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Consumer Responses to AI Assistance across the Purchase Journey: A Cognitive – Affective Perspective

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Abstract

Artificial intelligence (AI) has swiftly transitioned from a science-fiction notion to a dominant influence on daily life and commercial operations. The rapid expansion of generative AI, as demonstrated by ChatGPT attaining 100 million users in just two months, underscores its increasing impact on consumer-technology dynamics. AI is anticipated to add as much as USD 15.7 trillion to global GDP by 2030, making its position in retail and digital marketing increasingly critical. AI tools already assist consumers across the purchasing process, from information retrieval to decision-making.
This study analyzes the impact of AI tools on consumer reactions throughout the purchasing process by exploring the cognitive (satisfaction) and affective (arousal) mechanisms that determine continuance intention. Using a survey with a 5-point Likert scale, this study employed a quantitative methodology. The survey was conducted online utilizing a convenience sampling method. The sample comprised 421 respondents from Vietnam, aged 18 to 50 years. The respondents are individuals who have previously engaged in AI-assisted purchase transactions. Subsequent to screening, the data were evaluated with the Structural Equation Model (SEM), conducted with SmartPLS 3. The results revealed two simultaneous psychological paths: the cognitive path (satisfaction) and the affective path (arousal). Satisfaction serves as a complementary mediator linking functional attributes to continuation intention, whereas arousal fully mediates the effects of personalization and anthropomorphism. The MGA results indicated that gender differences (male – female) and product type differences (utilitarian – hedonic) influence the formation of cognitive and emotional responses, rather than their translation into behavioral intention.

Keywords: Artificial Intelligence; AI tools; Satisfaction; Arousal

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1. Introduction

In recent years, artificial intelligence (AI) has significantly advanced, transcending its roots in science fiction to become an integral component of human existence, encompassing the workplace, entertainment, and daily routines such as eating and sleeping [1]. The rapid expansion of generative AI technologies is highlighted by ChatGPT, which attained 100 million users within two months of its inception, profoundly altering the interaction between consumers and enterprises with technology [2]. According to PwC's forecasts, global GDP may increase by as much as 14% by 2030 due to AI, representing an additional USD 15.7 trillion, hence being the most significant commercial opportunity in the current dynamic economy. The most significant sectoral advancements are anticipated in various areas, including healthcare, education, and retail, as AI is gradually significantly improving efficiency and productivity. These projections suggest that AI is evolving into a crucial and essential element for enterprises globally [3].

In this context, the retail and digital marketing industries are experiencing a significant transformation whereby AI tools are no longer solely auxiliary technologies but have evolved into primary catalysts for consumer engagement and behavioral modification. Consumers are increasingly depending on virtual assistants (such as Apple Siri, Microsoft Copilot, and Google Assistant) to retrieve product information, while emerging generations of product recommendation systems driven by machine learning and big data now facilitate highly personalized experiences by providing suggestions based on consumers' previous behaviors. Specifically, instruments such as AI chatbots, voice search, and intelligent targeting AI are empowering marketers to comprehend consumer requirements in real time and to automate procedures to enhance business performance [4]. Similarly, transformations are becoming apparent in the tourism sector, where AI-assisted technologies are redefining how visitors discover places, evaluate travel options, and make booking decisions. Virtual assistants and AI-powered recommendation systems are extensively incorporated into online travel platforms, facilitating consumers in navigating intricate travel information by proposing itineraries, accommodations, and tailored travel experiences based on historical preferences and contextual data. In this setting, conversational chatbots, intelligent search interfaces, and predictive recommendation engines function not only as decision-support tools but also as experience-shaping mechanisms that influence travelers' cognitive evaluations and emotional anticipation throughout the travel planning and booking journey. Understanding the role of AI in this purchasing journey is not only a trend but also a critical requirement for capturing how technology is transforming purchasing decisions and shopping experiences in the digital era.

Despite the increasing interest in the role of AI in marketing, e-commerce, and customer experience management, the majority of AI-focused marketing research has concentrated on discrete applications, including chatbots, virtual assistants, and independent recommendation systems. These studies often investigate either cognitive aspects associated with AI tools – such as the performance of AI services [5], perceived communication quality [6] – or emotive elements like arousal [7], with limited attention to how these aspects jointly interact when AI functions as an integrated support system throughout the purchase journey. Nevertheless, these studies have not yet framed AI as an all-encompassing "toolkit" that assists consumers during the complete purchasing process. Current research employing the S–O–R framework in artificial intelligence contexts generally conceptualizes the "organism" via cognitive variables (such as perceived value, attitude, or trust) and a singular emotional state (pleasure/arousal). However, as previously mentioned, scant studies concurrently examine satisfaction or arousal as two sequential affective mechanisms that collectively influence continuance intention. This establishes a study gap in comprehending how both functional features (usefulness, information quality) and human-AI interaction attributes (personalization, anthropomorphism) concurrently affect consumer responses across the whole purchasing journey. Moreover, recent studies have inadequately explored the correlation between arousal (emotional response) and satisfaction (cognitive evaluation), as well as the influence of this emotional pathway on the sustained utilization of AI as a decision-making assistant throughout the purchasing process. Notably, limited research has compared these two elements to assess whether heightened emotional responses ultimately lead to consumer satisfaction throughout the purchasing journey.

Based on the identified gaps, the research's purpose is to answer the following fundamental research issues:

1. How do the functional attributes and human – AI interaction cues of AI tools separately and collectively influence customers' cognitive (satisfaction) and affective (arousal) responses during AI-assisted purchase decision-making?
2. Which psychological pathway – cognitive (satisfaction) or affective (arousal) – plays a more prominent role in driving continuance intention toward AI tools?
3. Do gender and product type moderate the cognitive and affective mechanisms in driving continuance intention toward AI tools?

2. Literature review and hypothesis

2.1. Theoretical background

The role of AI tools in consumers' purchase journey

The extensive integration of AI into retail and service industries has fundamentally altered the consumer purchasing process, prompting companies to transition from conventional touchpoints to an intelligent digital ecosystem for customer contact. Throughout the pre-purchase, purchase, and post-purchase phases, AI significantly influences consumers' purchasing decisions, and several studies have aimed to classify the role of AI in relation to different phases of the customer journey [8].

During the pre-purchase phase, AI technologies are crucial in eliciting requests and facilitating information search. Recommendation systems utilize collaborative filtering and content-based algorithms to examine users' browsing histories and preferences, therefore producing highly personalized product recommendations that minimize customers' search time and costs [9]. The emergence of generative AI (e.g., ChatGPT, Gemini, Copilot) has progressively altered the manner in which customers seek information about products and services. Customers now utilize AI systems for immediate, synthesized, and highly individualized advice on product and service information, rather than depending exclusively on conventional keyword-based search engines [10].

