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Exploring User Acceptance of Chatbot AI: A Triangulated Framework Integrating TAM, ECTM, and TPB Constructs

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Abstract

Artificial intelligence-powered chatbots have revolutionized e-commerce by providing personalized customer interactions, real-time support, and streamlined purchase processes. Despite their widespread adoption, sustained user engagement remains challenging, requiring deeper insights into cognitive, affective, and social determinants of long-term usage. This study addresses this gap by integrating the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Expectation-Confirmation Theory Model (ECTM) into a comprehensive triangulated framework to examine user acceptance and continued purchase intention toward AI chatbots in online shopping. The research investigates direct effects of confirmation, information quality, perceived usefulness (PU), perceived ease of use (PEOU), attitude, and subjective norm on satisfaction, alongside satisfaction's mediating role in predicting continued purchase intention. Data were collected from 504 respondents with prior AI chatbot experience in online shopping via purposive sampling, using validated 6-point Likert scales. Partial least squares structural equation modeling (PLS-SEM) was conducted using SmartPLS 4. Results confirm that confirmation (β=0.178, p=0.037), information quality (β=0.269, p<0.001), PU (β=0.152, p=0.005), PEOU (β=0.235, p<0.001), and attitude (β=0.184, p=0.001) significantly predict satisfaction, which strongly influences continued purchase intention (β=0.868, p<0.001). Subjective norm exhibited no significant effect (β=-0.003, p=0.954). Satisfaction fully mediates ECTM and TAM pathways, underscoring experiential confirmation and system quality's dominance over social influences in post-adoption behavior. Theoretically, this study validates an integrated model advancing post-adoption theory in AI contexts. Practically, findings guide e-commerce platforms to enhance chatbot retention by prioritizing information accuracy, usability, and expectation alignment rather than social norms.

Keywords: TAM, TPB, ECTM, Satisfaction, Continued Purchase Intention

1. Introduction

The rapid advancement of Artificial Intelligence (AI) technologies has transformed online retail, with AI-powered chatbots serving as integral tools for enhancing customer service and streamlining purchase processes [1], [2]. These systems provide personalized interactions, real-time support, and efficient transactions, driving their prevalence in e-commerce [3]. However, despite growing adoption, user acceptance and sustained usage remain critical challenges requiring rigorous investigation to ensure long-term engagement and satisfaction [4].

Existing literature on technology adoption primarily examines initial acceptance via models like the Technology Acceptance Model (TAM), which emphasizes perceived usefulness and ease of use [5], [6], and the Theory of Planned Behavior (TPB), focusing on attitudinal, normative, and control beliefs [7], [8]. The Expectation-Confirmation Theory Model (ECTM) complements these by explaining post-adoption behaviors through expectation-experience alignment and satisfaction [9], [10]. Yet, these models are often applied separately, yielding fragmented insights into chatbot AI dynamics.

This study integrates TAM, TPB, and ECTM into a triangulated framework to examine user acceptance and continued purchase intention in AI chatbot-enabled online shopping. In this study, triangulation refers to theoretical triangulation, whereby multiple complementary theoretical perspectives, TAM, TPB, and ECTM, are integrated to capture different dimensions of user acceptance and post-adoption behavior. It investigates direct and indirect effects of confirmation,

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information quality, perceived usefulness, perceived ease of use, attitude, and subjective norm on satisfaction and continued intention, with satisfaction as a key mediator. Although prior continuance models such as the Expectation–Confirmation Model acknowledge satisfaction as a key mediator between confirmation and continuance intention, limited research has examined this mediating mechanism within integrated frameworks combining TAM, TPB, and ECTM in the specific context of AI chatbot–enabled online shopping.

This study advances research on AI chatbot use in e-commerce by testing a triangulated model that integrates ECTM, TAM, and TPB. It examines how confirmation, information quality, perceived usefulness, perceived ease of use, attitude, and subjective norm shape satisfaction and continued purchase intention, with satisfaction as a central mediator. The model clarifies how experiential, cognitive, and social factors jointly drive post-adoption behavior. The study contributes a synergistic framework that explains both acceptance and sustained engagement. Findings offer actionable guidance for platform designers and marketers to improve chatbot functionality, user experience, satisfaction, and long term customer loyalty over time.

