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), which is a suitable method to use with complex models that include mediation and moderation without requiring very strict normality assumptions (Hair, 2014). The PLS-SEM is especially suitable in studies in which the focus is on prediction and theoretical extrapolation, as identified in the current study. The analysis procedure was as follows: the evaluation of the measurement model was conducted to determine its reliability and validity; the evaluation of the structural model was implemented to test direct, mediating, and moderating hypotheses.

5. Results and Discussion

The demographic characteristics of the respondents show that the final sample included 377 valid responses, which represents a diverse and relevant group of consumers studying the AI-enabled online purchasing behavior in the context of the UK. The sample was gender balanced where both male and female respondents were sufficiently represented so that the results cannot be skewed to any one gender group. Regarding age, most of the respondents were aged between the economically active and digitally active age groups, specifically young and middle-aged adults, who are more inclined to make online purchases and use AI-assisted services like recommendations and automated assistance. In terms of education, most participants had a minimum of an undergraduate degree, which implied the level of digital literacy and mental capacity to assess AI-driven purchasing systems. Moreover, the respondents expressed different degrees of online shopping frequency, with a significant percentage stating that they used mobile internet and AI-based applications on a regular basis. Such demographic heterogeneity increases the representativeness of the sample and facilitates the strength of further analyses of behavioral intention, satisfaction and trust in AI.

Table 1: Convergent Validity Test

Constructs	items	Loading	VIF	Alpha	CR	AVE
BIP	BIP1	0.883	2.146	0.86	0.862	0.782
	BIP2	0.892	2.237			
	BIP3	0.877	2.157			
CS	CS1	0.896	2.359	0.879	0.879	0.805
	CS2	0.897	2.402			
	CS3	0.898	2.501			
EE	EE1	0.807	1.693	0.786	0.793	0.608
	EE2	0.769	1.514			
	EE3	0.797	1.516			
	EE4	0.744	1.54			
HBT	HBT1	0.706	1.419	0.776	0.791	0.597
	HBT2	0.762	1.489			
	HBT3	0.809	1.606			
	HBT4	0.81	1.555			
HM	HM1	0.883	2.144	0.866	0.872	0.788
	HM2	0.898	2.262			
	HM3	0.882	2.336			
PE	PE1	0.786	1.534	0.775	0.776	0.597
	PE2	0.773	1.536			
	PE3	0.774	1.526			
	PE4	0.759	1.443			
TAI	TAI1	0.906	2.721	0.897	0.9	0.829
	TAI2	0.904	2.628			
	TAI3	0.922	2.882			
TC	TC1	0.82	1.682	0.781	0.799	0.602
	TC2	0.745	1.496			
	TC3	0.717	1.421			
	TC4	0.817	1.56			

According to the results reported in Table 1, the reliability of the measurement model is strong for all indicators, and the construct validity is satisfactory for all latent variables. All standardized factor loadings are above the recommended threshold of 0.70 which indicates that each of the measurement items has a substantial contribution to its respective construct and is an adequate reflection of the theoretical concept in question. This proves that the items used in the research are specified and empirically sound. Additionally, the VIF of all indicators is much lower than the generally accepted cutoff values, which confirms the lack of multicollinearity between measurement items. As a result, the indicators are not over correlated, and each of them provides a distinct explanatory power, thus improving the stability and accuracy of the estimated parameters. These results are a strong argument of the reliability of the indicators and a guarantee that the measurement model is not prone to estimation bias due to redundancy of the indicators. The results also support the internal consistency and convergent validity of constructs used in the model. Cronbach alpha coefficients on all constructs were above the required minimum of 0.70 thus reflecting a high level of internal consistency amongst the items involved. Similarly, composite reliability (CR) scores were higher than the recommended value, and this increased the reliability strength of the measurement scales. Regarding convergent validity, average variance extracted (AVE) of each construct was greater than 0.50, which shows that each latent variable accounts for more than half of the variance of the observed indicators. Thus, the constructs give true representations of their underlying theoretical domains, and measurement error is relatively low. Collectively, these results show that the measurement model provides evidence of established criteria of reliability and validity, providing a solid empirical foundation upon which to proceed with the evaluation of the structural model and subsequent hypothesis testing.