During the purchasing phase, businesses utilize diverse AI technologies with distinct supportive functions to enhance consumer decision-making and streamline transactions. Virtual assistants and chatbots not only respond to inquiries but also function as sales agents, enhancing conversion via natural conversational interfaces

[11]. Moreover, businesses are progressively implementing AI technology, like digital signs, service robots, and AI-powered self-checkout systems and cashierless stores, to enhance the convenience and efficiency of in-store transactions [7].

In the post-purchase phase, AI is essential for sustaining relationships and overseeing consumer loyalty. Predictive analytics technologies allow companies to identify consumers at risk of attrition and to provide suitable retention methods [11]. Robotic process automation (RPA) facilitates the rapid management of return and post-sales inquiries, while chatbots offer customer service, assisting in the resolution of complaints and maintaining consumer satisfaction with the brand [4].

SOR Theoretical Framework

The models and theories employed in the research are the SOR framework, the TAM, and the STP, which stand for "stimulus-organism-response," "technology acceptance model," and "social presence theory," respectively.

Among the many domains that have found widespread use of the SOR model, a psychological framework created by Mehrabian and Russell, are e-commerce and marketing. According to [12], the SOR model suggests that external elements or agents, known as stimuli, impact people's psychological, emotional, and cognitive states, eliciting responses in the form of behaviors and attitudes. The three primary components of the SOR model are used to describe the customer buying journey in this research, including AI tools' characteristics, the customer's perception, and the customer's behavior. In this study, the factors in AI tools' characteristics (AI functional attributes and human-AI interaction) serve as stimuli (S), influencing the customer's perception – the inner cognitive & affective aspects (satisfaction and arousal) of customers (O), which in turn leads to the continuance intention to utilize AI tools' support in the purchase journey (R). The SOR model continues to be extensively employed in research on online purchasing behavior, despite its initial development predating the advent of the Internet. In the context of retail and specifically online shopping, [13] used the SOR model to explain how convenience-related variables impact buying behavior. Additionally, [14] assessed these impacts using the SOR model.

Technology Acceptance Model

Building upon the Theory of Reasoned Action (TRA), [15] introduced the Technology Acceptance Model (TAM). The perceived usefulness and ease of use are affected by external factors outside the user's control, including system design, training quality, and societal effects, as indicated in this model. User attitudes are shaped by both perspectives, which subsequently impact their desire to use and ultimately their actual usage. This study aims to investigate the correlation between customers' cognitive and affective views of AI tools and their inclination to persist in utilizing these tools to facilitate the purchasing process. The independent variables in this study include perceived utility and perceived ease of use under the Technology Acceptance Model (TAM).

Social Presence Theory

Social Presence Theory was first proposed by [16], describes how various communication media differ in their ability to convey the perception of another individual being genuinely and psychologically present within an interaction. The theory suggests that media vary in the extent of social indicators they convey (including verbal, nonverbal, and affective signals), which influences perceptions of intimacy and immediacy between participants. In this study, it is argued that AI tools exhibiting greater perceived social presence – primarily influenced by personalization and anthropomorphism – are more likely to generate heightened arousal and satisfaction, consequently enhancing customers' intention to continue to utilize AI tools' support in the purchase journey.

2.2. AI tools' characteristics and Customer's perception

Perceived usefulness

In the Technology Acceptance Model, perceived usefulness is characterized as "the extent to which an individual believes that utilizing a specific system would improve his or her job performance" [15]. In research employing the UTAUT model, this idea is sometimes termed "performance expectancy," denoting the expected advantages of productivity and efficiency associated with the utilization of new technology [17]. In the context of AI-assisted purchase, perceived usefulness is associated with consumers' belief that AI assistance would enhance the convenience of their purchase transaction.

The impact of perceived usefulness on perceived value has been firmly demonstrated. Prior research has continuously validated the correlation between perceived usefulness (performance/functional advantages) and satisfaction, as seen by several studies, especially within the realm of AI applications in tourism, hospitality, and retail. The study by [18] demonstrates that perceived usefulness is positively correlated with customer confidence in the use of AI chatbots. [19] enhanced the ECT model, demonstrating that consumers' satisfaction levels improve when they regard AI technology as successful and beneficial in service management. Research by [20] indicates that when visitors recognize the technical and practical benefits (usefulness) of a product, their satisfaction with their decision increases.

Thus, we hypothesize:

H1: Perceived usefulness when using AI tools has a positive influence on customers' satisfaction in the purchase journey.

Information quality

The efficacy of an information system may be assessed by its information quality, which significantly influences user satisfaction [21]. This research defines "information quality" as the consumers' perception of the relevance, trustworthiness, and overall quality of the AI technologies utilized during the purchasing process. The research indicates that this is the paramount factor of AI products influencing customer satisfaction [10].

Numerous studies have established a robust and favorable correlation between information quality and consumer satisfaction. [5] indicates that the quality of AI information, encompassing correctness and timeliness, correlates positively and significantly with pleasure about AI information. [22] examined the impact of quality issues (such as misinformation or AI "hallucinations") on users. The results show that visitor acceptance and satisfaction with ChatGPT's suggestions significantly decreased as poor-quality issues became apparent. [23] designates information quality, assessed by correctness, format, completeness, and timeliness, as a critical quality factor. The findings from the structural model study indicate that information quality significantly enhances user satisfaction. The provision of comprehensive, precise, and truthful information is seen as a critical determinant of consumer satisfaction.

Thus, we hypothesize:

H2: Information quality of AI tools has a positive influence on customers' satisfaction in the purchase journey.

Personalization

AI is considered a solution to enhance the digital experience by providing personalized content. Personalization is a central variable or concept in many studies on the application of AI in marketing and consumer behavior, especially in digital and retail contexts. The term "personalization" refers to the practice of tailoring a marketing campaign to each individual customer by considering their interests, demographics, and other characteristics [24]. Its goal is to increase customer engagement, satisfaction, and loyalty. In this study, the personalization factor of AI tools refers to AI personalization systems, such as predictive recommendation tools, chatbot assistants, and other forms of customized placements, which increasingly intervene in consumer decision-making processes in real time. AI-enabled personalization is considered a technological novelty in the interaction process. This novelty is a fundamental characteristic of technological innovation [7]. Studies have demonstrated that novelty triggers curiosity and stimulates consumer excitement. Successful personalization is often perceived through hedonic value, i.e., enjoyable, fun, and stimulating experiences. Providing personalized recommendations is believed to fulfill consumers' hedonic needs, thereby generating excitement and arousal [25].

