Enhancement of Customer Experience and Purchase Intention: Benefits of Generative Artificial Intelligence in the Retail Industry

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Abstract

Generative artificial intelligence (AI) has major benefits, including the automation of data processing, the generation of content, and the optimization of decision-making processes. These capabilities substantially enhance the operational efficiency of enterprises while improving user experience and facilitating business growth through personalized recommendations. In this study, we used social support theory to explore how emotions, information, and social assistance influence individual psychology. We also used SPSS and SmartPLS 3.0 to determine the role of generative AI in the retail sector. Taken together, our findings indicate that product descriptions, visual aids, customer interaction, and personalization significantly shape customers' experience and involvement, which in turn directly influence their purchasing behavior and intentions.

Keywords: Product description, Visual aid, Customer experience, Personalization, Involvement

1 Introduction

Generative artificial intelligence (AI) is projected to reach a global valuation of US$11.4 billion by 2024, achieving a substantial growth rate of 153% from US$4.5 billion in 2022 [1]. This expansion primarily stems from the increasing demand for automation and optimization technologies across various sectors, particularly in logistics, manufacturing, and health care. In the logistics industry, generative AI is regarded as an emerging topic, with more than 60% of organizations expected to implement this technology by 2025 [1].

Generative AI has substantially improved the operational efficiency of Taiwan's retail sector, primarily by enhancing customer experience. Because generative AI facilitates the analysis of customer behavioral data and purchase history, it enables highly personalized recommendations and marketing strategies that greatly enhance customer satisfaction and loyalty [2]. In addition, generative AI increases the efficiency and uniformity of product descriptions and content generation. Automatically generated product descriptions provide accurate information and mitigate the inconsistencies that are often associated with manual compilation, thereby improving the efficiency of content production. Generative AI has yielded major benefits in the field of customer service [3]. Automated customer service systems powered by generative AI can respond to inquiries in real time, which shortens service response time and relieves the burden of manual customer service, ultimately enhancing overall service efficiency.

Generative AI provides insights for market trend analysis and sales forecasting through data-driven models. By enabling the synthesis and analysis of extensive market data and customer behavior, generative AI can identify emerging trends and sales opportunities, helping retailers develop more precise strategies. This robust analytical capability enables retailers to gain deeper insights into market dynamics, which in turn strengthens their competitive advantage [4].

Many theories in the retail industry focus on customer behavior. Ardhanari et al. [5] applied the theory of planned behavior to predict individuals' behavioral intentions and actual behaviors, particularly in purchase and consumption scenarios. This theory has helped retailers understand customers' shopping intentions and predict their purchase behaviors. Kumar et al. [6] used a technology acceptance model to explore customers' acceptance of new technologies such as online shopping platforms and mobile payments. This model revealed crucial factors in technology acceptance.

Marquina et al. [7] employed social exchange theory to explore customer loyalty and customer relationship management and determine how the reciprocal relationship between customers and retailers affects customer behavior. Cai et al. [8] applied the unified theory of acceptance and use of technology to examine how customers accept and use e-commerce and innovative retail technologies, thereby providing theoretical support for the adoption of new technologies. Despite their valuable insights, these studies overlook the role of personal emotional and instrumental support in the contexts of purchase and consumption, particularly the role of support from friends, family, and social networks in customer decision-making. This research gap highlights the need for further exploration of how emotional support and social networks influence modern retail environments to enhance the understanding of customer decision-making.

Several challenges are often encountered in the retail industry. First, traditional retail recommendation systems

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typically depend on static data and cannot dynamically adapt to the evolving needs of customers, leading to irrelevant or inaccurate recommendations. Second, manual programming can result in inaccurate or nonuniform information, potentially influencing customers' purchasing decisions. Finally, retail market analyses should be capable of promptly capturing market dynamics.

In this study, we used social support theory to examine the influence of emotions, information, and practical assistance received through social networks on individuals' psychological states. Generative AI can automatically generate personalized support information within social networks, thereby strengthening the connections between individuals and groups. This approach provides immediate and precise resources for coping with stress, enhancing psychological comfort, facilitating social integration, and fostering a sense of belonging, ultimately enhancing customers' overall purchase intentions.

