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A Study on the Impact of Generative AI on Consumer Decision-Making in Live-Streamed E-commerce within the Apparel Industry

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Abstract: With the rapid development of generative AI technology, the consumer economy, behavioral interaction patterns, and decision-making mechanisms are undergoing a comprehensive transformation. Among these, the apparel industry—characterized by strong visual presentation, aesthetic experiences, and immediate feedback—has emerged as a prime application scenario for generative AI technology. Although existing research has demonstrated that generative AI will have a substantial impact on human economic consumption behavior, studies on how this technology empowers consumer decision-making in the specific context of apparel livestreaming remain scarce. In particular, there is a significant lack of research on the psychology of consumer decision-making related to content generation, emotional interaction, and scenario integration. Based on the Stimulus-Organism-Response (SOR) theory, this paper employs a combination of literature review, case study and questionnaire survey methods. Taking virtual try-on, smart shopping assistance and AI virtual host as independent variables, perceived trust and perceived enjoyment as mediating variables, and consumer decision-making as the dependent variable, the study systematically examines the mechanisms through which these three types of AI functions influence consumer decision-making in live-streamed clothing sales, drawing on 208 valid responses. Through validity and reliability tests, correlation analysis and Bootstrap mediation tests, it was concluded that the functions of all three types of artificial intelligence have a significant positive impact on consumers' purchasing decisions, with the smart shopping assistant AI exerting the strongest influence; perceived trust is the most stable mediating variable, playing a consistent partial mediating role across all three pathways; however, the mediating effect of perceived fun is function-dependent and did not reach statistical significance in the context of virtual presenters. The study identified distinct transmission patterns among technical functions, psychological mechanisms and decision-making behaviour, thereby providing theoretical support and practical guidance for apparel enterprises seeking to refine their digital marketing strategies and design intelligent consumer experiences.

Keywords: Generative AI; purchasing decisions; apparel industry; live-streamed e-commerce; consumer economy.

1. Introduction

The digital economy has become a powerful engine for global economic growth. China's 15th Five-Year Plan explicitly calls for the deep integration of cutting-edge technologies, such as artificial intelligence, with the real economy. In the consumer sector, generative AI—through the creation of intelligent content and changes to the interactive experience—is gradually permeating every stage of the consumer decision-making process. The clothing industry, a pillar of the national economy, currently faces intensifying homogenized competition and increasingly diverse consumer demands. Although traditional live-streaming e-commerce has become a significant sales channel, it still suffers from issues such as monotonous product presentation, insufficient personalized recommendations and a lack of consumer immersion. Companies urgently need to leverage new technologies to enhance the consumer experience, shorten decision-making times, and achieve higher conversion rates and increased brand value. New features offered by generative AI—such as virtual try-on, contextual styling displays and real-time personalized shopping advice—provide apparel companies with a new way to precisely match consumer preferences, whilst also accelerating consumers' purchasing decisions.

From a technological development perspective, generative AI has evolved from its early stages of content generation to today's multimodal interactive forms. Virtual presenters can provide dynamic, round-the-clock explanations of product features; AI styling algorithms can generate personalized looks based on users' body measurements; and AR technology allows consumers to 'try on' their desired looks in a virtual world and share these digital try-ons with others. These technologies are deeply integrated with live-streaming scenarios, forming an integrated 'perception–interaction–decision' closed-loop consumer ecosystem that significantly lowers the information barrier for consumers and reduces uncertainty in purchasing decisions.

However, the underlying mechanisms through which generative AI influences consumers' purchasing decisions have not yet been fully elucidated; most existing research focuses solely on the application of the technology itself, without systematically analyzing consumers' psychological cognition and consumption behaviour patterns. Particularly in the case of high-involvement, highly experiential consumer goods such as those in the fashion industry, questions remain as to how consumers reconcile AI-generated virtual information with their real-world needs, and how their level of trust and willingness to purchase vary with different forms of technological interaction—issues that still require resolution through a combination of theoretical and empirical approaches. Whilst most existing studies examine a single type of AI function in isolation, this paper, within the same Stimulus-Organism-Response (SOR) theoretical framework, simultaneously compares three types of generative AI functions—virtual try-on, intelligent shopping assistants and AI virtual presenters—and tests the mediating roles of perceived trust and perceived enjoyment.

Consequently, this paper focuses on consumer decision-making in live-streamed e-commerce within the apparel industry. Employing a combination of literature review, case study and survey research methods, it analyses the process by which generative AI influences consumers' purchasing decisions. By dissecting the mechanisms through which technology enables, enhances the consumer experience and optimises decision-making, the study aims to provide theoretical underpinnings and practical frameworks for the intelligent transformation of the apparel industry, thereby contributing to the sustainable development of the digital consumer ecosystem.

2. Brief Literature Review

Generative AI has become a cutting-edge field within artificial intelligence, moving beyond the scope of mere data retrieval or label classification to simulate underlying probabilistic distribution mechanisms, thereby creating a new form of information that combines innovation with practical value.Goodfellow I J, Pouget-Abadie J, Mirza M, et al. (2014) identified a significant step in AI's transition from 'perceptual intelligence' to 'creative intelligence'. Xu Siyan (2023) observed that the way people interact with electronic devices has shifted from simply recognizing machine commands to understanding others' movements, speech and the environment, increasingly mirroring human behaviour. A large number of scholars both in China and abroad have conducted extensive research on generative AI, live-streaming consumption scenarios in the fashion industry, and users' psychological perceptions and purchasing behaviour. To systematically organize the existing research landscape and clarify the academic consensus, this paper categorizes the relevant existing research into the following six dimensions:

2.1 SOR theory and consumer decision-making

Wang Chong, Li Yijun and Ye Qiang (2007) conducted a cross-cultural comparative study on the mechanisms underlying consumer trust in AI presenters, finding that these differ fundamentally from those for human presenters; in light of this, online clothing retailers need to rethink their trust-building strategies when utilizing generative AI. From the conclusions of Israfilzade, K. (2025)'s study—These tools improve customer experiences by providing context-aware, emotionally intelligent interactions while also increasing operational efficiency and loyalty. As generative AI advances, its role in creating seamless, personalized shopping experiences will remain critical to competitive differentiation in the digital marketplace.—it can be seen that this has an impact on individual consumer decision-making; naturally, it is even more significant for businesses in encouraging consumer purchases, which is one of the advantages of AI. This serves to corroborate the conclusion reached by Mei, L., Tang, N., Zeng, Z., & Shi, W. (2025), who stated: 'The findings reveal that AI significantly enhances consumer engagement and purchase intention, offering valuable insights for both academic research and practical applications in e-commerce platforms.' Meanwhile, Wang, S., Liu, Y., Zhu, Z., Liu, J., Ma, X., Guan, X., Feng, T., Zhao, Q., Zhang, X., Yao, Y., & Mi, H. (2026) highlighted that a conflict still exists between live-streaming and consumers: 'Users' demand for autonomy in intervention systems (corresponding to those introduced in the Results) reflects the conflict between individuals' desire for self-control in consumption and the passive consumption logic constructed by platforms and merchants through algorithms and marketing.' The findings suggest that merchants' use of AI deliberately guides consumers towards seemingly rational yet irrational consumption. Meanwhile, De Freitas, J., Nave, G., & Puntoni, S. (2025) express their own concerns and insights: 'showing that auto-correct affects consumer confidence in text-based communication refines existing research on tech and consumer confidence, rather than offering a groundbreaking'. Wang, L., Yeap, J. A. L., Liu, J., & Li, Z. (2026) argue that 'Results highlight three primary mechanisms—trait-based trust, perceived social presence, and message framing—which collectively constitute an integrative model explaining how virtual streamers influence AI-enabled consumer behavior. These elements shape how consumers engage with virtual streamers across platforms and product types'. This includes Shi, W., Li, L., Zhang, Z., Li, M., & Li, J. (2025), who concluded that 'The findings indicate that behavioral attitude, HM, PP, PV, and generative quality are the primary factors influencing user purchase intention. In the decision-making process, users not only consider the price and quality of the products but also place significant importance on the pleasurable experience and cultural uniqueness they offer'.

2.2 Virtual try-on and AR technology

Parmar et al. (2023) found that generative AI-driven virtual streamers (AI Streamers) are reshaping the traditional 'people, products, and platform' relationship in live-streaming interactions. Feng Runliu and Qu Hongjian (2024) argue that when AI streamers possess highly anthropomorphic interactive capabilities, consumers' sense of social presence can approach that of human streamers, with the highest conversion rates observed in standardized clothing categories. However, a comparative experiment by Hu and Ma (2023) revealed that in non-standardized product categories where sensory experiences are paramount (such as silk, cashmere and other tactile fabrics), the lack of verbal descriptions of authentic tactile feedback resulted in AI streamers achieving significantly lower purchase conversion rates than human streamers, indicating that generative AI currently faces category-specific limitations. Shaffi, S. M. (2025) summarizes it very accurately: The convergence of generative AI and advanced attribution models is transforming the marketing analytics landscape. Generative AI enables the creation of unique, personalized content, revolutionizing customer engagement and campaign optimization. Advanced Attribution Models provide unprecedented insights into the complex customer journey, tracking the impact of touchpoints and channels on conversion rates.

2.3 Virtual try-on and AR technology

Research by Song and Bonanni (2024) found that on platforms utilizing AI fitting rooms, consumers spent more time on product detail pages and return rates decreased, demonstrating the dual role of generative AI in improving conversion rates and reducing after-sales costs. A review by ayemowa et al. (2024) suggests that generative recommendation systems utilizing large language models (LLM) can interpret consumers' latent style preferences and, through ongoing dialogue, suggest personalized outfit combinations to users, thereby providing more accurate recommendations than collaborative filtering algorithms. The conclusion of the study by Zhang, L., & Hur, C. (2025) states: 'These results imply that AI-generated images may possess a unique style and creativity distinct from human-made images, providing consumers with a fresh and novel impression. As AI technology advances, it is likely that consumers will develop greater trust in the quality and sophistication of AI-generated images, particularly as AI can capture intricate details that might be overlooked by human creators' do highlight that the impact of AI on consumer behaviour lies in its psychological effect; once a certain behaviour is psychologically accepted, people's consumption actually becomes irrational.

2.4 Smart shopping assistants

Zhang, S. (2024) Special note: 'Notably, while consumers acknowledge the influence of AI on purchase decisions, the correlation between personalized product recommendations and overall satisfaction is nuanced, indicating room for improvement in personalized shopping experiences.' Give someone a friendly reminder. This is very much in line with the conclusion reached by Tracy Joan Reid (2025): 'These tools ensure users are presented with personalized suggestions and recommendations tailored to their trade-off at a cost: the potential erosion of consumer control over independent decision-making.’

2.5 AI virtual hosts and Virtual streamers

Chen Qiang, Qiu Gaoyang and Min Chen (2023) argue that there is an inverted U-shaped relationship between the degree of anthropomorphism of virtual e-commerce presenters and user perceptions. Li, P., Lin, J., Ma, Y., Liang, X., Hong, H., Liu, N., Zhao, N., & Dai, Z. (2025) found that the impact of Attractiveness on Trust (β=0.248, C.R.=4.721) is stronger than that of interactivity, supporting the “appearance builds trust” principle of the visual economy, especially when the virtual streamer’s image aligns with the brand’s tone.