2. Literature Review

2.1. Grand theory

The foundation of this research lies in integrating three widely recognized theoretical frameworks: the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Expectation-Confirmation Theory Model (ECTM). TAM, developed by Davis [6], posits that perceived usefulness and perceived ease of use are primary predictors of technology adoption. TPB, introduced by Ajzen [7], extends behavioral studies by incorporating attitudes, subjective norms, and perceived behavioral control as antecedents to intention. In this study, the TPB framework is selectively operationalized using attitude and subjective norm. Perceived behavioral control is not included because AI chatbot interactions in online shopping typically involve minimal technical barriers, making users' perceived control over the behavior relatively uniform and less predictive of continuance intention [8]. ECTM, originating from Oliver's [11] disconfirmation theory, highlights the pivotal role of confirmation and satisfaction in shaping consumers' post-purchase behaviors. Together, these frameworks provide a robust lens to explore how satisfaction mediates the relationship between antecedents and continued use intention.

2.2. ECTM and Satisfaction

2.2.1. Confirmation and satisfaction

Confirmation refers to the extent to which consumers' pre-purchase expectations align with their actual experiences after using a product or service [12]. In Expectation Confirmation Theory, consumers first form expectations, then interact with the service, and finally compare outcomes with prior beliefs, leading to confirmation or disconfirmation [13]. This evaluation directly shapes satisfaction [14]. In digital contexts, the Expectation Confirmation Technology Model defines confirmation as the degree to which system performance meets or exceeds initial expectations [9].

Extensive research identifies confirmation as a key driver of satisfaction. Empirical studies show that when experiences meet expectations, users report higher satisfaction in online learning, chatbot banking, and social media contexts [15], [16], [17]. These findings consistently support ECT's central proposition that expectation alignment fosters positive post use evaluations. Although ECT has evolved into both parsimonious and extended models, some scholars argue that satisfaction also reflects motivations, emotions, and sociocultural influences beyond confirmation alone [18], [19]. Nonetheless, contemporary literature largely agrees that confirmation remains a foundational mechanism in shaping satisfaction, especially in service and technology adoption settings. According to Expectation–Confirmation Theory, users evaluate whether a system meets their prior expectations, and this post-usage evaluation directly determines satisfaction levels, which subsequently influence continued usage behavior. Based on these statements above we propose the following hypotheses:

H1: Confirmation influences satisfaction.

2.2.2. Information Quality and satisfaction

Information quality is a central criterion for evaluating the success of information systems, encompassing the relevance, accuracy, completeness, timeliness, and understandability of the information generated and delivered by a system [20]. It represents the semantic value of system outputs and directly influences user satisfaction and continuance behavior [14]. When information is reliable, up-to-date, and aligned with user needs, it supports effective decision making and improves overall user experience [21]. In digital environments characterized by information overload, high information quality helps reduce uncertainty and cognitive effort, enabling users to process content efficiently and confidently.

The DeLone and McLean Information Systems Success Model [22] positions information quality as one of the core dimensions of system success. Within this framework, information quality influences user satisfaction because accurate, relevant, and timely information enhances users' cognitive evaluation of system performance and the perceived value of system outputs. Satisfaction arises when systems deliver accurate, complete, and relevant information that meets user expectations [23]. Accuracy minimizes errors, completeness ensures sufficient detail, and timeliness guarantees availability when needed [24]. Together, these attributes strengthen perceived usefulness and system credibility.

Empirical evidence consistently links information quality to satisfaction across domains. Mobile health users report greater satisfaction when applications provide structured and reliable content [25]. In e learning, precise and timely materials enhance learning effectiveness and satisfaction [26]. In AI chatbots, clear and coherent responses foster satisfaction, trust, and commitment [27]. Scholars further emphasize that information quality is multidimensional and task dependent, where relevance and clarity are critical [28]. Overall, robust evidence across education, finance, healthcare, and AI services confirms that high information quality is vital for satisfaction and continued use [17], [29]. Ensuring superior information quality is therefore a strategic priority for organizations seeking sustained user engagement. From the perspective of the information systems success literature, high information quality enhances users' cognitive evaluation of system performance, which in turn strengthens satisfaction with the digital service. Based on these statements above we propose the following hypotheses:

H2: Information quality influences satisfaction.

2.3. TAM and Continued Purchase Intention

2.3.1. Perceived Usefulness and Satisfaction

Perceived usefulness refers to the degree to which a technology enhances users' performance and productivity [6]. As a core construct in the TAM, it plays a crucial role in explaining user satisfaction and continued usage or purchase intentions. The concept reflects users' beliefs that a system provides tangible benefits, helps accomplish tasks more efficiently, and improves decision quality [30]. When users perceive real value in a technology, they are more likely to evaluate their experience positively.

A substantial body of empirical research confirms the positive effect of perceived usefulness on satisfaction across digital contexts. For example, Alshammari and Babu [31] find that satisfaction increases when users believe AI tools simplify complex tasks or generate valuable insights. Similarly, Saqr et al. [32] report that the perceived utility of AI driven e learning platforms is strongly associated with user satisfaction, indicating that functional value shapes both cognitive and emotional responses.

