IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 22 July 2025, accepted 16 August 2025, date of publication 20 August 2025, date of current version 27 August 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3600564

RESEARCH ARTICLE

Exploring the Impact Mechanism of AIGC-Driven Social Media Marketing Content on Consumer Decision-Making Behavior: A Two-Stage Hybrid Approach

JIACHENG LUO [1,2], KEWEI ZHANG [2], AND JIANG DU [1]
[1] Faculty of Art and Communication, Kunming University of Science and Technology, Kunming, Yunnan 650500, China
[2] Department of Smart Experience Design, Graduate School of Techno Design, Kookmin University, Seoul 02707, Republic of Korea
Corresponding author: Jiang Du (20170010@kust.edu.cn)

ABSTRACT The swift rise of ChatGPT and the growing integration of AI-generated content (AIGC) technologies are reshaping the digital marketing landscape in profound ways. These advancements are not only changing how social media marketing content is produced, but also altering its underlying characteristics. Despite this shift, there remains a noticeable gap in empirical research on how businesses and brands can effectively harness AIGC to drive consumer engagement. This study draws on the Stimulus–Organism–Response (SOR) theoretical framework to examine how AI-generated content influences consumer cognition, builds trust, and ultimately shapes decision-making behavior. Based on 348 valid survey responses, we employed a mixed-methods approach that integrates Partial Least Squares Structural Equation Modeling (PLS-SEM) with Artificial Neural Network (ANN) analysis. The findings indicate that entertainment, interactivity, trend relevance, electronic word-of-mouth, and visual appeal all positively influence both perceived value and trust. In contrast, customization was found to enhance perceived value only. Both perceived value and trust were shown to significantly increase consumers' purchase intentions. The ANN model further supported the PLS-SEM results, confirming consistency across methods. Among the predictors, entertainment ($\beta = 0.176$, ni $= 86.28\%$) was most influential for perceived value, EWOM ($\beta = 0.192$, ni $= 85.94\%$) played a key role in shaping trust, and perceived value ($\beta = 0.344$, ni $= 99.19\%$) had the strongest impact on purchase intention. These insights contribute to a deeper theoretical understanding of social media marketing and consumer behavior, while also offering actionable recommendations for businesses aiming to refine their content strategies in an AIGC-driven environment. Additionally, the study highlights promising directions for the evolution of digital consumption and the long-term sustainability of brand development.

INDEX TERMS AI-generated content (AIGC), social media marketing content (SMMC), purchase intention, artificial neural network (ANN), SOR theory.

I. INTRODUCTION

In the era of the digital economy, the swift evolution of internet and mobile technologies is fundamentally transforming how consumers live and access information. Traditional marketing methods are increasingly constrained by limited communication efficiency and creative expression, pushing businesses to embrace digital marketing strategies that enable more accurate audience targeting and brand communication [1]. Since the introduction of ChatGPT 3.5 by OpenAI in 2022, AI-powered generative content has gained widespread traction, bringing a wave of innovation to digital marketing [2]. With the help of deep learning and multimodal generation techniques, AI-generated content (AIGC)

The associate editor coordinating the review of this manuscript and approving it for publication was Arianna D'Ulizia.

can automatically produce a range of formats—from text and images to videos—streamlining the content creation process and allowing for greater customization [3], [4]. As a result, the way consumers interact with and interpret marketing messages is undergoing a notable shift [5].

At the same time, social media platforms like WeChat, TikTok, and Xiaohongshu have become vital spaces for brands to engage with users. These platforms excel in real-time interaction, targeted content delivery, and expansive reach [6]. More than just communication tools, they serve as bridges for fostering emotional connections and building trust between brands and their audiences. However, simply being present on these platforms is not enough; the real challenge lies in crafting content that is both meaningful and valuable to consumers.

Numerous studies have highlighted that high-quality, memorable social media content can enhance brand recognition, encourage user engagement, and drive consumer action [7], [8]. However, traditional social media marketing content often suffers from severe content homogenization, limited interactivity, and a low degree of personalization [9]. To counter these shortcomings, AIGC-infused marketing materials offer greater creative flexibility. By incorporating elements such as engaging entertainment, dynamic interactivity, tailored personalization, and refined aesthetics, these materials more effectively capture consumer attention, spark emotional resonance, and shape perceptions of value and trust—all of which are key drivers of purchasing behavior. In this way, AI-generated content is reshaping not only what social media marketing looks like but also how it is perceived and experienced by consumers [10]. Against this backdrop, this study applies the SOR framework to examine how AI-generated content influences consumer decision-making in the context of social media marketing, with a particular focus on the roles of perceived value and trust.

While prior research has explored dimensions such as entertainment, interactivity, trendiness, personalization, and word-of-mouth [11], [12], there remains a lack of systematic inquiry into how AI-generated content transforms these features and contributes to the formation of consumer trust and value perception. Additionally, the aesthetic dimension of marketing content—despite its relevance to brand image and trust—has often been underappreciated [13]. As AI-generated media becomes more sophisticated, consumer expectations for visual quality and aesthetic appeal are rising [14], and existing frameworks may no longer be sufficient to capture these evolving preferences. To bridge this gap, the current study expands the conventional five-dimensional model by adding aesthetics as a sixth dimension. This enhancement enables a more holistic view of content characteristics, especially in terms of the visual and artistic strengths of AI-generated media. Using the SOR model, marketing content is positioned as the external stimulus that shapes internal consumer responses—cognitive (perceived value) and emotional (trust)—which then influence their behavioral intentions. To deepen the analysis, this research combines PLS-SEM with ANN, providing a nuanced view of how various content elements contribute to purchase intention through the mediating roles of value perception and trust. This integrated framework offers new perspectives on the logic of digital marketing in the age of generative AI and provides actionable insights for brands seeking to enhance their social media strategies through the intelligent use of AIGC.

The remainder of this study is structured as follows: Chapter 2 reviews and synthesizes key theoretical developments in the relevant field and presents the main hypotheses of the study. Chapter 3 outlines the critical steps of the research process, including questionnaire design, data collection, and the analytical methods employed. Chapter 4 presents and interprets the core findings derived from the hybrid-method analytical approach. Chapter 5 provides an in-depth discussion of the research results. Chapter 6 identifies the study's limitations and proposes directions for future research. Chapter 7 offers a summary and conclusion of the entire study.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

A. SOCIAL MEDIA MARKETING CONTENT (SMMC) CHARACTERISTICS

Amid the ongoing surge of digital transformation, social media has become an indispensable pillar of contemporary digital marketing [15]. In essence, social media marketing encompasses a strategic approach where businesses utilize a range of platforms to connect with consumers through creative content, interactive engagement, and the exchange of information. The materials shared—whether image-text posts, short videos, or other media formats—form the backbone of social media marketing content. Unlike broad marketing strategies, content creation focuses more narrowly on what messages are delivered and how they are visually and emotionally conveyed. These elements play a crucial role in capturing user attention, shaping emotional responses, and guiding behavioral choices [16], [17].