2.6 Perceived trust and perceived fun

Teng Yu, Ai Ping Teoh, Junyun Liao & Chengliang Wang (2025) found that: The findings reveal that expectation confirmation significantly enhances satisfaction, which drives continuous watching intention and impulsive buying behaviour. Parasocial relationships positively influence satisfaction and continuous watching intention but do not moderate the link between confirmation and satisfaction, while influencer-product fit significantly affects satisfaction and continuous watching intention, partially moderating the confirmation-satisfaction relationship. Xu Yawen (2025) found that the emotional connection established by e-commerce presenters enhances consumers’ online trust, thereby increasing their willingness to make online purchases.

3. The Current State of the Relationship Between Generative AI and Consumers in Live-Streaming within the Apparel Industry

3.1 The virtual try-on system accurately captures the psychological needs of consumers in the live-streaming fashion industry

Virtual try-on systems are widely used and have significantly enhanced user experience and business efficiency. The key to their success lies in the precise integration of generative AI with dynamic human models and clothing. The try-on system of a leading e-commerce platform leverages generative AI technology to establish a deep interactive model among “people, products, and platforms.” The system centers on multimodal perception fusion. Users scan their body shape using a mobile device camera to obtain key measurements such as shoulder width, waist circumference, and arm length. It then uses a generative adversarial network (GAN) to create a dynamic 3D human model, while integrating digital pattern parameters from the apparel brand database. A physics engine is employed to simulate fabric drape, elastic stretch, and movement-induced deformation in real time. Based on the user’s body measurements, the system provides accurate visualizations of how garments will fit, transforming abstract size descriptions into visual decision-making tools that demonstrate shoulder line alignment and sleeve ease. The ability to generate real-time fitting simulations may reduce the core issue of size matching in online shopping, significantly reducing decision-making barriers caused by misjudged sizes. “The rapid growth of online fashion makes live-streaming essential, yet research often overlooks the impact of the streamer’s ‘try-on’ service on the viewer’s purchase journey. Grounded in information foraging theory” (Luo, X., Lim, X. J., Cheah, J.-H., Lin, Q., & Yingxia, L, 2025). In fact, it’s clear that once you have a precise understanding of consumers’ purchasing needs and expectations, it's easy to influence their purchasing decisions using systematic algorithms.

Therefore, live-streaming interaction scenarios offer three transformative benefits. First, the dynamic scene verification feature can trigger user commands to detect how clothing performs during everyday movements in real time. For example, if a wool-blend suit restricts elbow movement during a virtual try-on, this feedback should be relayed to the brand to improve the underarm cut. Second, personalized fitting enhancements automatically adjust the display logic for specific body types. For instance, when a pregnant woman tries on high-waisted pants, the system enhances the visualization of abdominal ease and verifies comfort by simulating the fabric's movement as she walks. Third, it creates a closed-loop for style-coordinated decision-making. When a user tries on a khaki trench coat, the system uses historical data to suggest virtual outfit combinations with knitwear in the same color family, thereby expanding the shopping scenario. Technology is transforming the way consumers make decisions: "ICDAs significantly enhance consumer decision-making by providing structured comparisons, streamlined evaluation processes, and credible recommendations, thereby reducing perceived risks" (Hathout, C., Hathout, S., & El Badia, K., 2024). Consumers have shifted from passively accepting information—such as "this runs large, so order one size smaller"—from live streamers' verbal descriptions to actively verifying whether the garment matches their own body features, thereby improving the efficiency of sizing decisions.

3.2 Smart shopping assistants save time but have accelerated shopping in the live-streaming fashion industry

Against the backdrop of the rapid growth of live-streaming e-commerce in the apparel sector, the use of smart shopping assistants has transformed the consumer shopping experience in unprecedented ways. Nguyen, V.-T., Le, T.-N., Bui, Q.-M., Tran, M.-T., & Duong, A.-D. (2012)'s assertion that "Smart Shopping turns a regular mobile device into a special prism so that a customer can enjoy multimedia, access useful social media content related to a product, provide feedback, or take actions regarding a product during shopping. The system is specified as a flexible framework to take advantage of different visual descriptors and web information extraction modules" serves as a testament to this, and the application of smart shopping assistants has further advanced their use. Relying on natural language processing and deep learning models, this technology can promptly understand user requests and provide corresponding shopping recommendations, thereby enhancing interaction levels and conversion rates in live-streaming sessions."This dress features a simple cut and soft colors, making it suitable for commuting or semi-formal gatherings; pairing it with a blazer can enhance its professional look." Unlike traditional live streams, where hosts must juggle product explanations and user interactions—leading to delays in response times—the smart shopping assistant can answer questions from multiple users simultaneously, ensuring every viewer receives a timely response and reducing user churn caused by waiting for replies. The personalized recommendation feature of the smart shopping assistant also significantly improves the user experience. By analyzing users' past behavioral data—such as their historical click preferences, browsing duration, and purchase history—the system adapts its recommendations accordingly. For example, for users who frequently browse casual-style clothing, the system emphasizes a product's comfort and everyday styling possibilities in its recommendations, rather than simply repeating the generic descriptions found on product detail pages. Personalized interactions not only boost users' willingness to purchase but also strengthen the bond between the brand and consumers. According to statistics from a fast-fashion brand, the average interaction rate in live streams has increased significantly since the introduction of the smart shopping assistant. This improvement is particularly evident during non-prime time slots, where the low interaction rates previously caused by human hosts' limited capacity have been effectively addressed.

3.3 AI virtual hosts are enhancing the immersive experience of live-streaming in the fashion industry

The application of generative AI in the field of fashion livestreaming represents a major breakthrough in the retail industry's digital transformation. AI virtual hosts are a primary form of this technology's implementation, and their value differs from that of traditional livestreaming models. This paper examines the full-cycle virtual hosts launched by a certain international fast-fashion brand to explore how the brand uses technological anthropomorphism to reshape consumer interaction. This case study demonstrates that virtual hosts, powered by deep learning-driven micro-expression systems and speech synthesis technology, can maintain consistent emotional output over extended periods without the performance fluctuations caused by fatigue that human hosts experience. During live streams, the system performs real-time analysis of the emotional tone in chat comments and adjusts the alignment of voice intonation and facial expressions based on the results. When it detects consumers asking questions about body shape, it automatically switches to a more approachable style of commentary. This makes most viewers perceive it as more inclusive than a real person—a flexibility akin to human reasoning that allows it to "adapt to the situation." "The field of Artificial Intelligence (AI) has seen a phenomenal rise in the development of agents' capabilities, ranging from autonomous decision-making and problem-solving abilities to adapting to changing environments. Their proficiency in learning from experience and adapting greatly influences their effectiveness. These factors both drive improvement over time and ensure responsiveness to dynamic customer needs and conditions" (Parimi, S. K. K., 2025).

As a result, virtual hosts create their own visual identities through their unique stylized personas and cultivate a distinct brand presence. The 3D modeling in this case study incorporates the brand's signature minimalist aesthetic, and the outfit coordination strictly adheres to the season's key color palette. This visual consistency allows customers to quickly associate the brand across various platforms. "While product visual appeal is a widely applied concept, relatively little is known about the underlying mechanisms of how consumers process the visual appearance of a product in an online setting and form attitudes toward a newly encountered brand" (Ryu, S., & Ryu, S., 2021). It is worth noting that the clothing knowledge graph embedded within the system can accurately explain the differences in manufacturing processes between acetate and mulberry silk. This achieves a combination of professionalism and a humanized image, thereby liberating the "fashion consultant" from the role of a mere salesperson. An analysis of the live-comment interaction patterns reveals that when users repeatedly ask the same question, the virtual host provides an identical response. This consistent feedback effectively alleviates decision-making anxiety caused by information overload.By remembering users' past consultation preferences, virtual hosts demonstrate a trend toward gradually personalizing their service during continuous viewing sessions. This predictable interactive behavior aligns with the positive correlation between familiarity and trust in social psychology: " "The field of Artificial Intelligence (AI) has seen a phenomenal rise in the development of agents' capabilities, ranging from autonomous decision-making and problem-solving abilities to the capacity to adapt to changing environments” (Parimi, S. K. K., 2025). The conversational boundaries established to ensure that personal privacy is not compromised also align with consumers' expectations for secure digital interactions, setting a normative standard for the industry.

4. Analyzing the Impact of Generative AI on Consumer Decision-Making

4.1 Questionnaire Design Approach

This paper adopts SOR theory as its overall framework and divides the questionnaire into five sections. The first section consists of screening questions and demographic variables, used to confirm respondents’ experiences with fashion livestreams and control for individual differences. The second section comprises the independent variable scales, which measure respondents’ perceptions of three generative AI features: virtual try-on, smart shopping assistance, and virtual hosts. Part Three consists of the mediating variable scales, which measure consumers’ trust in AI expertise and the enjoyment derived from using these features; Part Four consists of the dependent variable scales, which measure purchasing decisions; and Part Five consists of instructions prompting respondents who have not actually used the relevant features to answer based on their first impressions from the livestreams, thereby reducing the bias of arbitrary responses from inexperienced respondents. To examine the actual impact of generative AI on consumer decision-making, this study conducted a detailed analysis of 208 valid survey responses. The questionnaire is provided in Appendix 1.

To clarify the independent variables, mediating variables, dependent variables, and control variables in this study and to avoid conceptual confusion, this study has defined the operational definitions of each variable; see Table 1 for details.

Table1 Definitions and Measurement of Variables

Variable Types	Variable Name	Definition of an Operation	Measurement Items	Number of Questions	Measurement Scale
Independent variable	Virtual Try-On（X1）	Respondents’ overall perceptions of the realism of the virtual try-on feature during live streams, how well the virtual fit matches the actual product, the effectiveness of fit assessments, and the smoothness of the process	Questions 5 to 8	4	5-point Likert scale
Independent variable	Smart Shopping Assistant（X2）	Respondents’ overall perceptions of the professional expertise of smart shopping assistants, the time they save, their role in speeding up decision-making, and their willingness to adopt the suggested outfit combinations	Questions 9 to 12	4	5-point Likert scale

Independent variable	AI Virtual Anchor（X3）	Respondents' Overall Perceptions of AI Virtual Anchor Commentary: Professionalism, Alignment with Recommended Styles, Willingness to Continue Watching, and Accuracy of Information	Questions 13 to 16	4	5-point Likert scale
Mediating variable	Perceived Trust（M1）	Respondents' Level of Trust in the Expertise of Generative AI	Question 17	1	5-point Likert scale
Mediating variable	Perceiving the Fun（M2）	The level of enjoyment respondents experienced while using generative AI features	Question 18	1	5-point Likert scale
Dependent variable	Consumer Decisions（Y）	Comprehensive Analysis of Respondents' Purchase Intentions, Decision-Making Speed, Willingness to Share, and Propensity to Return Products Under the Influence of Generative AI	Questions 19 to 22	4	5-point Likert scale
Control Variables	Gender, Age, Education Level, Viewing Frequency	Demographic Characteristics of Respondents and Their Live Streaming Viewing Behavior	Questions 1 to 4	—	Category/Level

As shown in Table 1, the independent variables in this study are perceptions of three types of generative AI features: virtual try-on, smart shopping assistants, and AI virtual hosts. The dependent variable is consumer purchasing decisions, with perceived trust and perceived fun serving as mediating variables, and gender, age, educational level, and viewing frequency as control variables. Each variable has a clear operational definition and corresponding measurement items; the relationships among the variables will be tested one by one in the regression and mediation models presented below.