Table 2: HTMT Ratio

	BIP	CS	EE	HBT	HM	PE	TAI	TC
BIP								
CS	0.44							
EE	0.214	0.473						
HBT	0.362	0.57	0.23					
HM	0.251	0.374	0.129	0.194				
PE	0.328	0.447	0.268	0.279	0.102			
TAI	0.429	0.521	0.422	0.488	0.375	0.476		
TC	0.24	0.048	0.107	0.141	0.067	0.081	0.06	

According to the results presented in Table 2, the Heterotrait-Monotrait (HTMT) ratio analysis provides strong evidence of discriminant validity within the measurement model. All HTMT values between construct pairs are well below the generally accepted conservative value of 0.85, thus indicating that each construct is empirically distinct from the other. The relatively low HTMT ratios suggest that there is little overlap between constructs and support the premise that the indicators associated with each latent variable capture conceptual domains that are unique to them. As a result, the measurement items do not capture similar phenomena redundantly, and the constructs are differentiated clearly within the model. In particular, such constructs as Behavioral Intention to Purchase (BIP), Customer Satisfaction (CS), Effort Expectancy (EE), Habit (HBT), Hedonic Motivation (HM), Performance Expectancy (PE), Trust in AI (TAI), and Task Complexity (TC) demonstrate sufficient levels of discriminant validity thus supporting the conceptual clarity of the measurement framework. In addition, the theoretical relationships are also reflected in the distribution of HTMT values among constructs but maintain sufficient discriminant separation. Although some construct pairs, e.g. Customer Satisfaction and Trust in AI, or Habit and Trust in AI, show moderately elevated HTMT ratios, all values are within comfortable limits, indicating related but empirically distinguishable constructs. Like, Task Complexity indicates particularly low HTMT values compared to all the other constructs to further confirm the unique position of this construct within the model. Overall, the assessment of HTMT provides reliable evidence of a high degree of discriminant validity, providing support to the assertion that the measurement model discriminates between conceptually disparate constructs. In addition, these results serve as sound justification to proceed to structural model evaluation and hypothesis-testing.

Table 3: Fornell Larcker

	BIP	CS	EE	HBT	HM	PE	TAI	TC
BIP	0.884							
CS	0.383	0.897						
EE	0.175	0.397	0.78					
HBT	0.302	0.479	0.18	0.773				
HM	0.219	0.328	0.107	0.16	0.888			
PE	0.267	0.37	0.211	0.218	0.083	0.773		
TAI	0.379	0.464	0.358	0.416	0.333	0.397	0.91	
TC	0.201	-0.002	0.081	0.113	0.033	0.01	0.04	0.776

The results presented in Table 3 provide further evidence for discriminant validity using the Fornell-Larcker criterion, providing support for the robustness of the measurement model.