Thus, we hypothesize:

H3: Personalization of AI tools has a positive influence on customers' arousal in the purchase journey.

Anthropomorphism

Anthropomorphism is the tendency to attribute human qualities and characteristics, such as emotions, personality, or thinking, to non-human agents (such as robots or AI tools) [26], [27]. In the purchase journey, this humanization transforms sterile digital interfaces into conversational experiences, increasing perceived warmth and social presence, which aligns with the SOR framework, where anthropomorphism acts as a stimulus, heightening emotional states.

Empirical studies confirm anthropomorphism elevates arousal – a state of physiological and psychological activation characterized by excitement and heightened attention – by triggering curiosity, novelty, and hedonic pleasure during shopping [28] [29].

Thus, we hypothesize:

H4: Anthropomorphism of AI tools has a positive influence on customers' satisfaction in the purchase journey.

2.3. Satisfaction and continuance intention of AI Tools' usage in the purchase journey

In the scope of AI-assisted tools in the purchase journey, customer satisfaction may arise from the fulfillment of expectations for the advantages provided by AI tools, including time efficiency, precise information, and immediate assistance. When customer expectations are fulfilled, they will tend to feel satisfied. It is the satisfaction derived from the benefits of AI tools that pushed them to intend to persist in pursuing assistance from AI tools for future transactions.

Certain studies have demonstrated customer reactions, clarifying the correlation between expectation confirmation, perceived utility, contentment, and continuing intention as per the Expectation Confirmation Model (ECM) [30][31][32]. Numerous studies concerning smart products and services have demonstrated the correlation between pleasure and continued usage scenarios [33][34].

Thus, we hypothesize:

H5: Satisfaction has a positive influence on the continuance intention of AI tools' usage in the purchase journey.

2.4. Arousal and continuance intention of AI Tools' usage in the purchase journey

The Pleasure–Arousal–Dominance (PAD) paradigm, established by Mehrabian and Russell, defines arousal as the degree of excitement, stimulation, or activation that an individual encounters in a certain context. Arousal, within the framework of consumer behavior, refers to the extent of excitement, stimulation, activity, and alertness experienced by consumers in reaction to an external stimulus [12]. These emotional impulses frequently arise from recent advancements in technology, like the degree of customization and the human characteristics of AI systems.

When consumer-technology interactions yield pleasurable and captivating experiences, customers are inclined to develop a desire for continued usage of those technologies in the future. Numerous prior research studies have demonstrated a positive correlation between consumers' emotional states and their intention to persist in usage, indicating that reported enjoyment and perceived ease of use are more significant determinants of usage intention than perceived usefulness [35]. Likewise, additional research has substantiated the considerable influence of perceived enjoyment on users' attitudes towards voice user interfaces (VUIs), subsequently affecting their intention to persist in using them [36]. Furthermore, it has been demonstrated that perceived enjoyment and user engagement yield profound insights into continued usage behavior within the realm of blogs [37].

Thus, we hypothesize:

H6: Arousal has a positive influence on the continuance intention of AI tools' usage in the purchase journey.

2.5. The mediating role of satisfaction between AI tools' functional attributes and continuance intention of AI tools' usage in the purchase journey

Satisfaction is regarded as a fundamental and extensively utilized element in research on user behavior, especially within technology acceptance frameworks like the Technology Acceptance Model (TAM) and the Expectation-Confirmation Model (ECM). Numerous consumer behavior research models have validated the mediating function of satisfaction, particularly with technology and AI applications, based on these ideas.

Arthur Huang's study [19] on AI applications for hotel and tourism services indicates that happiness with AI is a crucial indicator of future usage intentions. [23] on online travel agency (OTA) chatbots employed satisfaction as a mediating variable in the effect chain, whereby satisfaction was derived from perceived information quality, utility, and enjoyment, thus exerting a favorable influence on the intention to continue usage.

Research by [38] on chatbot services in Vietnam's banking industry combined the Expectation-Confirmation Model (ECM) with the DeLone and McLean Information Systems Success Model (D&M ISS). The research findings demonstrate that contentment, alongside trust and perceived utility, is one of the three critical determinants that directly affect the intention to persist in utilizing chatbot services.

Thus, we hypothesize:

H7a: Satisfaction mediates the relationship of perceived usefulness when using AI tools and continuance intention of AI tools' usage.

H7b: Satisfaction mediates the relationship of information quality when using AI tools and continuance intention of AI tools' usage.

2.6. The mediating role of arousal between AI tools' human-like interaction attributes and continuance intention of AI tools' usage in the purchase journey

Satisfaction is frequently regarded as a prevalent cognitive mediating variable in user behavior research, while arousal is examined as an affective mediating variable in several studies within the same domain. Comprehensive models of user behavior, such as the Expectation–Confirmation Model (ECM) and the Technology Acceptance Model (TAM), are frequently amalgamated to concurrently elucidate the cognitive assessment process and the emotional reactions of users. The mediating effect of arousal and analogous emotional states, such as flow, perceived enjoyment, or pleasure, has been well acknowledged as a significant factor influencing continuing use intention in several prior research studies.

In the realm of AI services within the tourist and hospitality industry, perceived enjoyment serves as a partial mediator in the correlation between expectation confirmation or perceived performance and the desire to persist in utilizing the service [19]. Furthermore, [28] highlighted that arousal significantly influences the intention to persist in utilizing ChatGPT, consequently underscoring the crucial significance of emotional reactions in shaping future AI usage behavior.

Thus, we hypothesize:

H8a: Arousal mediates the relationship of personalization of AI tools and continuance intention of AI tools' usage.

H8b: Arousal mediates the relationship of anthropomorphism of AI tools and continuance intention of AI tools' usage.

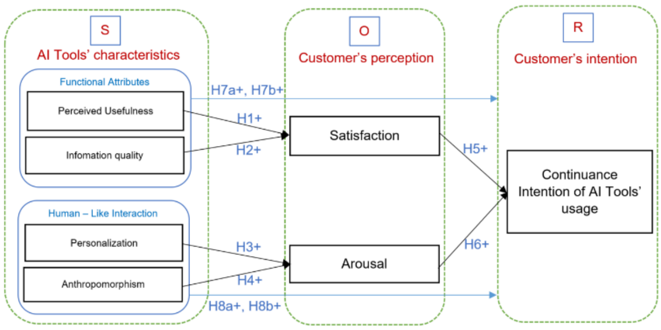

Figure 1. Research model

3. Methodology

Measurement instruments

All measuring indicators in this research were derived from prior esteemed studies. The survey questions were modified in expression, language, and meaning to guarantee their appropriateness for the specific research context. The modifications were solely linguistic and did not change or misrepresent the meaning of the original scales.