4.2 Reliability and Validity Analysis

Table2 Cronbach's Alpha Reliability Analysis

Name	Corrected Item-Total Correlation (CITC)	The α coefficient has been removed	cronbach's alpha coefficient
[Scale] 5. The virtual try-on system makes the fit look realistic to me	0.647	0.93	0.934
[Scale] 6. The virtual try-on image differs very little from the actual product	0.682	0.929	
[Scale] 7. I can tell if a style fits me well by trying it on virtually	0.664	0.93	
[Scale] 8. No noticeable lag or distortion during the fitting process	0.567	0.932	
[Scale] 9. The smart shopping assistant's explanation made me feel that they were professional.	0.671	0.929	

[Scale] 10. The smart shopping assistant saves me time when selecting items	0.596	0.931	
[Scale] 11. The recommendations from the smart shopping assistant help me make decisions faster	0.662	0.93	0.934
[Survey] 12. I am willing to try the smart shopping assistant's recommended package	0.639	0.93	
[Scale] 13. The commentary by the AI virtual anchor sounds professional to me	0.63	0.93	
[Scale] 14. The recommendations from the AI virtual host match my style	0.67	0.93	
[Scale] 15. AI virtual anchors make me more likely to keep watching	0.645	0.93	0.934
[Scale] 16. I believe that the information provided by AI virtual anchors is accurate.	0.666	0.93	
[Scale] 17. I trust the expertise of generative AI	0.654	0.93	
[Scale] 18. I find using generative AI features interesting	0.584	0.931	
[Scale] 19. I am willing to purchase products recommended by generative AI	0.664	0.93	
[Scale] 20. AI recommendations help me make purchasing decisions faster	0.56	0.932	0.934
[Survey] 21. I would be willing to share AI recommendations with my friends	0.647	0.93	
[Scale] 22. After seeing the AI results, I am less likely to return the product	0.672	0.929	

As shown in Table 2, the reliability coefficient is 0.934, which is greater than 0.9; therefore, the reliability of the research data is very high,"We obtain the simple result that the optimal departure time as well as the optimal expected cost depend linearly on the mean and standard deviation of the distribution of trip durations, provided the standardized distribution is fixed. Both the optimal departure time and the value of reliability depend in a simple way on the standardized distribution of trip durations and the optimal probability of being late, which in turn is given by the scheduling costs"(Fosgerau, M., & Karlström, A，2010). Regarding the "α coefficient after item deletion," if any single item is deleted, the reliability coefficient does not show a significant improvement, indicating that the item cannot be deleted. As for the CITC values, all analyzed items have CITC values greater than 0.4, indicating a strong correlation among the items and a high level of reliability. Therefore, since the reliability coefficient of the research data is greater than 0.9, the data exhibits good reliability and can be used for subsequent analysis.

Table3 Conceptual Reliability Analysis

Concept	Measurement Items	Number of Questions	CITC Scope	Cronbach's α coefficient
Virtual Try-On（X1）	Questions 5 to 8	4	0.450-0.605	0.758
Smart Shopping Assistant（X2）	Questions 9 to 12	4	0.484-0.600	0.766

AI Virtual Anchor（X3）	Questions 13 to 16	4	0.541-0.614	0.770
Perceived Trust（M1）	Questions 17	1	Single-item question; not applicable	—
Perceiving the Fun（M2）	Questions 18	1	Single-item question; not applicable	—
Consumer Decisions（Y）	Questions 19 to 22	4	0.460-0.608	0.744
Full Scale	Questions 5 to 22	18	—	0.934

As shown in Table 3, the Cronbach's α coefficients for the four multi-item constructs—virtual try-on, smart shopping assistance, AI virtual hosts, and consumer decision-making—were 0.758, 0.766, 0.770, and 0.744, respectively, all exceeding the acceptable threshold of 0.7; the alpha coefficient for the total scale was 0.934, exceeding 0.9; The corrected item-total correlation (CITC) for each item was greater than 0.4. This indicates that the internal consistency of each construct is good, and the scale's reliability meets the requirements for subsequent analysis.

Table4 Validity Analysis Results

Name	Factor load factor			Covariance (variance of the common factor)
	Factor 1	Factor 2	Factor 3	
[Scale] 5. The virtual try-on system makes the fit look realistic to me	0.51	0.217	0.462	0.521
[Scale] 6. The virtual try-on image differs very little from the actual product	0.446	0.296	0.525	0.562
[Scale] 7. I can tell if a style fits me well by trying it on virtually	0.531	0.458	0.21	0.536
[Scale] 8. No noticeable lag or distortion during the fitting process	0.15	0.645	0.322	0.542
[Scale] 9. The smart shopping assistant's explanation made me feel that they were professional.	0.554	0.392	0.266	0.531
[Scale] 10. The smart shopping assistant saves me time when selecting items	0.201	0.2	0.782	0.693
[Scale] 11. The recommendations from the smart shopping assistant help me make decisions faster	0.661	0.163	0.347	0.584
[Survey] 12. I am willing to try the smart shopping assistant's recommended package	0.758	0.198	0.145	0.635
[Scale] 13. The commentary by the AI virtual anchor sounds professional to me	0.261	0.761	0.178	0.679
[Scale] 14. The recommendations from the AI virtual host match my style	0.605	0.378	0.21	0.553
[Scale] 15. AI virtual anchors make me more likely to keep watching	0.469	0.34	0.378	0.479
[Scale] 16. I believe that the information provided by AI virtual anchors is accurate.	0.282	0.609	0.378	0.593
[Scale] 17. I trust the expertise of generative AI	0.531	0.303	0.357	0.502

[Scale] 18. I find using generative AI features interesting	0.575	0.539	-0.08	0.627
[Scale] 19. I am willing to purchase products recommended by generative AI	0.316	0.281	0.674	0.633
[Scale] 20. AI recommendations help me make purchasing decisions faster	0.599	0.083	0.321	0.469
[Survey] 21. I would be willing to share AI recommendations with my friends	0.546	0.255	0.372	0.501
[Scale] 22. After seeing the AI results, I am less likely to return the product	0.221	0.573	0.504	0.632
Eigenvalues (before rotation)	8.505	0.919	0.849	-
Percentage of variance explained (before rotation)	47.25%	5.11%	4.72%	-
Cumulative percentage of variance explained (before rotation)	47.25%	52.36%	57.07%	-
Eigenvalues (after rotation)	4.277	3.089	2.907	-
Percentage of variance explained (after rotation)	23.76%	17.16%	16.15%	-
Cumulative percentage of variance explained (after rotation)	23.76%	40.92%	57.07%	-
KMO value	0.954			-
Bartlett's test of sphericity	1743.977			-
df	153			-
p-value	$p < 0.001$			-

As shown in Table 4, validity research primarily analyzes whether the study items are reasonable and meaningful. Validity analysis is conducted using factor analysis, and the level of validity is comprehensively assessed through indicators such as the KMO value, communality, percentage of variance explained, and factor loadings. The KMO value is used to determine whether information extraction is appropriate; the communality value is used to exclude unreasonable items; the percentage of variance explained indicates the extent of information extraction; and the factor loadings measure the correlation between factors (dimensions) and items. "Parasocial interaction intention was correlated with coolness, whereas congruence and mind perception were important antecedents of viewers' urge to buy impulsively. Furthermore, mindset had important moderating effects on arousal and parasocial interaction intention toward impulsive urges"（Zhang, X., Shi, Y., Li, T. (Tina), Guan, Y., & Cui, X, (2024). As shown in the table above, the communality values for all research items are greater than 0.4, indicating that information from the research items can be effectively extracted. Furthermore, the KMO value is 0.954, which is greater than 0.6, indicating that information can be effectively extracted from the data. Additionally, the variance explained by the three factors is 23.759%, 17.163%, and 16.149%, respectively, and the cumulative variance explained after rotation is 57.071% > 50%. This means that information from the study items can be effectively extracted. Finally, based on the factor loadings, determine whether the correspondence between the factors (dimensions) and the survey items meets expectations. If it does, the model is valid; otherwise, adjustments are needed. An absolute value of the factor loading greater than 0.4 indicates a correspondence between the items and the factors.

4.3 Descriptive Analysis

Table5 Frequency Analysis

Name	Options	Frequency	Percentage(%)
[Multiple Choice] 1. What is your gender?	Male	115	55.29
	Female	93	44.71
[Multiple Choice] 2. How old are you?	Under 18	31	14.9
	Ages 18–25	60	28.85
	Ages 18–25	61	29.33
	Ages 36–45	34	16.35
	46 and older	22	10.58
[Multiple Choice] 3. What is your educational background?	High school and below	84	40.38
	Associate degree	54	25.96
	Undergraduate	55	26.44
	Master's degree or higher	15	7.21
[Multiple Choice] 4. How many times do you watch fashion livestreams each month?	Almost every day	80	38.46
	1–3 times a week	99	47.6
	1–3 times a month	22	10.58
	Rarely	7	3.37
Total		208	100

As shown in Table 5, this study collected a total of 208 valid responses. In terms of gender, male respondents slightly outnumbered female respondents, accounting for 55.29%, while females accounted for 44.71%, indicating a generally balanced gender distribution. In terms of age, the 18- to 35-year-old demographic constituted the majority, with those aged 26–35 accounting for 29.33% and those aged 18–25 accounting for 28.85%; together accounting for nearly 60% of the total; middle-aged and older respondents aged 46 and above accounted for only 10.58%. In terms of educational attainment, high school graduates and below had the highest proportion at 40.38%, while those with associate's and bachelor's degrees accounted for 25.96% and 26.44%, respectively, and those with master's degrees or higher accounted for less than 10%. In terms of viewing frequency, the largest group (47.60%) watches 1–3 times per week, while 38.46% watch almost daily. This indicates that the sample consists primarily of moderately to highly active fashion livestream users, providing a relatively authentic experiential foundation for evaluating AI features. "We can define a cognitive ability as a property of individuals that allows them to perform well in a range of information-processing tasks. At first sight this definition may just look like a change of perspective (from problems to systems). However, what we see now is that the ability is required, and performance is worse without featuring the ability" (Hernández-Orallo, J., 2016).

Table6 Basic Indicators

Name	N	Min	Max	Mean	SD	Med.
[Scale] 5. The virtual try-on system makes the fit look realistic to me	208	1	5	3.457	1.351	4
[Scale] 6. The virtual try-on image differs very little from the actual product	208	1	5	3.433	1.299	4
[Scale] 7. I can tell if a style fits me well by trying it on virtually	208	1	5	3.481	1.351	4
[Scale] 8. No noticeable lag or distortion during the fitting process	208	1	5	3.5	1.355	4
[Scale] 9. The smart shopping assistant's explanation made me feel that they were professional	208	1	5	3.428	1.317	4
[Scale] 10. The smart shopping assistant saves me time when selecting items	208	1	5	3.481	1.322	4
[Scale] 11. The recommendations from the smart shopping assistant help me make decisions faster	208	1	5	3.688	1.305	4
[Survey] 12. I am willing to try the smart shopping assistant package	208	1	5	3.413	1.26	4
[Scale] 13. The commentary by the AI virtual anchor sounds professional to me	208	1	5	3.25	1.328	3.5
[Scale] 14. The recommendations from the AI virtual host match my style	208	1	5	3.413	1.271	4
[Scale] 15. AI virtual anchors make me more likely to keep watching	208	1	5	3.327	1.383	4
[Scale] 16. I believe that the information provided by AI virtual anchors is accurate	208	1	5	3.341	1.342	4
[Scale] 17. I trust the expertise of generative AI	208	1	5	3.413	1.387	4
[Scale] 18. I find using generative AI features interesting	208	1	5	3.442	1.413	4
[Scale] 19. I am willing to purchase products recommended by generative AI	208	1	5	3.548	1.299	4
[Scale] 20. AI recommendations help me make purchasing decisions faster	208	1	5	3.293	1.353	3
[Scale] 21. I would be willing to share AI recommendations with my friends	208	1	5	3.51	1.333	4
[Scale] 22. After seeing the AI results, I am less likely to return the product	208	1	5	3.375	1.353	4