Historically, consumer access to marketing content was limited to traditional media outlets. Today, thanks to rapid developments in artificial intelligence, individuals can effortlessly interact with AI-generated content. This new form of media—visually polished, up-to-date, and generally perceived as credible—has the power to quickly attract attention and influence consumer decision-making. Consequently, producing high-quality content is now a core tactic for broadening market reach, building consumer trust, and enhancing user loyalty. For enterprises, content serves not just as a means of tactical outreach, but also as a powerful lever for sustainable growth. In an increasingly saturated marketplace, content development must emphasize value and creativity—not just volume. Continuously delivering content that is engaging, relevant, and well-crafted has become one of the most effective ways for brands to elevate their presence and impact.

Previous studies have laid the foundation for understanding key content features in social media marketing. Notably, Kim and Ko were among the first to identify five essential characteristics: entertainment, interaction, trendiness, customization, and word of mouth [18]. However, their findings suggested that only three—entertainment, interaction, and word of mouth—had a significant positive impact on purchase intentions, mediated by customer equity factors such as perceived value and brand equity [17]. Building on this framework, later scholars extended the model to explore its relevance in areas such as consumer behavior [19], satisfaction [20], value co-creation [21], and brand loyalty [22]. For instance, Seo and Park [23] examined these dimensions within the airline industry, incorporating perceived risk into their analysis. Cheung et al. [21] reconceptualized the model as a four-dimensional construct—entertainment, customization, interaction, and trendiness—while Koay et al. [24] and Chen and Qasim [25] expanded the framework to include informativeness alongside the original dimensions. Collectively, these studies affirm that content traits such as strong interactivity and high entertainment value can significantly enhance consumers' cognitive and emotional responses, thereby strengthening purchase intent and brand attachment.

With the advent of the digital age, content production has entered a new phase. AIGC has introduced a fundamentally different paradigm, particularly in its ability to automatically generate visually stunning, stylized, and artistically rich content through deep learning. While AI-generated content also involves other potential psychological mechanisms, such as "perceived authenticity," "novelty," and the "uncanny valley effect," these mechanisms often depend on users' cognitive judgments regarding the source of the content or the AI's identity, making them more context-dependent and cognitively demanding. In contrast, visual experience, as the first perceptual stage in information transmission, serves as an immediate, low cognitive load perceptual cue that more easily elicits intuitive emotional responses from consumers upon their initial exposure to marketing content. As such, it has become a critical component in evaluating content quality [26]. This aligns with the principles of dual-process theory, where visual and emotional cues play a key role in shaping initial impressions. Additionally, Li and Yeh [27] demonstrated that visual design not only enhances user engagement but also directly influences perceived trust and value, particularly in digital environments saturated with algorithmically generated content. Hussain et al. [28] demonstrated that aesthetic design not only shapes first impressions but also influences consumers' perceived product value by triggering emotional resonance and aesthetic pleasure. Advances in artificial intelligence now allow businesses to generate visually impactful and artistically sophisticated content through automated means. These aesthetic elements increasingly align with consumer preferences for richer visual and emotional engagement.

Although other AI features are also worthy of study, based on the main use cases of AIGC on social media and consumers' visual content reception methods, this study believes that "aesthetics" is currently the most universal, easily recognizable, and practical dimension. However, through existing literature has paid limited attention to the role of visual aesthetics in social media marketing—particularly under the growing influence of AIGC. Given that aesthetics is among the most immediate and intuitive aspects of consumer perception, their influence warrants deeper investigation. This study, therefore, introduces aesthetics as an additional content dimension, aiming to provide a more comprehensive understanding of how AIGC influences consumer decision-making through multilayered cognitive and experiential pathways.

B. APPLICATION OF AIGC IN MARKETING

AIGC marks a new phase in content creation, where various forms of media—including text, images, video, audio, and even code—are produced automatically using deep learning and generative models. Building on the foundations laid by user-generated content (UGC) and professionally generated content (PGC), AIGC signifies the next step in the evolution of digital content [3]. As the technology rapidly advances, AIGC is emerging as a transformative force in digital marketing [29]. By harnessing sophisticated algorithms, it can efficiently produce multimodal content, reduce production costs, and deliver highly personalized materials tailored to specific consumer needs [30].

With the continued development of the internet industry, social media marketing has emerged as a central component of digital marketing strategies [31]. In this context, an increasing number of companies and business influencers are turning to AIGC to enhance their presence and performance on social media platforms [10]. By leveraging this technology, marketers can quickly produce creative and compelling content that meets the growing demand for high-quality, personalized communication. For example, Ogilvy & Mather has pointed out that many essential marketing functions can now be supported or streamlined with the help of AI [5]. In response to shifting market dynamics and in pursuit of broader reach and engagement, McDonald's has utilized AIGC tools to drive short-term sales while supporting long-term brand positioning through more dynamic social media strategies [32].

AIGC is thus playing a transformative role in marketing by challenging conventional approaches and delivering tangible improvements in both brand visibility and consumer interaction [33]. On the entertainment front, it enables the automated production of imaginative and engaging content that effectively captures user attention and fosters emotional connections [34]. In terms of interactivity, AIGC generated posts often include features that allow for real-time user engagement—such as commenting, sharing, and instant feedback—thereby strengthening the two-way relationship between brands and their audiences. Moreover, the capacity to personalize content based on user data, combined with visually polished and aesthetically pleasing presentation, makes AIGC output particularly appealing. These attributes not only enhance how consumers perceive brand messaging but also contribute significantly to product recognition, consumer trust, and ultimately, purchasing decisions. As a result, exploring how AIGC-enabled content influences consumer behavior on social media has become an increasingly vital area of inquiry in both current and future marketing research.

C. STIMULUS-ORGANISM-RESPONSE (SOR) MODEL

Originally proposed by Mehrabian and Russell in 1974, the SOR model has its roots in psychology and behavioral science and remains a foundational framework for understanding individual behavior [35]. Within the field of consumer behavior, the SOR model emphasizes the critical role of individuals' psychological processes, typically unfolding across three stages. The Stimulus (S) stage includes external influences such as marketing strategies, advertising content, and product features. The Organism (O) stage reflects internal consumer responses—emotional, cognitive, and attitudinal. Finally, the Response (R) stage captures observable behaviors like purchase decisions, brand loyalty, and satisfaction with product use [36]. As a central platform for information dissemination and user interaction, social media plays a key role in enhancing brand visibility and promoting products by enabling the rapid and widespread sharing of information about both new and existing offerings. Given this, applying the SOR model to social media marketing provides marketers with a valuable tool for not only improving the effectiveness of their campaigns but also gaining deeper insights into—and better predictions of—consumer behavior.

Due to its clarity and explanatory power, the SOR framework has been widely adopted in research on consumer responses across marketing and e-commerce domains [37]. For instance, Koay et al. [38] examined how perceived social media marketing activities affect consumers' purchase intentions through the lens of the SOR model. Similarly, Kumar and Hsieh [39] used this framework to explore the impact of such activities on brand experience and their subsequent influence on ongoing usage and brand loyalty. Sharma et al. [40] also applied the SOR model in the context of digital advertising, analyzing how social media marketing influences consumers' purchasing intentions. Collectively, these studies underscore the model's value in mapping the links between external stimuli, internal psychological states, and consumer behavior. Building on this foundation, the present study applies the SOR framework to examine how characteristics of social media—particularly in the context of artificial intelligence—shape consumers' intentions to adopt and engage.