The survey used a 5-point Likert scale, where 1 indicates strong disagreement, and 5 means strong agreement. The author used a 5-point Likert scale based on prior studies indicating its prevalence in social science research [39]. Moreover, the 5-point scale has demonstrated superior dependability compared to the 3-point scale regarding both reliability and information quality in scale creation, while facilitating decision-making for responders. In comparison to a 7-point scale, a 5-point scale exhibits no substantial difference in reliability while maintaining convenience for survey respondents [40].

Prior to administering the official survey, the author solicited feedback from three experienced researchers and colleagues in pertinent fields to evaluate the questionnaire, ensuring content validity and logical organization of questions and reducing the likelihood of misunderstanding or ambiguity in phrasing.

Operational definitions for each variable were established and displayed in Table 1 to measure the effectiveness of each component in the study.

Table 1. Operational definition

Construct	Item	Definition	No of questions	Reference
Perceived Usefulness of AI Tools	USE	The extent to which the use of AI tools is useful and improves users' performance	5	[41]
Information Quality of AI Tools	INF	The extent to which the use of AI tools is relevant, reliable, and high-quality	5	[42]
Personalization of AI Tools	PER	The extent to which AI systems customize product suggestions and interactions for users.	5	[43]
Perceived Anthropomorphism of AI Tools	ANT	The extent to which AI tools are perceived as possessing human-like qualities, emotions, personality, and reasoning.	5	[44] [45]
Satisfaction	SAT	The extent to which AI systems satisfy users' efficiency, accuracy, and support needs.	5	[46]
Arousal	ARO	The extent of excitement, stimulation, activity, and alertness experienced by consumers in reaction to an external stimulus	5	[12]
Continuance Intention of AI Tools' usage	INT	The extent to which a user experiences excitement, stimulation, and alertness when interacting with AI tools.	3	[47]

Data and methods

The research model was empirically assessed using data obtained from a cross-sectional survey. The author used Google Forms as the principal instrument for administering the survey and gathering data. The questionnaire was disseminated across many channels to engage respondents. To identify the suitable respondents, the first session of the questionnaire asked whether they had ever shopped at retailers that use AI tools to assist the purchasing process. If the respondent answered affirmatively, they were permitted to complete the questions. Participants might advance to the subsequent page only after responding to all questions on the current page.

For structural equation modeling, the author determined the minimum sample size using the Free Statistics Calculators webpage (danielsoper.com) [48]. The relevant data was input to determine the sample size for the expected effect size, requisite statistical power, number of observable variables, number of latent variables, and significance level, which were 0.1, 0.8, 35, 7, and 0.05. The minimum required sample size to be submitted is 100. Despite the a priori power analysis indicating a minimal sample size of 100, we collected 432 samples to facilitate future data filtering and to guarantee sufficient statistical power for further Multigroup Analysis (MGA) studies. Following the screening process, data that was either missing or incorrect and did not fulfill the criteria was eliminated, yielding 421 valid responses for subsequent analysis.

For Multigroup Analysis (MGA), gender and product type were selected as focal groups for multigroup analysis. Previous studies indicate that gender differences may affect emotional processing and technological engagement behaviors, especially in AI-mediated contexts where affective responses like arousal are crucial. Male and female consumers frequently demonstrate distinct sensitivity to personalization features and anthropomorphic characteristics, making gender a theoretically relevant segmentation variable for testing variations in cognitive and affective mechanisms. In addition, product type represents an important contextual factor that differentiates utilitarian and hedonic consumption goals. Studies on consumer behavior suggest that utilitarian products tend to prioritize functional evaluations, while hedonic products elicit more robust emotive and experiential responses. Therefore, examining product type allows this study to assess whether the cognitive pathway (via satisfaction) and the affective pathway (via arousal) operate differently across consumption contexts. Together, these moderators provide theoretically grounded boundary conditions that help clarify the robustness of the proposed Stimulus–Organism–Response framework.

Table 2. Profile of respondents

Demographic	Category	Subject (N = 421)	
		Frequency	Percentage (%)
Gender	Male	249	59.1
	Female	172	40.9
Age (years old)	18 - 25	384	91.2
	26 - 30	9	2.1
	31 - 40	26	6.2
	41 - 50	2	0.5
Education	Undergraduate	413	98.1
	Post graduate	8	1.9

Marriage status	Single	383	91
	Married	38	9
Employment status	Student	351	94.8
	Employed	48	11.4
	Self-employed	22	5.2
Monthly income (millions VND)	Under 5	312	74.1
	5 - 10	65	24.9
	10 - 20	40	9.5
	More than 30	4	1
Character	Introvert	178	42.3
	Extrovert	243	57.7
Hometown (Regions of Vietnam)	North	104	24.7
	Central	247	58.7
	South	70	16.6

4. Results

The partial least squares structural equation model (PLS-SEM) was employed to evaluate the measurement model and the structural model in this research.

4.1. Measurement model

The internal reliability

Composite reliability and Cronbach's alpha coefficient were initially evaluated to assess internal reliability. Reliability is deemed attained only when both coefficients exceed 0.7 [49]. All values (Cronbach's alpha and CR) in Table 2 are greater than 0.7, indicating a high level of reliability in the relationship between the variables that were observed and the overall variable .

Convergent validity and discriminant validity evaluation were deployed to assess the measurement model's validity. The convergent validity assessment is based on the item factor loadings and average variance extracted (AVE). All AVE values satisfy the suggested requirement, exceeding 0.50, with a range from 0.653 to 0.738 [50]. Furthermore, all outer loading coefficients are above the 0.70 criterion, and all indicators are statistically significant [51].

Discriminant Validity

The Heterotrait-Monotrait Ratio (HTMT) is frequently employed to evaluate the discriminant validity of constructs. According to [52], when the HTMT value is 0.85 or lower, it is considered appropriate to differentiate across construct pairs. Table 4 of this study shows that all HTMT values are less than 0.85. Consequently, the distinct value of the acknowledged measuring systems is assessed.