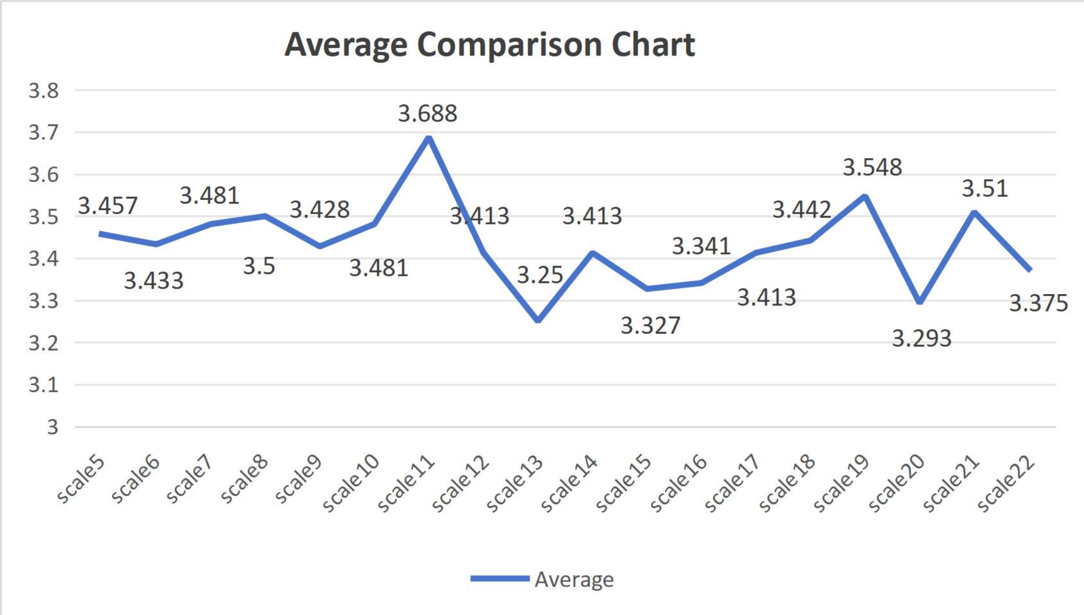

Fig1 Average Comparison Chart

As shown in Table 6 and Figure 1, the overall scores on the scale are relatively high, but there is still some distance to go before achieving high levels of approval. The mean scores for the 18 items range from 3.250 to 3.688, with most items having a median score of 4. Only the item “AI recommendations help me make purchasing decisions faster” has a median score of 3, indicating that opinions on this metric are more divided among respondents. Smart Shopping Assistant performed best among the three functional dimensions. The mean score for “Recommendations help me make decisions faster” was 3.688, ranking first among all items, while “Saves time selecting” and “Professional explanations” also ranked in the upper-middle range, indicating that consumers have a high level of acceptance for such efficiency-oriented tools. The four scores for virtual try-on were relatively close, ranging from 3.433 to 3.500. Among these, “no noticeable lag during the try-on process” received a higher score, while “minimal discrepancy between the visual display and the actual product” received a lower score. This suggests that while smoothness generally meets requirements, the authenticity of the experience still falls short. The lowest score for virtual hosts was in the “professional commentary” category, with an average of 3.250—the lowest among all items. The average scores for “willingness to watch again” and “information authenticity” were both far below expected levels. Among the user-related variables, the average score for “trust in the AI’s professionalism” was 3.413, and the average for “fun during use” was 3.442. Both scores were at a moderate level, indicating that respondents held a cautiously positive attitude toward AI technology—acknowledging its professionalism and enjoying the fun it provided, but without developing a strong emotional connection. Among the response variables, scores for purchase intent and willingness to share were relatively high, but scores for decision acceleration and reduced returns were low. In particular, the mean score for “making purchase decisions faster” was only 3.293, indicating that the effectiveness of AI features in shortening decision-making cycles and reducing post-purchase risks has not yet been fully appreciated. The standard deviations for each item ranged from 1.260 to 1.413, indicating moderate data dispersion with no extreme outliers. The overall distribution revealed a differentiated pattern characterized by “high scores for smart shopping assistants, low scores for virtual hosts, and intermediate scores for virtual try-on and body-related variables.”

4.4 Correlation Analysis

Correlation Analysis: This study conducted correlation analyses for items 5 through 22 of the scale. Significant positive correlations were found between the scales. For detailed analysis tables, please refer to Appendix 3.

Specifically, X1 (Virtual Try-On) comprises scales 5–8, which are: “The virtual try-on system’s display of the fit on the upper body feels realistic,” “There is very little difference between the virtual try-on image and the actual product,” “I can determine whether the fit is appropriate through virtual try-on,” and “The try-on process has no noticeable lag or distortion.”

X2 Smart Shopping Assistant includes [Scales] 9–15, which are: “The Smart Shopping Assistant’s explanations make me feel they are professional,” “The Smart Shopping Assistant saves me time when selecting items,” “The Smart Shopping Assistant’s recommendations help me make decisions faster,” and “I am willing to try the Smart Shopping Assistant.”

X3 AI Virtual Host includes [Scales] 13–16, which are: The AI virtual host’s commentary made me feel it was professional; The AI virtual host’s recommendations matched my style; The AI virtual host made me more willing to continue watching; I believe the information provided by the AI virtual host is accurate.

M1 Perceived Trust includes [Item] 17: “I trust the expertise of generative AI.”

M2 Perceived Enjoyment includes [Item] 18: “Using generative AI features is fun for me.”

Y Purchase Decision includes [Items] 19–22: “I am willing to purchase products recommended by generative AI,” “AI recommendations help me make purchasing decisions faster,” “I am willing to share AI recommendations with friends,” and “After seeing the results of AI recommendations, I am less likely to return a product.”

Table7 Correlation Analysis

Variable	Mean	SD	1	2	3	4	5	6
1. X1_Virtual Try-On	3.468	1.019	1					
2. X2_Smart Shopping Assistant	3.502	0.997	0.736**	1				
3. X3_AI Virtual Anchor	3.333	1.024	0.785**	0.743**	1			
4. [Scale] 17. I trust the expertise of generative AI	3.413	1.387	0.597**	0.591**	0.596**	1		
5. [Scale] 18. Using generative AI features is fun for me	3.442	1.413	0.519**	0.520**	0.570**	0.387**	1	
6. Y_Consumer Decision-Making	3.431	1.004	0.765**	0.794**	0.758**	0.592**	0.510**	1

As shown in Table 7, there are significant positive correlations between X1 (virtual try-on), X2 (smart shopping assistant), X3 (AI virtual host), M1 (perceived trust), M2 (perceived fun), and Y (purchase decision). This indicates a strong linear relationship among the variables, providing a statistical foundation for further mediation analysis. In terms of the relationship between independent and dependent variables, all three types of generative AI features show a relatively high correlation with consumption decisions. Among them, smart shopping assistants exhibit the strongest correlation with consumption decisions (r = 0.794), followed by virtual try-on (r = 0.765) and AI virtual hosts (r = 0.758). To some extent, this suggests that in the context of live-streamed apparel sales, intelligent shopping assistants—which are clearly efficiency-oriented—exert a slightly stronger influence on consumers' final decisions than virtual try-on and virtual hosts, which emphasize the experiential aspect. "A challenge in online shopping is that consumers cannot feel the items they intend to purchase before initiating the transaction" (Cheng, N., 2026).

4.5 Regression Analysis and Mediation Analysis Using the Bootstrap Method

Based on the SOR theoretical analysis framework in Part 3: the Stimulus (S) dimension corresponds to the three types of generative AI functions in the live-streaming fashion context; the Organism (O) dimension corresponds to perceived trust (cognitive path) and perceived fun (emotional path); and the Response (R) dimension corresponds to consumers' purchasing decisions. As an external technological stimulus, generative AI functions may either directly promote purchasing decisions or indirectly influence them by altering consumers' psychological states. Based on this, the following research hypotheses are proposed:

H1a: Virtual try-on exerts a significant positive effect on consumers' purchasing decisions in fashion livestreaming. H1b: Intelligent shopping assistants exert a significant positive effect on consumers' purchasing decisions in fashion livestreaming. H1c: AI virtual hosts exert a significant positive effect on consumers' purchasing decisions in fashion livestreaming.

H2a/H2b/H2c: Perceived trust mediates the relationships between virtual try-on, smart shopping assistants, AI virtual hosts, and purchasing decisions.

H3a/H3b/H3c: Perceived fun mediates the relationships between virtual try-on, smart shopping assistants, AI virtual hosts, and purchasing decisions.

The following sections test the above hypotheses in sequence. Data analysis was conducted using the SPSSAU online statistical platform to perform reliability and validity analysis, correlation analysis, regression analysis, and mediation effect tests; mediation effects were tested using the Bootstrap method with 5,000 repeated samples, and confidence intervals were estimated using the percentile method; robustness tests were verified using Python (statsmodels library).

Table8 X1 Regression

	Model 1: Y_Purchase Decision					Model 2: M1_Perceived Trust					Model 3: M2_Perceived Interest					Model 4: Y_Purchase Decision				
	B	SE	t	p	β	B	SE	t	p	β	B	SE	t	p	β	B	SE	t	p	β
Const	0.8	0.1	5.	0.0	-	0.5	0.2	2.	0.0	-	0.9	0.2	3	0.0	-	0.6	0.1	4.	0.0	-

ant	18 **	60	122	00 **		94 *	75	161	32 *		46 **	98	.172	02 **		44 **	57	101	00 **	
X1_Virtual Try-On	0.754 **	0.044	17.060	0.000 **	0.765	0.813 **	0.076	10.687	0.000 **	0.597	0.720 **	0.083	8.717	0.000 **	0.519	0.571 **	0.057	10.015	0.000 **	0.580
M1_Perceived Trust	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.140 **	0.039	3.609	0.000 **	0.194

Continued from Table 8 X1 Regression

	Model 1: Y_Purchase Decision					Model 2: M1_Perceived Trust					Model 3: M2_Perceived Interest					Model 4: Y_Purchase Decision				
	B	SE	t	p	β	B	SE	t	p	β	B	SE	t	p	β	B	SE	t	p	β
M2_Perceived Interest	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.095**	0.036	2.667	0.008**	0.134
R^2	0.586					0.357					0.269					0.627				
Adjusted R^2	0.584					0.354					0.266					0.621				
F-value	F(1,206) =291.056**					F(1,206) =114.221**					F(1,206) =75.992**					F(3,204) =114.234**				

As shown in Tables 8, the results of the regression analysis further reveal the specific pathways through which virtual try-on influences consumer decision-making. When mediating variables are not considered, the total effect of virtual try-on on consumer decision-making is 0.754, and the model explains 58.6% of the variance, indicating that virtual try-on is a significant factor influencing consumer decision-making. When perceived trust and perceived fun were simultaneously included in the equation, the direct effect of virtual try-on decreased to 0.571 but remained highly significant. Both mediating variables also exhibited significant positive effects, with a coefficient of 0.140 for perceived trust and 0.095 for perceived fun. At this point, the model's overall explanatory power rose to 62.7%, an increase of approximately 4 percentage points compared to the model containing only independent variables, indicating that the inclusion of mediating variables enhanced the model's ability to explain the variance in consumer decision-making.