D. HYPOTHESIS DEVELOPMENT

1) ENTERTAINMENT (ENT)

In this study, entertainment refers to the degree to which social media marketing content produced through artificial intelligence generative technologies provides consumers with enjoyment, amusement, and emotional satisfaction, thereby strengthening their positive perceptions of the brand and increasing their willingness to make a purchase [41], [42]. The more entertaining the content, the more likely it is to evoke positive emotional responses and leave favorable impressions on the audience. Moslehpour et al. [43], in their investigation of how social media marketing influences purchase intention, demonstrated that entertainment significantly enhances both PV and TR. Building on this foundation, the present study formulates the following hypotheses:

H1: ENT of AIGC-generated SMMC positively influences consumers' PV.

H2: ENT of AIGC-generated SMMC positively influences consumers' TR.

2) INTERACTION (INT)

In this study, interaction refers to the exchange of information and emotional engagement that occurs between consumers and social media marketing content created using generative technologies [41]. Highly interactive content often incorporates features such as real-time feedback, participatory scenarios, and other dynamic elements that enhance user involvement and experiential satisfaction [44]. Compared with traditional media formats [45], such interactive content strengthens the connection between consumers and brands, thereby promoting more effective value exchange [46]. Studies by Purwanto and Kuswandi [47] and Moslehpour et al. [43] have demonstrated that interaction plays a significant role in enhancing both PV and TR, which in turn influences consumer purchasing behavior. Based on these findings, the following hypotheses are proposed:

H3: INT of AIGC-generated SMMC positively influences consumers' PV.

H4: INT of AIGC-generated SMMC positively influences consumers' TR.

3) TRENDINESS (TRE)

In this study, trendiness refers to the degree to which AIGC-generated social media marketing content reflects current fashion trends and hot topics, thereby giving consumers the impression that the content is contemporary and in line with prevailing aesthetic norms [48]. Compared to traditional media, social media platforms allow consumers to access product-related information in a more timely and relevant manner, which not only enhances informational value but also strengthens brand credibility [42], [48], [49]. Prior research by Chafidon et al. [50] and Kakar et al. [51] confirms that the trendiness of content delivered through social media marketing significantly improves consumers' PV and TR. Based on these findings, this study proposes the following hypotheses:

H5: TRE of AIGC-generated SMMC positively influences consumers' PV.

H6: TRE of AIGC-generated SMMC positively influences consumers' TR.

4) CUSTOMIZATION (CUS)

In this study, customization refers to the extent to which AIGC-generated social media marketing content is tailored to meet individual consumers' personal interests and preferences [49], thereby enhancing their overall satisfaction and promoting trust [18], [52]. According to Chen and Lin [53], there is a strong link between the perceived effectiveness of social media marketing and the level of customization, which in turn has a positive effect on consumers' PV. Similarly, Ebrahim [17] found that personalized marketing content on social platforms plays a significant role in building consumer TR. Based on these insights, the study proposes the following hypotheses:

H7: CUS of AIGC-generated SMMC positively influences consumers' PV.

H8: CUS of AIGC-generated SMMC positively influences consumers' TR.

5) ELECTRONIC WORD-OF-MOUTH (EWOM)

In this study, electronic word-of-mouth refers to the positive reviews and recommendations that consumers share through online platforms about AIGC-generated social media marketing content, thereby facilitating broader and more favorable content dissemination [54]. Word-of-mouth has long been regarded as a key factor shaping consumer perceptions and behaviors [55]. Positive EWOM not only fosters favorable consumer attitudes but also contributes to increased trust and perceived value among other potential consumers [25]. Research by Chen and Lin [53] highlights the significant influence of EWOM on perceived value, while studies by Duan et al. [56] and Awad and Ragowsky [57] emphasize its direct effect on consumer trust and purchasing behavior. Based on these findings, the following hypotheses are proposed:

H9: EWOM of AIGC-generated SMMC positively influences consumers' PV.

H10: EWOM of AIGC-generated SMMC positively influences consumers' TR.

6) AESTHETICS (AES)

In this study, aesthetics refers to the visual attractiveness and artistic quality of AIGC-generated social media marketing content, including its overall design and presentation, which collectively enhance consumers' viewing experience and reinforce brand recognition. Hussain et al. [28], in their exploration of value co-creation within social media advertising, found that aesthetic appeal significantly boosts consumers' perceived value and positively affects their behavioral intentions. Likewise, Li and Yeh [27] demonstrated that strong design aesthetics play a critical role in building consumer trust in mobile commerce environments. Based on these insights, the following hypotheses are proposed:

H11: AES of AIGC-generated SMMC positively influences consumers' PV.

H12: AES of AIGC-generated SMMC positively influences consumers' TR.

7) PURCHASE INTENTION (PI)

In this study, purchase intention refers to consumers' favorable inclination toward engaging in future purchasing behavior as a result of exposure to AIGC-generated social media marketing content or services [58]. This concept not only reflects a consumer's stated willingness to buy but is also considered a reliable predictor of actual purchasing behavior [59]. According to Zeithaml [60], consumers' purchase decisions are largely shaped by their PV. Further research by Kim and Ko [58] and Chan et al. [61] has demonstrated that TR in social media marketing positively influences consumers' purchase intentions. Based on these findings, this study proposes the following hypotheses:

H13: PV of AIGC-generated SMMC positively influences consumers' PI.

H14: TR in AIGC-generated SMMC positively influences consumers' PI.

Therefore, this study constructs a new framework based on the SOR model, aiming to explore which external experiential stimuli in the context of AIGC-based social media marketing can effectively influence consumers' internal experiential states, thereby promoting their behavioral intentions. The independent variables include entertainment, interaction, trendiness, customization, electronic word-of-mouth, and aesthetics, all of which influence the dependent variable—purchase intention—through the mediating variables perceived value and trust. As shown in Figure 1.

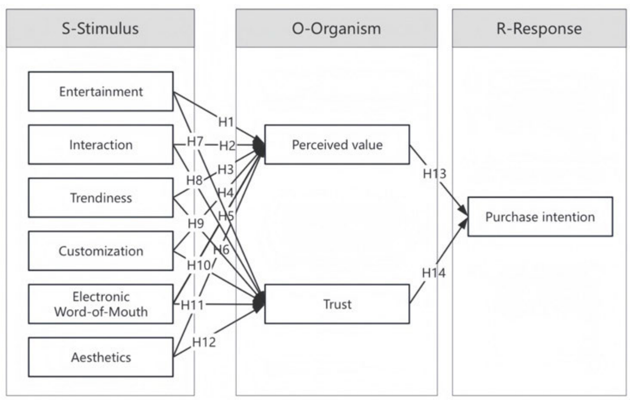

FIGURE 1. Theoretical framework.

III. METHODS

A. QUESTIONNAIRE DESIGN

The questionnaire for this study comprised two parts. Before participants began completing the survey, we provided a clear and concise explanation of the study's purpose and emphasized that participation was entirely voluntary. We also implemented an anonymous format to ensure the strict protection of respondents' personal information. The first section, participants were shown two different types of

TABLE 1. Questionnaire scales and references.