Table 3. Scale reliabilities

Construct	Items	Factor loading	Cronbach's Alpha	rho_A	CR	AVE
Perceived Usefulness	USE1	0.891	0.910	0.913	0.933	0.737
	USE2	0.895				
	USE3	0.862				
	USE4	0.850				
	USE5	0.790				
Infomation quality	INF1	0.838	0.877	0.878	0.910	0.670
	INF2	0.802				
	INF3	0.832				
	INF4	0.814				
	INF5	0.807				
Personalizat-ion	PER1	0.810	0.871	0.872	0.907	0.660
	PER2	0.866				
	PER3	0.823				
	PER4	0.776				
	PER5	0.786				
Anthropomo-rphism	ANT1	0.810	0.867	0.869	0.904	0.653
	ANT2	0.798				
	ANT3	0.823				
	ANT4	0.777				
	ANT5	0.831				
Satisfaction	SAT1	0.879	0.907	0.909	0.931	0.729
	SAT2	0.869				
	SAT3	0.861				
	SAT4	0.850				
	SAT5	0.808				
Arousal	ARO1	0.788	0.877	0.880	0.911	0.671
	ARO2	0.868				
	ARO3	0.801				
	ARO4	0.859				
	ARO5	0.776				
Continuance Intention	CI1	0.853	0.911	0.914	0.934	0.738
	CI2	0.803				
	CI3	0.883				
	CI4	0.890				
	CI5	0.866				

Table 4. Discriminant Validity

	ANT	ARO	CI	INF	PER	SAT	USE
ANT	0.808						
ARO	0.735	0.819					
CI	0.610	0.763	0.859				
INF	0.622	0.660	0.745	0.819			
PER	0.582	0.601	0.692	0.717	0.813		
SAT	0.588	0.718	0.769	0.708	0.671	0.854	
USE	0.511	0.608	0.753	0.752	0.743	0.691	0.858

4.2. Structural model

The PLS-SEM approach was employed to assess the hypotheses in this study utilizing SmartPLS 3.2.9 for Windows, accompanied by the bootstrapping method with 5000 resamples performed subsequently. The assessment of the structural model is conducted in a three-step sequence [52][53][54], comprising:

1. Evaluate the model fit using SRMR, RMS_theta, and NFI.
2. Evaluate The Variance Inflation Factor (VIF)
3. Evaluate the path coefficients and the variance elucidated by the endogenous variables (R^2).
4. Evaluate the level of Q^2.

First, the study initially evaluates model fit using the SRMR, RMS_theta, and NFI indices. In PLS-SEM, model fit is not a definitive criterion as it is in CB-SEM; it serves to bolster the model rather than to reject it. Provided that the SRMR ratio adheres to the standard and the remaining indices (RMS_theta and NFI) do not exceed the thresholds, they remain acceptable. The acceptable limit for SRMR in model fit is below 0.08. The acceptable threshold for RMS_theta must be below 0.12 [55]. An NFI ratio over 0.9 is deemed acceptable [53]. In this study model, the data for the SRMR, RMS_theta, and NFI indicators are presented as 0.092, 0.118, and 0.831, respectively. The data indicates that only the SRMR ratio & RMS_theta satisfy the acceptable threshold among the three indices. Although NFI did not fulfill the requirements, these ratios did not substantially violate them; however, they approached 0.9, which remains acceptable within PLS-SEM. Therefore, the subsequent step of evaluation is ongoing.

Second, the Variance Inflation Factor (VIF) is evaluated to define the multicollinearity issues among constructs. Table 5 shows that all indexes have variance inflation factors (VIF) lower than 3. According to [55], this model is improbable to demonstrate multicollinearity.

Table 5. Variance Inflation Factor

	ANT	ARO	CI	INF	PER	SAT	USE
ANT		1.513					
ARO			2.060				
CI							
INF						2.299	
PER		1.513					
SAT			2.060				
USE						2.299	

Third, the author then reevaluated the model using the bootstrapping approach with 5,000 resamples, setting a significance threshold of 0.05 to determine the significance levels and major path coefficients, as well as the variances (R^2) of endogenous variables.

According to [55], a model shows strong explanatory power with an R-squared value of 0.75, moderate strength with an R-squared value of 0.50, and a weak degree with an R-squared value of 0.25. The R^2 values demonstrate that the model accounts for a significant percentage of variance in continuation intention (R^2 = 0.683), whilst satisfaction (R^2 = 0.559) and arousal (R^2 = 0.585) show moderate to substantial explanatory power. As can be seen from Table 6, every single hypothesis in the study model is statistically significant.

Table 6. Path outcomes of the structural model

Hypothesis	Paths	Path coefficients	T statistics	P-values	Result
H1	USE→SAT	0.366	5.664	0.000	Supported
H2	INF→SAT	0.433	7.495	0.000	Supported
H3	PER→ARO	0.261	5.787	0.000	Supported
H4	ANT→ARO	0.583	14.112	0.000	Supported
H5	SAT→CI	0.457	8.533	0.000	Supported
H6	ARO→CI	0.435	8.082	0.000	Supported

This study investigated the mediating roles of satisfaction and arousal to evaluate their influence on the link between the functional features of AI tools, human-like interaction, and the desire to continue using AI tools. This analysis was conducted using bias-corrected bootstrap confidence intervals (CIs) at a 97.5% confidence level with 5,000 resampling iterations. Zhao reconceptualized mediation analysis by emphasizing the roles of direct and indirect effects, identifying five mediation types: complementary, competitive, indirect-only, direct-only, and no-effect nonmediation [56]. As shown in Table 8, the result indicated a complementary mediating effect of satisfaction, as both the direct and indirect effects of perceived usefulness and information quality on continuance intention are positive and significant. For arousal mediation analysis, the results demonstrated an indirect-only mediating effect, as the indirect effect is statistically significant, whereas the direct effects of personalization and anthropomorphism on continuance intention are insignificant. Hence, hypotheses 7 and 8 are supported.

Table 8. Mediation influence

Hypotheses	β	t value	p value	Bias-corrected [2.5%; 97.5%] CI		Result
				Low	High	
Panel A: H7						
H7a						
Path estimate	0.250	5.219	0.000	0.156	0.347	Accepted
H7a: USE →SAT→ CI	0.082	3.297	0.001	0.041	0.139	Accepted
Total Effects (H7a)	0.332	6.943	0.000	0.239	0.424	Accepted
H7b						
Path estimate	0.149	3.040	0.002	0.053	0.247	Accepted
H7b: INF→SAT→ CI	0.097	0.026	0.000	0.052	0.153	Accepted
Total Effects (H7b)	0.246	5.086	0.000	0.154	0.343	Accepted
Panel B: H8						
H8a						
Path estimate	0.064	1.386	0.166	-0.022	0.159	Rejected
H8a: PER→ARO→ CI	0.085	4.318	0.000	0.050	0.127	Accepted
Total effects (H8a):	0.149	2.925	0.003	0.053	0.256	Accepted
H8b						
Path estimate	-0.019	0.442	0.658	-0.102	0.064	Rejected
H8b: ANT→ARO→CI	0.191	6.143	0.000	0.135	0.258	Accepted
Total effects (H8b)	0.172	4.406	0.000	0.095	0.251	Accepted

