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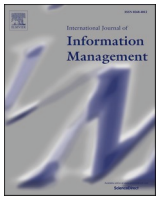

The impact of generative AI shopping assistants on E-commerce consumer motivation and behavior: Consumer-AI interaction design

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ABSTRACT

Generative AI (Gen AI) shopping assistants have been extensively studied—both theoretically and empirically—for their impact on consumer experiences in developed-country e-commerce platforms. However, cultural, economic, and technological differences may constrain applicability in developing-country contexts. This study examines both the "lights and shadows" of Gen AI shopping assistants in developing countries, focusing on how these assistants shape the consumer motivation–behaviour process. We conduct a review from the perspectives of human–computer interaction (HCI), cognitive psychology, and marketing to assess the current state and challenges of Gen AI shopping assistants. Based on this review, we have developed the Motivation–Expectation Management Model (MEMM) to complete the following cycle: Motivation → HCI → Expectation Confirmation → Satisfaction and Repurchase → (feedback to) Motivation. We then collect data from consumers using the "Taobao Wenwen" Gen AI shopping assistant within the Taobao app in China and employ a mixed-methods approach to test the significance, importance, and necessity of the MEMM. (1) Extrinsic motivation exerts a greater influence on personalzation and UX than intrinsic motivation; (2) Mediation chains linking user experience, expectation confirmation, satisfaction, and repurchase intention are significant, with some relationships supported across significance, importance, and necessity analyses, while others are only partially consistent. In summary, MEMM provides both theoretical and empirical grounding for studying Gen AI shopping assistants in developing-country contexts, helps elucidate the consumer–Gen AI interaction mechanisms at play, and offers strategic guidance for sustaining a continuous cycle of interaction optimisation in e-commerce markets.

1. Introduction

Based on expert reports and forecasts, from 2024 to 2030, the Generative AI (Gen AI) market is expected to grow at a compound annual growth rate of 36.5 %, and the global Gen AI market size is projected to reach USD 356.1 billion by 2030 (Jaiswal et al., 2023). Recent scholarship has emphasized the dual "lights and shadows" of artificial intelligence—illustrating how users can feel both served and exploited (Belanche et al., 2020; Belanche et al., 2024; Belk et al., 2023) and even empowered or replaced by AI systems (Flavián et al., 2023). For example, Gen AI, as exemplified by ChatGPT, is revolutionizing the e-commerce industry and exerting a significant influence on consumer experience and decision-making, showing promising prospects (Cao and Cao, 2023; Dwivedi et al., 2023). Gen AI transforms the human-computer interaction mode of traditional digital voice assistants (such as Siri, Alexa, Cortana, Google Assistant, etc.) through smarter human-computer interaction, personalized mechanisms, and natural language understanding, thereby greatly impacting consumer decision-making (Aw et al., 2022; Bock et al., 2020; Coker and Thakur, 2024; Duan et al., 2019; Molinillo et al., 2023). The e-commerce Gen AI shopping assistant is a digital voice assistant based on Gen AI, designed to enhance consumer shopping experiences and assist decision-making (Yadav et al., 2024). In developed markets, the German e-commerce platform Zalando launched its ChatGPT Fashion Assistant in 2023, which made it a market leader in Europe within a year and increased its user base. In the United States, eBay's ShopBot, which also utilizes ChatGPT technology, has secured an important position in the U.S. e-commerce market (Thakur et al., 2024). In developing markets, for instance, Alibaba's Taobao in China launched the "Taobao Wenwen" Gen AI shopping assistant in September 2023, accumulating over 5 million user experiences, with highly active users averaging more than eight queries per day. However, statistics show that about 25 % of user queries are non-shopping related, and there is currently no clear data indicating that it has significantly increased transaction volume and user base (Chen, 2023). Related reports indicate that in Southeast Asia, the e-commerce platform Lazada launched a Gen AI shopping assistant

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called AI Lazzie in 2024 (Rosanti et al., 2025); in surveys, 88 % of respondents expressed willingness to use it, but there is no clear data confirming an increase in transaction volume. Clearly, Gen AI shopping assistants have enhanced commercial value and consumer experience for e-commerce platforms in developed countries, but their advantages in developing markets remain less apparent, with opportunities and challenges coexisting.

Research on consumer behaviour regarding e-commerce shopping assistants (such as acceptance, trust, satisfaction, social interaction, and user experience) has received attention (Bawack et al., 2024; Singh et al., 2024). However, existing studies exhibit the following gaps: First, in terms of device environments, Kautish and Khare (2022) explored the application and impact of interface design in e-commerce shopping assistants under extended reality (XR) environments. Yet, statistics indicate that e-commerce Gen AI shopping assistants on mobile platforms have a larger user base. However, there is no systematic research on how to develop interface design strategies for Gen AI shopping assistants based on mobile e-commerce consumers' needs. Second, regarding the theoretical model, current Gen AI shopping assistant studies focus on analysing consumer acceptance using the Technology Acceptance Model (TAM) (Chakraborty et al., 2024). While TAM can reveal basic consumer acceptance, it tends to oversimplify and lacks depth in explaining multi-scenario phenomena (Zaineldeen et al., 2020). For instance, how do Gen AI shopping assistants influence various stages of the customer journey (pre-purchase, purchase, and post-purchase)? How does the use of Gen AI improve customer or user experience? These questions are difficult to explore in depth using only TAM. Third, regarding the context, research on Gen AI shopping assistants in developed countries is relatively mature (Kiyomiya et al., 2024), but their research background is mostly based on consumption patterns, technological foundations, and cultural habits in Europe and the United States, which differ greatly from market conditions in developing countries. Exploring Gen AI shopping assistant research in developing countries can not only fill theoretical gaps but also promote localised optimisation of technology, enhancing the practical value of shopping assistants in emerging markets. Fourth, regarding the methodology, existing consumer behaviour studies on Gen AI shopping assistants primarily employ SEM methods (Aldaihani et al., 2024; Pathak et al., 2025) and rarely use the SEM-ANN hybrid method (Al-Emran et al., 2024). However, the human-computer interaction issues of Gen AI shopping assistants exhibit nonlinearity and complexity, and ANN can compensate for SEM's shortcomings in explaining such nonlinear and complex problems (Zaidan et al., 2023). Loh et al. (2022) indicated that introducing NCA into the SEM-ANN hybrid method can validate the necessity relationships among variables and reveal bottleneck factors that must be present to achieve high-level outcomes. Compared to SEM-ANN, the SEM-ANN-NCA hybrid approach has been rarely applied in Gen AI consumer behaviour research. In summary, consumer research on e-commerce Gen AI shopping assistants in the context of developing countries faces multiple methodological and contextual research gaps (Gude, 2023). To address these gaps and move beyond methodological novelty, we adopt a theory-driven SEM-ANN-NCA approach. Specifically, SEM enables hypothesis testing rooted in self-determination and expectation confirmation theory, ANN uncovers hidden nonlinear dynamics that cannot be captured by linear SEM paths, and NCA reveals which predictors are indispensable for achieving desired behavioural outcomes. This triangulation allows us to not only test linear effects but also explore their boundary conditions and necessity logic. In doing so, we provide a richer and more nuanced theoretical understanding of Gen AI consumer behaviour in complex human-machine interactions.

Given the above research gaps, objectives, and questions, the research aims to (1) systematically develop interface design strategies for Gen AI shopping assistants based on mobile e-commerce consumer needs to enhance consumer experience. (2) Investigate how Gen AI shopping assistants can improve user experience at different stages of the customer journey (pre-purchase, purchase, and post-purchase) by examining consumer motivation, behaviour, and the transformation process. (3) Explore the research path and differences between Gen AI shopping assistants in developing countries and those in developed markets. (4) Study Gen AI consumer behaviour using the SEM-ANN-NCA hybrid method.

RQ1: How can interactive interface design strategies for mobile e-commerce Gen AI shopping assistants be developed to enhance user experience and purchase intention? **RQ2:** How can the different stages of consumer motivation and behaviour in using e-commerce Gen AI shopping assistants be leveraged to improve the shopping process user experience? **RQ3:** How do the research paths for Gen AI shopping assistants in developing countries differ from those in developed countries? **RQ4:** What additional significance and advantages does the SEM-ANN-NCA hybrid method bring to Gen AI consumer behaviour research?

Based on the above research objectives, the paper is organised as follows: First, the introduction outlines the research gap and clarifies the research objectives and questions. Second, the Literature Review and Hypothesis Development section begins by summarising the hot trends in Gen AI consumer behaviour research, then reviews relevant studies based on SDT and ECT to reinforce the research gap and the uniqueness of this study, subsequently proposing research hypotheses and constructing the model. Third, the Methodology section describes the development of measurement scales and sample data collection, employing an SEM-ANN-NCA hybrid method for data analysis to explore the linear, non-linear, non-compensatory, and necessary relationships among model variables and details the research methods and experimental procedures. Fourth, the Results section presents the data analysis findings and verifies whether they meet the statistical standards. Fifth, the Discussion section addresses the research objectives and questions based on the data analysis results, discussing the transformation mechanism from consumer motivation to behaviour and interactive interface design strategies and comparing with previous studies to analyse the theoretical and practical contributions of this research. Finally, the Conclusion section summarises the study's innovations and value and provides deeper insights into its limitations.

Theoretical Contribution: The research model may provide a new theoretical framework for Gen AI consumer behaviour research. By employing the SEM-ANN-NCA hybrid method, the study potentially offers deeper theoretical insights and new directions for future researchers. Practical Contribution: This study has multiple stakeholders, including e-commerce platforms, designers, and consumers. First, it provides guidance for e-commerce platforms regarding technology applications and business strategies to enhance market competitiveness and user experience. Second, it offers practical recommendations for designers and operators to optimise the design and management of Gen AI shopping assistants. Additionally, by enhancing the shopping experience and satisfaction, the study brings tangible benefits to consumers, strengthening their shopping experience and platform loyalty. These contributions play a significant role in the development of e-commerce and Gen AI shopping assistants.

2. Literature review and theoretical model

2.1. Related research basis

Gen AI has a wide range of implications for consumer behavior. In the field of advertising and marketing, it generates ad copy, product descriptions, and marketing materials based on audience characteristics and preferences (Wang et al., 2023). In the field of e-commerce, Gen AI serves consumers with personalized recommendation systems by analyzing their historical behavior and preferences (Krishnan and Mariappan, 2024). For example, Netflix uses it to recommend movies and TV shows that users are likely to like. Furthermore, Gen AI is extensively employed in virtual assistants and online customer support across multiple companies to respond to inquiries from consumers and offer solutions (Feng et al., 2024). Among them, Gen AI virtual assistants

are most popular in the e-commerce field (Yadav et al., 2024), and the most widely seen model is the chatbot as the carrier, while Gen AI shopping assistant is the embodiment of Gen AI virtual assistants in shopping platforms. Compared to traditional chatbot virtual assistants, Gen AI shopping assistants have stronger natural conversational capabilities, personalized services, complex task processing capabilities, and flexibility than traditional chatbot virtual assistants (Gupta et al., 2023).

In addition to the popular chatbot-assisted search feature, several major companies have identified virtual fitting, meta-universe stores, and personalized recommendation systems as their primary research and development initiatives when it comes to the use of Gen AI in shopping platforms (Google, Amazon, and Nike). Regarding particular Gen AI shopping assistants, eBay Inc.'s ShopBot in the US offers customers a good, individualized service experience. Customers can communicate with the shopping assistant via text, voice, or shared photos (Thakur et al., 2024). According to the study, as of 2023, eBay Inc. has a total transaction value of $73.2 billion; it sits on 132 million active users, mainly in the United States. Zalando Germany is one of the most successful online retailers in Europe, especially in the fashion sector (Brehm, 2019). According to relevant reports, in April 2023 the Zalando platform launched a ChatGPT-based fashion assistant, which can personalize product pairings and recommendations based on a consumer's specific description of the application scenario (e.g., time, place, weather, etc.) Zalando operates in 17 countries and currently serves over 48 million active users. Its total revenues in the first half of 2023 approached 4 billion euros. Because of this, Gen AI shopping assistants have a strong commercial presence in developed economies. Although they have not yet reached full commercialization, developing nations are actively pursuing Gen AI shopping assistants. According to a McKinsey report, the Chinese Gen AI market is projected to expand at a rate of roughly RMB 66 billion by 2022.Leading e-commerce companies in China, such as Alibaba's Taobao and JD.com (Chen, 2023), are increasingly emphasizing the development of Gen AI shopping assistants. Since 2024, they have embedded Gen AI shopping assistants into their platforms, with frequent and rapid iterations. For instance, "Taobao Wenwen" on Taobao and "Jingyan" on JD.com are the results of applying their independently developed large language models. However, in the current Chinese market, the value of Gen AI shopping assistants is not yet prominently demonstrated, as users primarily utilize them as ChatGPT-like tools rather than shopping assistants.

Based on the WOS core literature search, empirical studies on Gen AI consumers were summarized and found to focus more on chatbot application scenarios (Table 1). In addition, we also found that more scholars used the TAM to conduct research for ChatGPT. The application scenarios of related consumption involve beauty, social media, community, enterprise, fashion, retailers, and travel. Chang and Park (2024) looked at the differences in the effects on consumers between regular AI-recommended consumption and Gen AI-recommended consumption. Kim et al. (2024) studied the user experience of ChatGPT by integrating TAM, SOR, and attachment theory. We believe that consumer acceptance studies conducted for Gen AI technology and application scenarios have achieved some success. However, there are certain drawbacks to the continuous customer experience, especially in terms of customer motivation and repurchase propensity. Relevant research lacks thinking from the perspective of consumers' intrinsic motivation and also lacks in-depth discussion on the psychological characteristics of consumers before and after purchase. By going deeper into the demands and pain points of the consumer, thorough research in this area can yield a better design strategy for the Gen AI shopping assistant. The traditional TAM is simple and easy to use, but because it has been used too often, it is prone to flaws in terms of innovation (Christensen et al., 2024; Mogaji et al., 2024). While ECT is better at identifying consumers' pre-, post-, and repurchase willingness, SDT is more successful at identifying consumers' intrinsic and extrinsic motivation. In the process of consumers' interaction with e-commerce platforms, the Gen AI shopping assistant influences consumers' experience and trust through personalized

Table 1
Summary of some empirical studies on Gen AI consumer behavior.