Perceived usefulness also interacts with related values. Jo [33] highlights that utilitarian value can mediate its impact on adoption, as users must understand system capabilities to appreciate benefits. Overall, perceived usefulness is a key determinant of satisfaction and continuance, as technologies that improve performance foster positive evaluations, emotional satisfaction, and sustained adoption [34]. From a cognitive evaluation perspective, users who perceive a technology as useful interpret the system as delivering meaningful performance benefits, which generates positive evaluative judgments and ultimately increases satisfaction with the service. Based on these statements above, we propose the following hypothesis:

H3: Perceived usefulness positively influences user satisfaction.

2.3.2. Perceived Ease of Use and Satisfaction

Perceived ease of use refers to the degree to which users believe that interacting with a system requires minimal effort [31]. As a central construct in the Technology Acceptance Model, it significantly influences user satisfaction and continuance intention [35]. This concept emphasizes simplicity, intuitive design, and low complexity in shaping positive user experiences [36]. When systems are easy to learn and operate, users can concentrate on achieving their objectives rather than managing technical features, resulting in more favorable evaluations.

Extensive research confirms the positive relationship between perceived ease of use and satisfaction across various technologies. Lun et al. [36] report that clear layouts and straightforward navigation significantly enhance satisfaction in adoption contexts. Users who perceive systems as easy to operate tend to form more positive attitudes and emotional responses. In AI environments, Alshammari and Babu [31] find that chatbots with simple and responsive interactions increase satisfaction, trust, and sustained engagement. Ngubelanga and Duffett [37] further show that ease of use strengthens perceived usefulness by enabling efficient task completion.

Overall, perceived ease of use reduces cognitive burden and fosters positive cognitive and emotional reactions, promoting sustained engagement and loyalty across digital services. According to the Technology Acceptance Model, systems that are easier to use reduce users' cognitive effort and facilitate positive evaluations, which can enhance satisfaction with the technology. Based on these statements above we propose the following hypotheses:

H4: Perceived ease of use positively influences user satisfaction.

2.4. TPB and Continued Purchase Intention.

2.4.1. Attitude and Satisfaction

Although the Theory of Planned Behavior (TPB) posits attitude as a direct antecedent of behavioral intention [7], post-adoption literature extends this framework by proposing that attitude shapes experiential satisfaction through cognitive framing and affective evaluation of the technology experience [31]. Attitude refers to an individual's overall positive or negative evaluation of performing a behavior and is a central predictor of intention in the Theory of Planned Behavior [7]. It captures how strongly users view a technology as beneficial, enjoyable, or useful for meeting their needs [16]. In AI chatbot contexts, favorable attitudes reflect perceptions of the system as helpful, efficient, or enjoyable [38]. When users hold positive cognitive-affective evaluations of the chatbot interaction, these appraisals directly enhance satisfaction with the service experience. Empirical studies confirm that positive attitudes toward technology services correlate with higher satisfaction levels, as favorable predispositions color post-usage evaluations [31], [39]. Therefore, consistent with theoretical extensions of TPB in post-adoption contexts, attitude is expected to positively influence user satisfaction. Based on these statements above we propose the following hypotheses:

H5: Attitude positively influences satisfaction.

2.4.2. Subjective Norm and Satisfaction

While TPB positions subjective norm as a determinant of behavioral intention [7], emerging post-adoption research suggests social influence may indirectly shape satisfaction through experiential validation or alignment with referent group expectations, emerging post-adoption research suggests social influence may indirectly shape satisfaction through experiential validation or alignment with referent group expectations [40]. Subjective norm, a key construct in the Theory of Planned Behavior, refers to perceived social pressure to perform or avoid a behavior [7]. It reflects how family, friends, peers, and society shape an individual's intention to adopt or continue using a technology [41]. In consumer contexts, users often consider others' opinions when evaluating digital services.

In AI chatbot environments, positive social endorsement (e.g., recommendations from trusted others) can reinforce user confidence and positively influence satisfaction judgments, particularly when personal experience is ambiguous [40], [42]. As chatbots become embedded in e-commerce, social cues may complement personal evaluations [43], [44]. Thus, following theoretical extensions linking normative beliefs to experiential outcomes, subjective norm is hypothesized to positively influence satisfaction. Based on these statements above we propose the following hypotheses:

H6: Subjective norm positively influences satisfaction.

2.5. Satisfaction and Continued Purchase Intention.

Customer satisfaction is a pivotal psychological and behavioral construct that significantly influences post-adoption behaviors, particularly continued purchase intention, the consumer's willingness to repeatedly engage in transactions with a service or platform over time [45], [46]. Customer satisfaction is a pivotal psychological construct that influences post-adoption behaviors, particularly continued purchase intention in digital service environments [47].