Finally, a blindfolded evaluation of the Q^2 data's predictive validity was carried out in SmartPLS, with an omission distance D set to 7. Concerning the predictive power of the cross-validated redundancy, Q^2 evaluates the route model's capacity to indirectly forecast the endogenous measurement items by the use of their latent variables' prediction through the related structural linkages. It is exclusively calculated for endogenous constructs [49]. Based on the blindfolding technique, Stone-Geisser's Q^2 was used to assess the structural model's predictive validity. For an endogenous construct, the model is predictively significant if the Q^2 value is greater than zero. Furthermore, Q^2 values of 0.02, 0.15, and 0.35 are regarded as indicative of small, medium, and large degrees of predictive relevance, respectively [49]. Blindfolding analysis indicates that the Q^2 values for satisfaction (Q^2 = 0.402), arousal (Q^2 = 0.387), and continuance intention (Q^2 = 0.499) all surpass the threshold of 0.35. Table 7 demonstrates that the model exhibits significant predictive validity for the endogenous variables (satisfaction, arousal, and continuance intention). Thus, the model is considered to possess substantial predictive capability.

Table 7. Results of Q^2 level assessment

Construct	Predictive Relevance Q^2			
	Construct Cross-validated Communality		Construct Cross-Validated Redundancy	
SAT	0.586	Strong predictive power	0.403	Strong predictive power
ARO	0.503	Strong predictive power	0.387	Strong predictive power
CI	0.601	Strong predictive power	0.499	Strong predictive power
USE	0.599	Strong predictive power	-	-
INF	0.501	Strong predictive power	-	-
PER	0.486	Strong predictive power	-	-
ANT	0.477	Strong predictive power	-	-

The research performed a multi-group analysis (MGA) based on gender and product category. For gender, the findings indicate that gender significantly affects the correlations between anthropomorphism and arousal, as well as between personalization and arousal ($p < 0.05$). However, there are no significant gender differences in the correlations between functional characteristics and satisfaction, nor in the effects of satisfaction and arousal on continuation intention. The findings regarding gender are comprehensively presented in Table 9.

Table 9. Gender

Hypotheses	Male		Female		Difference	Difference
	Coefficient	t-value	Coefficient	t-value	β diff (Male – Female)	p-value
H1 (USE → SAT)	0.324	3.905	0.464	5.588	-0.141	0.220
H2 (INF → SAT)	0.486	6.702	0.315	3.856	0.171	0.110
H3 (PER → ARO)	0.194	4.083	0.422	5.836	-0.228	0.006
H4 (ANT → ARO)	0.686	16.516	0.362	4.635	0.325	0.000
H5 (SAT → CI)	0.430	6.250	0.517	7.870	-0.087	0.370
H6 (ARO → CI)	0.472	6.917	0.353	5.410	0.119	0.218
H7a (USE → SAT → CI)	0.139	2.982	0.240	4.266	-0.101	0.160
H7b (INF → SAT → CI)	0.209	4.679	0.163	3.442	0.046	0.465
H8a (PER → ARO → CI)	0.091	3.144	0.149	3.836	-0.057	0.240
H8b (ANT → ARO → CI)	0.234	6.851	0.128	3.393	0.196	0.002

For the product category, the MGA results indicate that product type considerably moderates the impact of personalization on arousal, with this connection varying between hedonic and utilitarian items. Conversely, no notable changes are detected in the impact of functional attributes on satisfaction or in the associations connecting consumer perceptions to continuation intention. The results on the product category of PLS-SEM are shown in Table 10.

Table 10. Product Type

Hypotheses	Hedonic		Ulititarian		Difference	Difference
	Coefficient	t-value	Coefficient	t-value	β diff (Hedonic – Utilitarian)	p-value
H1 (USE → SAT)	0.311	4.224	0.619	5.580	-0.308	0.013

H2 (INF → SAT)	0.441	7.485	0.289	2.464	0.153	0.218
H3 (PER → ARO)	0.216	4.544	0.458	5.260	-0.241	0.017
H4 (ANT → ARO)	0.597	13.281	0.451	5.175	0.146	0.124
H5 (SAT → CI)	0.435	6.982	0.560	6.392	-0.124	0.260
H6 (ARO → CI)	0.443	6.998	0.365	4.027	0.077	0.477
H7a (USE → SAT → CI)	0.135	3.205	0.347	4.123	-0.211	0.011
H7b (INF → SAT → CI)	0.192	5.300	0.162	2.302	0.031	0.664
H8a (PER → ARO → CI)	0.096	3.314	0.167	2.832	-0.072	0.266
H8b (ANT → ARO → CI)	0.264	6.814	0.165	3.532	0.099	0.107