Variable	Items	Questions	Reference
Entertainment (ENT)	ENT1	I find AIGC-generated SMMC very interesting.	[12], [58]
	ENT2	AIGC-generated SMMC brings me a sense of entertainment and relaxation.	
	ENT3	I can clearly feel the fun and amusement brought by AIGC-generated SMMC.	
	ENT4	I am willing to spend more time watching AIGC-generated SMMC.	
Interaction (INT)	INT1	AIGC-generated SMMC makes me more willing to express my opinions.	[58], [62], [63]
	INT2	Through AIGC-generated SMMC, I can easily communicate or converse with other users.	
	INT3	I can share information with other users through AIGC-generated SMMC.	
	INT4	I can interact bidirectionally with activities involving AIGC-generated SMMC.	
Trendiness (TRE)	TRE1	AIGC-generated SMMC provides the latest information.	[58], [64]
	TRE2	AIGC-generated SMMC is currently very popular.	
	TRE3	Through AIGC-generated SMMC, I can find necessary updates about products.	
Customization (CUS)	CUS1	AIGC-generated SMMC is customized based on my interests or behaviors.	[12], [21], [58]
	CUS2	AIGC-generated SMMC better fits my personal preferences.	
	CUS3	AIGC-generated SMM platforms are easy for me to use.	
Electronic Word-of-Mouth (EWOM)	EWOM1	I would like to share AIGC-generated SMMC with my friends.	[12], [65]
	EWOM2	I would like to share AIGC-generated SMMC on my personal platforms.	
	EWOM3	I would share opinions gained from AIGC-generated SMM platforms with my friends.	
Aesthetics (AES)	AES1	I find AIGC-generated SMMC visually stimulating.	[66], [67]
	AES2	I believe AIGC-generated SMMC offers a high level of aesthetics.	
	AES3	Using AIGC-generated SMMC is visually pleasing.	
Perceived value (PV)	PV1	I believe AIGC-generated SMMC helps me better understand the value of the product.	[68], [69], [70]
	PV2	AIGC-generated SMMC is useful and valuable to me.	
	PV3	AIGC-generated SMMC makes the product/brand seem more worthwhile to purchase.	
	PV4	I believe the product or service promoted through AIGC-generated SMMC offers excellent value for money.	
Trust (TR)	TR1	I believe AIGC-generated SMMC is accurate and truthful.	[71], [72]
	TR2	I have a high level of trust in AIGC-generated SMMC.	
	TR3	AIGC-generated SMMC makes me feel that the brand is reliable.	
	TR4	AIGC-generated SMMC reflects the characteristics of the brand and products truthfully.	
Purchase Intention (PI)	PI1	AIGC-generated SMMC increases my desire to purchase.	[73], [74], [75]
	PI2	AIGC-generated SMMC enhances my intention to make a purchase.	
	PI3	AIGC-generated SMMC strengthens my confidence in purchasing the product.	
	PI4	AIGC-generated SMMC makes me willing to try and buy the product.	

social media content—human-generated and AI-generated—to ensure they could clearly distinguish between the two before proceeding with subsequent evaluations. The second part collected basic demographic data, including gender, age, education level, income level, usage background, and usage frequency. The third part aligned with our research model, with all scale items developed and adapted from prior studies to fit the context of AIGC-driven social media marketing. Specifically, the scale draws on the work of Kim et al., with adaptations for ENT (4 items), INT (4 items), TRE (3 items), CUS (3 items), EWOM (3 items), and AES (3 items). The items measuring PV (4 items) were adapted from Yang et al., while TR (4 items) was adapted from the study by Hong et al. Lastly, PI (4 items) was adapted from Duffett et al. All items were measured using a five-point Likert scale, ranging from "1 = strongly disagree" to "5 = strongly agree," as presented in the table 1.

Since the questionnaire was originally drafted in English, but recognizing the diverse language backgrounds of our respondents, we retained professional translators to render all measurement items into Chinese and then performed a back-translation to ensure consistency between the source and target versions. Additionally, we scrupulously adhered to academic ethical standards to protect respondents' rights and interests. Accordingly, before participants began the survey, we clearly informed them that all collected data would be used exclusively for academic research, contained no commercial purpose, and that their personal privacy would be rigorously safeguarded.

B. SAMPLING AND DATA COLLECTION

This study employed a quantitative research method to test the proposed model and conducted a cross-sectional online survey between February and March 2025. The questionnaire was created and distributed via Questionnaire Star (https://www.wjx.cn/, accessed on February 10, 2025), a professional online survey platform in China, using both a direct link and a QR code. Utilizing a snowball sampling approach [76], [77], researchers disseminated the questionnaire through various social media platforms, including WeChat, QQ, and Xiaohongshu, to invite respondents from diverse age groups and regions, thereby ensuring participant diversity (as shown in table 2). All participation was voluntary, with no conflicts of interest throughout the process, and respondents were informed that they could withdraw from the survey at any point.

This study distributed 400 questionnaires online. After a rigorous review by two researchers, 52 responses were excluded due to insincere answers or excessively rapid completion, resulting in 348 valid questionnaires and an effective response rate of 87%. Hill and Hamilton [78] has noted that, in multivariate statistical analyses, a sample size at least ten times greater than the number of measurement items per construct satisfies basic research requirements. Moreover, empirical guidelines proposed by Alwosheel et al. [79] recommend that the sample size not be less than fifty times the total number of adjustable parameters. By these criteria, the sample collected in this study conforms to established social science norms and possesses sufficient representativeness and statistical validity.

TABLE 2. Participant demographic information (n = 348).

Category	Items	Frequency	Rate (%)
Gender	Male	156	44.83
	Female	192	55.17
Age (years)	< 18	38	10.92
	18-25	55	15.80
	26-35	93	26.72
	36-46	81	23.28
	46-55	51	14.66
	> 55	30	8.62
Education level	Middle school or below	24	18.55
	High school	37	10.63
	Vocational college	53	15.23
	Bachelor's degree	135	38.79
	Graduate degree or above	99	28.45
Monthly Income (RMB)	< 3000	47	13.51
	3001-6000	81	23.28
	6001-10000	167	47.99
	> 10000	53	15.23
Social Media Platforms	WeChat	154	44.25
	Weibo	36	10.34
	Douyin (TikTok)	75	21.55
	Xiaohongshu (RED)	66	18.97
	QQ	17	4.89
Daily Usage Duration (hours)	Less than 1	31	8.91
	1-2	79	22.70
	2-3	109	31.32
	3-4	71	20.40
	More than 5	58	16.67
Usage experience	Yes	348	100

C. ANALYSIS METHODS

This study employs a multi-stage analytical approach combining Partial Least Squares Structural Equation Modeling (PLS-SEM) and Artificial Neural Networks (ANN) to explore the interplay between compensatory linear and non-compensatory nonlinear relationships within the model [80]. Previous research has indicated that linear methods such as PLS-SEM may have certain limitations when it comes to behavioral prediction [81]. In contrast, ANN—an advanced nonlinear statistical technique rooted in artificial intelligence and machine learning—offers high predictive accuracy and reduces the risk of oversimplification in decision-making processes [82]. Studies by Quan et al. [83] and Nguyen et al. [84] have emphasized the significance of this integrated approach. Accordingly, this study first uses Smart PLS 4.1.1 to conduct PLS-SEM analysis for hypothesis testing, followed by ANN analysis using IBM SPSS 26 to determine causal relationships and assess their relative importance.