In the context of Chatbot AI-driven shopping experiences, satisfaction emerges as a critical mediator between user experience and long-term behavioral intentions [48]. When users interact with an AI chatbot for product inquiries, recommendations, or transaction processing, their level of satisfaction depends on factors such as response accuracy, speed, personalization, usefulness, and interactivy [49]. Positive interactions that align with or surpass user expectations lead to higher satisfaction, which in turn fosters trust, loyalty, and the intention to continue purchasing through the same channel. Based on these statements above we propose the following hypotheses:

H7: Satisfaction positively influences continued purchase intention.

2.5.1. ECTM to Continued intention, mediated by satisfaction

The Expectation Confirmation Theory Model explains how initial expectations shape long term behavioral intentions in technology mediated services. Within the ECTM framework, confirmation enhances satisfaction, which subsequently strengthens continued purchase intention in digital service contexts. Empirical evidence confirms this sequential mechanism. Nguyen et al. [17] show that confirmation significantly enhances satisfaction in chatbot banking services, which then increases continuance intention. Thus, satisfaction functions as a key psychological mechanism translating positive evaluations into sustained behavior.

Information quality also plays a critical role in digital service environments. Defined as the accuracy, relevance, completeness, and clarity of system output, high information quality reduces uncertainty and improves decision making. Lee and Sung [14] find that clear and timely information increases satisfaction and continued engagement in online exchanges. Similarly, Almaiah et al. [25] demonstrate that accurate and structured information enhances satisfaction and repurchase intention. Building on this evidence, this study posits that confirmation and information quality influence continued purchase intention indirectly through satisfaction. Hence, the following hypotheses are proposed:

H8: Confirmation positively influences continued purchase intention, mediated by satisfaction.

H9: Information quality positively influences continued purchase intention, mediated by satisfaction.

2.5.2. TAM to Continued intention, mediated by satisfaction

The Technology Acceptance Model identifies perceived usefulness and perceived ease of use as key determinants of technology acceptance and continuance [50]. When users perceive that an AI chatbot improves efficiency, supports decision making, and facilitates transactions, they evaluate the experience more positively, leading to greater satisfaction [51]. Satisfaction then translates functional benefits into sustained behavioral intentions. Empirical evidence supports this mediating mechanism. She et al. [15] show that satisfaction fully mediates the effect of perceived usefulness on continued use, while Nguyen et al. [17] report similar findings in banking chatbots.

Perceived ease of use also enhances satisfaction and subsequent behavioral intention. Studies consistently confirm that user friendly systems increase satisfaction, which then drives repurchase intention [31], [52]. Therefore, both constructs are expected to influence continued purchase intention indirectly through satisfaction. Therefore, the following hypotheses are proposed:

H10: Perceived ease of use positively influences continued purchase intention, mediated by satisfaction.

H11: Perceived usefulness positively influences continued purchase intention, mediated by satisfaction.

2.5.3. TPB to Continued Intention, Mediated by Satisfaction

Attitude plays a central role in fostering long term engagement with AI chatbots in e-commerce [53]. A favorable attitude reflects perceptions of chatbots as helpful, efficient, and enjoyable, strengthening both cognitive and emotional responses during interaction [54]. Empirical evidence indicates that positive attitudes significantly increase continuance intention toward technology-based services [55]. When users perceive chatbots as valuable tools that enhance efficiency and access to information, they are more likely to experience satisfaction, which links initial evaluations to sustained behavioral intention [56]. This mediating role of satisfaction is particularly salient in dynamic and emotionally engaging service contexts.

Subjective norm also shapes technology adoption through social influence [57], [58]. Users often rely on reference groups when deciding to adopt or continue chatbot use [59]. Social endorsement strengthens attitude and acceptance, indirectly enhancing satisfaction [60]. Therefore, the following hypotheses are proposed:

H12: Attitude positively influences continued purchase intention, mediated by satisfaction.

H13: Subjective norm positively influences continued purchase intention, mediated by satisfaction.

All hypotheses in this study are illustrated in figure 1.