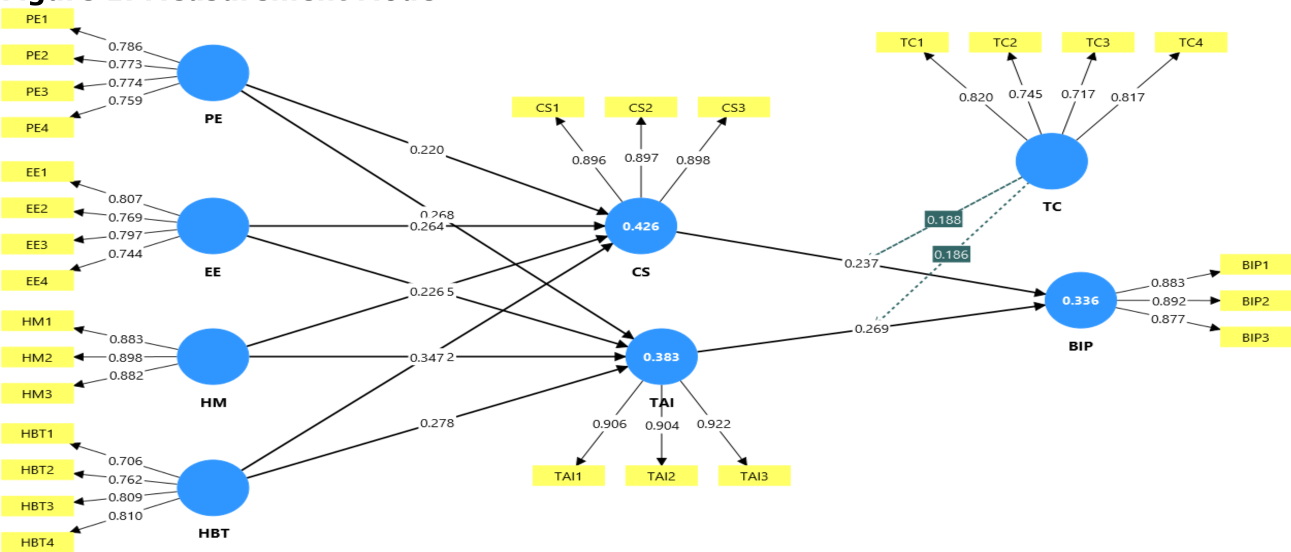
Specifically, the square root of the average variance extracted (AVE) of each construct is higher than the correlations of that construct with the rest of the constructs in the model, meaning that each latent variable has more variance in common with its own items of measurement than with other constructs, which is a necessary condition of discriminant validity. The diagonal elements of Table 3, which are the square roots of AVE, consistently exceed the off diagonal correlations among constructs, reflecting the empirical distinctiveness of the constructs. In addition, the Fornell-Larcker results reveal that behavioral intention to purchase (BIP), customer satisfaction (CS), effort expectancy (EE), habit (HBT), hedonic motivation (HM), performance expectancy (PE), trust in AI (TAI), and task complexity (TC) are conceptually and statistically differentiated. Even in cases of moderate correlations, e.g., between customer satisfaction and trust in AI or between habit and trust in AI, the square roots of AVE are still considerably greater than the (respective) correlation coefficients. This means that we have theoretically meaningful associations while not destroying the distinctiveness of the constructs. Like, task complexity has very low correlations with most of constructs, which further underlines unique conceptual role of task complexity in AI-enabled purchasing contexts. Overall, the Fornell-Larcker assessment contributes to the HTMT results by providing support for the adequacy of the discriminant validity from a covariance-based perspective. Together, these results provide strong empirical evidence that the measurement model captures different dimensions of consumer behavior in purchasing environments with an artificial intelligence backbone, and, thus, supports its suitability for further structural model evaluation and hypothesis testing.

Table 4: Cross Loadings

	BIP	CS	EE	HBT	HM	PE	TAI	TC
BIP1	0.883	0.337	0.146	0.269	0.209	0.252	0.342	0.178
BIP2	0.892	0.339	0.157	0.275	0.182	0.238	0.345	0.202
BIP3	0.877	0.340	0.162	0.257	0.190	0.219	0.315	0.151
CS1	0.337	0.896	0.373	0.415	0.349	0.339	0.424	0.023
CS2	0.354	0.897	0.338	0.444	0.300	0.326	0.402	0.012
CS3	0.340	0.898	0.357	0.430	0.230	0.330	0.423	-0.042
EE1	0.126	0.316	0.807	0.142	0.131	0.161	0.283	0.079
EE2	0.151	0.306	0.769	0.123	0.084	0.173	0.263	0.061
EE3	0.135	0.349	0.797	0.129	0.057	0.174	0.319	0.048
EE4	0.138	0.255	0.744	0.177	0.060	0.146	0.243	0.066
HBT1	0.155	0.279	0.115	0.706	0.112	0.122	0.248	0.038
HBT2	0.238	0.350	0.113	0.762	0.106	0.209	0.309	0.095
HBT3	0.280	0.425	0.135	0.809	0.086	0.222	0.318	0.098
HBT4	0.243	0.404	0.185	0.810	0.185	0.119	0.391	0.106
HM1	0.186	0.319	0.118	0.169	0.883	0.114	0.276	0.028
HM2	0.239	0.282	0.115	0.108	0.898	0.039	0.349	0.022
HM3	0.150	0.271	0.044	0.154	0.882	0.070	0.254	0.039
PE1	0.186	0.309	0.204	0.182	0.062	0.786	0.304	0.042
PE2	0.189	0.258	0.156	0.168	0.040	0.773	0.316	-0.017
PE3	0.273	0.270	0.142	0.107	0.070	0.774	0.311	-0.004
PE4	0.181	0.304	0.147	0.214	0.083	0.759	0.296	0.008
TAI1	0.321	0.419	0.309	0.362	0.318	0.338	0.906	0.034
TAI2	0.329	0.384	0.324	0.344	0.295	0.383	0.904	0.019
TAI3	0.381	0.46	0.343	0.425	0.297	0.362	0.922	0.055
TC1	0.167	0.03	0.105	0.062	0.019	0.02	0.029	0.82
TC2	0.134	-0.012	0.062	0.096	0.072	-0.072	-0.017	0.745
TC3	0.127	-0.02	0.068	0.085	-0.036	0.063	0.038	0.717
TC4	0.185	-0.01	0.023	0.11	0.04	0.016	0.064	0.817