IV. RESULTS

A. MODEL FIT

In conducting the PLS-SEM structural equation modeling analysis, two key fit indices were selected to evaluate the model's suitability: the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI). SRMR assesses the degree of discrepancy between the observed correlation matrix and the model-implied correlation matrix; lower values indicate better model fit, with values below 0.08 generally considered acceptable [85]. On the other hand, NFI measures the incremental fit of the model, with values closer to 1 indicating a stronger correspondence between the proposed model and the observed data [86]. In this study, the SRMR was measured at 0.045 and the NFI reached 0.808, suggesting that the model demonstrates a good overall fit.

B. COMMON METHOD BIAS

Common method bias (CMB) refers to systematic errors arising from the use of a single measurement method, and it is one of the key issues that must be addressed in structural equation modeling. To minimize the influence of CMB, most existing studies adopt two main approaches: program control and statistical control [87]. Program control involves measures taken during the research design phase—such as temporal separation and anonymous responses—to reduce CMB at its source. In this study, anonymity was ensured, and the questionnaire was carefully designed with appropriate length and question sequencing to help mitigate potential bias.

Statistical control refers to the application of statistical techniques during the data analysis stage, such as Harman's single-factor test and the marker variable technique, to detect and control for CMB. The results of Harman's test showed that the first common factor accounted for 24.884% of the total variance, which is well below the critical threshold of 40%, indicating that the measurement items did not load excessively onto a single factor [88].

Furthermore, we employed the marker variable technique to conduct an additional test for CMB [89]. This method involves introducing a theoretically unrelated marker variable to assess its impact on the outcome variable, thereby evaluating the presence of CMB. The results showed that the marker variable had no significant effect on purchase intention ($p = 0.203 > 0.05$), and the R^2 values before and after adding the marker variable were 0.229 and 0.233, respectively—indicating no substantial difference.

In addition, following the recommendations of Leguina [90], we calculated the variance inflation factor (VIF) for

TABLE 3. The results of the construct assessment.

Path	VIF	Path	VIF
ENT -> PV	1.192	CUS -> TR	1.156
ENT -> TR	1.192	EWOM -> PV	1.207
INT -> PV	1.103	EWOM -> TR	1.207
INT -> TR	1.103	AES -> PV	1.138
TRE -> PV	1.079	AES -> TR	1.138
TRE -> TR	1.079	PV -> PI	1.127
CUS -> PV	1.156	TR -> PI	1.127

both endogenous and exogenous latent constructs to further assess potential method bias. A VIF value $\leq$ 3.3 suggests the absence of issues related to common method variance. As shown in Table 3, all VIF values in this study ranged from 1.079 to 1.207, which are well below the threshold.

Taken together, these results provide strong evidence that serious common method bias is not present in this study.

C. RELIABILITY AND VALIDITY ANALYSIS

Reliability and validity are critical indicators used to assess the quality of a questionnaire. Reliability refers to the consistency and stability of the measurement results, indicating the degree to which the measured data can be trusted [91]. Validity refers to the effectiveness of the instrument, the extent to which it accurately reflects the true situation, and is typically assessed using factor analysis to determine whether the items in the study are reasonable [92]. To evaluate the reliability and validity of the questionnaire used in this study, we conducted factor analysis using PLS-SEM and calculated Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). Generally, Cronbach's alpha and CR values above 0.7 indicate good internal consistency, and values above 0.8 suggest high reliability [93]. AVE is used to assess convergent validity, with values above 0.5 indicating that the scale has satisfactory convergent validity [94]. Furthermore, factor loadings reflect the degree of correlation and consistency between observed variables and latent constructs. Higher values suggest stronger associations between the observed variable and its corresponding latent construct. Typically, a factor loading above 0.7 is considered indicative of a strong relationship [95].

In this study, Cronbach's alpha, CR (including rho_A and rho_C), and AVE all met the recommended thresholds. Additionally, all factor loadings under each construct exceeded 0.7 (as shown in Table 4). These results indicate that the measurement model demonstrates excellent internal consistency, reliability, and convergent validity, thereby ensuring a high level of credibility in the research findings.

To assess discriminant validity and the independence of latent variables, this study calculated and analyzed three commonly used indicators: the Fornell–Larcker criterion, the Heterotrait–Monotrait Ratio (HTMT), and cross loadings. First, as shown in Table 5, the square root of the AVE for each latent variable is greater than its correlation coefficients with other latent variables. This indicates that the latent variables

TABLE 4. Reliability and validity analysis.

	AVE	CR(rho_a)	CR(rho_c)	α
ENT	0.747	0.897	0.922	0.887
INT	0.631	0.814	0.872	0.805
TRE	0.690	0.776	0.870	0.775
CUS	0.741	0.833	0.896	0.826
EWOM	0.689	0.777	0.869	0.774
AES	0.759	0.842	0.904	0.842
PV	0.699	0.857	0.903	0.857
TR	0.718	0.869	0.910	0.869
PI	0.713	0.870	0.908	0.866

are statistically distinct from one another, and the model demonstrates satisfactory discriminant validity [93]. Second, as presented in Table 6, all HTMT values range from 0.140 to 0.486—well below the threshold of 0.85—suggesting clear differentiation among the constructs and strong discriminant validity [85]. In addition, Table 7 shows that each observed variable has a higher factor loading on its corresponding latent construct than on any other construct, further confirming good discriminant validity.

Overall, these results indicate that the measurement model has a good model fit, demonstrates strong reliability, and possesses adequate convergent and discriminant validity.

D. HYPOTHESIS TESTING

This study employed the bootstrapping method with repeated resampling, randomly drawing 5,000 new samples to test the path coefficients. As shown in Figure 2 and Table 8, ENT has a significant positive effect on PV ($\beta = 0.176$, $p = 0.001$) and TR ($\beta = 0.112$, $p = 0.029$), thus H1 and H2 are supported. INT also exerts a positive influence on PV ($\beta = 0.169$, $p = 0.001$) and TR ($\beta = 0.105$, $p = 0.041$), supporting H3 and H4. TRE also shows a positive effect on PV ($\beta = 0.106$, $p = 0.037$) and TR ($\beta = 0.164$, $p = 0.002$), thereby confirming H5 and H6. CUS shows a significant positive relationship with PV ($\beta = 0.109$, $p = 0.030$), supporting H7. However, CUS has no significant effect on TR ($\beta = 0.072$, $p = 0.212$), thus H8 is not supported. EWOM exerts a significant positive effect on both PV ($\beta = 0.138$, $p = 0.008$) and TR ($\beta = 0.192$, $p = 0.001$), thereby H9 and H10 are supported. AES also exerts a significant positive impact on PV ($\beta = 0.140$, $p = 0.011$) and TR ($\beta = 0.113$, $p = 0.037$), confirming H11 and H12. Furthermore, both PV ($\beta = 0.344$, $p < 0.001$) and TR ($\beta = 0.237$, $p < 0.001$) have positive impacts on PI, thus supporting H13 and H14.