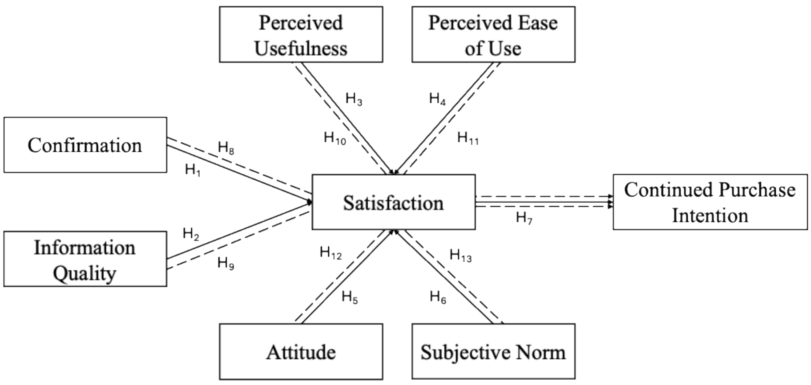

Figure. 1. Framework research

3. Methodology

This study surveyed 504 respondents with prior experience using AI chatbots in online shopping. The sample was designed to ensure demographic diversity and improve generalizability. Female respondents comprised 57.0 percent of the sample and males 43.0 percent. Most participants held a bachelor's degree at 64.3 percent, followed by master's degrees at 20.2 percent, high school diplomas at 10.7 percent, and doctoral degrees at 4.8 percent, indicating a predominantly well-educated sample.

Nearly half of the respondents worked in professional and technical occupations at 48.2 percent. Others were employed in education at 19.4 percent, business and management at 15.1 percent, government or public service at 9.5 percent, and other sectors at 7.7 percent. Chatbot use was most common in e-commerce at 55.2 percent, particularly on major platforms, followed by financial services at 17.6 percent and telecommunications at 12.3 percent.

Data were collected through purposive sampling targeting experienced chatbot users. Respondents were required to have interacted with an AI chatbot in an online shopping context at least once within the previous six months to ensure that their evaluations were based on relatively recent experience. The survey was distributed online through major e-commerce user communities and social media platforms where AI chatbot interactions are commonly experienced. Participants were invited to participate voluntarily and were screened to confirm their prior experience using AI chatbots in online shopping contexts. A 6-point Likert scale was applied to capture perceptual variation [61]. An even-numbered scale was used to avoid a neutral midpoint and encourage respondents to express a directional evaluation, thereby reducing central tendency bias in perception-based assessments. Eight latent constructs were measured using validated scales adapted from prior studies. The measurement items were slightly adapted to fit the AI chatbot context in online shopping. Minor wording adjustments were made to ensure contextual relevance while preserving the original conceptual meaning of each construct. The questionnaire was translated into Indonesian and reviewed to ensure clarity and consistency with the original measurement scales.

Information quality (4 items) and repurchase intention (3 items) were adapted from Almaiah et al. [25]. Perceived usefulness (4 items), perceived ease of use (3 items), and satisfaction (4 items) were measured using scales developed by Drwish et al. [26]. Subjective norm (4 items) was adapted from Xia et al. [62].

4. Results and Discussion

4.1. Evaluation of the Measurement Model

The evaluation of the measurement model, or outer model, represents a crucial step in assessing construct validity and reliability. As shown in table 1, all latent variables demonstrate strong psychometric properties, supporting their suitability for structural analysis. Reliability was examined using Cronbach's Alpha and Composite Reliability, with all values exceeding the recommended threshold of 0.7 [63]. Satisfaction reported the highest reliability scores (α = 0.905, CR = 0.933), followed by information quality (α = 0.880, CR = 0.917) and attitude (α = 0.864, CR = 0.917), indicating strong internal consistency and scale stability.

Convergent validity was assessed using Average Variance Extracted, which evaluates the proportion of variance captured by a construct relative to measurement error (Cheung et al., 2023). All constructs exceeded the 0.5 benchmark. Satisfaction (AVE = 0.778), Confirmation (AVE = 0.758), and perceived ease of use (AVE = 0.751) demonstrated particularly strong convergent validity, confirming that the indicators adequately represent their respective constructs.

Additionally, all item outer loadings were above 0.7, meeting recommended standards and further supporting the robustness and reliability of the measurement instruments employed in this study. In addition, discriminant validity was assessed using the Heterotrait–Monotrait (HTMT) ratio, and indicator cross-loadings were examined to ensure that each indicator loaded more strongly on its intended construct than on other constructs. All HTMT values were below the recommended threshold, confirming adequate discriminant validity among the constructs.