According to Table 4, the analysis shows that the cross loadings analysis provides very strong evidence for the discriminant validity of the measurement model. The loadings clearly show that each item achieves its maximum factor loading on the theoretically anticipated construct with respect to all alternative constructs. Such a pattern develops a strong and proper association between indicators and latent variables, thus supporting the correct specification of the items. For example, items that measure behavioral intention to purchase (BIP), customer satisfaction (CS), effort expectancy (EE), habit (HBT), hedonic motivation (HM), performance expectancy (PE), trust in AI (TAI) and task complexity (TC) consistently produce significantly higher loadings on their intended constructs than on unrelated constructs. These results confirm that the indicators have been successful in drawing the conceptual boundaries of their respective constructs with no unnecessary overlap. In addition, the relatively low cross loadings on extraneous constructs further support the integrity of the measurement instrument. Even when constructs are theoretically linked, as is the case between customer satisfaction and trust in AI or between habit and behavioral intention to purchase, the cross-loadings are still very much subordinate to the main loadings, preserving the empirical distinctiveness of constructs. Task-complexity items have exceptional cross-loadings with other constructs underlining their unique conceptual role in the model. Collectively, these cross-loading results provide evidence for the conclusions based on analyses of convergent validity, heterotrait-monotrait ratio, and Fornell-Larcker criterion, presenting empirical evidence that each construct is empirically differentiated and measured with precision. As a result, the measurement model meets all critical reliability and validity standards, which establishes a solid methodological foundation. Accordingly, the study may proceed confidently to the evaluation of the structural model and hypothesis testing with the interrelationship among constructs being interpretable without apprehension about measurement overlapping or construct ambiguity.

Figure 1: Measurement Model



According to Figure 1, the measurement model shows that all constructs are reliably and appropriately operationalized through their respective indicators. The standardized loadings of all the observed variables on their respective latent constructs are high and statistically significant, suggesting that the selected items provide an adequate measure of the theoretical dimensions they are designed to measure. In particular, the constructs of the UTAUT2 framework, i.e., performance expectancy, effort expectancy, hedonic motivation, and habits are well-represented by their indicators with consistently high loadings which confirm the robustness and suitability of the adopted scales of measures. This gives clear evidence that the indicators are closely related to their underlying constructs and reflect the conceptual foundations of technology acceptance and technology in use behavior in AI-enabled purchasing situations. Similarly, the constructs of customer satisfaction, trust in AI, complexity of task, and behavioral intention to purchase show high internal consistency and strong indicator-construct relations, which confirm precise and coherent operationalization. In addition to indicator reliability, the model indicates that the endogenous constructs account for a significant proportion of variance as indicated by their R2 values showing satisfactory explanatory power of the measurement framework. This indicates that the latent variables have a meaningful contribution to explaining the variation in customer satisfaction, trust in AI, and the intention to purchase behavior. Overall, the measurement model shows good empirical evidence for the reliability and validity of all constructs used in the study. Collectively, these results confirm that the measurement architecture is theoretically grounded and empirically sound and, therefore, provides a good foundation to test the proposed relationships within the structural model.