1.1 Generative AI in the Retail Industry

Generative AI is a novel technological paradigm that relies on AI to autonomously generate novel content based on existing data. In the retail industry, this technology can be used to analyze customer behavior, product information, and market trends, enabling the generation of personalized product recommendations, precise virtual fitting experiences, and accurate demand forecasting models. Many studies have indicated that generative AI can generate new content of practical value, which can in turn assist retailers in optimizing customer experiences, enhancing sales efficacy, and improving inventory management [9]. Consequently, simulating diverse shopping scenarios and customer patterns provides retailers with enhanced flexibility and precision, enabling them to promptly respond to market fluctuations [10]. Despite the potential of generative AI, challenges pertaining to data security, technical costs, and other considerations may hinder its implementation.

Generative AI has rapidly advanced, with major progress achieved in both the technological and application domains. By utilizing deep learning and neural networks, this technology can meticulously examine vast amounts of customer behavioral data and market trends, facilitating the generation of personalized content, such as product recommendations, demand forecasts, and virtual experiences. This approach considerably enhances customer interactions and business operations [1]. Furthermore, the advancement of generative AI has resulted in the generation of genuine content that is responsive to customer demand, thereby enhancing the quality of customer experiences and improving business decision-making. These major benefits of generative AI, particularly in terms of processing complex data patterns and generating novel data, have enabled retailers to implement sophisticated solutions for refined market analyses and strategic planning [11].

1.2 Social Support Theory

In principle, social support theory explores how individuals receive emotional, instrumental, informational, and evaluative support from social networks to manage stress and improve their quality of life. Social support is a key factor that influences customer shopping behavior, business operations, and employee work conditions in the retail industry [12]. This theory emphasizes the major influence of social support on psychological and physical well-being, demonstrating how such support fosters improved mental health and behavioral outcomes [13].

Social support can be divided into three distinct categories: emotional support, informational support, and evaluative support. First, emotional support refers to the care, empathy, and encouragement that individuals receive from their social circles, providing psychological comfort during stress or adversity. This type of support enhances emotional resilience and self-efficacy, enabling individuals to face challenges with a more positive outlook. Emotional support is typically provided by friends, partners, and colleagues [14]. Second, informational support refers to the advice, knowledge, or guidance that individuals receive, contributing to their decision-making and problem-solving processes. This type of support may include practical insights, strategies, or new knowledge, often sourced from experts, colleagues, or other network members, improving an individual's ability to navigate uncertain scenarios [15]. Third, evaluative support comprises positive feedback and recognition, which can enhance self-esteem and confidence [16]. This type of support often originates from authoritative figures, colleagues, or social groups, validating an individual's actions or decisions and fostering positive self-evaluation, motivation, and continued progress. Overall, social support theory is a framework that provides a lens for examining customer behavior in the retail industry, particularly with the rapid shifts observed in market dynamics.

2 Research Design

2.1 Research Structure

Figure 1 shows the hypothesized relationships between the constructs examined in present study. The study constructed a research framework and identified relevant dimensions on the basis of literature findings. We examined the effect of generative AI on customer purchase intentions across various retail channels. Specifically, we explored the purchase intention of customers who have used generative AI, focusing on the influence of several factors identified in the literature. We also evaluated the importance of applying generative AI in the retail industry, using the study of Zhang [17] as our primary reference. Overall, we identified the following seven variables from the literature: product description, visual aids, interaction, personalization, experience, involvement, and purchase intention.

2.2 Hypothesis Development

Providing clear, detailed, and accurate product descriptions enables customers to access comprehensive product information, which in turn increases their confidence and sense of security during their shopping

experience. Lancaster and Massingham [18] argued that effective product descriptions can alleviate customers' concerns regarding product performance and features, thereby enhancing their overall experience. Generative AI can facilitate the automated production of high-quality product descriptions, thereby enhancing their accuracy and relevance. This approach enables a comprehensive understanding of products, leading to increased satisfaction levels [19]. When product descriptions are detailed, accurate, and appealing, customers tend to engage in active information search and evaluation, which in turn increases their interest in and engagement with the product [20-21]. High-quality product descriptions provide essential information that deepens customers' understanding of product features and supports their exploration. In addition, generative AI enhances the quality and relevance of product descriptions, enabling customers to focus during the selection process [22].