E. ARTIFICIAL NEURAL NETWORK (ANN) RESULTS

Research has shown that PLS-SEM is only capable of capturing linear relationships within a single-stage model [96], making it particularly suitable for exploratory studies aimed at developing or refining relatively immature theories. However, this limitation may result in overly simplified models [97]. In this study, several path relationships in the model may exhibit nonlinear patterns of change. For instance, the

TABLE 5. Discriminant validity (Fornell–Larcker criterion).

	AES	CUS	ENT	EWOM	INT	PI	PV	TR	TRE
AES	0.871								
CUS	0.221	0.861							
ENT	0.192	0.286	0.865						
EWOM	0.259	0.229	0.283	0.830					
INT	0.209	0.145	0.231	0.184	0.794				
PI	0.292	0.260	0.361	0.312	0.337	0.844			
PV	0.282	0.264	0.325	0.305	0.292	0.423	0.836		
TR	0.242	0.215	0.253	0.327	0.218	0.352	0.335	0.847	
TRE	0.122	0.166	0.123	0.234	0.108	0.188	0.213	0.259	0.831

TABLE 6. Discriminant validity (HTMT values).

	AES	CUS	ENT	EWOM	INT	PI	PV	TR	TRE
AES									
CUS	0.266								
ENT	0.223	0.330							
EWOM	0.321	0.288	0.345						
INT	0.256	0.180	0.277	0.234					
PI	0.342	0.308	0.413	0.379	0.403				
PV	0.331	0.313	0.369	0.374	0.348	0.486			
TR	0.283	0.252	0.289	0.398	0.260	0.405	0.388		
TRE	0.150	0.207	0.154	0.301	0.140	0.227	0.261	0.316	

TABLE 7. Discriminant validity (cross loadings).

	AES	CUS	ENT	EWOM	INT	PI	PV	TR	TRE
AES1	0.878	0.246	0.161	0.231	0.180	0.255	0.248	0.216	0.076
AES2	0.867	0.161	0.169	0.209	0.184	0.222	0.212	0.231	0.109
AES3	0.869	0.167	0.172	0.237	0.182	0.285	0.275	0.186	0.133
CUS1	0.174	0.878	0.280	0.200	0.096	0.228	0.242	0.216	0.157
CUS2	0.172	0.857	0.212	0.172	0.142	0.230	0.228	0.163	0.125
CUS3	0.228	0.848	0.242	0.221	0.142	0.215	0.211	0.173	0.146
ENT1	0.176	0.278	0.924	0.276	0.208	0.334	0.307	0.234	0.104
ENT2	0.173	0.205	0.803	0.242	0.166	0.287	0.203	0.213	0.185
ENT3	0.167	0.266	0.874	0.263	0.232	0.341	0.279	0.230	0.064
ENT4	0.151	0.233	0.853	0.202	0.189	0.285	0.321	0.198	0.090
EWOM1	0.225	0.176	0.196	0.842	0.185	0.286	0.260	0.295	0.193
EWOM2	0.219	0.165	0.273	0.843	0.158	0.253	0.263	0.256	0.230
EWOM3	0.201	0.233	0.240	0.804	0.111	0.235	0.235	0.261	0.158
INT1	0.139	0.136	0.179	0.133	0.832	0.283	0.289	0.163	0.083
INT2	0.177	0.120	0.186	0.135	0.767	0.310	0.198	0.211	0.050
INT3	0.192	0.087	0.140	0.151	0.821	0.234	0.229	0.177	0.073
INT4	0.162	0.117	0.241	0.173	0.754	0.242	0.202	0.140	0.147
PI1	0.251	0.221	0.268	0.277	0.262	0.842	0.420	0.297	0.197
PI2	0.221	0.202	0.331	0.276	0.291	0.828	0.346	0.312	0.147
PI3	0.291	0.211	0.290	0.269	0.279	0.841	0.300	0.302	0.172
PI4	0.227	0.245	0.335	0.228	0.309	0.865	0.349	0.276	0.113
PV1	0.269	0.190	0.230	0.258	0.259	0.367	0.835	0.290	0.171
PV2	0.251	0.203	0.290	0.234	0.253	0.340	0.838	0.262	0.127
PV3	0.157	0.236	0.320	0.264	0.236	0.339	0.833	0.255	0.216
PV4	0.264	0.254	0.250	0.263	0.229	0.367	0.838	0.313	0.197
TR1	0.200	0.176	0.238	0.307	0.181	0.306	0.244	0.843	0.173
TR2	0.234	0.198	0.212	0.256	0.194	0.313	0.317	0.876	0.215
TR3	0.175	0.156	0.188	0.269	0.180	0.286	0.297	0.816	0.271
TR4	0.211	0.199	0.218	0.275	0.183	0.287	0.278	0.852	0.222
TRE1	0.065	0.153	0.086	0.184	0.074	0.150	0.171	0.205	0.817
TRE2	0.114	0.143	0.124	0.220	0.096	0.180	0.184	0.217	0.853
TRE3	0.124	0.120	0.097	0.178	0.098	0.139	0.175	0.224	0.821

impact of aesthetics on perceived value may exhibit diminishing marginal effects, and the impact of trust on purchase intention may also exhibit a saturation trend. Therefore, in order to better assess both linear and nonlinear relationships and enhance decision-making capability [98], we have decided to incorporate the new research methods at this stage.

TABLE 8. Analysis of pathway relationships.

Path	β	SD	t-Value	p	CIs(2.5-97.5%)	Result
ENT -> PV	0.176	0.053	3.305	0.001	(0.072;0.279)	Supported
ENT -> TR	0.112	0.051	2.188	0.029	(0.013;0.213)	Supported
INT -> PV	0.169	0.049	3.428	0.001	(0.074;0.269)	Supported
INT -> TR	0.105	0.051	2.044	0.041	(0.007;0.207)	Supported
TRE -> PV	0.106	0.051	2.092	0.037	(0.010;0.207)	Supported
TRE -> TR	0.164	0.053	3.109	0.002	(0.060;0.265)	Supported
CUS -> PV	0.109	0.050	2.172	0.030	(0.009;0.208)	Supported
CUS -> TR	0.072	0.058	1.247	0.212	(-0.040;0.188)	Unsupported
EWOM -> PV	0.138	0.052	2.648	0.008	(0.036;0.243)	Supported
EWOM -> TR	0.192	0.058	3.312	0.001	(0.078;0.304)	Supported
AES -> PV	0.140	0.055	2.551	0.011	(0.028;0.243)	Supported
AES -> TR	0.113	0.054	2.084	0.037	(0.006;0.217)	Supported
PV -> PI	0.344	0.047	7.287	0.000	(0.253;0.437)	Supported
TR -> PI	0.237	0.054	4.342	0.000	(0.129;0.343)	Supported

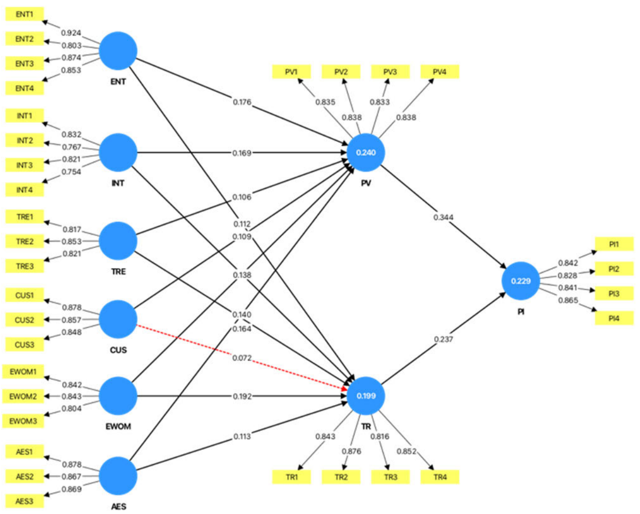

FIGURE 2. Results of the PLS structural model.