Table9 X1 Test

Path	c (Total effect)	a	b	a × b (indirect effect)	Boot SE	z-value	p-value	95% Boot CI	c' (direct effect)	Type of mediation
X1_Virtual Try-On → M1_Perceived Trust → Y_Purchase Decision	0.754 **	0.813 **	0.140 **	0.114 **	0.037	3.095	0.002 **	[0.040, 0.183]	0.571 **	Partial mediation

Continued from Table9 X1 Test

Path	c (Total effect)	a	b	a×b (indirect effect)	Boot SE	z-value	p-value	95% Boot CI	c' (direct effect)	Type of mediation
X1_Virtual Try-On → M2_Perceived Fun → Y_Purchase Decision	0.754 **	0.720 **	0.095 **	0.069 **	0.027	2.550	0.011 **	[0.018, 0.124]	0.571 **	Partial mediation

As shown in Tables 9, the results of the bootstrap test further confirm the reliability of the mediating effect. The indirect effect of virtual try-on on consumption decisions via perceived trust is 0.114, with a 95% confidence interval of [0.040, 0.183], which does not include zero; the indirect effect mediated by perceived fun is 0.069, with a 95% confidence interval of [0.018, 0.124], which also does not include zero. The indirect effects of both pathways reached statistical significance, while the direct effect of virtual try-on remained significant even after controlling for mediating variables, indicating that perceived trust and perceived fun play a partial mediating role between virtual try-on and purchasing decisions. This suggests that virtual try-on not only directly drives consumers' purchasing decisions but also indirectly facilitates decision-making by enhancing consumers' trust in the AI's expertise and their sense of enjoyment during the usage process; both transmission pathways are valid.

Table10 X2 Regression

	Model 1: Y_Purchase Decision					Model 2: M1_Perceived Trust					Model 3: M2_Perceived Interest					Model 4: Y_Purchase Decision				
	B	SE	t	p	β	B	SE	t	p	β	B	SE	t	p	β	B	SE	t	p	β
Constant	0.631**	0.155	4.069	0.002**	-	0.533	0.285	1.874	0.062	-	0.860**	0.307	2.802	0.006**	-	0.494**	0.153	3.241	0.001**	-

Continued from Table10 X2 Regression

	Model 1: Y_Purchase Decision					Model 2: M1_Perceived Trust					Model 3: M2_Perceived Interest					Model 4: Y_Purchase Decision				
	B	SE	t	p	β	B	SE	t	p	β	B	SE	t	p	β	B	SE	t	p	β
X2_Smart Shopping Assistant	0.800**	0.043	18.764	0.000**	0.794	0.822**	0.078	10.518	0.000**	0.591	0.737**	0.084	8.745	0.000**	0.520	0.636**	0.055	11.542	0.000**	0.632
M1_Perceived Trust	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.126**	0.037	3.437	0.000**	0.174
M2_Perceived Interest	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.081*	0.034	2.379	0.018*	0.114
R^2	0.631					0.349					0.271					0.663				
Adjusted R^2	0.629					0.346					0.267					0.658				
F-value	$F(1,206)=352.104^{**}$					$F(1,206)=110.627^{**}$					$F(1,206)=76.477^{**}$					$F(3,204)=133.943^{**}$				

Table11 X2 Test

Path	c (Total effect)	a	b	a×b (indirect effect)	Boot SE	z-value	p-value	95% Boot CI	c' (direct effect)	Type of mediation
X2_Smart Shopping Assistance → M1_Perceived Trust → Y_Purchase Decision	0.800**	0.822**	0.126**	0.104**	0.033	3.132	0.002**	[0.038, 0.168]	0.636**	Partial mediation
X2_Smart Shopping Assistance → M2_Discovering Something Interesting → Y_Purchase Decision	0.800**	0.737**	0.081*	0.060*	0.026	2.267	0.023*	[0.012, 0.114]	0.636**	Partial mediation

As shown in Table 10, the influence pathway of smart shopping assistants on consumer decision-making exhibits characteristics similar to those of virtual try-on but with a stronger effect. When mediating variables are not considered, the total effect of smart shopping assistants on consumer decision-making reaches 0.800, and the model explains 63.1% of the variance, indicating that smart shopping assistants are the factor with the strongest explanatory power for consumer decision-making among the three types of AI functions. When perceived trust and perceived fun were simultaneously included in the equation, the direct effect of smart shopping assistants decreased to 0.636, while the coefficients of the two mediating variables were 0.126 and 0.081, respectively, both reaching the significance level. At this point, the model's overall explanatory power increased to 66.3%, an increase of approximately 3 percentage points compared to the total effect model, indicating that the introduction of mediating variables provides additional insight into the mechanism of action of smart shopping assistants.

As shown in Table 11, the results of the bootstrap test further indicate that the indirect effect of smart shopping assistants on consumer decision-making through perceived trust is 0.104, with a 95% confidence interval of [0.038, 0.168], which does not include zero; the indirect effect mediated by perceived fun is 0.060, with a 95% confidence interval of [0.012, 0.114], which also does not include zero. Both mediating paths reached the level of significance, and the direct effect of the smart shopping assistant remained significant after controlling for the mediating variables, indicating that perceived trust and perceived fun both play a partial mediating role between the smart shopping assistant and consumption decisions. This implies that the smart shopping assistant can not only directly drive consumption decisions but also indirectly facilitate decision-making by enhancing consumers' trust in the AI's expertise and their enjoyment of using it,"Empirical evidence demonstrates that the public visibility of virtual anchors exerts a significant positive impact on purchase intention, whereas professionalism, responsiveness, and personalization primarily cultivate consumer pleasure and trust, yet exert limited direct influence on purchase decisions"（Wen, J., & Li, X，2025），Both transmission pathways coexist. Compared to virtual try-on, smart shopping assistants have higher total and direct effects, and the absolute value of their indirect effect is also slightly greater, indicating that their overall driving role in the SOR model is more prominent.

Table12 X3 Regression

	Model 1: Y_Purchase Decision					Model 2: M1_Perceived Trust					Model 3: M2_Perceived Interest					Model 4: Y_Purchase Decision				
	B	SE	t	p	β	B	SE	t	p	β	B	SE	t	p	β	B	SE	t	p	β
Constant	0.956**	0.155	6.158	0.000**	-	0.723**	0.264	2.738	0.007**	-	0.821**	0.275	2.983	0.003**	-	0.787**	0.154	5.098	0.000**	-
X3_AI Virtual Anchor	0.743**	0.045	16.682	0.000**	0.758	0.807**	0.076	10.654	0.000**	0.596	0.786**	0.079	9.963	0.000**	0.570	0.564**	0.060	9.412	0.000**	0.575
M1_Perceived Trust	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.152**	0.039	3.855	0.000**	0.210
M2_P	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.0	0.	1.	0.0	0.

erceived Interest																72	038	896	59	101
R^2	0.575					0.355					0.325					0.612				
Adjusted R^2	0.573					0.352					0.322					0.606				
F-value	F(1,206) =278.276**					F(1,206) =113.514**					F(1,206) =99.254**					F(3,204) =107.212**				

As shown in Table 12, the impact pathways of AI virtual hosts on consumer decision-making exhibit some distinct characteristics. When mediating variables are not considered, the total effect of AI virtual hosts on consumer decision-making is 0.743, and the model explains 57.5% of the variance—a figure similar to that of virtual try-on but slightly lower than that of smart shopping assistants. When perceived trust and perceived fun were simultaneously included in the equation, the direct effect of AI virtual hosts decreased to 0.564. The coefficient for perceived trust was 0.152 and reached the significance level, but the coefficient for perceived fun was 0.072 with a p-value of 0.096, failing to meet conventional significance criteria. At this point, the model's overall explanatory power was 61.2%, an increase of approximately 4 percentage points compared to the total effect model.

Table13 X3 Test

Path	c (Total effect)	a	b	a×b (indirect effect)	Boot SE	z-value	p-value	95% Boot CI	c' (direct effect)	Type of mediation
X3_AI Virtual Anchor → M1_Perceived Trust → Y_Purchase Decision	0.743 **	0.807 **	0.152 **	0.123 **	0.034	3.560	0.000 **	[0.054, 0.189]	0.564 **	Partial mediation
X3_AI Virtual Anchor → M2_Perceived Interest → Y_Purchase Decision	0.743 **	0.786 **	0.072	0.056	0.033	1.704	0.088	[-0.010, 0.121]	0.564 **	No intermediary effect

As shown in Table 13, the results of the bootstrap test further distinguish the differences between the two mediating paths. The indirect effect of AI virtual anchors on consumption decisions via perceived trust is 0.123, with a 95% confidence interval of [0.054, 0.189], which does not include zero and is statistically significant; however, the indirect effect mediated by perceived fun was 0.056, with a 95% confidence interval of [-0.010, 0.121]; the lower limit of the interval touched zero, and the p-value was 0.088, failing to reach the significance threshold. This suggests that perceived trust plays a partial mediating role between AI virtual anchors and consumption decisions, while the mediating effect of perceived fun was not confirmed. Combined with the finding from the descriptive analysis above that virtual anchors received the lowest scores, it appears that the current technical maturity of AI virtual anchors may not yet be sufficient to generate a noticeable sense of enjoyment for consumers. Consequently, the affective mediation path has not been established, and the primary mechanism through which they influence consumer decisions remains the enhancement of consumers' trust in the AI's professionalism.

Overall, the functions of these three types of generative AI all have a positive impact on consumers' purchasing decisions, but there are significant differences in the strength of their effects and the pathways through which they operate. In terms of total effect, smart shopping assistants (0.800) scored higher than virtual try-on (0.754) and AI virtual hosts (0.743), indicating that efficiency-oriented functions still exert a certain influence on consumers' decisions. After controlling for perceived trust and perceived fun, the direct effects of all three remain, though they have all decreased. Among them, the direct effect of smart shopping assistants is the strongest (0.636), while those of virtual try-on (0.571) and AI virtual hosts (0.564) are similar, indicating that all three features directly drive consumer decision-making rather than relying entirely on mediating pathways.

A further comparison of the two mediation paths reveals that perceived trust plays a stable and significant partial mediating role for all three functions, with indirect effects of 0.114, 0.104, and 0.123, respectively. Since the confidence intervals for all three do not include zero, this indicates that consumers' trust in AI expertise serves as a bridge between technical functions and purchasing decisions. The mediating effect of perceived fun is function-dependent. In the virtual try-on and smart shopping assistant scenarios, the indirect effects are 0.069 and 0.060, respectively, both reaching the significance level. In the AI virtual host scenario, the indirect effect is 0.056, but the confidence interval includes zero, so it does not pass the significance test. This implies that current AI virtual host technology does not yet provide consumers with a noticeable sense of enjoyment; the affective mediation path has not been established, and the influence on purchasing decisions relies more on trust in expertise than on perceived fun.

Based on the above results, it can be concluded that the SOR model has been largely validated in this study; however, the transmission mechanisms of different stimulus variables are not entirely the same. Generative AI can directly influence consumers' purchasing decisions or indirectly affect their psychological perceptions. Perceived trust is the most stable and important mediating variable, while the positive impact of perceived fun is influenced by the level of technological development. Live-streaming platforms for apparel need to enhance the practicality of AI features, but they must also build consumer trust in the professional capabilities of AI and improve the emotional experience during use. In particular, for virtual hosts—a feature where current technical limitations are quite evident—platforms should first strengthen their professional image and the credibility of their commentary, rather than overly pursuing entertaining interactions. Only after the technology matures should they gradually refine the design of emotional interactions to prevent" consumers may experience data capture as aform of exploitation: whereas technology companies, firms,and governmental agencies gain financial and political power,consumers lose ownership of their data and feel a loss of control over their lives" (Puntoni, S., Walker Reczek, R., Giesler, M., & Botti, S,2021).