H1a: The quality of product descriptions has a positive effect on customer experience.

H1b: The quality of product descriptions has a positive effect on customer involvement.

Product visual aids facilitate clear and intuitive product representation, thereby enhancing customer perception and understanding [23-24]. When customers use visual aids to access more specific product information, their overall shopping experience improves, which in turn increases their enjoyment and satisfaction [25]. Detailed and engaging visual aids can effectively capture customers' attention, encouraging them to invest more time and effort into exploring product information [26]. High-quality visual aids improve the visual representation of products, thereby enhancing customers' understanding of product features and attributes, which in turn fosters a strong sense of involvement and engagement [27].

H2a: The quality of visual aids has a positive effect on customer experience.

H2b: The quality of visual aids has a positive effect on customer involvement.

Customers who engage in active interactions with brands or retail platforms tend to experience high levels of involvement and satisfaction [28-29]. Effective interactions enable immediate feedback and support, which in turn enhances customers' perception of control over the shopping process and improves their overall experience. Generative AI can facilitate natural and efficient customer interactions, further enhancing the customers' experience [30]. Customers who engage in proactive interactions with a brand tend to exhibit increased interest and commitment to the brand and its products. These interactions encourage customers to proactively seek and exchange information, which in turn enhances their engagement in the shopping experience. Generative AI facilitates the provision of real-time and personalized interaction experiences, which enhance customer involvement [31].

H3a: Customers' interactions have a positive effect on their experience.

H3b: Customers' interactions have a positive effect on their involvement.

Customers tend to experience increased appreciation and care from brands or retail platforms when they receive services tailored to their specific needs [32]. Targeted services substantially enhance customer satisfaction, enabling customers to enjoy greater comfort and pleasure while shopping. Generative AI employs analytical techniques to examine customers' behaviors and preferences and deliver personalized recommendations and services that optimize the customer experience [33]. When customers receive services that match their personal preferences and needs, they tend to experience an increased sense of involvement and attention [34]. This targeted approach increases customers' interest in a brand or product, leading to greater engagement with both the shopping process and related interactions. Generative AI can provide accurate, personalized recommendations based on personal information and behavioral patterns, enhancing customer engagement and encouraging the investment of time and effort into the shopping experience [35].

H4a: The level of personalization has a positive effect on customer experience.

H4b: The level of personalization has a positive effect on customer engagement.

Delivering a positive shopping experience leads to trust and satisfaction with a brand, establishing an emotional connection that directly influences purchasing decisions [36]. Overall, the quality of the customer experience extends beyond the shopping environment and service interactions to include the ease of information retrieval, the accuracy of product recommendations, and the overall smoothness of the purchasing process [37]. When these experiential elements are optimized, customers tend to develop a purchase intention because they perceive comfort and efficiency throughout their shopping experience. Furthermore, delivering a positive customer experience fosters customer loyalty and brand identification, increasing the likelihood of repurchasing in subsequent transactions [22]. Generative AI can substantially enhance the customer experience, leveraging personalized recommendations, automated customer service, and precise product descriptions to improve convenience and interactivity, thereby increasing customers' purchase intentions.

H5: The quality of the customer experience has a positive effect on customers' purchase intention.

When customers become more involved with a product or brand, they tend to invest considerably more time and energy to understand and interact with it, which in turn improves their experience during shopping [38-39]. A high level of customer involvement indicates that great attention is paid to product information, which is then explored in greater depth. This approach enhances the customer's understanding of a product and increases their shopping satisfaction [40]. Generative AI facilitates the provision of personalized recommendations and real-time interaction support, which may further enhance customer involvement.

When customers perceive a sense of autonomy and agency during their shopping experience, they tend to report more positive and enjoyable experiences overall.

H6: The level of customer involvement has a positive effect on customers' purchase intention.