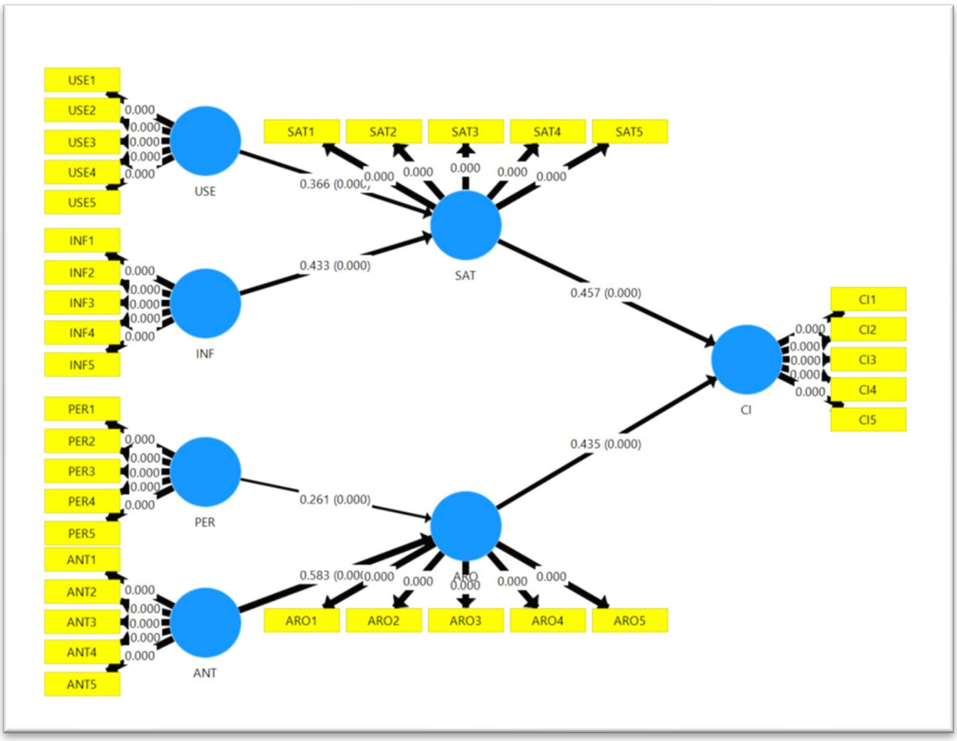

Figure 2. Measurement Model

5. Discussion

5.1. Main paths

H1. (USE → SAT): Supported

The findings demonstrated that the usefulness of AI tools positively influences consumer satisfaction throughout the purchase process. The notable correlation between utility and satisfaction has been demonstrated to be substantial in several prior research studies. Huang's findings [19] suggested that perceived performance is a key predictor of satisfaction with AI and plans for future use. Ku and Chen's research demonstrated that when visitors acknowledge the technical and practical advantages (usefulness) of a product, their satisfaction with their selection enhances [20].

H2. (INF → SAT): Supported

The quality of information provided by AI tools significantly influences consumer satisfaction during the purchase process. Prior study further corroborated this correlation. [5] asserted that the quality of AI information, encompassing its correctness and timeliness, is positively and strongly connected with pleasure pertaining to AI information. [10] analyzed the effects of quality concerns, including disinformation and AI "hallucinations," on users. The findings indicate that visitor acceptability and contentment with ChatGPT's recommendations markedly diminished when deficiencies in quality emerged. [23] designates information quality, evaluated via accuracy, format, completeness, and timeliness, as a critical quality criterion.

H3. (PER → ARO): Supported

According to the results, consumers' emotional arousal throughout the purchase process is greatly affected by the personalization of AI tools. This link has been similarly proven in several prior studies. The research indicated that uniqueness incites interest and enhances customer enthusiasm. Successful customization is frequently recognized by hedonic value, denoting pleasurable, delightful, and stimulating experiences. Delivering tailored suggestions is thought to satisfy customers' hedonic desires, thereby eliciting pleasure and arousal [25].

H4. (ANT → ARO): Supported

This study also identified a substantial link between anthropotheism and arousal. This aligns seamlessly with other prior investigations. Empirical research demonstrated that anthropomorphism enhances arousal – a condition of physiological and psychological activation marked by excitement and increased attention – by stimulating curiosity, novelty, and hedonic enjoyment in the shopping experience [28] [29].

H5. (SAT → CI): Supported

This study also confirmed the substantial association between customer satisfaction and the continuance intention in utilizing AI tools. Several prior investigations have similarly exhibited analogous results. Various research has elucidated consumer responses, delineating the relationship among expectation confirmation, perceived usefulness, satisfaction, and continuance intention according to the Expectation Confirmation Model (ECM) [30][31][32]. Multiple research on intelligent goods and services has evidenced the relationship between enjoyment and sustained usage contexts [33][34].

H6. (ARO → CI): Supported

The research further validated that emotional arousal positively influences customers' continuance decision in utilizing AI technologies during the purchase process. This aligns entirely with prior findings. Numerous prior research have shown a favorable correlation between customers' emotional states and their intention to continue using, suggesting that reported enjoyment and perceived ease of use are more critical drivers of usage intention than perceived usefulness. Moreover, further study has confirmed the significant impact of perceived enjoyment on users' attitudes towards voice user interfaces (VUIs), which in turn influences their desire to continue using them [36]. Moreover, it has been shown that reported satisfaction and user involvement offer significant insights into ongoing usage behavior in the context of blogs [37].

5.2. Mediation paths

Panel A – H7: Mediation through satisfaction (SAT)

Satisfaction (SAT) demonstrated a complementary mediating influence in the links between the functional characteristics of AI tools and the desire to continue usage. Perceived usefulness and information quality influence continuing intention both directly and indirectly via satisfaction. This trend suggests that satisfaction functions as a cognitive assessment tool, enabling customers to evaluate the instrumental advantages, efficacy, and decision-making help offered by AI products. These findings correspond with expectation-based and value-driven approaches, indicating that functional performance is a crucial factor influencing user satisfaction and subsequent behavioral intention.

Panel B – H8: Mediation through arousal (ARO)

Arousal (ARO) has a full mediation effect on the relationships between features of human – AI interaction – specifically personalization and anthropomorphism – and the intention to continue engagement. The lack of notable direct impacts, together with pronounced indirect effects through arousal, suggests that these interactional characteristics largely affect behavioral intention by provoking emotional stimulation and experiencing involvement, rather than through direct cognitive assessment. This underscores the function of arousal as an affective mechanism, encapsulating customers' enthusiasm, engagement, and emotional activity during AI-assisted interactions.

5.3. Multiple groups analysis (MGA)

Gender

The MGA results indicate that gender does not moderate most cognitive-behavioral linkages, although it significantly moderates the emotional mechanisms (arousal) associated with the humanized and customized interactions with AI tools.

The findings show that there are no gender differences in the connection between functional characteristics (USE/INF), satisfaction, and continuance intention (H1, H2, H5, H7). The usefulness and quality of information are rational properties, so it is quite logical that the use of AI technologies has become effectively "gender-neutral." Men and women assess the efficacy, accuracy, and value of AI in a comparable manner. Moreover, AI applications (such as AI assistants, recommender systems, and decision aids) are predominantly engineered to optimize for a wide user base, hence diminishing the significance of gender disparities in assessing efficacy. Continuance intention is a logical conduct, so when functional advantages and pleasure are proven, gender ceases to be a significant distinguishing element.

Simultaneously, gender significantly moderates human-like interactions and arousal connections (H3, H4). Research indicates that various genders exhibit distinct responses to social cues; women often demonstrate heightened sensitivity to relational and emotional signals, whereas males tend to react more robustly to notions of control, agency, and logic. The customization and anthropomorphism of AI technologies foster a sense of caring, social presence, and "human-like" engagement, resulting in varying levels of arousal intensity between genders.

Regarding the mediation effect, a gender difference was observed exclusively through the mediator ARO (H8b), but not through the mediating factors SAT (H7a, H7b). In a parallel vein to the preceding argument, gender solely presents a potential impediment to the exploration of deeper emotional pathways. Anthropomorphism moderates intention through arousal, a potent affective mechanism, whereas satisfaction represents a more stable and rational condition. Furthermore, anthropomorphism exhibits a greater social presence than personalization, thereby facilitating the elicitation of social interaction and emotional connection. Consequently, anthropomorphism is readily susceptible to gender-related moderation.