According to the results of Table 5, the structural model empirically supports the hypothesized direct relationships. The results indicate that the performance expectancy, effort expectancy, hedonic motivation, and habits are positively and significantly influence customer satisfaction. Among these variables, habit is the most influential factor on customer satisfaction, and this means that regular and frequent use of AI-enabled purchase sites is a decisive factor in influencing the level of satisfaction in customers. On an equal note, each of the four UTAUT2 constructs exerts a strong positive influence on trust in AI, which indicates that as consumers believe AI systems to be useful, easy to use, enjoyable, and familiar, confidence in AI-driven decision support is more likely to grow. These findings affirm that acceptance beliefs are significant antecedents of both satisfaction and trust, which uphold the theoretical assumptions based on UTAUT2 and trust-related perspectives. The findings also show that customer satisfaction and trust in artificial intelligence have significant positive impacts on behavioral intention to purchase. This result highlights the importance of evaluative judgments and trust in AI systems as the main factors influencing consumer intentions to buy in AI-enabled settings and not acceptance beliefs.

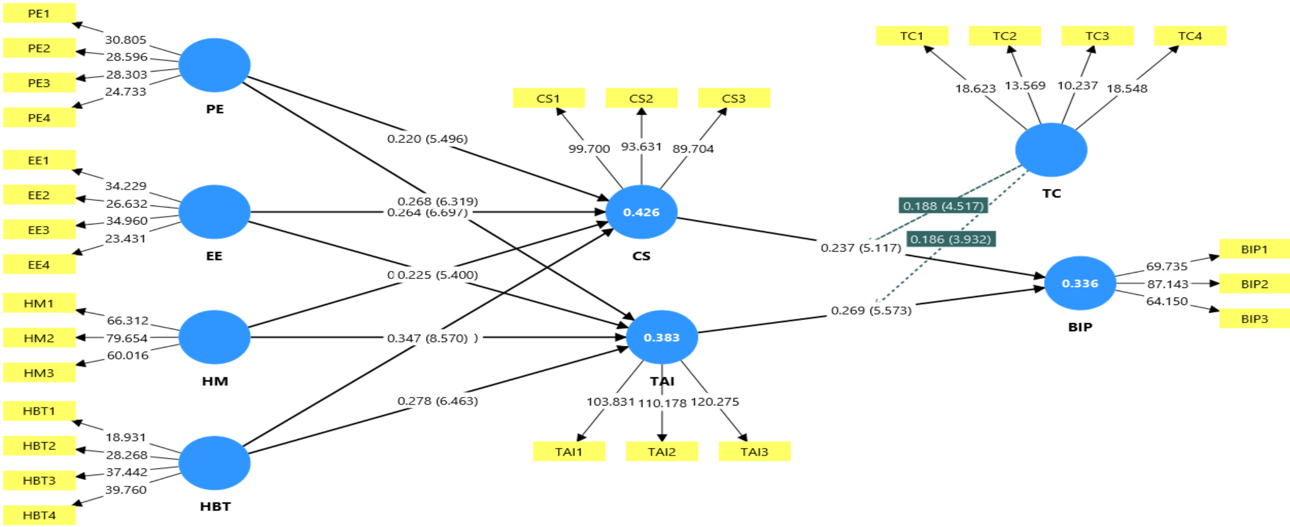
Table 5: Path Analysis

Hypothesis		Beta	STDEV	T statistics	P values	Conclusion
H1	PE -> CS	0.220	0.040	5.496	0.000	Supported
H2	EE -> CS	0.264	0.039	6.697	0.000	Supported
H3	HM -> CS	0.226	0.039	5.772	0.000	Supported
H4	HBT -> CS	0.347	0.040	8.570	0.000	Supported
H5	PE -> TAI	0.268	0.042	6.319	0.000	Supported
H6	EE -> TAI	0.225	0.042	5.400	0.000	Supported
H7	HM -> TAI	0.242	0.042	5.711	0.000	Supported
H8	HBT -> TAI	0.278	0.043	6.463	0.000	Supported
H9	CS -> BIP	0.237	0.046	5.117	0.000	Supported
H10	TAI -> BIP	0.269	0.048	5.573	0.000	Supported
H11	TC x CS -> BIP	0.188	0.042	4.517	0.000	Supported
H12	TC x TAI -> BIP	0.186	0.047	3.932	0.000	Supported
H13	PE -> CS -> BIP	0.052	0.015	3.515	0.000	Supported
H14	EE -> CS -> BIP	0.063	0.015	4.045	0.000	Supported
H15	HM -> CS -> BIP	0.054	0.014	3.817	0.000	Supported
H16	HBT -> CS -> BIP	0.082	0.018	4.481	0.000	Supported
H17	PE -> TAI -> BIP	0.072	0.018	4.055	0.000	Supported
H18	EE -> TAI -> BIP	0.061	0.016	3.889	0.000	Supported
H19	HM -> TAI -> BIP	0.065	0.016	4.121	0.000	Supported
H20	HBT -> TAI -> BIP	0.075	0.019	4.011	0.000	Supported