Sources	Theory	Application areas	Research focus
Ameen et al., (2021)	Trust Commitment Theory and Service Quality Model	Color matching tools and chatbot services in beauty brand apps	Analyze how AI integration in shopping can improve the AI customer experience.
Bilal et al., (2024)	Social support theory	Consumer and supplier interactions in social media	The impact of AI on consumer experience and consumer engagement, experience, satisfaction, and purchase intentions on social media. The moderating role of emotional attachment in consumer satisfaction and purchase intention.
Kwangsawad and Jattmart, 2022	TAM+DOI	Consumers use chatbots in community businesses	Consumer Perceptions, Barriers, and Perceived Risks that Influence Consumers' Willingness to Continue Using Chatbot Services in Community Businesses.
Chung et al., (2020)	Multivariate composition	Chatbots in Luxury Fashion Retail Brands	Measuring chatbot views on customer interaction, entertainment, fashion, customization, and problem-solving.
Rese et al., (2020)	TAM+U&G	Chatbots in retailer customer communication	TAM is compared to U&G theory and both methods are applied to measure the acceptance of the text-based "Emma" chatbot by the target segment.
Li and Lee, (2024)	Affordability realization theory and communication theory	Impact of ChatGPT on Users' Adoption of Travel Decisions	A critical examination of how ChatGPT influences users to shift from new adopters to loyal advocates in the context of travel decision-making.
Chang and Park, (2024)	Multivariate composition	Comparison of ChatGPT and AI Recommender Systems on Consumers	Differences in the impact of existing AI recommendation systems and ChatGPT recommendations on consumer choice? What are the processes through which they influence consumer trust in recommended products? Is high brand awareness moderated?
Kim et al., (2024)	TAM + SOR + Attachment Theory	ChatGPT User Experience	Examining the interactions between perceived usability, perceived fun, perceived responsiveness, and intention to continue using ChatGPT.

recommendations and interface design methods. Based on the previously mentioned viewpoints, a research proposal is presented in which the model is constructed by combining AI-HCI factors (Personalization, Interface design aesthetics, User experience, and Perceived trust) and SDT and ECT at the same time. In contrast to empirical research models on related subjects, our model allows for a more thorough exploration of the alterations in consumers' psychological characteristics related to consumption. The model offers a rich theoretical framework and a rich perspective for the discussions and research findings because of its broad explanatory power and deep theoretical understanding. It simultaneously encompasses the domains of psychology, marketing, and HCI. We aim to conduct the study using a mixed SEM-ANN-NCA approach, which is not common in similar studies, and the approach has strong explanatory power in terms of the discussion of results. As a result, this study can offer design and business strategies for implementing Gen AI shopping assistants on e-commerce platforms in developing nations.

2.2. Self-determination theory (SDT)

SDT, which examines behavior from the perspective of an individual's motivation cuts—which are typically divided into extrinsic and intrinsic motivation—is one of the central tenets of positive psychology (Deci and Ryan, 1985). Intrinsic motivation is spontaneous and does not rely on external rewards or punishments but rather stems from the individual's interest and pleasure in the task itself. A subset of controlled motivation is extrinsic motivation, which is the act of acting under the influence of external norms, standards, regulations, or incentives. To improve the design and development of HCI systems, SDT has been used in the field of artificial intelligence to measure consumer psychological needs and motivations (Shen et al., 2023; Yang and Aurisicchio, 2021). In the field of AI marketing and empirical research, TAM has been widely used due to its practicality and simplicity (Christensen et al., 2024; Mogaji et al., 2024). It is important to note that TAM ignores people's intrinsic motivation in favor of concentrating solely on external factors in its research. In addition, TAM is somewhat limited in its explanatory power outside the technical domain. In contrast, SDT focuses on consumers' intrinsic motivation and well-being and has broader explanatory power in different domains (Kumar et al., 2018; Tobon et al., 2020).c

This study searched relevant literature from three databases: Web of Science, ScienceDirect, and Google Scholar, using the following keyword combinations: "Self-Determination Theory or SDT," "Generative Artificial Intelligence or Generative AI," and "Consumer Behavior or Consumers." The search results reveal that the field of education is currently a research hotspot (Chiu, 2024; Latikka et al., 2023). To systematically summarise recent SDT-based AI/Gen AI consumer behaviour research, Table 2 consolidates key studies—Jiang et al. (2022), Kamoonpuri and Sengar (2024), Han (2021), Fan and Liu (2022), Lv and Huang (2024), Liu et al. (2025), Paul et al. (2023), and Vrontis et al. (2024)—by their theoretical frameworks, methods, and research foci. As shown in Table 2, most studies rely on SEM and its variants to test linear effects of motivation variables on adoption or continued use; a few employ ANOVA (Jiang et al., 2022) or Analytic Hierarchy Process (AHP) (Kamoonpuri and Sengar, 2024) for multidimensional evaluations. However, none have examined nonlinear dynamics or necessary conditions in Gen AI contexts. Theoretically, Han (2021) integrated SDT with TAM to explain e-wardrobe adoption, while Fan and Liu (2022) and Lv and Huang (2024) explored the influence of algorithmic autonomy and personalzation on behaviour, indicating a preliminary application of SDT in algorithmic decision-making. Yet the interplay between SDT's motivational dimensions and concrete HCI design elements (e.g., UI/UX) remains underexplored.

Building on these gaps, our study retains the core SDT constructs of extrinsic and intrinsic motivation but integrates them with HCI variables of personalzation and user experience. Using a mixed SEM-ANN-NCA approach, we test linear, nonlinear, and necessity effects to construct a more comprehensive, Gen AI-adapted motivation–behaviour framework for shopping assistants.

Table 2
An Inductive Analysis of the SDT-Based AI/Gen AI Consumer Behavior Research Literature.

Source	Other theory	Methods	Research focus
Jiang et al. (2022)	Social Presence, Retailer Innovation	SEM、ANOVA	The Impact of Retail Chatbots on Chinese Consumers' Continued Willingness to Use and Purchase.
Kamoonpuri and Sengar (2024)	Valley of Terror Theory	AHP	Consumer attitudes toward AI voice shopping.
Han (2021)	TAM	SEM	Chinese consumers' willingness to adopt e-Wardrobe.
Fan and Liu, (2022)	No	Regression analysis, mediation, moderation	The impact of AI algorithmic agent autonomy on consumer purchase decisions.
Lv and Huang, 2024	No	SEM and other hybrid studies	The Impact of Personalized Recommendations on Donation Intentions in Charitable Advertising.
Liu et al. (2025)	Experience economy framework	SEM	The impact of Gen AI-incarnated virtual travel guides on the psychological needs of older adults.
Paul et al. (2023)	No	Comprehensive	Gen AI Consumer Engagement, Customer Service & Personalized Shopping.
Vrontis et al. (2024)	No	Comprehensive	The impact of SDT on Gen AI consumer sentiment.

2.3. Expectation confirmation theory (ECT)

ECT comes under marketing and is used to explain the results of comparative studies of consumer pre-purchase and post-purchase satisfaction (Oliver, 1980). Expectation refers to the consumer's anticipation of the performance, quality, and value of a good before purchasing it. Confirmation, on the other hand, refers to the comparison of the actual assessment of the good after consumption with the previous expectations. The comparison's result has an impact on consumer satisfaction: satisfaction falls if the post-consumption assessment is lower than anticipated, and satisfaction rises if it is higher. Satisfaction further influences consumers' willingness to continue purchasing, i.e., the higher the satisfaction, the higher the willingness to continue purchasing accordingly. In the field of AI, ECT is often applied to evaluate the user experience and performance of research systems (Huang and Yu, 2023; Sohail et al., 2021), and it is also used to measure the user's willingness to continue using the system.

This study reviewed relevant literature from Web of Science, ScienceDirect, and Google Scholar using the following keyword combinations for database searches: "Expectation-Confirmation Theory or ECT," "Generative Artificial Intelligence or Generative AI," and "Consumer Behavior or Consumer." The search results indicate that in the ECT-based Gen AI consumer behavior domain, information systems have attracted significant attention. To systematically capture the state of ECT-based AI/Gen AI consumer behaviour research, Table 3 summarises key studies—Liang et al. (2023), Gonçalves et al. (2024); Rahi et al. (2024); Hu et al. (2024), Huang et al. (2024), Bhatnagr et al. (2024), Sohail et al. (2021), Silalahi (2024), Hermann and Puntoni (2024), and Nan et al. (2024)—by their complementary theories, methods, and research focuses. As Table 3 shows, most investigations employ SEM to test how AI recommendations and service realism influence consumer

Table 3
An Inductive Analysis of the ECT-Based AI/Gen AI Consumer Behavior Research Literature.

Source	Other theory	Methods	Research focus
Liang et al. (2023)	Information ecology theory, information homogenization, individual innovation, social impact, personalized recommendation quality, platform interaction quality	SEM	The impact of AI recommendation on consumer purchase intention under information cocoon effect.
Gonçalves et al. (2024)	autonomy	Experiment, ANOVA, mediation, interviews	The impact of AI recommendations on consumer decision-making on streaming platforms.
Rahi et al. (2024)	Robot appearance, diffusion of innovations, theory of planned behavior	SEM, regulation	Consumer intention to use and acceptance of service robotics.
Hu et al. (2024)	social response theory (SRT)	T-test, mediator	The effect of AI customer service agent realism on customer satisfaction and repeat purchase intentions in service recovery.
Huang et al. (2024)	Perceived Performance, Perceived Enjoyment	SEM	The effect of hotel travel service AI on consumer enjoyment and willingness to use.
Bhatnagr et al. (2024)	Perceptual intelligence, anthropomorphism, quality of interaction	SEM	Continued intentional use of AI-enabled digital banking.
Sohail et al. (2021)	Uncertainty Reduction Theory (URT)	SEM	User satisfaction with AI customer relationship management chatbots.
Silalahi (2024)	No	Overview	From AI to Gen The impact of AI on consumer behavior.
Hermann and Puntoni (2024)	Likelihood modeling (ELM), information quality, interaction quality, etc.	SEM	Gen AI's personalized recommendations for sustainable behaviors.
Nan et al. (2024)	Information systems success theory, privacy issues, perceived innovativeness	SEM	Consumer Intent and Recommendation Factors for Ongoing Use of Gen AI.

confirmation, satisfaction, and repurchase intention. A few studies extend this with experiments and ANOVA (Gonçalves et al., 2024), t-tests and mediation analyses (Hu et al., 2024), or regulatory frameworks (Rahi et al., 2024). Despite these contributions, no prior work has examined nonlinear or necessity effects in Gen AI contexts, nor have they systematically linked ECT's confirmation–satisfaction–repurchase chain with specific HCI factors such as interface aesthetics and real-time feedback.

Building on this gap, our study applies ECT to Gen AI shopping assistants by integrating confirmation, satisfaction, and repurchase intention with HCI variables (personalzation, UI/UX, and perceived trust). We then use a mixed SEM-ANN-NCA approach to test linear, nonlinear, and necessary-condition hypotheses. This allows us to uncover not only the average effects of expectation confirmation processes but also the boundary and indispensable conditions under which Gen AI assistants' long-term consumer engagement.

2.4. Motivation expectation management model (MEMM)

Based on the research foundations of SDT and ECT (Deci and Ryan, 1985; Oliver, 1980) and grounded in the rapidly growing e-commerce market in developing countries (Chen, 2023), we propose the Motivation-Expectation Management Model (MEMM; Fig. 1). Unlike previous studies that view SDT and ECT as different perspectives, MEMM introduces two new constructs. (1) Expectation management: the ability of Gen AI assistants to dynamically adjust and meet user expectations through personalised recommendations, real-time interface feedback, and trust-building features (Mirnig et al., 2014; Parasuraman et al., 1991). This extends the static 'validation' concept of ECT into an ongoing adaptive process (Teece et al., 1997). (2) Motivational feedback: the mechanism by which feedback from realised satisfaction and repeat purchase behaviour reshapes the user's intrinsic and extrinsic motivational states (Bem, 1972), creating a dynamic cycle of continuous engagement. MEMM model aims to extend the motivational perspective in HCI and provide theoretical guidance and optimisation strategies for future Gen AI system design.

In the model logic, motivation consists of intrinsic drivers (e.g., autonomy, competence; Deci and Ryan, 2000) and extrinsic incentives (e.g., discounts, rewards; Eisenberger and Cameron, 1996), which initiate user participation. Expectation management then transforms this motivation into tailored system actions, resulting in satisfaction and repurchase intentions. At the same time, user satisfaction and repurchase behaviours feed back to reinforce motivational perceptions, driving the formation of higher levels of interaction and willingness to participate. This dual path not only presents a linear motivation-expectation-outcome chain but also reflects a dynamic evolutionary closed loop between behavioural motivation and platform optimisation. By explicitly embedding motivational feedback into the model (Kamhawy et al., 2021; Szalma, 2014), MEMM captures how each round of confirmations and re-purchases informs the next fluctuating machine-driven round, which happens to be an innovation lacking in traditional SDT/ECT applications. Thus, this unified framework answers three questions:1. Why do users engage? (Motivation) 2. How are expectations realised or adjusted? (Expectation management) 3. What results were generated, and how do these results drive future motivation? (Satisfaction, repurchase and motivational feedback). Conceptually, this generates both a linear causal chain and a dynamic feedback loop, whereby willingness to repurchase informs and refines subsequent motivations, allowing the Gen AI assistant to learn and optimise in successive interactions.

In these markets, digital infrastructure, consumer trust, and regulatory environments are markedly different from those in developed countries (Mannuru et al., 2023), and in developing countries, behavioural patterns may be nonlinear, and certain drivers may be necessary but not sufficient (Al-Emran et al., 2024; Costa et al., 2024). To rigorously test this model in this context, we used a hybrid SEM-ANN-NCA approach to fully reveal linear causality, nonlinear interactions, and the structure of necessity among the variables. SEM was used to validate the path relationships between motivation, expectation management, and outcome variables. ANN captured complex nonlinear interactions that traditional statistical methods could not reveal. NCA judged which elements were necessary to achieve high satisfaction and repurchase intention. This mixed-methods strategy aims to increase the robustness of the analysis in order to more closely match the complex mechanisms used in practice.