Table 1. Outer Loading Results

Code	Items	Outer Loading	Source
	Confirmation α=0.840, CR= 0.904, AVE=0.758		
CON1	My experience with using the AI chatbot was better than I had expected.	0.855	[16]
CON2	The service provided by the AI chatbot in the online store exceeded my expectations.	0.895	
CON3	Overall, most of my expectations regarding the use of the AI chatbot were met.	0.862	
	Information quality α=0.880, CR=0.917, AVE=0.735		
INFO1	The information provided by the chatbot AI is useful.	0.849	[25]
INFO2	The information provided by the chatbot AI is understandable.	0.869	
INFO3	The information provided by the chatbot AI is interesting.	0.867	
INFO4	The information provided by the chatbot AI is reliable.	0.844	
	Perceived ease of use α=0.834, CR=0.900, AVE=0.751		
PEOU1	I find AI chatbots used in online stores familiar to use.	0.867	[26]
PEOU2	Using AI chatbots in online stores does not require much mental effort from me.	0.871	
PEOU3	In general, AI chatbots in online stores are easy to use.	0.861	
	Perceived usefulness α=0.869, CR=0.911, AVE=0.719		
PU1	AI chatbots used in online stores help me complete my shopping tasks efficiently and quickly.	0.843	[26]
PU2	AI chatbots used in online stores help improve my shopping experience.	0.886	
PU3	AI chatbots used in online stores enhance my effectiveness in making purchasing decisions.	0.811	

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PU4	AI chatbots used in online stores are effective and efficient tools for customer interaction.	0.850	
	Attitude α=0.864, CR=0.917, AVE=0.786		
ATT1	I feel positive about using AI chatbots when shopping online.	0.890	
ATT2	I enjoy interacting with AI chatbots while shopping online.	0.874	[16]
ATT3	It is a sensible choice to use AI chatbots when purchasing from online stores.	0.896	
	Subjective norm α= 0.853, CR=0.901, AVE=0.694		
SN1	My family, relatives, and close friends significantly influence my decision to shop at online stores that use AI chatbots.	0.826	
SN2	My colleagues and supervisors (or classmates and teachers, if applicable) significantly influence my decision to shop at online stores that use AI chatbots.	0.826	[62]
SN3	Other consumers or people whose opinions I value significantly influence my decision to shop at online stores that use AI chatbots.	0.835	
SN4	Experts in e-commerce significantly influence my decision to shop at online stores that use AI chatbots.	0.845	
	Satisfaction α=0.905, CR=0.933, AVE=0.778		
SAT1	Using online stores with AI chatbots meets my shopping needs.	0.881	
SAT2	Shopping through online stores with AI chatbots is enjoyable for me.	0.899	[26]
SAT3	I feel happy when interacting with AI chatbots while shopping online.	0.900	
SAT4	I believe AI chatbots in online stores help me make better purchasing decisions.	0.848	
	Repurchase intention α=0.864, CR=0.917, AVE=0.786		
INT1	I intend to shop at stores that use AI chatbots in the future.	0.898	
INT2	I will frequently shop at online stores that use AI chatbots.	0.873	[25]
INT3	I will recommend others to shop at online stores that use AI chatbots.	0.889	

Discriminant validity, presented in table 2, confirms that each construct is empirically distinct. This was assessed by comparing the square root of the AVE for each construct with its correlations with other constructs. In all cases, the square root of the AVE exceeded the corresponding inter-construct correlations. For example, the square root of AVE for satisfaction (0.882) is higher than its correlations with attitude (0.817) and perceived usefulness (0.824), indicating adequate differentiation. Likewise, information quality shows a square root of AVE of 0.857, which surpasses its correlations with perceived usefulness (0.658) and subjective norm (0.698). These results confirm that the constructs are conceptually distinct and free from significant overlap.

Table 2. Discriminant Validity

	ATT	**CON**	**INT**	**INFO**	**PEU**	**PU**	**SAT**	**SN**
Attitude	0.887							
Confirmation	0.711	0.871						
Continued purchase intention	0.753	0.796	0.887					
Information quality	0.826	0.692	0.756	0.857				
Perceived usefulness	0.688	0.801	0.755	0.658	0.848			
Perceived ease of use	0.771	0.754	0.797	0.769	0.706	0.867		
Satisfaction	0.817	0.792	0.868	0.824	0.762	0.824	0.882	
Subjective norm	0.692	0.747	0.749	0.698	0.761	0.714	0.729	0.833

Multicollinearity was assessed using Variance Inflation Factor values. All VIF values were below the threshold of 5, with the highest value of 3.897 for the path from attitude to satisfaction. These results indicate that multicollinearity is not a concern, allowing reliable interpretation of the structural relationships. Although the structural path from satisfaction to continued purchase intention shows a relatively high coefficient (β = 0.868), additional validity tests indicate that this relationship is not driven by measurement redundancy. Discriminant validity results using both the Fornell–Larcker criterion and the HTMT ratio confirm that satisfaction and continued purchase intention remain empirically distinct constructs. Therefore, the strong relationship likely reflects the central role of satisfaction in shaping continued purchasing decisions in AI chatbot–assisted online shopping contexts rather than conceptual overlap.