Furthermore, the moderation analysis shows that task complexity significantly supports the relationships between customer satisfaction and behavioral intention to purchase, and trust in AI and behavioral intention to purchase. Therefore, purchase-related activities that are more complicated lead to a higher likelihood among the satisfied consumers and consumers who trust AI to use the AI-assisted platforms and make purchase decisions. The results are in line with task-relevant and decision support theories, which focus on the significance of situational circumstances in influencing consumer behavior. The results of the mediation analysis give additional understanding of the mechanisms underlying the model. Customer satisfaction plays a significant role in mediating the following relationships between performance expectancy, effort expectancy, hedonic motivation, habit and behavioral intention to purchase. Similarly, trust in AI is a strong mediator of these UTAUT2 constructs and behavioral intentions. This shows that acceptance beliefs affect the purchase intention indirectly through satisfaction and trust and not necessarily through direct effects. In general, the findings indicate a strong trend of direct, mediating, and moderating relationships, which confirms the explanatory value of the framework suggested and justifies all hypothesized relationships that were put forward in the research.

As shown in Figure 2, the structural model has a strong explanatory power and statistically significant interrelationships between the variables under investigation. The results suggest that performance expectancy, effort expectancy, hedonic motivation, and habit have meaningful impacts on customer satisfaction and trust in AI, and thus, confirm their role as crucial antecedents of AI-enabled purchasing behavior. The ratio of explained variance indicates that a significant part of customer satisfaction and trust in AI can be explained by these UTAUT2 constructs, and behavioral intention to purchase is also satisfactorily explained by customer satisfaction and trust in AI. Furthermore, interaction effects indicate that task complexity increases the impact of customer satisfaction and trust in AI on behavioral intention to purchase, which means that consumers are more dependent on satisfaction and trust when they encounter complex purchase-related tasks. Overall, the structural model supports the suggested theoretical model by confirming the presence of direct, mediating, and moderating associations thus showing its relevance in explaining consumer purchase intention in AI-assisted digital commerce settings.

Figure 2: Structural Model



6. Discussion

The findings of this study give solid evidence to all the suggested hypotheses (H1-H20) and present powerful theoretical and empirical data regarding consumer behavior in AI-enabled purchasing in the UK. First, the results validate that performance expectancy, effort expectancy, hedonic motivation and habit have a significant positive impact on customer satisfaction (H1-H4). This implies that the consumers are more satisfied when the AI-enabled purchasing systems assist them to attain improved results, convenient to operate, they give pleasure and utilized frequently. These findings are completely aligned with UTAUT2, which focuses on the presence of functional benefits, ease, enjoyment, and habitual use in influencing user evaluation (Venkatesh, Thong, & Xu, 2012). The same has been observed in mobile commerce, e-banking, and AI-supported services, where efficiency and user experience are improved with technology and, consequently, satisfaction is higher (Cao, 2024; Ferreira Barbosa et al., 2021; Kalinić et al., 2019). It is also revealed that performance expectancy, effort expectancy, hedonic motivation, and habit have a positive impact on trust in AI (H5–H8). These results suggest that consumers will trust AI systems more when they believe they can be useful, easy to deal with, fun to use, and familiar with through use. This is in line with Trust Theory, which opines that trust is formed because of succeeding and positive system performance over time. Other previous researchers on AI chatbots, virtual assistants, and intelligent systems also discovered that perceived usefulness and ease of use are relevant determinants of trust in AI (García de Blanes Sebastián et al., 2024; Ho & Cheung, 2024; Zhang et al., 2025). More specifically, habit enhances trust, decreases the level of uncertainty, and builds confidence in AI-supported decision-making.