3. Hypothesis development

3.1. From user motivation to perceived interaction quality

3.1.1. Intrinsic user motivation

According to SDT, AU and CO are the two core psychological needs that constitute an individual's intrinsic motivation (Deci and Ryan, 1985; Deci and Ryan, 2000; Gao et al., 2018; Ashfaq et al., 2019). Both have been widely shown to motivate higher levels of behavioural engagement and positive emotional experiences in users in intelligent

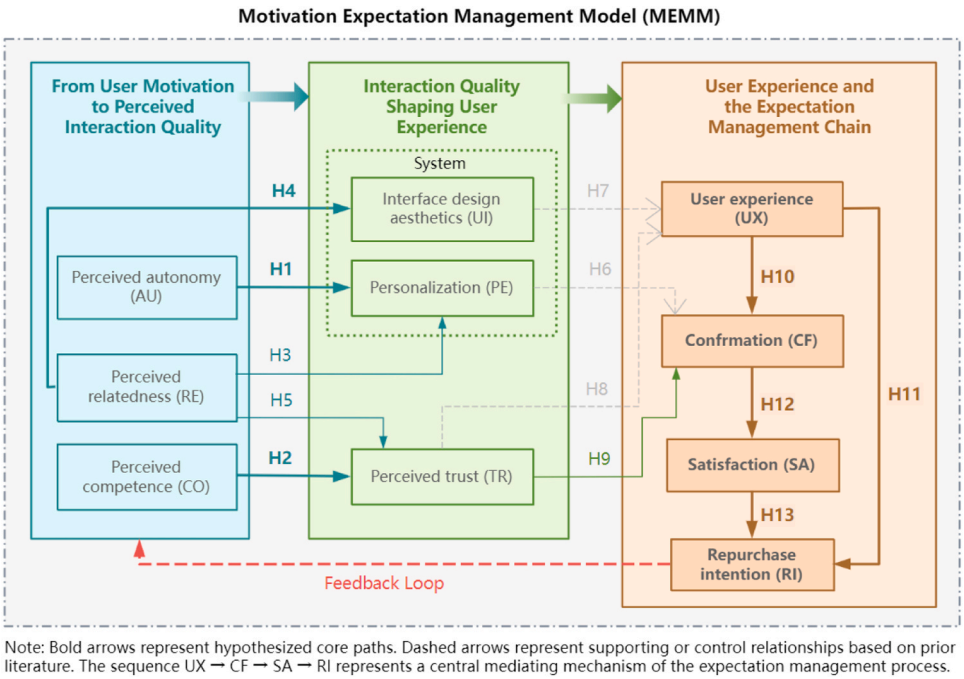

Fig. 1. Motivation expectation management model (MEMM).

interactive systems (Ryan and Deci, 2017). The phenomenon of 'Autonomous Exploration Drive' refers to the idea that increased autonomy leads individuals to exhibit exploratory behaviours and personalised preferences." That is, when users perceive that their behaviour is not manipulated or constrained by the system but rather driven by autonomy, they actively participate in the setting of "personalised preferences" and develop a positive sense of identity (Sundar, 2008). Alamri et al. (2020) found that personalised recommendations based on self-directed paths of learning significantly increased students' intrinsic motivation. students' intrinsic motivation. "Cognitive congruence" refers to the fact that increased competence drives the user's confidence in "being able to collaborate with the system on shopping tasks". That is, it strengthens the user's understanding of the AI system's intent and behavioural logic and reduces uncertainty and usage anxiety, which in turn leads to a stable trust relationship.

In Gen AI shopping assistants, the system usually utilises natural language processing, context awareness, and multimodal feedback mechanisms to strengthen the user's sense of control and mastery. On the one hand, when the system actively recognises the user's preferences and provides diversified recommendation options, the user is more likely to feel a sense of autonomy that "the choice is made by me," which enhances the positive identification with the interaction process of the system (Hu et al., 2021; Shen et al., 2023). On the other hand, as users gradually understand and navigate the operating logic of AI assistants, they develop a sense of competence in the system, thinking, "I can use it skilfully," which is a prerequisite for building trust in the system (Wang and Li, 2014; Yang and Aurisicchio, 2021). Compared with the passive recommendation based on clicking behaviour in traditional e-commerce platforms, the Gen AI assistant constructs an active negotiation-based interaction mechanism through "conversational intent recognition + dynamic feedback", which is a process of stimulating and mobilising users' motivation. This mechanism transforms the user's intrinsic motivation from an external input to a behavioural driving variable, which significantly expands the explanatory power of the SDT theory in the HCI environment and makes up for the lack of attention to the subjective motivation mechanism of the user in personalised recommendation research. Therefore, this study argues that when consumers feel a high degree of autonomy and a sense of competence mastery during their interaction with Gen AI shopping assistants, it will enhance their positive experience of personalised recommendations and trust in the system, respectively, thus activating the subsequent expectation management chain.

H1: Consumers' intrinsic motivation of perceived autonomy has a significant positive impact on their personalised experience with Gen AI shopping assistants.

H2: Consumers' intrinsic motivation for perceived competence has a significant positive effect on their trust in the Gen AI shopping assistants.

3.1.2. *User extrinsic motivation*

In SDT, RE refers to the sense of social connectedness that an individual experiences with others or a system in a particular situation (Deci and Ryan, 2000). Unlike AU and CO as intrinsic motivation variables, RE emphasises the role of external social contextual factors in driving individual motivation, especially whether users feel a sense of understanding, responsiveness, and belonging during interactions. In particular, in the interaction between the e-commerce platform and the Gen AI shopping assistant, users' extrinsic motivation is manifested through the following three main aspects:

(1) Enhanced interaction feedback and personalised experience: interaction feedback is the core factor driving user engagement and identification in personalised services (Zhu and Chang, 2016). When the Gen AI shopping assistant can optimise understanding of user preferences, provide timely feedback, and continuously optimise recommended content, personalised recommendations not only enhance the user's sense of identification with the recommended results but also stimulate the user's emotional resonance of participation and being understood. At this time, the personalised experience perceived by the user does not only come from the improvement of the system's matching degree but also from the response and sense of participation gained during the interaction process, which is the core mechanism of RE.

(2) Cultural fit and aesthetic experience in visual design: visual design is not only embodied in the interface aesthetics of the system but also in the cultural suitability and interaction compatibility, which is especially important in cross-cultural application scenarios (Aljaroodi et al., 2023; Crilly et al., 2004). The Gen AI shopping assistant generates with users; after the Gen AI shopping assistant interacts with users in a

"multi-frequency contextualised" way, the visual factors of the local culture (e.g., style, colour, layout, icons, symbols, etc.) are more and more compatible with the users' needs, which transforms the interface from an "information carrier" to an "emotionally resonant carrier". This changes the interface from "information carrier" to "emotional resonance carrier".

(3) Social connection with the system and trust building: RE also constitutes the social basis for trust building; Sirdeshmukh et al. (2002) pointed out that trust building depends not only on the effectiveness of the system's functions, but also on whether the user feels that the system "understands him/her" and reflects his/her interests. Whether the Gen AI shopping assistant makes users perceive that it "understands me" or "has my best interests at heart" will have a direct impact on their trust. The assistant builds trust emotionally through feedback mechanisms, which increases the willingness to use it over time. This interaction-based trust is not limited to acceptance of the technology itself but also includes identification with the interaction. Therefore, we propose the hypothesis:

H3: Consumers' extrinsic motivation in terms of perceived relevance has a significant positive impact on their personalised experience with the Gen AI shopping assistants.

H4: Consumers' extrinsic motivation in perceived relevance has a significant positive effect on their aesthetic evaluation of the Gen AI shopping assistants' interface design.

H5: Consumers' extrinsic motivation for perceived relevance has a significant positive effect on their trust in Gen AI shopping assistants.

3.2. Interaction quality perception shapes user experience

3.2.1. System interaction quality

System interaction quality is the user's comprehensive perception of key elements such as system responsiveness, interface expressiveness, and service matching during the HCI process. In the assistant, PE and UI are the two core dimensions that constitute the system interaction quality. Together, they shape the user's initial judgement on whether the system "understands me" and "is trustworthy" and are the key entry points for driving the user experience and expectation management mechanism.

As the core path of cognitive confirmation, the personalisation mechanism emphasises the ability of the system to accurately respond to user preferences and adjust the service content, thus reducing cognitive load and improving experience perception (Adomavicius and Tuzhilin, 2005; Glushko and Nomorosa, 2013; Guo et al., 2019). Compared with the static feature-based matching in traditional recommender systems, Gen AI shopping assistants form a dynamic feedback mechanism based on language understanding and contextual learning so that each round of interaction has a certain degree of "customisation" and "novelty". This mechanism not only strengthens the user's sense of participation but also enhances the user's CF of the system's recommendations through the perception of "being understood" and "being responded to" (Casteleiro-Pitrez, 2024; Cabrera et al., 2020). Second, UI not only carries the function of visual pleasure but also assumes a regulating role in interaction logic, information architecture, and contextual feedback. Whether the UI allows users to "understand", "find", and "use" determines whether the interaction between users and Gen AI shopping assistants is smooth and effective (Sutcliffe, 2022; Wu & Huang, (2021)). Especially in multi-round conversational interactions, Gen AI assistants shape the sense of immersion through colour adaptation, layout adjustment, micro-animation feedback, etc., and build a unified experience tone with multi-modal inputs and outputs, thus reinforcing the UX dimension of the system. Finally, PE and UI do not act independently on user cognition but rather reinforce each other to form a dual-core system for the interaction quality of the system: PE reinforces cognitive confirmation through content matching, while UI enhances interaction immersion through formal presentation, and the two synergistically amplify the user's overall evaluation of the service capability of the Gen AI shopping assistant. Based on this, we propose the following hypothesis:

H6: Consumers' perception of Gen AI shopping assistant's personalised experience has a significant positive effect on their expectation confirmation.

H7: Consumers' evaluation of the aesthetic design of the Gen AI shopping assistant interface will positively and significantly influence their user experience.

3.2.2. System interaction trust

In Gen AI shopping assistants, system TR is not only a prerequisite for user acceptance of the technology but also a key mechanism that connects the user's sense of competence with the perception of experience. It determines whether the user is willing to "cede control" and establish psychological dependence on the system (McKnight et al., 2002; Shin, 2021). In the AI context, users are usually confronted with an opaque, algorithm-driven black box system, and their judgement of the system's "comprehensibility", "response logic", and "reliability of intent" significantly affects their willingness to engage in deeper interactions. The three-dimensional trust structure (competence, benevolence, and honesty) proposed by Gefen et al. (2003) is suitable for explaining users' trust construction paths towards AI assistants – among which "competence perception" is the most fundamental dimension, i.e., "competence" is the most important dimension, i.e., "competence" is the most important dimension of AI assistants. It is the most fundamental dimension, i.e., whether the user believes that the system is "capable of accomplishing the task", whereas "benevolence" and "honesty" are related to whether the user believes that the system is "on my side". Especially in the Gen AI assistant, users often interact with the system continuously through natural language, and if the system can accurately recognise semantic intent, timely adjust the answer, and maintain the consistency of the interaction, users will gradually form the psychological judgement that "it understands me." This "sense of social agency" transforms the AI system from a cold tool to an "intentional" communicator and enhances the social perceptual basis of trust (Symons and Abumusab, 2024). Furthermore, trust has a significant 'cognitive offloading' function (Lee and See, 2004; Pavlou and Gefen, 2004). When users trust the system's processing power and value stance, they will no longer frequently assess the accuracy of each round of interaction but will instead redirect their cognitive resources to the task itself, resulting in a smoother immersion experience. This mechanism explains why technical performance alone does not translate into a high-quality experience but must rely on the mediating process of "trust as lubrication". The following hypotheses are therefore proposed:

H8: Consumers' trust in the Gen AI shopping assistants will positively and significantly influence their user experience.

H8a: Consumers' trust in Gen AI assistants moderates the relationship between perceived competence and user experience.

H8b: Consumer trust in the Gen AI assistants moderates the relationship between perceived relevance and user experience.

System trust also significantly affects users' judgement of whether a service performs as expected, which in ECT theory is a subjective evaluation based on the gap between expected and actual outcomes (Oliver, 1980). However, in the dynamic learning Gen AI assistant, the user's "confirmation process" tends to be gradually adjusted in multiple rounds of interaction. At this point, "trust" plays a key moderating role: high-trust users are more inclined to tolerate initial deviations and pay more attention to the system's feedback and adjustment capabilities, and thus are more likely to form a cognitive judgement that the system's performance is generally acceptable in the subsequent rounds of interaction (Gefen, 2000; Huang et al., 2022). In other words, trust extends the static assumptions of the traditional ECT model to make expectation confirmation dynamically adjustable. The following hypothesis is therefore proposed:

H9: Consumers' trust in the Gen AI shopping assistants positively and significantly influences their expectation confirmation for both the platform and the assistant.

3.3. User experience connectivity expectation management

3.3.1. User experience

UX is the central hub in the entire "expectation management chain" in the context of Gen AI shopping assistant usage. It guides the user from initial contact to final behaviour by integrating perceived value, emotional response, and functional effectiveness (Seiferth et al., 2023; Zhu et al., 2023). Unlike existing research, Gen AI provides a "dynamically evolving" experiential process, based on natural language processing and contextual adaptation capabilities, with the ability to provide real-time feedback and adjustments to content, shaping a more interactive, personalised, and emotionally resonant experiential mechanism (Epstein et al., 2022). Theoretically, the positive perception of UX contributes to the reinforcement of "cognitive coherence", i.e., the perception of consistency between user expectations and the system (Van Der Heijden, 2004). When details such as recommendation results, interface response, and conversational tone consistently match user expectations, users are more likely to form a "this is what I want" judgement, thus increasing their CF (Teo et al., 2015). However, the impact of UX on CF is not a single point but rather a "reinforcement loop" that accumulates with the number of interactions: each positive experience further reinforces the user's belief in the system's capabilities and reduces the cost of tolerating potential failures. UX profoundly influences behavioural patterns at the cognitive level. It has been found that quality UX becomes embedded in behavioural inertia (Limayem et al., 2007), where users no longer make one-off decisions based on "Is it worth it to continue?" but rather develop automated reuse behaviours out of familiarity and trust. Reuse behaviours in the context of Gen AI are more focused on the user's perception of the overall experience process in terms of the system's capabilities. The reuse behaviour in the context of Gen AI is more focused on the user's emotional attachment and psychological belonging to the overall experience process in terms of system capabilities (Pavlou and Gefen, 2004). Thus, UX is not only a source of one-time transaction satisfaction but also a fundamental driver of reuse and the formation of long-term relationships.