4.2. Hypothesis Results

Table 3 reports the structural model results, including the direction, magnitude, and significance of the hypothesized relationships. Confirmation has a positive and significant effect on Satisfaction ($\beta = 0.178$, $t = 2.090$, $p = 0.037$), supporting H1. This finding indicates that when AI chatbot performance meets or exceeds user expectations, overall satisfaction increases.

Information quality emerges as one of the strongest predictors of Satisfaction ($\beta = 0.269$, $t = 4.215$, $p < 0.001$), supporting H2. Users who receive accurate, relevant, and clear information report higher satisfaction levels. Perceived usefulness also significantly influences satisfaction ($\beta = 0.152$, $t = 2.841$, $p = 0.005$), confirming H3. When chatbots enhance efficiency and support better decision making, users evaluate their experience more positively.

Perceived ease of use demonstrates a strong positive effect on Satisfaction ($\beta = 0.235$, $t = 3.742$, $p < 0.001$), supporting H4, suggesting that intuitive and effortless interaction fosters favorable evaluations. Attitude likewise has a significant impact on satisfaction ($\beta = 0.184$, $t = 3.219$, $p = 0.001$), supporting H5. In contrast, subjective norm does not significantly affect satisfaction ($\beta = -0.003$, $t = 0.058$, $p = 0.954$), leading to the rejection of H6. This result may indicate that satisfaction with AI chatbot interactions in online shopping is primarily driven by individual experiential evaluations rather than social influence. Unlike technology adoption decisions that often depend on peer or social expectations, satisfaction represents a post-usage evaluation based on perceived performance and interaction quality. In the context of AI chatbot-assisted shopping, users may rely more on personal utility and service experience than on external social pressures when forming satisfaction judgments. Finally, satisfaction strongly predicts continued purchase intention ($\beta = 0.868$, $t = 41.443$, $p < 0.001$), supporting H7 and confirming its central role in long-term behavioral intention.

Table 3. Path Coefficients

	Hypotheses	β	T Statistic	P Values
H1	Confirmation → Satisfaction	0.178	2.090	0.037
H2	Information quality → Satisfaction	0.269	4.215	0.000
H3	Perceived usefulness → Satisfaction	0.152	2.841	0.005
H4	Perceived ease of use → Satisfaction	0.235	3.742	0.000
H5	Attitude → Satisfaction	0.184	3.219	0.001
H6	Subjective norm → Satisfaction	-0.003	0.058	0.954
H7	Satisfaction → Continued purchase intention	0.868	41.443	0.000

The indirect effects reported in table 4 provide strong support for the mediating role of Satisfaction in most hypothesized relationships. Confirmation has a positive and significant indirect effect on continued purchase intention through satisfaction ($\beta = 0.155$, $p = 0.038$), supporting H8. This finding suggests that when chatbot performance meets or exceeds expectations, enhanced satisfaction translates into stronger continuance intention.

Information quality also demonstrates a significant indirect effect ($\beta = 0.234$, $p < 0.001$), supporting H9. When users receive accurate, relevant, and understandable information, their satisfaction increases, which subsequently strengthens continued purchase intention. Similarly, perceived usefulness significantly affects continuance intention via Satisfaction ($\beta = 0.132$, $p = 0.005$), supporting H11. Chatbots that improve efficiency and decision making enhance satisfaction, thereby encouraging repurchase intention.

Perceived ease of use shows a strong indirect effect ($\beta = 0.204$, $p < 0.001$), supporting H10, indicating that user friendly and effortless interaction promotes satisfaction and future engagement. Attitude also exerts a significant indirect influence through Satisfaction ($\beta = 0.160$, $p = 0.002$), supporting H12. In contrast, subjective norm does not have a significant indirect effect ($\beta = -0.002$, $p = 0.954$), leading to the rejection of H13.

Table 4. Mediating and Moderating effects

	Hypotheses	β	P Values
H8	Confirmation → Satisfaction → Continued purchase intention	0.155	0.038
H9	Information quality → Satisfaction → Continued purchase intention	0.234	0.000
H10	Perceived ease of use → Satisfaction → Continued purchase intention	0.204	0.000
H11	Perceived usefulness → Satisfaction → Continued purchase intention	0.132	0.005
H12	Attitude → Satisfaction → Continued purchase intention	0.160	0.002
H13	Subjective norm → Satisfaction → Continued purchase intention	-0.002	0.954

4.3. Discussion.

This study provides strong empirical support for the integrated framework explaining continued purchase intention toward AI chatbots in online shopping. Confirmation positively influences Satisfaction (H1: $\beta = 0.178$, $p = 0.037$), consistent with Expectation Confirmation Theory. When user experiences meet or exceed expectations, satisfaction increases, aligning with Nguyen et al. [17] and She et al. [15]. Forssell and Ratjen [13] similarly emphasize that post use evaluations are critical in shaping satisfaction in digital services.