Moreover, the findings support that customer satisfaction and AI trust have significant effect on behavioral intention to purchase (H9 and H10). It shows that consumers are more likely to shop with AI-enabled platforms when they are content with their experience and trust the AI systems concerned. These results are consistent with Expectation-Confirmation theory, which argues that, satisfied users are more inclined to remain and increase their usage intentions Subramanian et al. (2014) and with previous research that trust is a central factor in purchase intentions in AI-mediated contexts (Malhotra & Ramalingam, 2023; Xu et al., 2019). The mediation results also suggest that customer satisfaction and AI trust are central in mediating the relationships among UTAUT2 constructs and behavioral intention to purchase (H13 to H20). This means that the influence of the acceptance of beliefs in purchase intention is indirectly achieved through both satisfaction and trust and not directly. These findings are consistent with the existing literature that has established evaluative processes as the main mechanisms that convert technology beliefs into behavioral consequences (Kalinić et al., 2019; Plohl & Čuš Babič, 2024). Finally, the moderation analysis shows that the impact of customer satisfaction and trust in AI on purchase intention is enhanced by task complexity (H11 and H12). When it comes to more complex buying processes, consumers are more likely to use their satisfaction with the platform and their trust in AI systems in order to make purchases. The results are aligned with Theory of Technology Fit and the available literature on AI that argues that users require more AI support in situations that are complex and cognitively challenging. (Morgeson & Humphrey, 2006; Song & Lin, 2023; Xu et al., 2020). Additionally, the discussion shows that UTAUT2, satisfaction, trust in AI, and task complexity are interdependent, which together offer a comprehensive framework to explain consumer purchase intention in AI-based digital commerce.

7. Conclusion

The purpose of the research was to determine how consumers acceptance beliefs influence their purchasing intention in online purchasing settings facilitated by artificial intelligence (AI) through the combination of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the variables of customer satisfaction, trust in AI and task complexity. The findings based on the data gathered on 377 respondents in the UK context provide an overall explanation of how functional, experiential and habitual factors affect purchasing intentions via critical evaluative processes. The findings indicate that performance expectancy, effort expectancy, hedonic motivation and habit significantly affect customer satisfaction and trust in AI. In turn, customer satisfaction and trust in AI directly increase the behavioral intention to purchase and are important mediating pathways through which the acceptance beliefs are translated into intention. Moreover, task complexity reinforces the effect of satisfaction and trust on purchase intention and thus highlights the role of contextual conditions in AI-supported decision-making. In terms of the theoretical approach, the research has made several contributions. First, it expands the scope of UTAUT2 by showing that satisfaction and trust in AI are important psychological processes that mediate the relationship between acceptance beliefs and purchase intention. Second, the combination of Expectation-Confirmation Theory and Trust Theory ensures that the study provides a more detailed explanation of post-adoption assessments in AI-based buying situations. Third, the use of task complexity as a moderator contributes to the knowledge on when satisfaction and trust gain increased influence, thus creating a task-based boundary condition on technology acceptance research. These contributions provide a more comprehensive and situational-based approach to explaining consumer behavior in artificial intelligence-assisted online commerce.

The practical implications of the study are also important. Among online retailers and digital platform providers, the results suggest that the perceived usefulness, ease of use, and enjoyment of AI systems can significantly contribute to customer satisfaction and trust which are key predictors of purchase intention. These results can be supported by the consistent and reliable use of AI features. In addition to that, platform designers are advised to consider complex purchase tasks, since consumers are now turning to trust and satisfaction with AI assistance to make cognitively demanding decisions. To improve consumer confidence and increase purchasing outcomes, it is therefore possible to enhance the transparency, reliability, and user-friendliness of AI systems. The study has a few limitations despite its contributions. Cross-sectional design restricts the ability to make inferences about causality and future studies could take a longitudinal design to investigate satisfaction, trust and intention change over time. The research did not investigate the actual purchasing behavior; instead, it only investigated purchase intention, implying that future researchers might take the model a step further and investigate behavioral outcomes. Moreover, the UK context, which is an established digital setting, might limit generalization; future studies can provide the model to test it in different cultural or institutional contexts. Additional variables, including perceived risk, ethics, or transparency of AI systems, could also be taken into consideration in further extensions. Overall, the results of the current research indicate that the combination of acceptance beliefs, evaluative and contextual variables offer a substantive account of consumer purchase intention in AI-based digital commerce. The study improves the knowledge of how AI can be used to assist consumer decision-making in faster-growing digital markets by advancing theory and providing practical insights on the topic.

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