In recent years, research in the field of machine learning has made significant progress in modeling nonlinear structures, such as graph structure learning [99] and deep neural network architectures like autoencoders [100]. This study adopts an artificial neural network approach that is better suited for small sample sizes and offers greater interpretability. This method enables prediction even without predefined assumptions, benefiting from adaptive learning, real-time processing, and fault tolerance [101]. Findings by Lim et al. [102] indicate that the results obtained from ANN are more accurate than those from PLS-SEM. By utilizing the latent scores derived from PLS-SEM and integrating the SEM-ANN approach, model robustness can be improved and predictive power enhanced [98]. Accordingly, this study adopts a multi-analytical approach combining PLS-SEM and ANN.

1) ANN MODEL STRUCTURE

At this stage, the study constructs artificial neural networks using SPSS 26, based on the determinants validated through the SEM analysis described above. In line with most previous studies employing this technique, a single hidden layer is typically sufficient [101], [103], [104], as one hidden layer can approximate any continuous function. Therefore, this study adopts a simple Multilayer Perceptron (MLP) architecture comprising an input layer, one hidden layer, and an output layer. The number of neurons in the hidden layer was set to be generated automatically, and both the hidden and output layers used a sigmoid activation function.

Based on this setup, we developed three independent ANN models, each corresponding to one of the three exogenous variables. Specifically, PV has six key influencing factors (AES, CUS, ENT, EWOM, INT, and TRE); TR has five (AES, ENT, EWOM, INT, and TRE); and PI has two (PV and TR).

The specific structures of these models are illustrated in Figures 3.

2) VALIDITY OF THE ANN MODEL

To evaluate the validity of the ANN model, this study adopted a ten-fold cross-validation approach and calculated the Root Mean Square Error (RMSE) to effectively prevent model overfitting [80]. Following the methodological approach of Leong et al. [101], 90% of the dataset is used for training and 10% for testing. According to Taufiq-Hail et al. [105], multiple rounds of learning can minimize errors as much as possible while enhancing the accuracy of data predictions. Therefore, we calculated the RMSE for both the training and testing sets of each ANN model and further derived the average RMSE and standard deviation (SD) across all models to evaluate the overall performance. As supported by the literature, if the RMSE value falls within the range of 0 to a non-negative number, it typically indicates a good model fit—particularly in the context of assessing the fitting performance of ANN-based models [101].

As shown in Table 9, all RMSE values in the models are relatively low, ranging between 0.126 and 0.236 across the three ANN models. Specifically, the final RMSE values for the training sets in Models A, B, and C were 0.168, 0.189,

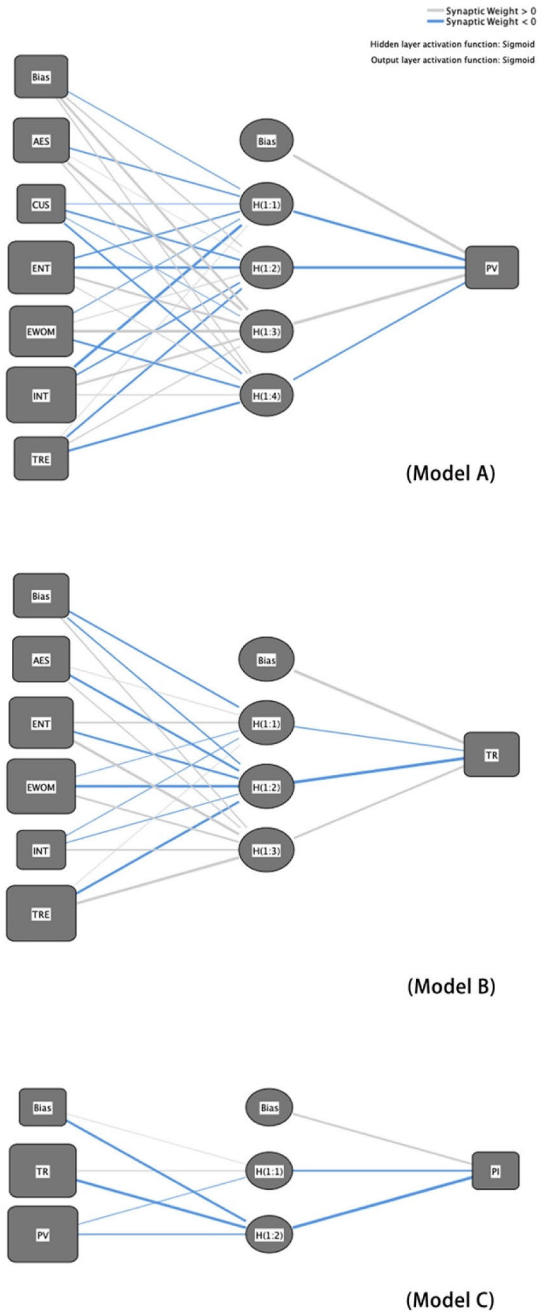

FIGURE 3. The structure of the ANN model (A, B, C).

and 0.180 respectively; while for the testing sets, the final RMSE values were 0.158, 0.181, and 0.168 respectively. Thus, we conclude that the ANN models employed in this study exhibit statistically good model fit and high predictive accuracy [106].

3) SENSITIVITY ANALYSIS: NONLINEAR RELATIONSHIPS

Sensitivity analysis, calculated based on the average importance of independent variables, is useful for predicting dependent variables [107]. Therefore, to assess the predictive strength of each input neuron in this study, a sensitivity analysis was conducted. The method is to divide its average relative importance by the highest relative importance and express the result as a percentage. As shown in Table 10, in Model A, ENT (86.28%) is the most important predictor of PV, followed by INT (81.17%), AES (81.14%), EWOM (81.06%), CUS (61.80%) and TRE (61.36%). In Model B, EWOM (85.94%) is the most important predictor of TR, followed by TRE (84.31%), AES (80.76%), ENT (61.15%) and INT (45.92%). In Model C, PV (99.19%) is the most important predictor of PI, followed by TR (77.48%).

4) COMPARATIVE STUDY OF PLS-SEM AND ANN

In this stage, the influence of each independent variable was ranked according to the results from both PLS-SEM and ANN models. The path coefficients from the SEM analysis were compared with the normalized relative importance values obtained from the ANN models. As shown in Table 11, the evaluation results from both methods are consistent.