Information quality significantly affects Satisfaction (H2: $\beta = 0.269$, $p < 0.001$), highlighting the importance of accurate, relevant, and reliable information. This result supports findings from mobile and online learning contexts [25], [26] and research underscoring clarity in chatbot communication [27]. Perceived usefulness also enhances Satisfaction (H3: $\beta = 0.152$, $p = 0.005$), confirming Technology Acceptance Model assumptions and aligning with Lee and Sung [64] and Saqr et al. [32]. Perceived ease of use demonstrates a strong positive effect (H4: $\beta = 0.235$, $p < 0.001$), consistent with Lun et al. [36]. Attitude further influences satisfaction (H5: $\beta = 0.184$, $p = 0.001$), reinforcing the importance of positive affect and evaluation in sustained technology engagement.

In contrast, subjective norm does not significantly affect Satisfaction (H6: $\beta = -0.003$, $p = 0.954$), challenging expectations derived from the Theory of Planned Behavior. This finding aligns with studies suggesting that social influence may affect initial adoption but not post usage evaluation. Alshakhsi et al. [60] report that social proof shapes AI acceptance but not satisfaction, while Aji et al. [57] and Granić [58] show that perceived usefulness and ease of use outweigh normative pressure in determining satisfaction.

Satisfaction emerges as the strongest predictor of continued purchase intention (H7: $\beta = 0.868$, $p < 0.001$), consistent with research on customer retention and digital banking engagement [45]. Mediation analysis confirms its central role. Confirmation (H8: $\beta = 0.155$, $p = 0.038$), information quality (H9: $\beta = 0.234$, $p < 0.001$), perceived ease of use (H10: $\beta = 0.204$, $p < 0.001$), perceived usefulness (H11: $\beta = 0.132$, $p = 0.005$), and attitude (H12: $\beta = 0.160$, $p = 0.002$) indirectly influence continuance through Satisfaction. Subjective norm shows no indirect effect (H13: $\beta = -0.002$, $p = 0.954$), indicating that continued purchase intention is driven primarily by personal experience rather than social pressure. Overall, Expectation Confirmation Theory demonstrates the strongest explanatory power in this context.

5. Conclusion

5.1. Implication

This study enhances understanding of continued purchase intention toward AI chatbots in online shopping by integrating the Technology Acceptance Model, Theory of Planned Behavior, and Expectation Confirmation Theory. The findings show that confirmation, information quality, perceived usefulness, perceived ease of use, and attitude significantly influence satisfaction, which emerges as the strongest predictor of continued purchase intention. Satisfaction fully mediates these relationships, highlighting its central role in post-adoption evaluation.

Subjective norm has no significant direct or indirect effect, indicating that social influence plays a limited role in sustained chatbot usage. Among the theoretical perspectives, Expectation Confirmation Theory demonstrates the strongest explanatory power, emphasizing experiential confirmation and information quality as key drivers of long-term engagement. Theoretically, the study reinforces the mediating role of Satisfaction and suggests that experiential and cognitive evaluations outweigh normative pressures in autonomous digital contexts.

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Managerially, firms should prioritize accurate and reliable information, intuitive interfaces, and consistent system performance. Ensuring that chatbot performance meets or exceeds user expectations is essential for strengthening satisfaction and fostering long term loyalty in AI enabled commerce platforms.

5.2. Limitation and Future Research

A key limitation of this study lies in the implicit assumption of technological homogeneity across chatbot platforms. Users may perceive AI chatbots as functionally similar despite differences in intelligence, personalization, and responsiveness, potentially masking platform specific effects.

Future research should compare different types of AI chatbots, such as rule based and generative systems, to examine whether varying levels of sophistication produce distinct cognitive and emotional responses. Longitudinal studies are also recommended to capture changes in user expectations and satisfaction over time, thereby providing deeper insight into the dynamics of sustained AI adoption.

6. Declarations

6.1. Author Contributions

Conceptualization: A.P., and P.W.; Methodology: A.P.; Software: A.P.; Validation: A.P., P.W., and A.W.; Formal Analysis: A.P., P.W., and A.W.; Investigation: A.P.; Resources: A.P.; Data Curation: A.P.; Writing Original Draft Preparation: A.P., P.W., and A.W.; Writing Review and Editing: A.P., P.W., and A.W.; Visualization: A.P. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

No external funding was received from governmental, commercial, or nonprofit organizations to conduct this research.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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