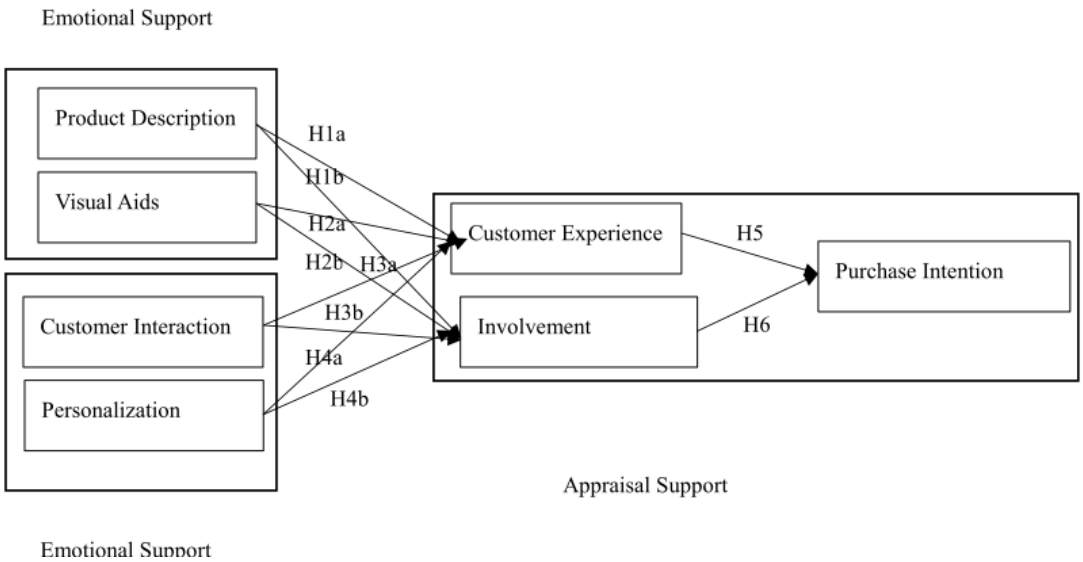

Figure 1. Research model

2.3 Measures

This study is primarily structured around the following components: product description, visual aids, customer interaction, personalization, customer experience, customer involvement, and customer purchase intention. A 7-point Likert scale was implemented for measurement.

Product description refers to how a company presents the characteristics and values associated with a certain product through textual, visual, or video-based media. Generative AI can be used to automatically generate personalized descriptions, thereby enhancing user experience and engagement. In this study, we primarily adopted measurement items for product description from McCabe and Nowlis [41].

Visual aids refer to the utilization of images, videos, or graphic techniques to enhance the presentation of a product. Generative AI can be used to automatically generate visual content, thereby enhancing the visual experience and purchasing decisions of customers. In this study, we primarily adopted measurement items for visual aids from Garcia-Retamero et al. [42].

Customer interaction refers to the two-way communication between customers and retailers, typically through social media, online platforms, or physical stores. Generative AI can enhance interaction efficiency and increase customer satisfaction by providing personalized responses and interactive content. In this study, we primarily adopted measurement items for customer interaction from Kim and Choi [43].

Personalization refers to the customization of products or services on the basis of individual preferences, behaviors, and needs. Generative AI can optimize user experience and purchase intention by automatically generating personalized recommendations and content through data analysis. In this study, we primarily adopted measurement items for personalization from Dhelim et al. [44].

Customer experience refers to the overall emotional and cognitive responses experienced by customers during the purchasing process. Generative AI can enhance user satisfaction and engagement during shopping through personalized recommendations and interactions. In this study, we primarily adopted measurement items for customer experience from Ameen et al. [45].

Customer involvement refers to the level of attention and participation that customers exhibit toward products or brands during the purchasing process. Generative AI can increase customers' interest and engagement with products through personalized interactions and recommendations. In this study, we primarily adopted measurement items for customer involvement from Parment [46].

Customer purchase intention refers to a customer's subjective tendency to purchase a specific product or service. Generative AI can stimulate customers' interest and increase their purchasing motivation through personalized recommendations and interactions. In this study, we primarily adopted measurement items for customer purchase intention from Pillai et al. [47].

2.4 Questionnaire Design

In this study, we established a conceptual framework based on the literature and validated this framework by employing pretests and a 3-point rating scale. We also modified the semantics of the measurement items depending on customer feedback regarding the use of generative AI services. A total of 2 professors from the department of information management and 10 doctoral students were invited to review and refine the semantics. In addition, a preliminary trial was conducted with users of generative AI. The items used to measure customer

face-to-face interactions were revised to ensure that the questionnaire format aligned with the current generative AI practices adopted in Taiwan's retail industry. In conclusion, a series of tests were conducted with a diverse range of customers to ensure the reliability and validity of the finalized questionnaire before its dissemination.