H10: Consumers' UX of the Gen AI shopping assistants positively and significantly influences their expectation confirmation of the assistant and platform.

H11: Consumers' user experience with the Gen AI shopping assistants positively and significantly influences their willingness to repurchase the Gen AI shopping assistant.

H10 and H11 have different UX focuses: H10 focuses on the cognitive calibration between system performance and user expectations, i.e., the rational level of "whether expectations are fulfilled". H11, on the other hand, emphasises the user's behavioural dependence and emotional attachment to the system, reflecting the emotional level of "whether I want to continue to use it". By placing UX in the key position of "cognitive confirmation-behavioural continuation", we emphasise its integration effect as a mediating variable. This leads to the concept of "trust-driven experiential behavioural chain", where TR is a key psychological resource for users to reduce perceived risk and increase willingness to participate in uncertain technological environments (Jared M. et al., 2017). In Gen AIractions, high TR enhances users' evaluation of interaction quality and also directly boosts RI by optimising UX. The chain aims to take up the motivational antecedents of H8a and H8b, articulating the psychological drivers of differentiation in terms of intrinsic and extrinsic motivation, respectively, and constructing a closure of the recursive transformational relationship of trust-experience-behaviour. The chain also demonstrates how trust serves as initial psychological capital that translates into sustained usage behaviours by enhancing UX. Mediates the formation of UX, enabling users to be more receptive to personalised recommendations and experiences and enhancing SA and loyalty, thereby contributing to the formation of RI.

H11a: Consumers' UX with Gen AI shopping assistants moderates the relationship between trust and repurchase intention.

3.3.2. Expectation management

Expectation management is not only the subsequent cognitive outcome of user experience but also a mediating mechanism that connects perception and behaviour, of which CF is the first link, which is based on the user's cognitive assessment of "whether the system's performance meets expectations" (Bhattacherjee, 2001). In the case of the Gen AI shopping assistant, CF is no longer determined by functionality alone but is deeply influenced by the quality of the entire UX. Interface fluency, contextual adaptation of recommendations, and interaction feedback speed all constitute core reference dimensions for CF evaluation. When users form the cognitive consistency experience of "the system is behaving as I thought it would" in multiple rounds of interactions, it will drive them to form a higher sense of confirmation (Teo et al., 2015). Compared with traditional static recommender systems, Gen AI has the ability of context recognition and dynamic adjustment, in which users experience the interactive impression of "understanding me" and "making progress", which will significantly enhance their confirmation expectations of the system's effectiveness (Jahng et al., 2002; Pu et al., 2012; Sohail et al., 2021). This implies that the path mechanism of UX → CF is not only a technical outcome judgement but also an experiential feedback based on the coupling of cognition and emotion during the interaction process.

H12: Consumers' confirmation of Gen AI shopping assistants and platforms has a significant positive effect on their satisfaction.

SA, as an emotional assessment variable, is precisely the emotionally integrated output of UX and CF working together. A high level of confirmation will significantly increase satisfaction, but this transformation is not automatic; it is influenced by the overall emotional climate of the user towards the experience process. When users perceive a congruent effect of the system's competence, understanding, and responsiveness during an interaction, they are more likely to develop positive emotions such as pleasure and trust, which steadily translate into satisfaction (Ashfaq et al., 2020; Oliver, 1980). In the Gen AI scenario, the continuous feedback mechanism allows the system and the user to continuously adjust the boundaries of their expectations during the interaction, building a closed-loop relationship of "cognitive confirmation-emotional enhancement". Ultimately, this satisfaction will drive the user's RI, which, unlike "product repurchase" on a typical trading platform, in the Gen AI scenario is more of a "re-entry decision" for a complete intelligent interactive experience. Instead of evaluating a one-time recommendation, users make behavioural judgements based on their continued tendency to "feel good, familiarity, and trust in the whole interaction process" (Li et al., 2024). Satisfaction plays the role of mediating the "emotion-driven-behavioural continuity" bridge.

H13: Consumers' satisfaction with the Gen AI shopping assistants and platform has a significant positive effect on their repurchase intention.

UX → CF → SA → RI constitutes a main path chain from experiential cognition, confirmation, and evaluation to emotional transformation and behavioural continuation. This path is not a linear transmission but a closed loop driven by dynamic cognitive regulation, emotional integration, and behavioural feedback.

3.4. Mediating chain and feedback closures

3.4.1. Mediation chain

Compared to the single mediators of H8a, H8b, and H11a in the previous paper, the integrated mediator chain can provide deeper theoretical insights into the relationship between users and Gen AI shopping assistants. The study aims to reveal how multilevel psychological processes continue to accumulate, transform, and amplify in the time dimension by demonstrating the dynamic evolution of UX between cognitive assessment, affective response, and behavioural decision-making. Specifically as follows:

(1) Cognitive Confirmation and Emotional Transformation Chain: In the assistant's usage context, UX first helps the user to confirm that his/

her cognitive expectations of the system are met by providing interactions that meet the user's expectations (Lin and Ng, 2024). With the confirmation of the user's cognition, the user's emotional response to the system begins to emerge, and this emotional feedback further deepens the user's recognition of and reliance on the system (Smith K. et al., 2023). Eventually, by enhancing the user's trust and emotional attachment to the platform, it promotes the formation of long-term RI. In other words, cognitive confirmation bridges the gap between the user's perception of the system's performance and its expectations; along with the enhancement of the sense of confirmation, the user enters into the stage of affective recognition and positively evaluates the system's quality through the SA; and finally, this chain reaction will be transformed into the user's RI, which embodies the dynamic evolution of cognitive to affective and then to dynamic evolution of behaviour.

(2) External relevance-driven design perception chain: this chain demonstrates the progressive mechanism from motivation to behaviour, highlighting the central role of system design in motivation transformation, especially cultural fit and aesthetic resonance in Gen AI scenarios (Jackson G et al., 2025). RE influences the user's emotional identification with the system and the quality of the experience by enhancing the aesthetic perception of the interface design. The interface is a source of emotional resonance and cultural appropriateness (Jackson G et al. The interface is a vehicle for emotional resonance and cultural fit, and when users perceive that the system interface fits with their cultural values and aesthetic preferences, the overall user experience is significantly enhanced, which ultimately translates into enhanced RI. This chain also emphasises the indirect role of external contextual fit and design perceptions on the user experience. The following hypotheses are therefore proposed:

H_M1: Consumers' user experience of the Gen AI shopping assistants positively influences their repurchase intention through the successive mediating effects of confirmation and satisfaction.

H_M2: Consumers' perceived relevance positively influences their repurchase intention through the successive mediating effects of the assistant's interface design and user experience.

3.4.2. Feedback closing the loop

Although RI is at the end of the structural path, its role is not limited to static outcome variables but constitutes a reverse driving mechanism that promotes the two-way evolution of the user and the system. (1) User perspective: motivational reinforcement of behaviour before perception. According to self-perception theory (Bem, 1972), individuals infer intrinsic motivation by observing their own behaviour. Repeatedly choosing to use the assistant and generating a high willingness to repurchase will be interpreted by the user as "I like this system" and "this assistant is helpful to me," which in turn will enhance autonomy and perceived competence and form a habitual pattern of use. (2) System perspective: from passive response to active adaptation. Users' continuous repurchase behaviour provides the system with the data basis for iterative optimisation, and the Gen AI system can dynamically adjust the recommendation algorithm and interface strategy based on indicators such as user preferences, feedback behaviour, and length of stay to achieve active adaptation and personalised evolution, further optimising the user experience and cognitive consistency. In short, this closed-loop mechanism of "behaviour-cognition-system evolution" reveals that users are both users of the technology and participants in the system optimisation and promote the co-evolution of humans and machines through continuous behaviour. Although this study does not directly test this mechanism in the empirical part, it provides a basis for future research on user habit formation and adaptive evolution of AI systems.

4. Materials and methods

Mature Gen AI shopping assistants in Western markets, such as Zalando's "Fashion Assistant" and Amazon's "Refus," have garnered significant attention. In contrast, Gen AI shopping assistants in developing countries lack maturity and focus. China's Alibaba Taobao app, renowned in the global e-commerce industry, has introduced the publicly accessible "Taobao Wenwen" Gen AI shopping assistant. This assistant offers enhanced interactive shopping experiences for consumers, such as identifying and recommending office desktop items through photo recognition. Recent iterations have enabled users to switch the conversational interface's language style, such as a professional and rational tone targeting male shoppers or a gentle and emotional tone for female shoppers. This personalized conversational language is reflected in various aspects of human-computer interaction, including text style, voice tone, and product recommendations. Given Alibaba's leading position in China's e-commerce market (with a consumer platform of 1 billion users), this study focuses on "Taobao Wenwen" (Fig. 2) as a case study, collecting behavioral data from users who have interacted with the assistant to research Gen AI shopping assistants.

4.1. Test for questionnaire design

The questionnaire was designed in three parts: (1) introduction and commitment to the study; (2) basic information; and (3) scale. Firstly, in the first part, the purpose of this questionnaire collection was introduced, the subjects' voluntariness was solicited, and the confidentiality of the results was promised. The specific information is as follows: "This research is all conducted anonymously, and the results are for academic research use. We will keep it strictly confidential and will not affect you. Thank you for your support and cooperation." In addition, we emphasized the authenticity of the data filled in by the subjects by using red font in the first part of the introduction. The specific information is as follows: "Please fill out the form as truthfully as you think. Please refrain from selecting "strongly disagree" or "strongly agree" in more than one consistent option. Secondly, in the second part of the basic information questions, the first question asked whether the subjects had ever used "Taobao Wenwen" in a multiple-choice way, and for those who filled in "no," we prompted them to end the questionnaire immediately. Moreover, their data were not included in the final sample data.

The study utilized a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). The test scales for each variable in this online questionnaire were borrowed from well-established scales that have been validated in the literature on the topic. First, given the deviation of the scales in the reference literature from the language used in the sample data collection setting, five experts in the field were invited to correct the translated scales for linguistic communication accuracy. Second, 50 online questionnaires were collected from the Chinese website "Questionnaire Star" and analyzed for reliability to examine whether the revised scale design could accommodate the effects of cultural, linguistic, and environmental variability in China. The reliability analysis ($\alpha = 0.781$) was found to be reliable. These efforts contribute to the robustness of the statistical results and the reliability of the conclusions of the data analysis (Moor and Benbasat, 1991; Gefen, 2002).

First, of the variables included in the SDT, the scales used to test the AU (number of factors: 4, α=0.851, AVE=0.590, CR=0.851) and CO (number of factors: 4, α=0.844, AVE=0.580, CR=0.847) variables were adapted from Nguyen et al. (2022), while the scales used to test the RE (number of factors: 3, $\alpha = 0.816$, AVE = 0.597, CR = 0.816) variables were adapted from Song et al. (2023). Second, among the variables included in the ECT, the scales used to test the CF (number of factors: 3, $\alpha = 0.837$, AVE = 0.634, CR = 0.839), SA (number of factors: 3, $\alpha = 0.864$, AVE = 0.614, CR = 0.864), and RI (number of factors: 3, $\alpha = 0.847$, AVE = 0.647, CR = 0.846) variables scales were adapted from Sharma et al. (2024). Third, among the variables included in the AI-HCI factor, the scale used to test the PE (factor number: 4, $\alpha = 0.825$, AVE = 0.544, CR = 0.826) variable was adapted from Li et al. (2023); the scale used to test the UI (factor number: 3, $\alpha = 0.822$, AVE = 0.608, CR = 0.823) variable was adapted from Cheng (2021); the scale used to test UX (number of

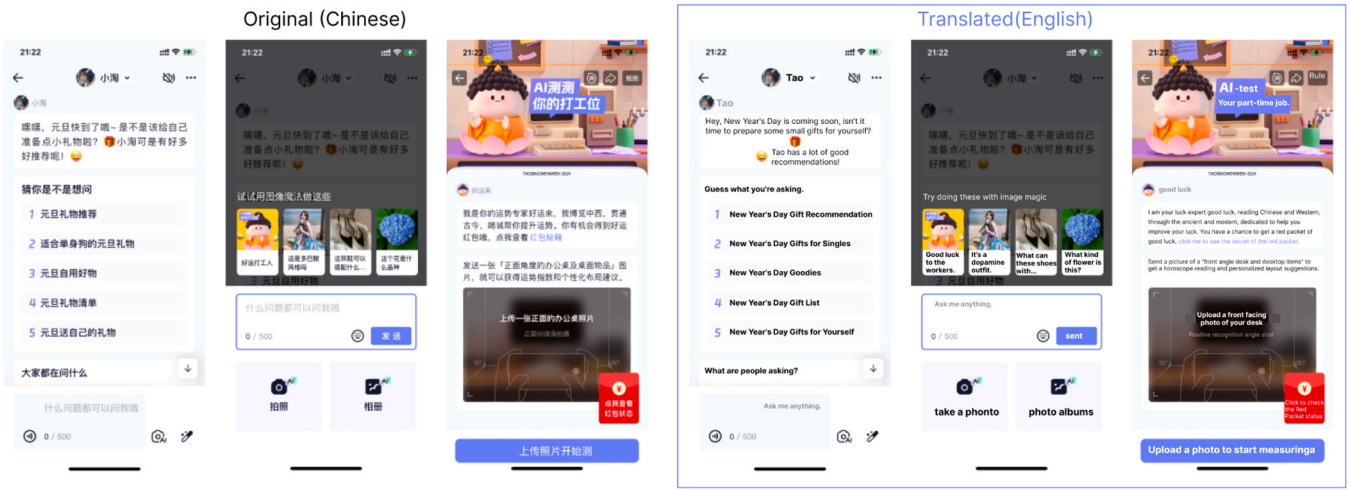

Fig. 2. The "Taobao Wenwen" Gen AI shopping assistant under Alibaba's Taobao app.

factors: 4, α = 0.829, AVE = 0.549, CR = 0.829) variables was adapted from Hsu and Chen (2018); the scale used to test TR (number of factors: 3, α = 0.815, AVE = 0.595, CR = 0.815) variables was adapted from Jain and Raghura (2024). Supplementary material contains the specific factors for all variables, original measurement question items, modified measurement question items, and references.