Product Type

The MGA results indicated that product type selectively moderates the cognitive processes (SAT) and somewhat influences the emotional mechanisms (ARO), but other connections (SAT → CI, ARO → CI) remain generally constant across both hedonic and utilitarian contexts. The findings indicate variations in hedonic and utilitarian contexts regarding the link between USE and SAT, with usefulness assuming a more significant role for utilitarian items (H1). This may be elucidated by the functional value of utilitarian items. Consumers purchasing utilitarian items frequently want attributes such as efficiency, time conservation, and precision in decision-making. Consequently, the efficacy of AI technologies significantly influences pleasure in this context.

Furthermore, a distinction is seen between hedonic and utilitarian situations regarding the link between personalization and arousal. Personalization is especially advantageous for hedonic items, as hedonic consumption is frequently linked to emotions. Personalization enhances the perception of being "understood," elevates engagement, and offers excitement. Arousal thus emerges as a pivotal element in the hedonic experience. Nonetheless, the results of this investigation show that the personalization aspect exerts a more significant influence on the utilitarian environment. Personalization may be seen as the ideal assessment of the efficacy of product customization in eliciting genuine emotions.

The findings indicated that product type moderates the association between perceived usefulness and continuing intention through satisfaction as a mediating variable (H7a). This is a logical approach, as utilitarian decision-making is both rational and systematic. Consequently, consumer purchasing of utilitarian items will be more rigorously governed than that of customers acquiring hedonic products.

6. Conclusion

6.1. Theoretical contributions

This study provides 5 key theoretical contributions to the literature on AI-supported consumer behavior. First, it expands the S–O–R framework by conceptualizing AI tools as an integrated set of functional properties and human-AI interactions, supporting consumers throughout their purchasing journey, hence addressing limitations of prior research that concentrated exclusively on singular AI applications. Second, the findings from this study suggest a two-way mechanism through which AI tools influence continued use intention, distinguishing between a cognitive path driven by satisfaction and an affective path driven by stimulation. Third, this research identifies gender and product type as boundary conditions within AI-enabled consumption, demonstrating that these factors modulate the formation of cognitive and affective responses, rather than their subsequent translation into continuance intention. This analysis enhances the S–O–R framework by emphasizing the disparity between stimulus–organism and organism–response interactions. This research contributes to a more sophisticated, context-sensitive comprehension of how artificial intelligence applications affect consumer behavior across diverse market segments and product categories. Fourth, by applying a process-oriented perspective, this study advances the literature on AI adoption and continued use by clarifying how consumers' internal states mediate the impact of AI characteristics on behavioral intentions. Finally, the model explains 68.3% of the variance in the continuance intention to use. Experimental results show that the proposed theoretical framework can be more effective in explaining the intention to continuously use interactive artificial intelligence.

6.2. Managerial implications

This study has several management implications as outlined below. First, given that AI tools affect customer behavior through two concurrent pathways, pleasure and arousal, enterprises should adopt a multidimensional approach to AI development. Businesses must concurrently pursue functional and experiential improvement. AI solutions must be engineered to augment perceived utility by delivering precise, prompt, and lucid information, hence improving information quality and bolstering user pleasure. Concurrently, from an experience standpoint, enterprises have to invest in emotional stimuli like content customization and enhanced humanization in human-AI interactions to elicit arousal and emotional involvement. The efficacy arises from the meticulous alignment of information systems (IS) strategy with user experience (UX) design, rather than only perceiving AI as a technological instrument.

Second, the research findings indicate that organizations must prioritize distinct AI tactics based on the product type, as utilitarian and hedonic products activate different psychological circuits. Consumers predominantly depend on cognitive assessments when determining their desire to persist in utilizing utilitarian items. Consequently, AI technologies in this context have to concentrate on decision assistance, encompassing comparison, information filtration, and the optimization of time and cost. AI recommendation systems in the insurance and banking industries must prioritize efficiency, accuracy, and dependability. In contrast, for hedonic items, the correlation between customization and arousal is significant, suggesting that emotions and experiences are crucial determinants of customer involvement. Consequently, AI in these situations must prioritize the development of profoundly individualized experiences, the enhancement of engaging interactions, and the stimulation of emotions. AI apps in fashion, entertainment, or travel ought to be engineered to optimize the emotional experience and value for consumers.

Third, the findings of the multi-group analysis (MGA) indicate that gender does not regulate the links between perception and behavioral intention; nevertheless, it significantly moderates the correlations between human-AI interaction features and arousal. Consequently, enterprises should not segment by gender while developing the fundamental tasks of AI, as both men and women assess the efficacy and advantages of AI technologies in mostly analogous manners. Gender must be taken into account in the design of AI interface and experiential components, including avatar aesthetics, vocal characteristics, degree of anthropomorphism, and communication modalities. This strategy enables enterprises to circumvent superfluous over-segmentation, optimize AI development and deployment costs, and simultaneously augment the efficacy of eliciting consumers' emotional reactions.

Finally, rather than using AI tools in a disjointed fashion, such as chatbots or standalone recommendation systems, enterprises should integrate AI technologies as a "digital staff assistant" that supports consumers throughout the full purchase process. AI must be included in an ecosystem that effectively facilitates all phases, from information acquisition and option comparison to alternative assessment and purchase decision-making. Perceiving AI as a digital staff assistant that supports organizations in optimizing the enduring value of AI to improve customer experience and promote sustained engagement.

6.3. Limitations and further research directions

Despite the study's contributions, it has a number of limitations that may be addressed by more extensive investigation in the future.

The study used cross-sectional data, which just represents the connection at a certain moment and fails to account for fluctuations in customer perceptions, emotions, and intents as the utilization of AI tools progressively escalates over time. Future research may utilize a longitudinal or experimental design to investigate the progression of satisfaction and arousal, along with the influence of AI tools at various phases of the consumer – AI interaction.

The study sample was gathered within a particular context and customer demographic in Vietnam, perhaps constraining the applicability of the findings to other markets, cultures, or sectors. Subsequent research should evaluate the model across other nations, diverse cultural contexts, or specialized sectors such as fintech, healthcare, and hospitality to determine the robustness of the suggested cognitive-affective process.

The study investigated the moderating effects of gender and product type; nevertheless, additional aspects that may affect customer responses to AI technologies remain unexamined. Subsequent research may enhance the model by including supplementary person and environmental factors, such as technological readiness, trust tendency, AI experience, or perceived risk levels, to elucidate the model further.

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