A questionnaire was designed using Google Forms and published on online platforms for purposive sampling. The questionnaire was distributed between September 1, 2024, and October 1, 2024. Data were collected through Google Forms, yielding a total of 469 valid questionnaires.

2.5 Common Method Variance

A common method variance test was conducted on all questionnaires. Harman's single-factor test and an exploratory factor analysis were used for all items. The results indicated that the first factor explained 20.610% of the variance, which is below the 50% threshold, indicating the absence of significant common method variance in the sample.

3 Empirical Research

3.1 Respondent Profile

In the following, we outline the basic demographic information of all respondents. In terms of sex ratio, male and female respondents accounted for 53.3% and 46.7% of the sample, respectively. In terms of age, those aged under 20 years accounted for 4.5% of the sample, those aged 21–30 years accounted for 42.6% of the sample, those aged 31–40 years accounted for 35.0% of the sample, those aged 41–50 years accounted for 13.9% of the sample, those aged 51–60 years accounted for 3.8% of the sample, and those aged over 60 years accounted for 0.2% of the sample. In terms of educational level, those with secondary school education accounted for 28.8% of the sample, those with a bachelor's degree accounted for 46.5% of the sample, and those with a degree higher than a postgraduate degree accounted for 24.7% of the sample. In terms of marital status, those who were single accounted for 61.2% of the sample, and those who were married accounted for 38.8% of the sample. Table 1 presents the distribution of the basic demographic data of the respondents.

3.2 Construct Reliability and Validity

We validated the proposed model in accordance with established standards, including an assessment of reliability and validity through Cronbach's alpha, composite reliability, and average variance extracted (AVE). Composite reliability is an index used to evaluate the internal consistency of measurement indicators for latent variables. Because composite reliability considers the weight of each measurement item, it is more accurate than other indicators in evaluating items of varying weights. Fornell and Larcker [48] suggested that a composite reliability value exceeding 0.7 indicates high internal consistency for a given measurement. In the present study, all composite reliability values exceeded 0.7, indicating that all constructs exhibited high internal consistency.

Nunnally [49] proposed that a Cronbach's alpha value exceeding 0.7 is acceptable, whereas a value greater than 0.8 is indicative of an appropriate exploratory scale. In the present study, all constructs had Cronbach's alpha values exceeding 0.7. Therefore, the data in this study exhibited high internal consistency. Furthermore, an AVE analysis was conducted to examine structural validity. AVE represents the proportion of variance in the observed indicators that a latent variable can explain. A high AVE value indicates that the latent variable can effectively explain the variance in its indicators, reflecting high convergent validity. Fornell and Larcker [48] suggested that an AVE value exceeding 0.5 indicates sufficient reliability and validity. All indicators in the present study exceeded this threshold, confirming the high reliability and validity of the study (Table 2).

Table 1. Basic demographics of the respondents

	N	%
Gender		
Male	250	53.3%
Female	219	46.7%
Age		
20 years<	21	4.5%
21~30 years	200	42.6%
31~40 years	164	35.0%
41~50 years	65	13.9%
51~60 years	18	3.8%
>61 years	1	0.2%
Education		
Secondary	135	28.8%
Bachelor	218	46.5%
Postgraduate (Master/PhD)	116	24.7%
Marital status		
Single	287	61.2%
Married	182	38.8%

Table 2. Construct reliability and validity

	Cronbach's alpha	rho_A	CR	AVE
Interaction	0.899	0.915	0.937	0.832
Personalization	0.863	0.865	0.917	0.786
Involvement	0.799	0.803	0.882	0.714
Product description	0.766	0.830	0.860	0.674
Visual aids	0.912	0.929	0.938	0.791
Purchase intention	0.770	0.827	0.851	0.593
Customer experience	0.872	0.872	0.921	0.796

Note: AVE, average variance extracted; CR, composite reliability.