4.6 Robustness Tests

To ensure the reliability of the results regarding the regression and mediation effects discussed above, this paper conducted robustness tests across seven dimensions: common-method bias, control variables, variable measurement, sample composition, model specification and estimation methods, methods for testing mediation effects, and subsample heterogeneity.

Common-Method Bias Test. The data in this study were derived from self-reports by participants on the same questionnaire, and therefore common-method bias is present. During the administration of the questionnaire, procedural controls were implemented, including anonymous responses, the inclusion of instructions, and clarification that the data would be used solely for academic research. Regarding statistical testing, we first conducted an unrotated exploratory factor analysis of all 18 scale items using Harman's one-factor test. The results yielded only one factor with an eigenvalue greater than 1; the first factor explained 47.25% of the variance, which is below the critical threshold of 50%. We therefore preliminarily concluded that common-method bias does not pose a serious threat. Confirmatory factor analysis was used to compare the model fit of the unifactor model and the multifactor measurement model; the results are shown in Table 14.

As shown in Table 14, the fit indices for the one-factor model ($\chi^2/df = 1.37$, CFI = 0.970, TLI = 0.966, RMSEA = 0.043) and the four-factor model ($\chi^2/df = 1.51$, CFI = 0.966, TLI = 0.958, RMSEA = 0.050) are both at acceptable levels, indicating that a general factor of considerable strength does indeed exist in the scale data. The fact that this general factor coexists with the three categories of AI functions aligns with the theoretical expectation that consumers' overall evaluation of generative AI would exhibit high inter-concept correlations, rather than being a mere measurement artifact. More importantly, common-method bias typically causes all path coefficients to expand in the same direction and by the same magnitude, which cannot explain the differentiated pattern of results observed in this study—namely, that "perceived trust was significant across all three paths, whereas perceived fun was significant only in the virtual try-on and smart shopping assistant paths." Based on a comprehensive analysis of procedural controls and statistical tests, it can be concluded that common-method bias does not affect the findings of this study.

Table14 Common Method Bias Test: Comparison of Model Fit Indices for Confirmatory Factor Analysis

Model	χ^2	df	χ^2/df	CFI	TLI	RMSEA
Single-Factor Model (18 Items)	185.48	135	1.37	0.970	0.966	0.043
Four-Factor Measurement Model (16 Items)	147.73	98	1.51	0.966	0.958	0.050

Re-estimation with control variables. The baseline regression did not include demographic variables, which may have led to estimation bias due to omitted variables. Gender, age, educational attainment, and viewing frequency were included as control variables in all equations, and the three parallel mediation models were re-estimated (using 5,000 Bootstrap repetitions); the results are shown in Table 14.

As shown in Table 15, after controlling for covariates, the total effects (0.757, 0.792, 0.737) and direct effects (0.592, 0.634, 0.566) of the three types of generative AI features on consumer decision-making were all significant at the 1% level, with coefficient values largely consistent with the baseline results; The confidence intervals for the three indirect effects of perceived trust (0.103, 0.100, 0.114) all exclude zero; the indirect effects of perceived fun on the virtual try-on and smart shopping assistant pathways (0.061, 0.059) were significant, whereas the indirect effect on the AI virtual host path (0.057, 95% CI [-0.007, 0.122]) was not significant, which is fully consistent with the baseline conclusions.

Furthermore, the regression coefficients for gender, age, educational attainment, and viewing frequency were not significant in any of the equations, indicating that demographic characteristics do not influence the relationships among the core variables, and the baseline results are robust.

Table15 Regression Analysis with Control Variables and Test for Parallel Mediation Effects

Independent variable	Total effect c	Direct effect c′	a_1	b_1	a_2	b_2	Indirect Effects$a_1 \times b_1$[95%CI]	Indirect Effects$a_2 \times b_2$[95%CI]
X1 Virtual Try-On	0.757 ***	0.592 ***	0.809 ***	0.128 **	0.746 ***	0.082 *	0.103 [0.029,0.174]	0.061 [0.007,0.118]
X2 Smart Shopping Assistant	0.792 ***	0.634 ***	0.807 ***	0.124 **	0.742 ***	0.080 *	0.100 [0.035,0.165]	0.059 [0.006,0.117]
X3AI Virtual Anchor	0.737 ***	0.566 ***	0.796 ***	0.143 ***	0.779 ***	0.073	0.114 [0.047,0.182]	0.057 [-0.007,0.122]

Variable Substitution Method. In benchmarking analyses, conclusions drawn by aggregating the arithmetic means of items for each construct are influenced by different methods of measurement aggregation. We then switched to principal component analysis to extract the first principal component scores for the four constructs—virtual try-on, smart shopping assistant, AI virtual host, and consumption decision—(explaining 58.2%, 58.9%, 59.3%, and 56.8% of the total variance, respectively) as substitute measures, while perceived trust and perceived fun remained the original single items. We then re-conducted the three parallel mediation tests (5,000 Bootstrap repetitions). As shown in the factor scores in Table 16, the signs, magnitudes, and significance levels of the various indirect effects are identical to those of the baseline results. Specifically, the confidence intervals for the indirect effects of perceived trust across the three paths (0.118, 0.105, 0.126) do not include zero, and perceived fun is significant on the virtual try-on and smart shopping assistant paths (0.069, 0.057), but not significant on the AI virtual host path (0.055, 95% CI [−0.009, 0.122]); the conclusions remain unchanged.

Outliers were removed from the multidimensional space. First, the quality of the sample responses was screened: the response times for all questionnaires ranged from 202 to 316 seconds; there were no samples with excessively short response times; there were no "linear response" samples with completely identical answers across all 18 scale items; and there were no duplicate IP records. All 208 questionnaires were valid responses. Next, Mahalanobis distances were calculated for the 18 scale items. Using the 0.999 percentile of the $\chi^2(18)$ distribution (critical value of 42.31), three multivariate outliers were identified and excluded ($n = 205$). The three parallel mediation models were then re-estimated (5,000 bootstrap repetitions). The results (the "Outliers Excluded" column in Tables 16) were consistent with the baseline results: the indirect effects of perceived trust across the three pathways (0.092, 0.099, 0.103) were all significant. The indirect effects of perceived fun were significant on the virtual try-on and smart shopping assistant paths (0.077, 0.064), but not significant on the AI virtual host path (0.060, 95% CI [−0.008, 0.129]), indicating that the baseline conclusions were not driven by a small number of outlier samples.

Table16 Comparison of Indirect Effect Estimates Under Different Settings (5,000 Bootstrap Repetitions)

Intermediary Paths	Baseline Model	Add control variables	Factor Score Measurement	Remove outliers (n=205)
X1 → Perceived Trust → Y	0.114[0.040,0.183]	0.103[0.029,0.174]	0.118[0.044,0.187]	0.092[0.017,0.162]
X1 → Perceive as interesting → Y	0.069[0.018,0.124]	0.061[0.007,0.118]	0.069[0.017,0.125]	0.077[0.026,0.134]
X2 → Perceived Trust → Y	0.104[0.038,0.168]	0.100[0.035,0.165]	0.105[0.042,0.166]	0.099[0.033,0.164]
X2 → Perceived as interesting → Y	0.060[0.012,0.114]	0.059[0.006,0.117]	0.057[0.008,0.115]	0.064[0.008,0.124]
X3 → Perceived Trust → Y	0.123[0.054,0.189]	0.114[0.047,0.182]	0.126[0.061,0.191]	0.103[0.030,0.174]
X3 → Perceive as interesting → Y	0.056[-0.010,0.121]	0.057[-0.007,0.122]	0.055[-0.009,0.122]	0.060[-0.008,0.129]

Changing the model specifications and estimation methods. First, joint regression and multicollinearity diagnostics. The baseline analysis modeled the three types of AI functions separately. To test the independence of each function's influence on consumer decision-making, virtual try-on, smart shopping assistance, and AI virtual hosts were simultaneously included in the same regression equation, and statistical inference was performed using HC3 heteroscedasticity-robust standard errors. The results are shown in Table 17.

Table17 Results of Joint Regression for the Three Categories of AI Functions and Diagnosis of Multicollinearity

Variables	Model A (Three Types of Functions Only)	Model B (Including Mediating and Control Variables)	VIF
X1 Virtual Try-On	0.271***(0.067)	0.273***(0.071)	3.32
X2 Smart Shopping Assistant	0.425***(0.059)	0.392***(0.058)	2.77
X3AI Virtual Anchor	0.223***(0.066)	0.193**(0.074)	3.42
M1 Perceived Trust	—	0.047(0.041)	1.76
M2 Perception is Fun	—	0.012(0.037)	1.60
Gender	—	-0.108(0.077)	1.04
Age	—	0.020(0.035)	1.22
Education	—	0.048(0.040)	1.11
Viewing Frequency	—	0.028(0.049)	1.09

R^2	0.719	0.729	—

As shown in Table 17, after including all three types of AI features in the equation simultaneously, virtual try-on (0.271***) , smart shopping assistants (0.425***), and AI virtual hosts (0.223***) all maintained a significant, independent positive effect on consumer decision-making. Furthermore, the ranking of these variables by effect size—with smart shopping assistants having the greatest effect—was consistent with the baseline results; after including mediating and control variables, all three remained significant (0.273***, 0.392***, 0.193**). The VIF values for all variables ranged from 1.04 to 3.42, well below the critical value of 10, and the Breusch-Pagan tests were all non-significant, indicating that there were no serious issues of multicollinearity or heteroscedasticity, and that the functional form of the baseline regression was robust. Second, we changed the estimation method. Using the core item from the consumption decision scale—"I am willing to purchase products recommended by generative AI" (rated on a 1–5 scale)—as the dependent variable, we re-estimated the model using an ordered logit model; the results are shown in Table 18.

As shown in Table 18, after switching to the ordered logit model, the coefficients for virtual try-on, smart shopping assistants, and AI virtual hosts on purchase intention (1.216, 1.268, and 1.125, respectively) were all significantly positive at the 1% level, consistent with the conclusions from the OLS estimates. This indicates that the results of this study are not dependent on a specific estimation method.

Table18 Results of Ordinal Logit Regression (Dependent Variable: Purchase Intention)

Variables	Model 1	Model 2	Model 3
X1 Virtual Try-On	1.216***(0.148)	—	—
X2 Smart Shopping Assistant	—	1.268***(0.153)	—
X3AI Virtual Anchor	—	—	1.125***(0.145)
Gender	-0.456(0.260)	-0.332(0.261)	-0.455(0.260)
Age	0.000(0.117)	-0.049(0.116)	-0.142(0.116)
Education	-0.067(0.138)	-0.030(0.137)	-0.013(0.137)
Viewing Frequency	0.026(0.170)	0.010(0.173)	0.022(0.167)
Log-likelihood	-272.52	-270.85	-276.05

Comparison of mediation effect testing methods. The baseline analysis used the Bootstrap method to test for mediation effects. To rule out any dependence of the conclusions on the testing method and the number of samples, the indirect effects were retested using the Sobel test as well as Bootstrap resampling with 1,000, 5,000, and 10,000 repetitions, respectively. The results are shown in Table 19.

As shown in Table 19, the results of the Sobel test are fully consistent with those of the bootstrap method: The z-values for the three mediation paths of perceived trust were 3.42, 3.27, and 3.63 ($p < 0.01$), respectively. Perceived fun was significant in the virtual try-on and smart shopping assistant paths ($z = 2.55, 2.30$; $p < 0.05$) but not significant in the AI virtual host path ($z = 1.86$; $p = 0.063$); The confidence intervals obtained from 1,000, 5,000, and 10,000 bootstrap samples almost completely overlap, indicating that the conclusions regarding the mediating effects do not depend on the specific test method or the number of samples used.