4.2. Procedures for data collection

Given that the target respondents for this study are Gen AI shopping assistant users, non-probability sampling techniques were used, select purposive sampling, to ensure that data was collected only from participants with experience using Gen AI. The study used a cross-sectional online survey method to recruit participants from various social platforms, ensuring broad representativeness of the sample in terms of region, social background, and user group type.

The sample size for this study was determined based on the sample size standards required for SEM analysis. According to Mitchell (2020), the sample size for SEM analysis should generally be 10–20 times the number of measurement items. Given that the study has 35 measurement items, the sample size should range from 350 to 700. The final sample of 360 valid responses meets the requirements for SEM analysis. The choice of sample size aims to ensure the statistical significance and interpretability of the study results.

The data collection process employed a multi-channel, distributed approach to ensure the diversity and representativeness of the sample. First, samples were recruited through the mutual fill-in community feature on the "Wenjuanxing" website, as well as social platforms such as QQ friends, QQ groups, WeChat friends, WeChat groups, Xiaohongshu APP friends, and Xiaohongshu APP groups. These platforms are highly interactive and effectively reach users from different backgrounds, enhancing the diversity of the sample. Given the wide user base of Chinese e-commerce platforms, this study did not use a single sampling method but instead adopted a multi-channel integrated approach to sample collection. The experiment was conducted in accordance with the Helsinki Declaration (World Medical Association, 2013).

To ensure the representativeness of the sample, strict screening criteria were applied during the four-month data collection period to ensure the quality and validity of the participant data. A multi-round screening process was conducted on the 500 collected sample data to eliminate invalid responses. In the first round of screening, we removed responses from participants who had never used Gen AI (N = 54). In the second round, responses from participants who completed the questionnaire in less than 90 s were removed (N = 65). In the third round, responses from participants who selected the same choice continuously were removed (N = 21). In the end, 360 valid sample responses were obtained, ensuring the accuracy of the data.

4.3. Distribution of population characteristics

In this study, the sample data of the subjects were demographically characterized in terms of gender, age group, education level, and annual household income range (N = 360, Appendix A). First, in terms of gender share, there were more males (N = 189, 52.5 %) than females (N = 171, 47.5 %). Second, in terms of the percentage of age groups, the largest percentage was for subjects aged 18–30 years (N = 203, 56.4 %); the second largest percentage was for subjects aged 31–45 years (N = 130, 36.1 %); the third largest percentage was for subjects younger than 18 years (N = 23, 6.4 %); and the smallest percentage was for subjects older than 45 years (N = 4, 1.1 %). Third, in terms of the percentage of education level, the largest percentage was for subjects with a bachelor's degree (N = 169, 46.9 %); the second largest percentage was for subjects with a master's degree (N = 121, 33.6 %); the third largest percentage was for subjects with a college degree or less (N = 58, 16.1 %); and the smallest percentage was for subjects with a doctoral degree (N = 12, 3.3 %). Fourth, in terms of the percentage of the range of annual household income, the largest percentage was for subject households with less than 150,000 RMB (N = 179, 49.7 %); the second largest percentage was for subject households with 150,000–300,000 RMB (N = 138, 38.3 %); the third largest percentage was for subject households with 300,000–500,000 RMB (N = 28, 7.8 %); and the smallest percentage was for subject households with 500,000 RMB or more (N = 15, 4.2 %).

4.4. Data analysis methods

The following is a progressive introduction to the SEM-ANN-NCA hybrid method used in this study:

SEM: The CB-SEM method has been widely used in Gen AI consumer behavior research (Kumar et al., 2025; Pandey & Rai, 2023). As a multivariate linear regression analysis method, CB-SEM can analyze the linear relationships between variables in the model (Hair et al., 2017). This study follows the CB-SEM analysis framework provided by existing research, covering multiple evaluation criteria such as reliability, model fit, convergent validity, composite reliability, discriminant validity, normality tests, and correlation analysis. SEM analysis was conducted using SPSS and AMOS software.

ANN: Although SEM hypothesis testing can explain the multivariate linear relationships between variables well, it lacks predictive accuracy when handling non-compensatory and non-linear relationships, which

may oversimplify the complexity of decision-making processes. ANN, on the other hand, can complement this limitation (Albahri et al., 2022). Due to the "black-box" nature of ANN, it is not suitable for hypothesis testing. Therefore, in this study, the independent variables from SEM are used as input neurons for ANN, and the dependent variables as output neurons, thereby combining the advantages of both methods. To avoid model overfitting, a 10-fold cross-validation method (training: 90 %, testing: 10 %) was applied, and the model's performance was validated using Root Mean Square Error (RMSE). Sensitivity analysis examines the normalized relative importance of multiple input neurons on the output neurons in the ANN model to determine the most critical input neurons. ANN analysis was performed using the multi-layer perceptron (MLP) module in SPSS's neural network.

NCA: Although the SEM-ANN hybrid method cannot verify the necessity of relationships between variables, the NCA method can complement this by identifying necessary conditions that were not detected by the former (Loh et al., 2022). NCA can verify the necessity of relationships between exogenous and endogenous variables (Leong et al., 2024). Furthermore, NCA helps identify key variables that may have a small influence but are critical to the model. NCA analysis was conducted using the NCA package in R language.

Finally, the results of the SEM-ANN-NCA methods were compared in this study, which not only strengthened the explanatory power of the theoretical model and research hypotheses but also extended its applicability. Albahri et al. (2022) reviewed the various application areas, publication volumes in journals, advantages, and challenges of the SEM-ANN hybrid method in research. Pandey and Rai (2023) employed the SEM-ANN hybrid method to study consumers' willingness to adopt AI-driven virtual assistants. Suryavanshi et al. (2024) used the SEM-ANN-NCA hybrid method to predict factors affecting customer relationship management (CRM) purchase intention. However, as of now, we have not found any literature that applies the SEM-ANN-NCA hybrid method in Gen AI consumer behavior research. Therefore, using the SEM-ANN-NCA hybrid method to study Gen AI shopping assistants' consumer behavior is both scientifically sound and of unique research value. Table 4 lists the testing standards and references used in the SEM-ANN-NCA hybrid method.

Table 4
Test Criteria and References for Each Method.

Methods	Test Standards	Source
Reliability analysis	In the range 0–1, the higher, the better. The minimum standard should not be less than 0.7.	Tavakol and Dennick (2011)
Model fit test	CMIN/DF: Greater than 1 less than 3 is excellent, greater than 3 less than 5 is good. RMSEA: Less than 0.05 is excellent, and less than 0.08 is good. IFI/TLI/CFI: Greater than 0.9 is excellent, and greater than 0.8 is good.	Albright and Park (2009)
Convergent validity and combinatorial reliability test	AVE values were at least greater than 0.5, and CR values were at least greater than 0.7.	Shrestha (2021)
Differentiation validity test	The correlation coefficients of the variables should be lower than the corresponding AVE square root values.	Henseler et al. (2015)
Normality test	The skewness factor should be less than 2, and the kurtosis factor should be less than 7.	Finney and DiStefano (2006)
Correlation analysis	The higher the value, the higher the correlation. Conversely, the lower it is.	Cohen et al. (2009)
SEM hypothesis testing	*** $p < 0.001$, ** $0.001 < p < 0.01$, * $0.01 < p < 0.05$, does not hold $p > 0.05$. * The more the more significant.	Bollen and Noble (2011)
RMSE Validation Analysis	In the range of 0–1, the lower it is the more accurate the prediction is.	Mutlu et al. (2008)
Sensitivity analysis	The higher the mean relative importance, the higher the priority of normalized relative importance.	Homma and Saltelli (1996)
Necessity analysis	When the p-value of the analyzed results is less than 0.05, it is a relationship of necessity.	Dul et al. (2020)

5. Results

5.1. Preliminary analysis

5.1.1. Common method bias

To assess common method bias (CMB) in this study, we conducted both VIF and Harman's Single-Factor Test. Both the VIF and Harman's Single-Factor Test results indicate that there is no significant common method bias in the data, and the regression analysis results are robust.

First, VIF was used to test multicollinearity. According to Hair et al. (2010), a VIF value > 10 indicates serious multicollinearity issues, VIF values between 3 and 5 indicate moderate collinearity, and VIF values < 3 suggest low collinearity risk. We performed VIF analysis on dependent variables with two or more independent variables in SPSS. The results show that the VIF values for all dependent variables ranged from 1.047 to 1.404, all below 3, indicating low collinearity risk and robust regression analysis results.

Second, to further verify the influence of method bias, Harman's Single-Factor Test was conducted. This method extracts factors using principal component analysis (PCA) and observes the percentage of variance explained by the first factor. If the first factor explains more than 50 % of the variance, significant common method bias may be present (Podsakoff et al., 2003). The results show that the first factor explained only 38.501 % of the variance, which is below 50 %, indicating no significant common method bias.

5.1.2. 5.1.2. Reliability and validity analysis and normality test

This section of data analysis will include the following methods: reliability analysis, convergent validity and composite reliability tests, descriptive statistics and normality analysis, and model fit assessment.

First, the reliability of the sample data collected in this study is high (Appendix B), with the reliability values of all variables exceeding 0.8, and the overall reliability ranging from 0.815 to 0.864. The composite reliability of all measurement items is 0.945, which is very reliable. Second, the results of the convergent validity and composite reliability tests for each variable are excellent. The AVE values of all variables exceed 0.5, ranging from 0.544 to 0.647. The CR values of all variables exceed 0.8, ranging from 0.815 to 0.864. Third, the results of the descriptive statistics and normality analysis (Appendix B) show that the descriptive statistics range from 4.58 to 5.32, indicating that the participants' perception of the research topic is at a medium-to-high level. Furthermore, the normality test results pass (Appendix B), with the skewness of all variables being less than 2 and the kurtosis being less than 7. Fourth, the results of the model fit assessment show that the model fit is excellent. The CMIN/DF is 1.512, RMSEA is 0.038, IFI is 0.962, TLI is 0.955, and CFI is 0.961.

5.1.3. Discriminant validity and correlation analysis

First, the results of the discriminant validity test passed the standards (Table 5), with the discriminant validity values of all variables being lower than the square root of the AVE values of each variable. Second, the correlation analysis results show that all r values are greater than 0, and the correlations between the variables are significant.

5.2. Structural equation model (SEM)

5.2.1. Direct hypothesis testing

First, conducting a model fit test before performing SEM hypothesis testing can improve the explanatory power of the SEM. The test results show that the model fit is excellent. The CMIN/DF is 2.359, RMSEA is

Table 5
Discriminant validity and correlation analysis.

variable	AU	CO	RE	PE	UI	UX	TR	CF	SA	RI
AU	**0.768**	.591**	.477**	.475**	.220**	.383**	.382**	.479**	.508**	.458**
CO	0.751	**0.762**	.534**	.474**	.284**	.525**	.475**	.505**	.517**	.496**
RE	0.601	0.679	**0.773**	.578**	.320**	.501**	.369**	.476**	.501**	.524**
PE	0.602	0.594	0.725	**0.738**	.246**	.441**	.458**	.480**	.448**	.482**
UI	0.277	0.355	0.378	0.305	**0.78**	.469**	.211**	.269**	.339**	.272**
UX	0.508	0.635	0.648	0.569	0.622	**0.741**	.425**	.559**	.536**	.483**
TR	0.456	0.61	0.485	0.595	0.26	0.558	**0.771**	.497**	.494**	.452**
CF	0.585	0.644	0.624	0.605	0.352	0.703	0.631	**0.796**	.646**	.571**
SA	0.635	0.629	0.632	0.572	0.386	0.653	0.605	0.781	**0.784**	.570**
RI	0.556	0.638	0.651	0.588	0.324	0.629	0.581	0.705	0.713	**0.804**

Note: Bolded diagonal font indicates the square root of the AVE. The font above the diagonal indicates correlation analysis results. ** significant at the 0.01 level (two-tailed). The font below the diagonal indicates discriminant validity results.

0.062, IFI is 0.892, TLI is 0.881, and CFI is 0.891. Second, according to the SEM hypothesis testing results and the SEM path analysis diagram (Table 6, Appendix C), all the research hypotheses are positively and significantly supported ($\beta > 0$, $p < 0.001$). Therefore, this model demonstrates strong explanatory power.

5.2.2. Mediation effect analysis

To delve deeper into the intrinsic mechanisms between the variables in the model, this study examined the mediating paths based on SEM using a 5000-times self-help method (Bootstrap) in AMOS. The structure of this analysis was similar to that of subsequent ANN and NCA analyses to ensure structural consistency in mixed-methods comparisons (Hayes, 2018; Albahri et al., 2021; Venkatesh et al., 2012). The results were as follows: (1) Single mediator path. First, CO had a significant indirect effect on UX via TR ($\beta = 0.089$, 95 % CI [0.007, 0.200]), and the direct impact remained significant ($\beta = 0.285$, $p < 0.001$), suggesting that trust partially mediates the relationship between perceived competence and user experience and that H8a holds. Second, the indirect effect of RE on UX via TR was significant ($\beta = 0.046$, 95 % CI [0.004, 0.126]), and the direct effect remained significant ($\beta = 0.307$, $p < 0.001$), suggesting that trust partially mediates the relationship between perceived relevance and user experience, with H8b holding. Third, the indirect effect of TR on RI via UX was not significant ($\beta = 0.027$, 95 % CI [-0.19, 0.131]), suggesting that H11a does not hold. (2) Successive mediated path tests. First, UX significantly affects RI through continuous mediation between CF and SA ($\beta = 0.073$, 95 % CI [0.019, 0.185]), but the direct effect is not significant; thus, it is a full mediation, suggesting that cognitive confirmation and affective satisfaction play a gradual role in transforming the user experience into repurchase intention, and H_M1 is established. Second, the effect of RE on RI through continuous mediation of UI and UX was not significant ($\beta = 0.023$, 95 % CI [-0.21, 0.089]), suggesting that H_M2 does not hold.

5.3. Artificial neural network (ANN)

Based on the SEM hypothesis testing results (Table 6, Appendix C), five ANN models (Appendix D) were constructed, each for PE, UX, TR, CF, and RI. Appendix E shows that the RMSE values of each ANN model range from 0.270 to 0.383, indicating good performance. Therefore, the ANN models exhibit high predictive accuracy. Sensitivity analysis results show (Table 7): First, when the model output is PE, the importance ranking of the predictor variables is as follows: RE (100 %) and AU (51.976 %). Second, when the model output is UX, the importance ranking of the predictor variables is as follows: UI (100 %) and TR (51.976 %); UI (100 %) and TR (71.233 %). Third, when the model output is TR, the importance ranking of the predictor variables is as follows: CO (100 %) and RE (24.194 %). Fourth, when the model output is CF, the importance ranking of the predictor variables is as follows: UX (100 %), TR (69.565 %), and PE (59.268 %). Fifth, when the model output is RI, the importance ranking of the predictor variables is as follows: SA (100 %), UX (69.565 %), and PE (59.268 %); SA (100 %) and UX (68.350 %).