The Fornell–Larcker criterion is used to evaluate the discriminant validity of latent variables in structural equation models. Discriminant validity refers to the ability to distinguish between multiple latent variables. According to the Fornell–Larcker criterion, the square root of the AVE of a latent variable should be greater than the correlation coefficients between that variable and other latent variables. Meeting this criterion indicates that the association between the latent variable and its measurement indicators is more robust than the associations between the latent variable and other variables, thereby establishing its discriminant validity [50]. In the present study, the square roots of the AVE values, per the Fornell–Larcker criterion, were greater than the correlation coefficients between the variables, indicating high discriminant validity (Table 3).

Table 3. Fornell–Larcker criterion results

	Interaction	Personalization	Involvement	Product description	Visual aids	Purchase intention	Customer experience
Interaction	0.912						
Personalization	0.127	0.886					
Involvement	0.219	0.346	0.845				
Product description	0.260	0.168	0.167	0.821			
Visual aids	0.037	0.334	0.195	0.094	0.889		
Purchase intention	0.149	0.422	0.476	0.123	0.305	0.770	
Customer experience	0.080	0.491	0.497	0.218	0.292	0.740	0.892

Cross-loadings are primarily used to evaluate the discriminant validity of indicators across latent variables. They precisely measure the loading of each observed variable on its corresponding latent variable and on other latent variables [51]. By comparing the loadings of indicators across multiple latent variables, this approach determines whether each indicator has a significant correlation with its associated latent variable, thereby confirming whether the latent variable can be distinguished from other variables. In this study, our findings revealed that the cross-loadings of the variables exhibited significant differences (Table 4).

Table 4. Cross-loading results

	Interaction	Personalization	Involvement	Product description	Visual aids	Purchase intention	Customer experience
Inv1	0.209	0.251	**0.824**	0.183	0.183	0.354	0.425
Inv2	0.135	0.286	**0.841**	0.156	0.160	0.414	0.399
Inv3	0.210	0.334	**0.869**	0.090	0.154	0.435	0.435
PI1	0.212	0.149	0.310	0.034	0.126	**0.723**	0.350
PI2	0.139	0.364	0.393	0.152	0.240	**0.847**	0.679
PI3	0.025	0.336	0.272	0.029	0.268	**0.708**	0.452
PI4	0.108	0.399	0.461	0.156	0.284	**0.874**	0.701
CE1	0.099	0.455	0.455	0.151	0.281	0.636	**0.894**
CE2	0.043	0.435	0.459	0.234	0.228	0.636	**0.907**
CE3	0.072	0.424	0.416	0.199	0.270	0.705	**0.875**
VA1	0.004	0.340	0.177	0.054	**0.874**	0.260	0.242
VA2	0.070	0.291	0.132	0.071	**0.879**	0.250	0.230
VA3	0.012	0.252	0.175	0.077	**0.891**	0.259	0.233
VA4	0.052	0.305	0.200	0.122	**0.912**	0.305	0.316
Per1	0.100	**0.888**	0.292	0.121	0.259	0.352	0.411
Per2	0.142	**0.914**	0.311	0.192	0.358	0.365	0.410
Per3	0.096	**0.857**	0.314	0.134	0.272	0.401	0.477
Int1	**0.937**	0.107	0.225	0.253	0.021	0.141	0.075
Int2	**0.939**	0.120	0.204	0.216	0.028	0.139	0.060
Int3	**0.857**	0.122	0.163	0.244	0.056	0.129	0.086
PD1	0.226	0.151	0.171	**0.887**	0.088	0.126	0.215
PD2	0.198	0.130	0.153	**0.850**	0.060	0.109	0.175
PD3	0.238	0.137	0.053	**0.715**	0.091	0.046	0.129

The heterotrait-to-monotrait ratio (HTMT) is an indicator used to measure discriminant validity between latent variables. Henseler et al. [52] suggested that an HTMT value of less than 0.85 indicates high discriminant validity. Meeting this criterion indicates that the correlations between multiple latent variables are not excessively high. In other words, these variables can be distinguished. Table 5 presents all HTMT values that met the aforementioned criterion (i.e., HTMT < 0.85).