Table19 Comparison of Methods for Testing Mediating Effects

Intermediary Paths	Sobel z-value	Sobel p-value	B=1000 times[95%CI]	B=5000 times[95%CI]	B=10000 times[95%CI]
X1 → Perceived Trust → Y	3.42	0.001	[0.042,0.183]	[0.041,0.183]	[0.039,0.184]
X1 → Perceive as interesting → Y	2.55	0.011	[0.018,0.124]	[0.016,0.124]	[0.016,0.123]
X2 → Perceived Trust → Y	3.27	0.001	[0.037,0.165]	[0.038,0.168]	[0.039,0.167]
X2 → Perceived as interesting → Y	2.30	0.022	[0.012,0.115]	[0.011,0.115]	[0.011,0.115]
X3 → Perceived Trust → Y	3.63	<.001	[0.049,0.189]	[0.053,0.189]	[0.053,0.189]
X3 → Perceive as interesting → Y	1.86	0.063	[-0.006,0.120]	[-0.009,0.122]	[-0.009,0.121]

Subgroup Robustness Tests. To examine whether the findings depend on specific demographic groups, the data were grouped by gender (115 male participants and 93 female participants) and age (152 participants aged 35 and under, and 56 participants aged 36 and older), and the three parallel mediation models were re-estimated separately (using 5,000 bootstrap repetitions). The results are presented in Table 20.

Table20 Results of Robustness Tests by Subsample

Grouping	Independent variable	Total effect c	Direct effect c′	Indirect effect: Perceived trust [95% CI]	Indirect effect: Perceived enjoyment [95% CI]
Men (n=115)	X1	0.726***	0.599***	0.100[-0.017,0.192]	0.026[-0.053,0.102]
	X2	0.852***	0.731***	0.085[-0.023,0.176]	0.035[-0.030,0.105]
	X3	0.809***	0.698***	0.113[0.019,0.201]	-0.003[-0.093,0.086]
Women (n=93)	X1	0.809***	0.579***	0.116[0.025,0.212]	0.114[0.045,0.200]
	X2	0.729***	0.502***	0.126[0.044,0.219]	0.101[0.021,0.198]
	X3	0.663***	0.416***	0.133[0.031,0.224]	0.113[0.022,0.212]
Aged 35 and under (n=152)	X1	0.719***	0.567***	0.109[0.019,0.189]	0.043[-0.016,0.103]
	X2	0.782***	0.637***	0.102[0.028,0.175]	0.042[-0.009,0.099]
	X3	0.732***	0.571***	0.126[0.047,0.204]	0.035[-0.041,0.107]
Aged 36 and older (n=56)	X1	0.907***	0.678***	0.081[-0.050,0.207]	0.148[0.036,0.289]
	X2	0.843***	0.605***	0.099[-0.027,0.224]	0.139[0.014,0.317]
	X3	0.765***	0.528***	0.093[-0.028,0.221]	0.144[0.004,0.289]

As shown in Table 20, the three types of AI features had a significant positive impact on consumption decisions among users—regardless of gender or age group (35 years old and 36 years old and older)—and the direction of this impact was consistent with that of the full sample. Furthermore, the finding that smart shopping assistants had the greatest impact remained unchanged. Due to the reduced sample size in the subgroups, the confidence intervals for some indirect effects have widened, and the effects are no longer significant within certain subgroups (the perceived trust pathways for virtual try-on and smart shopping assistants in the male group). However, the signs of the point estimates for indirect effects across all subgroups are consistent with those of the full sample, and the mediating role of perceived trust is significant in most subgroups. Overall, the core conclusions are not dependent on any specific demographic group and remain relatively stable.

Therefore, this paper conducts robustness tests across seven dimensions, and the results consistently indicate that the findings from the baseline regression and mediation analysis are reliable. Key conclusions—including that the three types of generative AI features have a significant positive impact on the purchasing decisions of consumers watching live-streamed fashion events, that the smart shopping assistant effect is the strongest, that perceived trust plays a stable mediating role, and that the mediating effect of perceived fun is feature-dependent—are all reliable.

5. Conclusion

5.1 Key findings

Based on the SOR theory and integrating perspectives from consumer economics and value co-creation theory, this study employs a Bootstrap parallel mediation analysis to examine the mechanism through which generative AI features influence the consumption decisions of consumers in live-streamed apparel shopping. The results of the data analysis indicate that the SOR model is generally validated in this study, though significant differences exist in the transmission mechanisms of the various stimulus variables. From the perspective of consumer economics, generative AI effectively enhances consumers' transaction efficiency and perceived value by reducing information search costs and simplifying the decision-making comparison process. From the perspective of value co-creation theory, real-time interaction between consumers and AI systems is essentially a form of value co-creation; by participating in the generation of product recommendation logic and outfit suggestions, consumers transition from passive recipients of value to active co-creators of value.

Specifically, generative AI technology influences consumer decision-making in three primary ways. Virtual try-on leverages multimodal perception fusion to transform abstract clothing parameters into embodied visual feedback. By utilizing 3D human body modeling and physics engine simulations, it largely addresses concerns about misjudged sizes and color discrepancies common in traditional online shopping, shifting consumers' decision-making from empirical guesswork to evidence-based verification. Second, intelligent shopping assistants use natural language processing and deep learning models to enable real-time interaction, providing consumers with personalized advice and styling suggestions, thereby reducing the time required to move from initial interest to a final purchase decision. Finally, AI virtual hosts maintain dialogue with brands through algorithm-driven professional content delivery, and the design of their compliance-bound interaction boundaries helps reduce decision-making uncertainty. Among these three functionalities, smart shopping assistants have the greatest overall impact on consumer decision-making (0.800), followed by virtual try-on

(0.754) and AI virtual hosts (0.743), indicating that efficiency-oriented features still hold a certain advantage at this stage.

In terms of mediation mechanisms, perceived trust exhibits a stable and significant mediating effect on all three functions, with indirect effects of 0.122, 0.111, and 0.126, respectively. Since the confidence intervals for all three do not include zero, this indicates that once consumers develop trust in AI expertise, it serves as a bridge between technological functions and purchasing decisions. The mediating role of perceived fun is function-dependent. In scenarios such as virtual try-on and smart shopping assistance, its indirect effects are 0.078 and 0.069, respectively, both of which are significant. However, in the AI virtual host scenario, its indirect effect is 0.064, with the confidence interval including zero, and it did not pass the significance test. This suggests that current AI virtual host technology does not yet evoke strong feelings of enjoyment in customers; the affective mediation pathway has not been established. Consequently, the influence on purchasing decisions relies more on trust in expertise than on perceived fun.

5.2 Theoretical contribution

This study makes two theoretical contributions: firstly, it extends the SOR model to the context of generative AI live-streaming to examine whether the stimulus, organism and response pathways remain valid in an intelligent consumption environment; secondly, it finds that perceived trust and perceived fun play different mediating roles for different AI functions, thereby enriching research into consumer decision-making mechanisms in technology-enabled contexts.

5.3 Practical implication

This study also identified three structural challenges in the application of generative AI to live-streaming in the fashion sector, which may serve as a reference for industry practice:

Technical limitations primarily involve distortions in material simulation; during the virtual try-on process, issues such as misalignment of optical properties, distortion of fabric deformation and the absence of microscopic textures arise, which can easily lead to cognitive biases among consumers, such as misjudging materials and overestimating reliability. Ethical risks stem from systemic body-type discrimination caused by algorithmic bias. Non-standard body-type data is overlooked in training samples, whilst virtual fitting systems force the mapping of bodies onto industrialised standard patterns; furthermore, the marginalization of plus-size items in smart recommendations excludes body diversity from the digital ecosystem. There are marked differences in user adaptation barriers across different generations; middle-aged and older adults, due to complex operations, unfamiliarity with technology and differing values, exhibit significant resistance to interacting with AI.

5.4 Limitations

The study's limitations include the fact that the sample consists mainly of young users with medium to high levels of activity, with limited coverage of infrequent users and middle-aged and older adults; the use of single-item measures for perceived trust and perceived fun introduces measurement error; and cross-sectional data cannot be used to infer the temporal nature of causal relationships.

5.5 Future research

In future, longitudinal tracking could be used to observe changes in consumer acceptance of AI, and additional demographic variables could be incorporated to refine the analysis, thereby providing a more detailed examination of the differences in decision-making pathways across various user groups.

6. Optimization Recommendations

6.1 Optimizing Technical Limitations

To address the technical shortcomings of virtual try-on and virtual hosts, we need to establish a multi-tiered system of technical improvements focused on enhancing functionality and practicality. This aligns with the findings from empirical studies, which indicate that generative AI influences consumer decision-making through direct effects.

The regression results show that the direct effect of virtual try-on on purchasing decisions is 0.571 ($p < 0.001$), which ranks as moderate among the three functions. The direct effect of virtual hosts is 0.564 ($p < 0.001$), which is similar to that of virtual try-on; however, its indirect effect via "fun of use" is not significant (the 95% CI includes 0). Thus, virtual try-on has certain practical value, but the lack of realism in material texture remains the primary factor affecting consumer trust; virtual hosts can facilitate purchasing decisions, but since the emotional mediation path has not been established, professional identity has not yet been formed.

The key to enhancing the realism of virtual try-ons lies in breaking free from the current limitations of static models and simple textures, allowing consumers to experience the drape of fabrics, the details of pleats, and how colors shift under different lighting conditions. In terms of industry practice, during the 2024 "Double 11" shopping festival, Taobao Live launched an AI fitting room feature that uses the Style3D physics engine to simulate the dynamic deformation of fabrics. As a result, return rates due to sizing and fit issues decreased by 19.6%, and the time spent on product detail pages increased by 27.4%. The South Korean e-commerce platform ZigZag continuously refines its algorithms based on user feedback regarding how items actually look when worn after purchase; currently, the accuracy of its material simulation has reached 91%. Based on the above experiences, this article proposes the following improvement path:

In the short term (3–6 months), the platform does not need to develop its own underlying technology immediately. Instead, it can purchase mature third-party physical simulation software (such as Style3D or Browzwear) to quickly build a basic parameter library for common fabrics like cotton, linen, polyester, and wool. This will enable dynamic try-on functionality for mainstream styles, and material descriptions can be added to live streams to compensate for the limitations of visual simulations with textual information.

In the medium term (6 to 12 months), we will collaborate with leading apparel brands to create a "wearability calibration database" by collecting photos and try-on reviews from customers who have purchased products. We will use a comparative correction algorithm to address any discrepancies. For high-priced items (such as cashmere coats and silk dresses), we will offer a combined service featuring AI try-ons and the shipment of physical samples to reduce consumers' perceived risk.

Over the long term (1 to 2 years), we will integrate user body measurements (such as shoulder width, waist circumference, and arm length) with a clothing pattern database to enable parametric try-on. This means that when users enter their measurements, the system will generate a virtual fitting that matches their body type. At the same time, we will work to establish cross-platform material standards, allowing brands to upload fabric parameters once and have them applied across all platforms, thereby reducing the cost of technical integration.