5.4. Necessary condition analysis (NCA)

The analysis results (Table 8) show that hypotheses H1, H3, H4, H5, H6, H8, H9, H10, H11, H12, and H13 are necessary, as their p-values are all below 0.05. However, hypotheses H2 and H7 have p-values greater than 0.05, indicating they are not necessary. Notably, for H2 (RE → UI), both CE-FDH and CR-FDH values are 0, with a p-value of 1, suggesting that the necessary relationship between RE and UI is very weak, and RE is not a necessary condition for UI.

5.5. Cross-method comparison and interpretation

The study compared SEM path coefficients, ANN normalized relative importance, and NCA CE-FDH values (Table 9), ranking them

Table 6
Analysis of structural equations.

Hypotheses	Relations			path coefficient	S.E.	C.R.	P	Results
H1	TR	< —	CO	0.539	0.064	7.985	***	Supported
H2	UI	< —	RE	0.411	0.064	6.296	***	Supported
H3	TR	< —	RE	0.313	0.056	5.206	***	Supported
H4	UX	< —	UI	0.531	0.059	8.876	***	Supported
H5	PE	< —	RE	0.632	0.054	8.912	***	Supported
H6	PE	< —	AU	0.362	0.049	6.295	***	Supported
H7	UX	< —	TR	0.486	0.064	7.964	***	Supported
H8	CF	< —	TR	0.341	0.062	5.092	***	Supported
H9	CF	< —	UX	0.398	0.059	5.974	***	Supported
H10	CF	< —	PE	0.283	0.06	5.227	***	Supported
H11	SA	< —	CF	0.806	0.067	11.619	***	Supported
H12	RI	< —	SA	0.546	0.083	7.975	***	Supported
H13	RI	< —	UX	0.283	0.065	4.48	***	Supported

Note: *** $p < 0.001$.

Table 7
Sensitivity analysis.

	Model A (Output: PE)		Model B (Output: UX)		Model C (Output: TR)		Model D (Output: CF)			Model E (Output: RI)	
Neural network	AU	RE	UI	TR	CO	RE	PE	UX	TR	UX	SA
ANN1	0.363	0.637	0.972	0.028	0.908	0.092	0.309	0.375	0.316	0.365	0.635
ANN2	0.410	0.590	0.541	0.459	0.771	0.229	0.258	0.481	0.261	0.275	0.725
ANN3	0.262	0.738	0.475	0.525	0.867	0.133	0.050	0.590	0.360	0.265	0.735
ANN4	0.428	0.572	0.618	0.382	0.874	0.126	0.294	0.463	0.243	0.593	0.407
ANN5	0.362	0.638	0.394	0.606	0.789	0.211	0.222	0.342	0.436	0.375	0.625
ANN6	0.354	0.646	0.568	0.432	0.816	0.184	0.488	0.301	0.211	0.373	0.627
ANN7	0.360	0.640	0.842	0.158	0.686	0.314	0.175	0.454	0.370	0.402	0.598
ANN8	0.269	0.731	0.457	0.543	0.774	0.226	0.258	0.475	0.267	0.435	0.565
ANN9	0.524	0.476	0.541	0.459	0.805	0.195	0.245	0.445	0.310	0.552	0.448
ANN10	0.084	0.916	0.430	0.570	0.765	0.235	0.291	0.441	0.267	0.426	0.574
Average relative importance	0.342	0.658	0.584	0.416	0.806	0.195	0.259	0.437	0.304	0.406	0.594
Normalized relative importance (%)	51.976	100.000	100.000	71.233	100.000	24.194	59.268	100.000	69.565	68.350	100.000

Table 8
Necessity Analysis.

Hypotheses	Relations			CE-FDH	p-value	CR-FDH	p-value
H1	TR	←	CO	0.139	0.000	0.093	0.000
H2	UI	←	RE	0.000	1.000	0.000	1.000
H3	TR	←	RE	0.167	0.000	0.113	0.000
H4	UX	←	UI	0.250	0.000	0.217	0.000
H5	PE	←	RE	0.139	0.000	0.069	0.000
H6	PE	←	AU	0.194	0.000	0.130	0.000
H7	UX	←	TR	0.111	0.081	0.056	0.081
H8	CF	←	TR	0.139	0.008	0.094	0.007
H9	CF	←	UX	0.250	0.000	0.217	0.000
H10	CF	←	PE	0.361	0.000	0.308	0.000
H11	SA	←	CF	0.222	0.000	0.186	0.000
H12	RI	←	SA	0.222	0.000	0.186	0.000
H13	RI	←	UX	0.139	0.000	0.069	0.003

accordingly. The results show that models B and E exhibit consistent rankings across SEM, ANN, and NCA, while models A, C, and D align in SEM and ANN. This indicates that all models have strong explanatory power in terms of linear, non-compensatory, and nonlinear relationships. Notably, models B and E also demonstrate strong explanatory power in terms of necessity relationships, further reinforcing their importance.

6. Discussion

Most of the results were significantly valid. However, there are undesirable ones; for example, in the comparison of SEM-ANN-NCA results (Table 9), only the models with UX and RI output structures showed consistency in SEM-ANN-NCA. The MEMM model constructed in this study aims to investigate the behavioural and potential mechanisms by which Gen AI shopping assistants influence consumer behaviour on e-commerce platforms. The study focused on Gen AI consumer behaviour, AI shopping assistants, and customer journeys (Table 10).

First. It was found that consumers' perceptions of Gen AI's personalised recommendation features were primarily driven by extrinsic motivation (β = 0.632, 100 %, CE-FDH = 0.194), followed by intrinsic motivation (β = 0.362, 51.976 %, CE-FDH = 0.139). In previous studies (Fan and Liu, 2022; Han, 2021; Lv and Huang, 2024; Liu et al., 2025; Hu et al., 2021), intrinsic motivation (i.e., autonomy and competence) under the SDT is usually regarded as a key factor influencing consumer behaviour. However, the present findings are not common in existing research on Gen AI consumer behaviour under SDT, so this study expands the role and influence of extrinsic motivation.SEM results identified some highly significant path coefficients, e.g., a highly personalised Gen AI shopping assistant significantly enhanced consumers' expectation confirmation (β = 0.283, 59.268 %, CE-FDH = 0.361), which in turn positively impacted shopping satisfaction (β = 0.806) and repurchase intention (β = 0.546, 100 %, CE-FDH = 0.222). This result is consistent with the findings of Cabrera et al. (2020). Furthermore, our findings extend the applicability of personalisation in ECT-based Gen AI consumer research by showing that consumer satisfaction is influenced by the accuracy of recommendations and the level of personalisation provided by Gen AI shopping assistants. The study also found that external incentives (e.g., discounts and reward points) not only increased the perceived value of personalised recommendations (β = 0.632, 100 %, CE-FDH = 0.139) but also contributed to improved UX and loyalty. This finding extends the literature on e-commerce consumer behaviour in Gen AI scenarios, as previous research has emphasised the critical role of external relevance in personalised advertising (Zhu & Chang, 2016). Finally, the "cognitive confirmation and emotional transformation chain" (H_M1) is supported.

Table 9
Comparison of SEM, ANN and NCA results.

SEM Path	SEM: Path Coefficient	ANN: Normalized relative importance (%)	NCA: CE-FDH	SEM Ranking	ANN Ranking	NCA Ranking	Remark
Model A (Output: PE)							
AU→PE	0.362	51.976	0.194	2	2	1	
RE→PE	0.632	100	0.139	1	1	2	
Model B (Output: UX)							
UI→UX	0.531	100	0.250	1	1	1	Match
TR→UX	0.486	71.233	0.111	2	2	2	Match
Model C (Output: TR)							
RE→TR	0.313	24.194	0.167	2	2	1	
CO→TR	0.539	100	0.139	1	1	2	
Model D (Output: CF)							
PE→CF	0.283	59.268	0.361	3	3	1	
UX→CF	0.398	100	0.250	1	1	2	
TR→CF	0.341	69.565	0.139	2	2	3	
Model E (Output: RI)							
UX→RI	0.283	68.35	0.139	2	2	2	Match
SA→RI	0.546	100	0.222	1	1	1	Match

Table 10
Research findings and insights.

Research dimensions	Key Findings	Theoretical Implications	Management Implications
Gen AI Consumer Behavior	Consumers' perceptions of personalised recommendation features are primarily driven by extrinsic motivation, followed by intrinsic motivation; both types of motivational roles indirectly enhance user experience through trust.	Extending SDT, we emphasise the dominant role of extrinsic motivation in technology acceptance and reveal the mediating mechanism of trust in transforming motivation into user experience.	We construct a "personalised recommendation + external motivation" system and embed trust enhancement modules, such as recommendation process transparency and social endorsement, to improve the user's sense of security and experience.
	Gen AI shopping assistants enhance consumer satisfaction and repurchase intention through the successive intermediary of confirmation→satisfaction; however, user experience itself is not enough to directly drive repurchase.	Integrating ECT and expanding the chain intermediary path of "Confirmation-Satisfaction-Repurchase", we point out that user experience needs to be transformed through cognitive and emotional layers in order to drive behavioural continuity.	The proposed mechanism is "adaptive expectation management", which uses AI to dynamically adjust and guide users' expectations, forming a positive feedback loop; meanwhile, it emphasises that repurchase intention can be enhanced through satisfaction management rather than pure experience enhancement.
Gen AI Shopping Assistant	User interface has the greatest impact on user experience, followed by perceived trust; however, the chain mediation through UI and UX is not significant for repurchase.	Expanding the relationship between UX and repurchase intention from the HCI perspective reveals that UI improves experience, but is not enough to drive long-term behaviour independently, and needs to be linked to satisfaction.	A transparent and intuitive UI can be designed to enhance immediate experience and trust, but at the same time, a satisfaction tracking mechanism (e.g., a post-interaction feedback questionnaire) can be used to truly promote repurchase.
	Consumers in developing countries are more likely to evaluate the trustworthiness of AI assistants based on the interface and interaction experience rather than data transparency.	Complement the trust formation mechanism under regional cultural differences and emphasise the criticality of interactive experience in developing markets.	Implement a dual-adaptation strategy of "localisation + personalisation" and design differentiated interaction modes for different markets to increase penetration and trust.
Customer Journey	Pre-purchase: Marketing experiences (e.g., recommendations that exceed expectations) have a greater impact on repurchase intent than personalised experiences.	Expand AI consumer decisioning to emphasise the importance of "surprise recommendations" in motivating purchases.	Design a "contextual recommendation" strategy, combined with AI-assisted matching and holiday-customised recommendations, to enhance the sense of novelty and purchase motivation.
	During the purchasing process, consumers' self-knowledge significantly enhances their trust in the Gen AI assistant, which in turn enhances the user experience through the mediation effect.	Combining trust theory and mediation effect, we reveal the dynamic formation mechanism of trust as "psychological capital" in the process of using a Gen AI assistant.	Develop a "Progressive Intelligent Guidance" function that allows users to select different modes (beginner/expert) based on their cognitive level, enhancing trust and control.
	Post-purchase: Gen AI optimises expectation confirmation and improves satisfaction, thus significantly driving repurchase intent through chain mediation.	Enrich the application of ECT in AI interactions, emphasising the decisive role of satisfaction and confirmation in "experience-behaviour" transformation.	Design the "Personalised Shopping Reflection" module to generate intelligent summaries and future recommendations based on purchase history to enhance repurchase rate and loyalty.

This suggests that experiences in the Gen AI context do not directly translate into reentry behaviours but need to go through a cascade of "anticipation-confirmation-emotion" psychological gates. The high quality of the "understood/responded to" interaction makes confirmation a prerequisite for emotional consolidation and emotion a direct driver of behavioural continuity.

Second, it was found that consumers' UX was primarily influenced by UI ($\beta = 0.531$, 100 %, CE-FDH = 0.25), followed by perceived trust ($\beta = 0.486$, 71.233 %, CE-FDH = 0.111). The results also found that UI ($\beta = 0.411$) was more likely to be driven by extrinsic motivation compared to perceived trust ($\beta = 0.313$). This emphasises that consumers' extrinsic motivation is a key factor in enhancing the UX of the e-commerce Gen AI shopping assistant. Although the positive influence of UI and TR on UX is a consensus in HCI research (Bach et al., 2024; Eren, 2021; Kaewkitipong et al., 2022; Wu and Huang, 2021), there is a lack of discussion on the relationship between extrinsic motivation and UI and TR in Gen AI consumer behaviour. This indirectly helps the development of innovative interaction interface design strategies. Second, consumers' trust in Gen AI assistants mainly comes from their self-perceived competence ($\beta = 0.539$, 100 %), followed by perceived extrinsic motivation ($\beta = 0.313$, 24.194 %), which suggests that trust is more rooted in subjective control (i.e., usability and fitness for purpose) rather than external factors. Existing AI consumer behaviour research has focused on the impact of intrinsic motivation (autonomy, competence) on trust (Liu et al., 2025; Vrontis et al., 2024), but lacks a focus on the impact of extrinsic motivation, a limitation that the present study helps to ameliorate. Finally, two single mediators of "trust-driven entry" (H8a, H8b) were supported. This suggests that both intrinsic competence and extrinsic relevance motives, in order for their effects to be stabilised and precipitated into better experience quality, require trust as a "psychological lubricant" to reduce uncertainty and cognitive monitoring costs and thus unleash the potential of the interaction.