Table 5. HTMT results

	Interaction	Personalization	Involvement	Product description	Visual aids	Purchase intention
Personalization	0.145					
Involvement	0.255	0.413				
Product description	0.323	0.208	0.198			
Visual aids	0.047	0.376	0.226	0.113		
Purchase intention	0.188	0.495	0.592	0.152	0.352	
Customer experience	0.091	0.563	0.595	0.257	0.321	0.463

3.3 Structural Model

Table 6 illustrates the comprehensive path analysis and mediation analysis results from our investigation. The empirical evidence demonstrates several significant relationships among the variables under examination. Customer interaction exhibited a robust positive effect on customer involvement (β = 0.308, t = 7.848), while simultaneously exerting a significant positive effect on customer experience (β = 0.178, t = 4.253). Similarly, personalization demonstrated substantial positive effect on both customer involvement (β = 0.335, t = 6.893) and customer experience (β = 0.443, t = 8.123), with the latter relationship displaying particularly strong statistical significance. Our analysis revealed that customer involvement positive effect purchase intention (β = 0.145, t = 4.410). Product description similarly showed positive effects on both customer involvement (β = 0.185, t = 3.991) and customer experience (β = 0.179, t = 3.649). Visual aids exhibited a significant positive relationship with customer experience (β = 0.120, t = 2.944). The most pronounced relationship identified was between customer experience and purchase intention (β = 0.668, t = 22.894), suggesting the critical role of experiential factors in driving purchase decisions. Notably, visual aids failed to demonstrate a statistically significant effect on customer involvement (β = 0.054, t = 1.168), indicating a potential limitation in their efficacy for enhancing involvement.

Table 6. Path and mediation analysis results

	β	$\bar{X}$	Standard Deviation (STDEV)	T test	2.5%	97.5%
Interaction→ Involvement	0.308	0.312	0.039	7.848	0.233	0.387
Interaction→ Customer experience	0.178	0.180	0.042	4.253	0.095	0.260
Personalization -> Involvement	0.335	0.334	0.049	6.893	0.232	0.429
Personalization→ Customer experience	0.443	0.442	0.055	8.123	0.337	0.549
Involvement→ Purchase intention_	0.145	0.146	0.033	4.410	0.085	0.208
Product description→ Involvement	0.185	0.193	0.046	3.991	0.286	0.099
Product description→ Customer experience	0.179	0.180	0.049	3.649	0.278	0.091
Visual aids→ Involvement	0.054	0.056	0.046	1.168	-0.035	0.143
Visual aids→ Customer experience	0.120	0.121	0.041	2.944	0.044	0.201
Customer experience→ Purchase intention	0.668	0.669	0.029	22.894	0.610	0.727
Mediation effect						
Interaction→ Involvement→ Purchase intention	0.044	0.046	0.012	3.576	0.025	0.072
Personalization→ Involvement → Purchase intention	0.048	0.049	0.014	3.552	0.023	0.079
Product description→ Involvement→ Purchase intention	0.027	0.028	0.009	2.982	0.048	0.012
Visual aids→ Involvement→ Purchase intention	0.008	0.008	0.007	1.048	-0.005	0.024
Interaction→ Customer experience →Purchase intention	0.119	0.121	0.029	4.155	0.064	0.175
Personalization→ Customer experience→ Purchase intention	0.296	0.295	0.039	7.505	0.225	0.373
Product description→ Customer experience→ Purchase intention	0.119	-0.120	0.033	3.659	0.187	0.061
Visual aids→ Customer experience→ Purchase intention	0.080	0.081	0.028	2.878	0.028	0.137

To further explore these relationships, a mediation analysis was performed utilizing the bootstrapping technique. The results underscored that the combined effect of customer interaction and involvement significantly and positive effect purchase intention (β = 0.044, t = 3.576). Similarly, personalization paired with customer involvement yielded a significant positive effect on purchase intention (β = 0.048, t = 3.552). The interplay between product description and customer involvement also positively and positive effect purchase intention (β = 0.027, t = 2.982). Furthermore, customer interaction coupled with customer experience significantly enhanced purchase intention (β = 0.119, t = 4.155), as did personalization combined with customer experience (β = 0.296, t = 7.873). The relationship between product description and customer experience likewise produced a significant positive effect on purchase intention (β = 0.119, t = 7.505), as did visual aids paired with customer experience (β = 0.080, t = 2.878). In contrast, the mediation pathway from visual aids through customer involvement to purchase intention was not statistically significant (β = 0.008, t = 1.048), as detailed in Table 6. These findings contribute to a deeper understanding of how generative AI-driven factors in logistics influence customer behavior and decision-making processes.