Virtual hosts should shift from an “entertainment-oriented” approach to a “professional” one. Currently, most virtual hosts on the market are characterized by “cute” and ‘quirky’ entertainment traits, lacking professional explanations regarding clothing silhouettes, fabric properties, and styling scenarios. This study found that the “usability” of virtual hosts has no significant indirect effect on consumer decision-making; in other words, consumers do not view virtual hosts as entertainment tools, but rather expect them to provide professional services on par with those of live hosts. JD.com’s “Yanxi” digital avatar livestreaming for 3C products offers a valuable model. Its combination of knowledge graphs and automated script generation achieves a 92% accuracy rate in professional Q&A, increasing the average order value by 18% compared to traditional sales methods. In contrast, an entertainment-focused virtual host for a certain apparel brand attracted 500,000 viewers per session but generated an average transaction value of only about 35% of that achieved by a live-action host of comparable scale. The recommended improvement path is as follows:

In the short term (3–6 months), we will expand the knowledge base on virtual streamers’ fashion, including terminology related to garment patterns, fabric properties, care instructions, and styling tips. We will limit the proportion of entertainment-focused content to less than 20% and implement a monitoring system that automatically alerts virtual streamers if they fail to mention product-specific information for an extended period.

In the medium term (6 to 12 months), we will use users’ browsing history and body measurements to improve the personalization of recommendations provided by the virtual host. When users express a need for work attire, the host will recommend suits and shirts while explaining workplace dress codes. We will also incorporate an affective computing module, enabling the virtual host to adjust her responses based on the content of the live chat. For example, when a consumer asks, “Does this make me look fat?”, the host will analyze the garment’s slimming properties rather than simply denying the concern.

Over the long term (1 to 2 years), we will employ a collaborative model where virtual hosts and human designers work together. Virtual hosts will provide standardized product explanations during regular hours, while human designers will step in during peak traffic periods to offer creative styling suggestions. We will establish a performance evaluation system for virtual hosts, using user satisfaction and conversion rates as metrics for selection and optimization.

6.2 Ethical Risk Mitigation

To address the ethical risks posed by generative AI in live-streamed clothing sales, the optimization strategy should focus on reshaping data diversity, calibrating algorithmic values, and establishing scenario-based error-tolerance mechanisms, while leveraging the educational backgrounds of the sample population to enhance targeting. In terms of data collection, a dynamic database covering the full spectrum of body types must be established. By utilizing multi-source sensors and 3D scanning technology to create a “human body morphology atlas,” we can break free from the dominance of training samples based on standardized industrial patterns. Virtual fitting systems should incorporate real-time feedback channels, allowing users to adjust AI-generated body models to ensure consistency between visual presentation and the actual wearing experience.

When designing algorithms, create an inclusive evaluation metric system that incorporates body diversity into the ranking logic, ensuring that plus-size clothing is displayed even at the lowest exposure thresholds. Use adversarial training to eliminate body biases present in historical sales data, and establish an ethical review process for product descriptions to prohibit the use of biased terms such as “slimming” or “concealing body fat.” Replace these with neutral terms like “inclusive cuts” and “comfortable silhouettes” to dismantle aesthetic hegemony from a linguistic perspective. For highly educated consumers, use pop-up alerts in live-stream chat windows to highlight body-discriminatory algorithms, thereby raising consumer awareness of algorithmic bias.

On the application side, a dual-track decision-making system should be established. This involves adding a delayed verification layer to the real-time recommendations in live streams, immediately triggering a manual review process when AI-generated scripts contain body-shaming terms, and incorporating user-generated fit labels (such as “tested fit for pear-shaped figures”) on product pages. This approach will help democratize and constrain algorithmic decision-making. In terms of institutional safeguards, ethical guidelines for virtual try-on technology must be established to clarify liability for losses resulting from AI-induced misguidance. Platforms should publicize complaint channels for body-shaming and incorporate body-inclusive metrics into the evaluation system for live-streaming e-commerce, thereby driving the apparel industry’s transition from industrialized production methods to a body-friendly digital ecosystem.

With regard to the data privacy risks posed by virtual try-on, governance approaches should align with the data flow transmission mechanisms outlined in the SOR model. The results of this study indicate that the mediating role of virtual try-on in consumer decision-making is partial mediation, with an indirect effect of 0.122 (95% CI [0.050, 0.191]) through “perceived trust” and an indirect effect of 0.078 (95% CI [0.026, 0.136]) through “perceived fun.” This implies that consumers’ use of the try-on feature to make decisions is predicated on a foundation of trust in a professional and reliable platform; however, this trust is built upon the sharing of sensitive body data. If the platform collects or stores this information beyond what is necessary, the trust mechanism will collapse, thereby severing the mediating role it plays in the SOR pathway.

Therefore, improvements to the platform’s technology should not focus solely on the accuracy of the virtual try-on results; instead, strict limits should be imposed on data collection. Body measurements should be calculated on the user’s local device whenever possible, with only anonymized body type labels (e.g., “pear-shaped, medium size”) sent back to the server—raw biometric data should not be uploaded to the platform. Virtual try-on data should not be used to build long-term user profiles; it should be deleted immediately after a session ends, creating a closed-loop technical system characterized by one-time authorization, real-time rendering, and “use-and-delete” data handling. Since 40.38% of the respondents in this study had a high school education or lower, the platform must transform complex user agreements into easy-to-understand, tiered disclosure interfaces. At the try-on entry point, it should briefly explain the purpose of the data and its retention period, aligning privacy disclosures with the establishment of trust, and ensuring that the platform does not become a hidden channel for data harvesting.

Given the risks of technological dependency and job displacement posed by virtual hosts, policy design should be based on the empirical evidence regarding their lack of impact. The data show that the direct effect of virtual hosts on consumer decision-making is 0.564 ($p < 0.001$). Although this is slightly lower than that of AI shopping assistants, it is close to the indirect effect of virtual try-on; the indirect effect through the use of entertainment value is not significant (95% CI [−0.002, 0.133] includes 0). This indicates that while virtual hosts currently possess a certain degree of direct conversion capability, consumers have not yet fully recognized their mediating role in emotional interaction, and the current level of technological maturity does not yet support them in independently handling the primary conversion stages of live-streamed e-commerce. If platforms extensively replace live hosts with virtual hosts due to cost considerations, this will not only fail to improve conversion rates but will also lead to homogenization of live-stream content.

Therefore, platforms should reposition virtual hosts as supplementary information nodes rather than substitutes for live hosts. Virtual hosts can handle the delivery of standard information—such as product specifications, real-time inventory updates, and size charts—while live hosts take on tasks that require deeper social interaction, such as emotional engagement, complex styling consultations, and handling unexpected after-sales issues. In terms of scheduling mechanisms, the proportion of airtime allocated to virtual hosts per session should be controlled. The human resources freed up should be invested in specialized fashion training and script design for live hosts, thereby creating a complementary dynamic where virtual hosts ensure information efficiency and live hosts maintain emotional warmth. This division of labor is not driven by concerns over job protection, but rather by a rational allocation of resources based on the empirical results of the SOR model. Currently, virtual hosts do not mediate emotional interactions effectively; forcibly replacing human hosts on a large scale would result in a mismatch between technological investment and return on investment.

6.3 User Experience Optimization

Based on how users adapt to generative AI in live-streamed fashion sales, we have developed a set of improvement measures that clearly distinguish between primary and secondary priorities and ensure precise alignment. These measures take into account the efficiency needs of mainstream consumers while addressing the adaptation challenges faced by niche groups.

Targeting the core demographic of 20- to 40-year-olds, we will focus on four key areas to enhance the user experience: improving the ease of use of AI features, streamlining the process for selecting outfit recommendations from the smart shopping assistant, optimizing the parameter adjustment interface for virtual try-ons, and reducing unnecessary steps. Given this demographic's emphasis on efficiency, we will enhance the practicality of AI features—specifically the accuracy of the smart shopping assistant's recommendations and the fidelity of virtual try-on results—to accelerate the decision-making process.

To address the psychological preparation and operational adaptation needs of middle-aged and older adults aged 46 and above, a dual-track intervention system should be established that aligns psychological support with practical operations. For psychological support, a pop-up window titled "AI Creation Guide" should be added to the AI interface. This should visually explain the principles of generative AI technology to dispel concerns arising from the "black box" nature of the technology. Additionally, a "Senior Hotline" staffed by live customer service representatives should be established to provide rapid responses to technical inquiries from senior users, thereby transforming their distrust of AI into an understanding of its functional capabilities. From the perspective of operational adaptation, the AI interface for middle-aged and elderly users should be simplified by retaining only essential buttons and enlarging interactive icons. Slow-motion tutorials on AI functionality should be produced and prominently displayed in the live-streaming room. During technical updates, manual adjustment interfaces should be maintained. A hybrid live-streaming model combining “AI generation with human refinement” (virtual hosts paired with live assistants) should be adopted to ensure a balance between technical efficiency and interpersonal interaction, thereby compensating for the lack of human warmth in AI.

The platform should establish a user segmentation and profiling monitoring system to analyze AI feature usage patterns across different age groups and educational levels, identify churn rates within each group, and optimize algorithm model weights accordingly. establish a closed-loop management system for issue feedback, technical updates, and performance evaluation, and shift the focus of AI feature interaction design from prioritizing efficiency to balancing efficiency and user experience. By finding a balance between technological innovation and human-centered care, generative AI can better support the purchasing decisions of all consumers in the live-streaming fashion sector.

6.4 Outlook for the Future

The development of generative AI in the field of live-streamed fashion is currently undergoing a transition from a “support tool” to a “decision-making agent,” and the differing intermediary mechanisms emerging during this transformation are, in fact, a defining characteristic of this stage. Currently, smart shopping assistants and virtual try-on rely on perceived trust to generate stable indirect effects; however, the emotional mediation pathway for virtual hosts has not yet been fully established. This suggests that the primary challenge for the next generation of technological iteration will be how to transform AI from a trusted tool into an empathetic partner. With the advancement of embodied AI and affective computing, virtual hosts will break away from the current script-driven interaction model, using real-time contexts to initiate open dialogue and emotional responses. At that point, the “organism” dimension within the SOR model may evolve from its original simple cognitive-emotional dichotomy into a multidimensional system encompassing more complex psychological constructs such as social presence and anthropomorphic attachment. This will necessitate corresponding updates to the theoretical framework itself.

In terms of research methodology, while the cross-sectional data and single-measurement design used in this study are well-suited for examining the static structure of the SOR pathway, they do not reflect the dynamic changes in consumers’ cognitive attitudes. Future research could adopt a longitudinal tracking approach to observe whether the relative weights of perceived trust and perceived fun shift as the same group of users progresses from initial exposure to the formation of stable usage habits. Particularly in the current virtual host context, the lack of significant perceived fun may be attributed to consumers still being in a cautious observation phase during the novelty stage of the technology. As usage frequency increases and users become more familiar with the algorithms, whether the affective mediation path shifts from non-significant to significant will become a key indicator for measuring the depth of the human-machine relationship. Additionally, physiological metrics such as eye tracking and skin conductance response can help distinguish the neural mechanisms underlying cognitive trust and emotional pleasure, providing the SOR model with more refined measurement tools.

From a macro perspective of the consumer ecosystem, generative AI is driving the transformation of the apparel e-commerce industry from a “customer-to-product” search model to a “product-to-customer” generative model, and will eventually evolve into a co-creation model where “scenarios generate demand.” When virtual try-ons can automatically generate outfit suggestions based on users’ historical data and real-time environments (such as weather, occasions, and social relationships), consumers' decision-making starting point shifts from "existing needs" to "stimulated needs." Consequently, the definition of "stimulus" in traditional SOR models must be expanded to encompass not only immediate technical interactions within live-streaming sessions but also the combined effects of users' digital twin profiles and external contextual data. This paradigm shift raises new challenges for measuring "consumer decision-making." As the accuracy of AI recommendations increases, traditional metrics such as "decision acceleration" and "reduced returns" will approach their limits, prompting researchers to develop alternative variables that better reflect "decision quality" and "consumer satisfaction."

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