From the perspective of e-commerce markets in developing countries, China's leading e-commerce platforms (Taobao, Jingdong) place considerable emphasis on AI shopping assistants (Chen, 2023). We believe that an interaction interface design that is easy to control and meets consumers' individual needs is the key to improving TR, UX, and SA in China and other developing countries. We suggest that the design of Gen AI shopping assistants in e-commerce platforms in developing countries should focus on the development of diverse and personalised interaction features to ensure that users with different ability levels can enjoy an equal experience. Even though our empirical analysis is based only on the Taobao Ask Gen AI shopping assistant in China, and the limited range of cases may affect its generalisability, China's status as the largest developing country, coupled with its well-developed e-commerce marketplace and the impact of the Belt and Road Initiative, make the results of this study an important reference value for other developing countries. We believe that the MEMM model and mechanisms are broadly relevant in emerging markets. Cultural, technological, and regulatory differences (e.g., payment infrastructure or data privacy regulations) may affect the magnitude of the path coefficients but are unlikely to change the general direction of the relationship. For example, future cross-country studies could examine whether lower mobile payment penetration in Southeast Asia raises the threshold for perceived competence (as our NCA results suggest) or whether higher regulatory trust in Latin America increases the salience of interface aesthetics. By situating our findings within the broader context of development economics and technology adoption (Hendricks et al., 2024; Volkova et al., 2021), we provide a concrete roadmap for academics and practitioners seeking to deploy Gen AI assistants outside of the Chinese market. In addition, the findings provide actionable guidance for implementing Gen AI in developing economies. For example, in

markets with low levels of digital literacy, the onboarding process should prioritise competency enhancement, while in regions with decentralised Internet access, strong feedback loops can be leveraged to maintain trust. This contextualised strategy is not only applicable in China but could also increase the adoption of Gen AI Assistant in regions such as India, Indonesia, or Nigeria. We also suggest modelling institutional/cultural differences in developing markets to compare the differentiated channelling of extrinsic motivation via UI/PE vs. TR in different contexts.

Third. The study also shows that the marketing experience provided by the Gen AI shopping assistant outweighs its personalised experience ($\beta = 0.283$, 59.268 %) in terms of its impact on repurchase intention ($\beta = 0.398$, 100 %). While Gen AI technology is important in e-commerce UX, the driver of business value is even more critical, as it stimulates expected consumer confirmation and promotes long-term retention. This suggests that the design of sub-functions of Gen AI shopping assistants should be aligned with business value-centred consumer motivations, and feedback mechanisms should be designed for all stages of the customer journey (pre-purchase, purchase, and post-purchase). In addition, this suggests that in e-commerce markets in developing countries, technology-driven personalisation must be based on delivering business value. In contrast to previous studies focusing on functionality, interaction, and consumer needs (Dhiman and Jamwal, 2023; Ritonummi, 2020; Cabrera et al., 2020), the present study extends the literature on the customer journey of Gen AI shopping assistants from the perspective of improving business benefits.

Two untested mediating hypotheses provide equally important insights. First, the lack of significance of H11a suggests that "trust-experience" is not yet sufficient to leverage re-entry behaviour on its own and that the "last mile" from behaviour experience is more dependent on the emotional reinforcement of "confirmation-satisfaction". The "last mile" for plantation is more dependent on the emotional consolidation of "confirmation" and "satisfaction". This is consistent with Sections 3.3 and 3.4, which emphasise that "experience is not a sufficient condition for behaviour" and also explain why the direct effect of UX on RI faded after the addition of CF and SA (full mediation): the core pivot of ECT was not bypassed. Second, the fact that H_M2 is not significant does not mean that UI or UX is invalid, as it has been demonstrated in SEM that UI positively and significantly affects UX, but for "aesthetic/cultural fit experience" to further drive RI, it still needs to be combined with the value assessment of "confirmation-satisfaction". However, for "aesthetic/cultural fit experience" to further drive RI, it still needs to be coupled with "validation-satisfaction" value assessment. In other words, extrinsic motivation enhances the experience through the pleasure and immersion brought by interface aesthetics, but behavioural continuity is difficult to occur in the absence of subsequent performance validation and emotional solidity. This suggests that value realisation, rather than aesthetic pleasure alone, is the decisive constraint at the behavioural level.

Finally, this study expands the methodological path for future research on Gen AI consumer behaviour. Existing studies of Gen AI consumer behaviour have mainly used SEM to explain the linear relationship between variables (Aldaihani et al., 2024; Pathak et al., 2025). However, the HCI of Gen AI shopping assistants is characterised by complexity and nonlinearity, and consumers' shopping behaviours on e-commerce platforms are also characterised by uncertainty. These issues cannot be fully elucidated using SEM alone. Therefore, this study incorporates ANN and NCA methods based on SEM to find solutions (Zaidan et al., 2023; Loh, 2022), providing a broader explanation of nonlinearity and necessity.

6.1. Theoretical contributions

Through an exploration of consumer motivational psychology and the psychological changes before and after shopping, this study constructs a consumer behavior model based on the integration of SDT, HCI, and ECT. This model is designed to explain and predict the sustained impact of Gen AI shopping assistants on consumers' experiences, including trust, user experience, satisfaction, and repurchase intention. The findings indicate that Gen AI shopping assistants equipped with highly personalized recommendation features are key in enhancing consumer satisfaction on e-commerce platforms and in promoting continued consumption. A user-centric interface design is identified as a sustainable development pathway for Gen AI shopping assistants; specifically, the design should comprehensively consider both extrinsic and intrinsic consumer motivations and align with corresponding HCI mechanisms. Overall, the proposed model, which integrates SDT and ECT in the context of Gen AI shopping assistants, makes significant contributions to both the e-commerce and HCI literature. Specifically, the study provides empirical evidence supporting the application of personalized recommendation functionalities on e-commerce platforms and supplements empirical research on the use of Gen AI in commercial services. In particular, concerning commercial applications in developing countries, the research offers new insights into consumer psychology and decision-making.

The study also contributes to the SDT literature. In contrast to previous research that has predominantly focused on the influence of intrinsic motivation on subjects (Liu et al., 2024; Hu et al., 2021), our findings confirm the hierarchical nature of motivation by emphasizing the dominant role of extrinsic motivation while also indicating that the sense of competence within intrinsic motivation is more suitable for explaining the observed phenomena than autonomy. This suggests that both the inherent characteristics of Gen AI shopping assistants and platform factors exert a critical influence on consumer behavior, thereby filling a gap in the literature on extrinsic motivation within the AI domain. Moreover, as empirical research on SDT has largely concentrated on educational contexts (Chiu, 2024; Latikka et al., 2023), our study extends its application to the field of consumer behavior and e-commerce. Furthermore, the study contributes to the ECT literature. While previous ECT-based research on consumer behavior has primarily focused on product-related effects (Huang and Yu, 2023; Sohail et al., 2021), our findings supplement this body of work by examining Gen AI's role in enhancing commercial value and motivational aspects, thereby contributing to the literature on e-commerce shopping assistants. We propose several strategies that integrate technological services, which diverge from earlier studies that predominantly focused on the expansion of UX (Huang and Yu, 2023).

This study also advances theoretical development from a methodological perspective by demonstrating the complementary value of a hybrid SEM-ANN-NCA approach. Specifically, SEM validates the hypothesis of linear relationships among latent variables derived from SDT and ECT. ANN uncovers hidden nonlinear dynamics in consumer behaviour, particularly the amplification or threshold effects of Gen AI features on SA and RI. NCA, in turn, identifies the threshold levels of variables that are required for achieving key outcomes such as UX and RI. This three-stage validation not only contributes methodological innovation but also enhances the robustness of theoretical inference under real-world complexity. Notably, inconsistencies across methods, such as certain paths being statistically significant in SEM but not necessarily in NCA, do not indicate contradiction but rather offer theoretical insights. A relationship may have a significant influence at the aggregate level (as shown by SEM), yet not be a bottleneck condition for outcome emergence (as shown by NCA). For instance, the path PE → CF shows a significant direct effect in SEM and contributes positively to ANN's nonlinear ranking. However, if other variables (e.g., UX or TR) are sufficiently strong, the outcome CF can still be achieved, leading NCA to deem PE a non-necessary condition. This type of analysis reveals the contingency and asymmetry of consumer psychology, deepening our understanding of when and under what conditions specific Gen AI features exert influence. Experimental results confirm that Gen AI shopping assistants can accurately predict consumer satisfaction through linear, nonlinear, and necessity-based quantitative models. This lays a solid

foundation for future studies employing a mixed-method SEM-ANN-NCA approach. Based on these findings, future research should further explore how the multidimensional experiences provided by conversational user interfaces can better meet consumer needs and compare emerging HCI methodologies with existing approaches to develop Gen AI shopping assistants that offer superior user experiences.

6.2. Practical contributions

For e-commerce platforms in developing countries, the market acceptance of Gen AI shopping assistants depends on their ability to meet consumer needs while enhancing user trust and experience precisely. On a personal level, Gen AI optimizes the shopping journey, improves decision-making efficiency, and reduces choice anxiety through intelligent guidance. It increases user retention and conversion rates for businesses, optimises supply chain management, and lowers operational costs. On a societal level, Gen AI supports the growth of the digital economy, drives consumption upgrades, and bridges the technology gap, providing intelligent shopping experiences for a wider audience. Based on this, we propose four optimisation strategies:

First, personalised recommendations + external incentives: precision matching and user-driven engagement. The value of Gen AI shopping assistants lies in refined user profiling and contextual awareness, but algorithmic accuracy alone is not enough—external incentives (such as discounts and social rewards) are equally crucial for enhancing user engagement. Therefore, e-commerce platforms should establish a "personalised recommendation + external incentive" system, integrating real-time incentives such as time-limited discounts, social reward points, and AI-assisted outfit pairing to create a decision-making loop. For example, when users browse products, the system can provide personalised discounts based on historical data and combine them with friend recommendations to increase conversion rates and loyalty.

Second, transparency + intuitive interface design: enhancing trust and sense of control. User experience determines the acceptance of Gen AI shopping assistants, and transparent recommendation logic and intuitive interactions are essential. Platforms should optimise visual hierarchy, highlight key information, reduce information overload, and use animations and interactive feedback to build trust. Additionally, an intelligent guidance mode can be implemented to offer a "beginner mode" and an "expert mode" based on user proficiency, enhancing the sense of control. Digital human interactions, combined with NLP and computer vision technology, can allow users to select products through visual presentation, reducing cognitive load and improving interaction fluidity.

Third, adaptive expectation management: continuously optimising the shopping experience. Gen AI shopping assistants should not only meet user needs but also proactively regulate expectations to create a positive feedback loop. Platforms can leverage user purchase data to provide personalised shopping recommendations and intelligent decision analysis, helping users optimise future choices. Meanwhile, the system can dynamically track user preferences and push unexpected recommendations at the right time, such as AI-assisted outfit pairing or holiday-specific suggestions, enhancing the element of surprise and purchase motivation, thereby increasing long-term loyalty.

Fourth, AIGC + UGC social engagement: strengthening market penetration. Research indicates that consumers in developing countries rely more on visual and interactive experiences to assess the credibility of AI assistants than on data transparency. Therefore, e-commerce platforms should adopt a "localised + personalised" strategy to enhance user trust and market acceptance through social engagement. For example, Gen AI assistants can be integrated into social platforms to promote user interaction and UGC content generation, automatically creating shopping guides and outfit suggestions while encouraging users to engage in secondary content creation and sharing. Additionally, mechanisms such as social challenges, purchase check-ins, and friend recommendations can amplify peer influence in shopping decisions, ultimately boosting market penetration.

6.3. Limitations and future research

This study explores the impact of e-commerce Gen AI shopping assistants on individuals, organizations, and society. However, certain limitations may affect the generalizability and applicability of the research findings. Therefore, we propose future research directions to enhance the value and contribution of this study.

In terms of data collection, the sample in this study mainly comes from China, lacking data from other developing countries such as India, Vietnam, or Thailand, which leads to weak regional representativeness. Moreover, significant cultural, technological, and infrastructural differences among developing countries may result in variations in how users perceive and interact with Gen AI shopping assistants. For instance, while Chinese users are generally more familiar with AI-powered features in mobile commerce ecosystems like Taobao, users in other regions may still rely on traditional or semi-automated shopping platforms. This contextual disparity may affect variables such as trust, satisfaction, and perceived usefulness. Future studies should consider how differing levels of digital literacy, AI exposure, and cultural attitudes toward automation influence user behavior in emerging markets. Comparative studies that systematically analyze these cross-national contextual differences can greatly enrich our understanding of Gen AI adoption trajectories in the Global South.

In addition, the study primarily focuses on individuals aged 18–45, with limited representation from minors and elderly populations, which may affect the applicability of findings across different age groups. The online survey method may also introduce subjective bias and reduce objectivity. The study did not employ random sampling, and the data collection period was relatively short, potentially affecting the generalizability of the results. Furthermore, this research is solely based on China's "Taobao Wenwen" platform, lacking an analysis of other Gen AI shopping assistants such as Amazon's Rufus or Flipkart's Flippi, which may limit its external validity. To address these limitations, future research could conduct cross-national online surveys comparing diverse market environments, adopt random sampling methods, and extend data collection periods to improve sample representativeness. Moreover, longitudinal and stratified sampling designs can help differentiate the impact of regional market maturity and AI infrastructure readiness.

Additionally, experimental methods such as eye-tracking and EEG could be incorporated to reduce the subjectivity of self-reported data and enhance the reliability of results. A multi-case study approach involving diverse Gen AI shopping assistants across platforms and regions could also increase external validity. Moreover, specialised research should be conducted on elderly users to explore their cognitive and behavioural characteristics when using Gen AI shopping assistants and to optimise senior-friendly interaction designs based on cognitive adaptability.

In terms of theoretical value and practical contributions, this study gives limited consideration to emotional factors in the HCI dimension, despite their critical role in e-commerce shopping behaviour. Additionally, the research does not thoroughly analyse how different personalisation strategies (e.g., personalised experience and recommendations) influence consumer behaviour throughout the shopping journey. Furthermore, the study provides limited specific guidance on task flow design and interface optimisation for Gen AI shopping assistants, affecting their practical applicability. To address these limitations, future research could introduce variables such as emotional attachment and emotional recognition into the model to explore how Gen AI shopping assistants shape consumers' emotional experiences. Moreover, personalisation variables should be refined to analyse the effects of different personalisation strategies at various stages of the consumer shopping journey. Additionally, models such as AHP or KANO could be used to evaluate optimisation paths for Gen AI shopping assistant design, enhancing the usability of interfaces and task

flows while providing more practical guidance for improving intelligent shopping assistants.