4 Results

In the context of generative AI in the retail industry, personalizing product descriptions has a major positive effect on customer experience. Utilizing generative AI enables merchants to automatically generate highly customizable product information based on their customers' preferences, needs, and historical data. These detailed descriptions are not only rich with information but also readily comprehensible, thereby effectively assisting customers in rapidly and accurately perceiving the functions and values of different products, which in turn enhances their shopping convenience and satisfaction. Social support theory posits that the provision of personalized information mitigates the uncertainty associated with available options, thereby substantially enhancing the overall consumption experience of the customer.

Generative AI can be used to generate personalized and detailed product descriptions consistent with the customers' specific needs. Providing personalized descriptions piques the interest of customers in products, encouraging them to actively engage in the shopping process. Social support theory posits that providing informational support reduces the decision-making pressure experienced by customers, strengthens their emotional connection to marketed products, increases their involvement in the purchase process, and promotes more proactive consumption behaviors.

In terms of visual aids, generative AI can generate high-quality visual content, including product images, three-dimensional views, and virtual fitting rooms, which can substantially enhance the perceived experience of customers. These visual materials not only facilitate the presentation of product information but also help customers develop an accurate understanding of a product's actual appearance and functionality. Social support theory posits that this visual assistance enhances customers' experience while fostering trust and satisfaction with products, thereby optimizing the overall shopping experience. Generative AI can considerably enhance customer interactions. Providing prompt feedback and personalized recommendations enables customers to engage with a product in a highly immersive manner, ensuring that their individual requirements are met. This dynamic interaction facilitates the shopping process and strengthens customers' sense of involvement and emotional connection to products. Social support theory suggests that this interaction provides emotional and informational support, enabling customers to perceive a brand as caring and essential, thereby enhancing their overall shopping experience.

Overall, the level of a customer's interaction has a significant and positive effect on their involvement. When customers engage in personalized interactions with brands or products through generative AI, the AI system can provide immediate feedback based on each customer's specific needs. This dynamic interaction mode enhances the sense of participation and identification among customers, enabling them to gain deeper insights into different products while fostering a proactive approach to purchasing decisions. Social support theory posits that this interaction mode provides both emotional and informational support, enabling customers to perceive a brand's benevolence and companionship, thereby increasing their involvement and purchase intention.

Personalized recommendations have a significant and positive effect on customer involvement. Generative AI can provide precise personalized recommendations and product information based on an analysis of customers' preferences, behaviors, and historical data. This personalization approach strengthens customers' identification with a brand and encourages them to participate. Social support theory posits that providing personalized recommendations alleviates the cognitive burden associated with decision-making while promoting the development of an enhanced emotional connection. This approach enhances customer engagement with the shopping experience.

Personalization has a positive effect on customer experience. Generative AI can provide highly customized product recommendations and services depending on the customers' past behaviors and preferences. This personalized experience makes customers feel valued and understood by a brand, which in turn enhances their satisfaction and loyalty. Social support theory suggests that this tailored support improves customers' shopping experience and provides satisfaction in both the emotional and informational dimensions, thereby promoting active brand interactions and customer behavior.

Customer experience has a positive effect on purchase intention. When generative AI is used to optimize customer experience through personalized product recommendations, prompt responses, and visual aids, the

overall satisfaction levels of customers with a specific brand tend to considerably increase. These high-quality experiences not only increase customers' trust in products but also enhance the convenience and enjoyment of the entire shopping process. Social support theory posits that a positive customer experience provides both emotional and informational support to customers, increasing their positivity and confidence in purchasing decisions and enhancing their purchase intention. When customers actively engage in the shopping process and interact with generative AI, they tend to deepen their understanding of the different products and brands. Strong customer involvement is usually associated with substantial interest and emotional investment, making customers perceive a high degree of confidence in their purchasing decisions. Social support theory suggests that a high degree of involvement provides both emotional and informational support, making customers feel valued and cared for by a brand, which further increases their purchase intention.

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