Finally, to further advance the field of e-commerce Gen AI shopping assistants, we propose the following future research questions: First, are there significant differences in how consumers from different countries use Gen AI shopping assistants? How do cultural, economic, and technological environments influence user experience and trust? For example, how do collectivist vs individualist cultures affect trust in algorithmic agents, or how does internet penetration and AI exposure modulate user expectations in low-resource settings? Second, how do different functions of Gen AI shopping assistants (e.g., product comparison, demand description, and image recognition) impact consumer shopping experiences? Which functions most effectively enhance consumers' purchase intentions? Furthermore, in extended reality environments such as VR/AR, how should the interaction design of Gen AI shopping assistants adapt to changes in consumer cognition? What are the key factors affecting consumers' understanding and acceptance?

7. Conclusion

This study reveals the consumer motivations and behavioural characteristics of Gen AI shopping assistants on e-commerce platforms in developing countries and proposes important theoretical breakthroughs and practical guidance: 1. The Dominant Role of Extrinsic Motivation: The study finds that compared to intrinsic motivation, extrinsic motivation has a stronger positive impact on UX, challenging traditional motivation theories. This not only enhances TR, SA, and RI but also profoundly shapes the consumer decision-making process. It highlights that Gen AI shopping assistants should prioritise stimulating extrinsic motivation to optimise user experience. 2. The Core Value of Personalised Interfaces: The critical role of UI in PE recommendations and overall consumer UX is validated. The study shows that optimising interface design can effectively improve user satisfaction and trust, providing clear strategic direction for the design of Gen AI shopping assistants. 3. Optimisation Pathways for Satisfaction: UX indirectly enhances SA through CF, which then influences RI, and this indirect effect is stronger than the direct pathway. This finding underscores the key role of SA in long-term user engagement, suggesting that e-commerce platforms should optimise UX and confirmation processes to boost user loyalty and repurchase intentions. 4. SEM-ANN-NCA Hybrid Method: This study uncovers linear, nonlinear, non-compensatory, and necessary relationships, improving the accuracy of predicting consumer motivations and behaviours. 5. Practical Value for Developing Country Markets: The research emphasises the dominant role of extrinsic motivation in e-commerce platforms in developing countries and validates the effectiveness of user-centred design, providing empirical support for optimising localised Gen AI shopping assistants. In conclusion, this study not only expands existing theories but also provides practical guidelines for the design and implementation of Gen AI shopping assistants.

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.

Appendix A

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Table 11
Distribution of population characteristics

Variable	Options	Frequency	Percentage
Gender	Male	189	52.5
	Female	171	47.5
Age	< 18	23	6.4
	18–30	203	56.4
	31–45	130	36.1
	> 45	4	1.1
Degree	College Degree and below	58	16.1
	Bachelor's Degree	169	46.9
	Master's Degree	121	33.6
	Doctoral Degree	12	3.3
Revenue	Below RMB 15,000	179	49.7
	RMB 15,000 - RMB 30,000	138	38.3
	RMB 30,000 - RMB 50,000	28	7.8
	RMB 50,000 and above	15	4.2

Appendix B

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Table 12
Reliability and validity analysis and normality test

Relations			Estimate	Average value	Standard deviation	Skewness	Kurtosis	AVE	CR	Alpha
AU	→	AU1	0.779	4.93	1.197	−1.076	1.216	0.59	0.851	0.851
AU	→	AU2	0.718	4.89	1.161	−0.91	0.978			
AU	→	AU3	0.757	4.75	1.219	−0.783	0.766			
AU	→	AU4	0.814	4.82	1.25	−0.84	0.67			
CO	→	CO1	0.806	5.19	1.237	−0.977	1.18	0.58	0.847	0.844
CO	→	CO2	0.763	5.05	1.287	−0.941	0.947			

(*continued on next page*)

Table 12 (*continued*)

Relations			Estimate	Average value	Standard deviation	Skewness	Kurtosis	AVE	CR	Alpha
CO	→	CO3	0.727	5.1	1.307	−0.768	0.516			
CO	→	CO4	0.748	4.78	1.37	−0.547	0.118			
RE	→	RE1	0.78	5.14	1.425	−0.74	0.096	0.597	0.816	0.816
RE	→	RE2	0.755	4.87	1.472	−0.594	−0.181			
RE	→	RE3	0.782	5.08	1.366	−0.801	0.693			
PE	→	PE1	0.731	5.31	1.193	−0.723	1.087	0.544	0.826	0.825
PE	→	PE2	0.747	5.2	1.346	−0.974	0.915			
PE	→	PE3	0.787	5.25	1.414	−1.037	0.909			
PE	→	PE4	0.682	5.07	1.346	−0.66	0.368			
UI	→	UI1	0.791	5.01	1.273	−0.485	0.012	0.608	0.823	0.822
UI	→	UI2	0.753	5.02	1.231	−0.528	0.147			
UI	→	UI3	0.795	4.97	1.382	−0.367	−0.342			
UX	→	UX1	0.794	5.04	1.313	−0.891	0.615	0.549	0.829	0.829
UX	→	UX2	0.688	4.58	1.378	−0.371	−0.303			
UX	→	UX3	0.767	4.77	1.378	−0.555	0.035			
UX	→	UX4	0.709	5	1.302	−0.634	0.38			
TR	→	TR1	0.8	5.09	1.377	−0.982	0.744	0.595	0.815	0.815
TR	→	TR2	0.75	5.21	1.403	−0.96	0.772			
TR	→	TR3	0.763	5.32	1.375	−0.9	0.665			
CF	→	CF1	0.826	4.78	1.205	−0.914	0.846	0.634	0.839	0.837
CF	→	CF2	0.756	4.75	1.186	−0.912	1.177			
CF	→	CF3	0.806	4.82	1.227	−0.812	0.822			
SA	→	SA1	0.781	4.82	1.161	−1.029	1.618	0.614	0.864	0.864
SA	→	SA2	0.764	4.87	1.257	−0.964	1.059			
SA	→	SA3	0.783	4.94	1.236	−0.791	0.816			
SA	→	SA4	0.807	4.91	1.256	−0.811	0.715			
RI	→	RI1	0.829	5.18	1.296	−0.987	1.183	0.647	0.846	0.847
RI	→	RI2	0.796	5.16	1.313	−0.876	0.773			
RI	→	RI3	0.787	5.24	1.338	−0.869	0.726			

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Appendix C

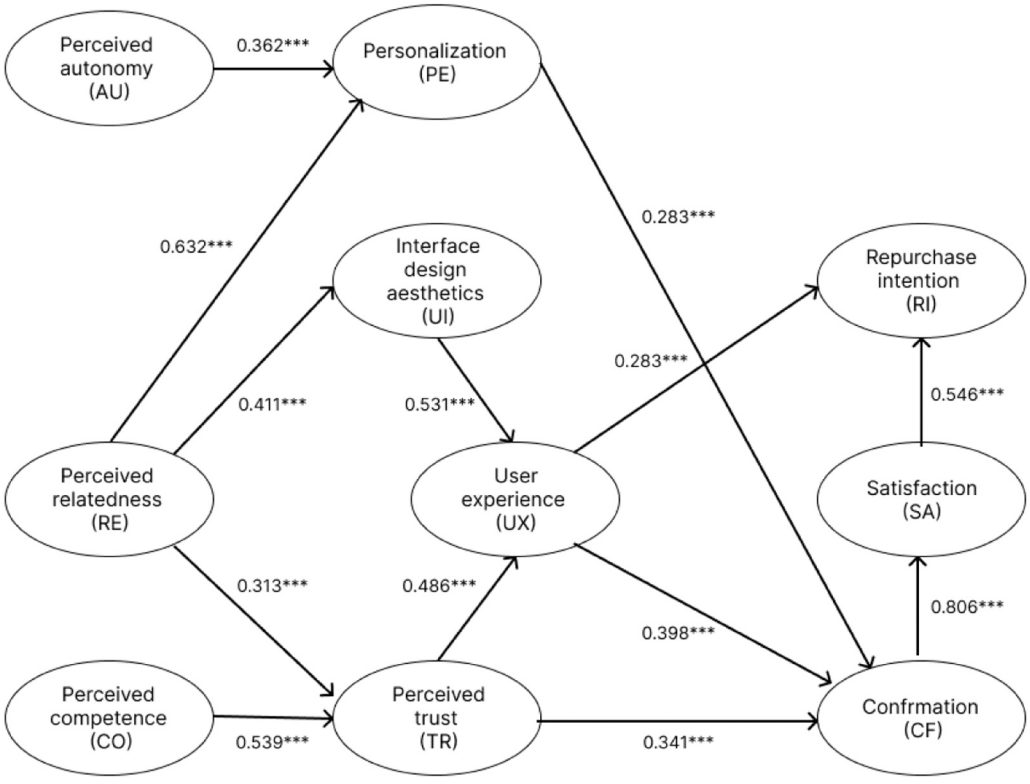

Fig. 3. SEM analysis diagram

Appendix D

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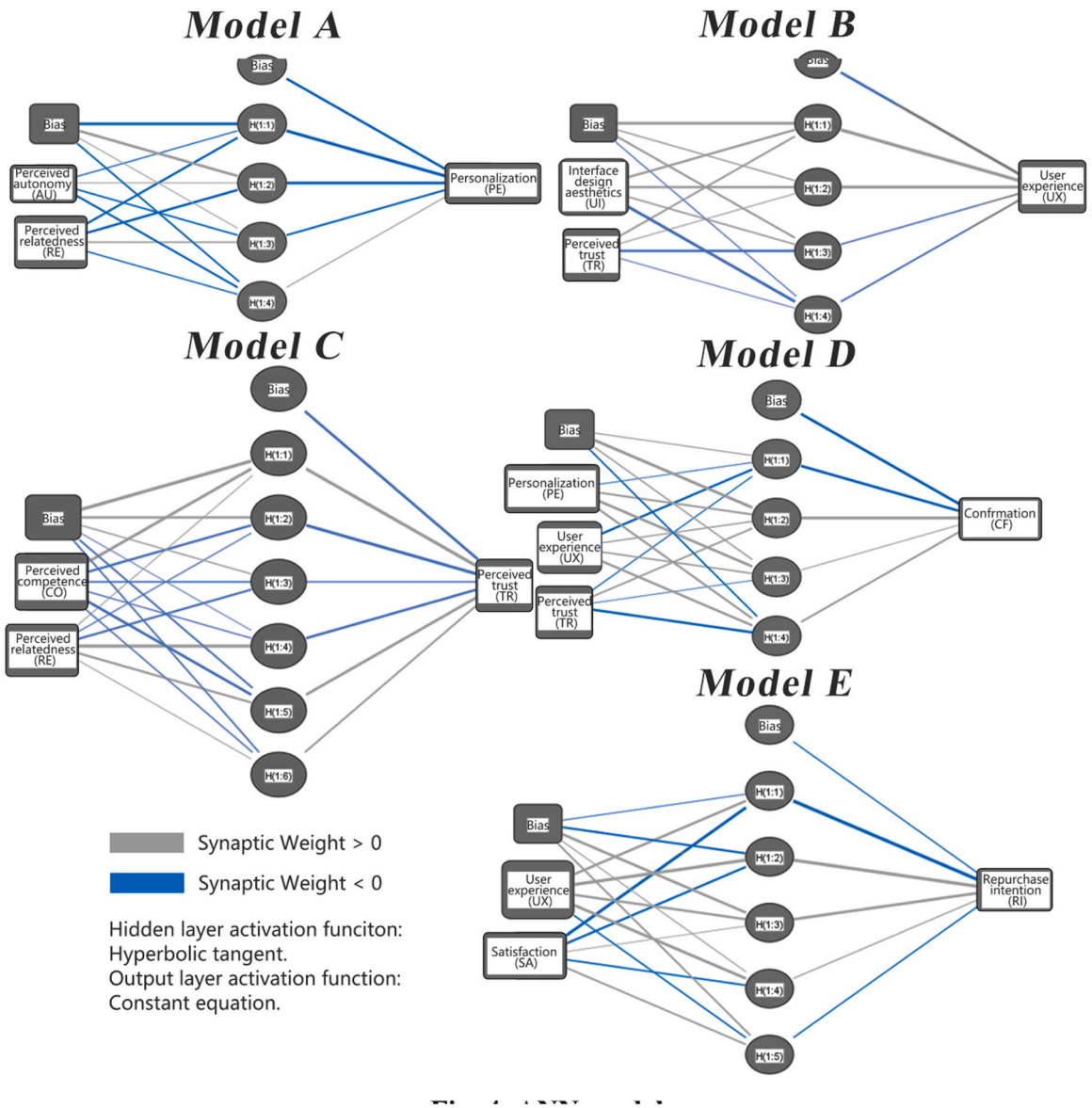

Fig. 4. ANN model

Appendix E

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Table 13
RMSE values test

	Model A		Model B		Model C		Model D		Model E	
	Input: AU,RE		Input: UI,TR		Input: RE,CO		Input: PE,UX,TR		Input: UX,SA	
	Output: PE		Output: UX		Output: TR		Output: CF		Output: RI	
Neural network	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing
ANN1	0.291	0.213	0.418	0.206	0.382	0.399	0.271	0.378	0.302	0.266
ANN2	0.304	0.140	0.323	0.399	0.395	0.335	0.302	0.245	0.344	0.244
ANN3	0.279	0.381	0.337	0.237	0.378	0.437	0.326	0.258	0.340	0.226
ANN4	0.295	0.237	0.338	0.329	0.413	0.384	0.305	0.286	0.316	0.305
ANN5	0.318	0.189	0.370	0.489	0.351	0.242	0.295	0.223	0.316	0.460
ANN6	0.297	0.235	0.329	0.409	0.367	0.307	0.346	0.203	0.325	0.276
ANN7	0.290	0.382	0.412	0.395	0.371	0.454	0.290	0.319	0.325	0.304
ANN8	0.427	0.394	0.338	0.329	0.373	0.178	0.274	0.404	0.332	0.562
ANN9	0.310	0.153	0.343	0.414	0.392	0.301	0.279	0.482	0.381	0.193

(*continued on next page*)

Table 13 (*continued*)

	Model A		Model B		Model C		Model D		Model E	
ANN10	0.364	0.377	0.340	0.279	0.410	0.217	0.300	0.143	0.295	0.254
Mean	0.318	0.270	0.355	0.349	0.383	0.325	0.299	0.294	0.328	0.309
SD	0.212	0.320	0.184	0.298	0.139	0.306	0.153	0.321	0.156	0.338

Data Availability

The data used in this study can be obtained by contacting the corresponding author.

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