In addition, to test the performance of the ANN model, we evaluated the percentage of variance (R^2) described by the ANN model using the formula, where S^2 is the variance of the preference output.

$$R^2 = 1 - \frac{RMSE}{S^2}$$

Through our calculations, we found that ANN can predict 83.6% of the variance in consumer decision-making behavior, which is higher than the 80.4% predicted by SEM, indicating that ANN has stronger predictive capabilities.

V. DISCUSSION

This study aims to explore how AIGC-driven social media marketing influences consumer behavior. External experiential stimuli were categorized into six dimensions: entertainment, interaction, trendiness, customization, electronic word-of-mouth, and aesthetics. Perceived value and trust were grouped as user experience states, while consumer behavior was represented by purchase intention. Based on empirical analyses using PLS-SEM and ANN, several key findings emerged:

First, the results indicate that ENT, INT, TRE, CUS, EWOM, and AES all have significant positive effects on perceived value. Among them, ENT exerts the most substantial influence, which is consistent with the findings of Moslehpour et al. [43] Entertaining content is effective in evoking emotional resonance and positive psychological experiences in consumers, thereby enhancing their perception of overall value. Similarly, INT also demonstrates a significant positive impact on perceived value. This finding contrasts with some previous studies [43], potentially due to differences in sample characteristics or research context. In this study, interactivity not only directly enhances the consumer experience but also contributes to perceived value by strengthening emotional bonds with the brand and increasing informational transparency. In addition, EWOM

TABLE 9. RMSE value for model A, B and C.

ANN	Model A		Model B		Model C	
	Input: ENT、INT、TRE、CUS、EWOM、AES		Input: ENT、INT、TRE、EWOM、AES		Input: PV、TR	
	Output: PV		Output: TR		Output: PI	
	Training RMSE	Testing RMSE	Training RMSE	Testing RMSE	Training RMSE	Testing RMSE
ANN1	0.165	0.126	0.187	0.183	0.178	0.163
ANN2	0.171	0.201	0.195	0.158	0.179	0.166
ANN3	0.154	0.183	0.190	0.159	0.178	0.154
ANN4	0.180	0.143	0.184	0.236	0.186	0.144
ANN5	0.183	0.141	0.186	0.197	0.177	0.166
ANN6	0.174	0.137	0.183	0.209	0.177	0.185
ANN7	0.154	0.183	0.187	0.192	0.182	0.178
ANN8	0.170	0.153	0.191	0.151	0.181	0.167
ANN9	0.169	0.172	0.196	0.162	0.175	0.169
ANN10	0.158	0.143	0.189	0.162	0.185	0.192
Mean	0.168	0.158	0.189	0.181	0.180	0.168
SD	0.010	0.025	0.004	0.027	0.004	0.014

TABLE 10. Sensitivity analysis.

Model A (Output: PV)			Model B (Output: TR)			Model C (Output: PI)		
Variable	Average Importance	Normalized Importance	Variable	Average Importance	Normalized Importance	Variable	Average Importance	Normalized Importance
ENT	0.193	86.28%	ENT	0.170	61.15%	PV	0.564	99.19%
INT	0.181	81.17%	INT	0.124	45.92%	TR	0.436	77.48%
TRE	0.133	61.36%	TRE	0.238	84.31%			
CUS	0.135	61.80%	EWOM	0.241	85.94%			
EWOM	0.180	81.06%	AES	0.229	80.76%			
AES	0.179	81.14%						

TABLE 11. Comparison between PLS-SEM and ANN results.

Path	PLS-SEM results: path coefficient	ANN results: normalized importance (%)	Ranking (PLS-SEM)	Ranking (ANN)	Remark
		Model A (Output: PV)			
ENT ->PV	0.176	86.28	1	1	Match
INT -> PV	0.169	81.17	2	2	Match
TRE -> PV	0.106	61.36	6	6	Match
CUS -> PV	0.109	61.80	5	5	Match
EWOM -> PV	0.138	81.06	4	4	Match
AES -> PV	0.140	81.14	3	3	Match
		Model B (Output: TR)			
ENT ->TR	0.112	61.15	4	4	Match
INT -> TR	0.105	45.92	5	5	Match
TRE -> TR	0.164	84.31	2	2	Match
EWOM -> TR	0.192	85.94	1	1	Match
AES -> TR	0.113	80.76	3	3	Match
		Model C (Output: PI)			
PV ->PI	0.344	99.19	1	1	Match
TR -> PI	0.237	77.48	2	2	Match

significantly influences perceived value, aligning with the findings of Algharabat [64]. When users are exposed to a high volume of positive feedback, they are likely to perceive the product or service as enjoying broad market approval, which in turn elevates their perception of value. Therefore, high-quality content generated by AIGC can be effectively used to support word-of-mouth communication, fostering the development of a positive reputation. Likewise, AES has a positive effect on perceived value, which is consistent with existing research [28]. Visually refined and artistically appealing content generated by AIGC can quickly capture consumer attention and elicit positive emotional responses. Particularly on social media—a highly visual platform—visual aesthetics not only enhance content appeal but also help shape a premium brand image, thereby strengthening consumer value recognition. In contrast, TRE and CUS have relatively weaker effects on perceived value, which aligns with the findings of Firat [108] and Chen and Lin [53]. When consumers first encounter avant-garde and trend-aligned content, they may associate it with high market competitiveness and value. Therefore, when using AIGC to generate trend-based content, it is essential to integrate fashion elements with the brand's core values. Similarly, AI technology enables higher precision in personalized customization, allowing for better alignment with consumers' specific needs, thereby significantly enhancing their overall perceived value.

Secondly, the study reveals that ENT, INT, TRE, EWOM, and AES all have significant positive effects on trust, whereas CUS does not exert a statistically significant impact. Among these, EWOM has the strongest influence on user trust, which aligns with the findings of Lee and Song [109]. When consumers encounter authentic feedback and recommendations from other users on social media, a social proof effect is triggered, reinforcing their sense of trust. Similarly, TRE demonstrates a highly significant impact on user trust, a conclusion also supported by Putra's research [110]. This is particularly relevant for younger consumer groups who seek fashion-forward and novel experiences—trendiness signals foresight and innovation, making it easier for consumers to establish trust in the brand. Moreover, AES positively contributes to trust, consistent with the conclusions of Karvonen [111]. High-quality visual experiences convey a sense of professionalism and premium brand quality, fostering emotional resonance among consumers, which is a key factor in building long-term trust. By contrast, ENT and INT have relatively weaker effects on user trust, a finding in line with the study by Moslehpour et al [43]. Entertaining content on social media can generate positive emotions in consumers, which in turn fosters favorable impressions and trust in the brand. This is further confirmed by Chang and Dong [112] and Jakic et al. [113], who found that continuous consumer interaction on social media enhances informational transparency and provides useful purchasing insights.

This study found that CUS does not have a significant impact on trust, which contradicts the findings of Li and Yeh [27]. We believe this discrepancy reflects the disconnect between "technical customization" and "emotional resonance" in the AIGC context. While AIGC can generate customized content with algorithmic precision, this customization primarily manifests as functional recommendations or content adjustments, lacking the deep emotional connection and individual care inherent in human expression. As a result, its direct role in building brand trust is not evident. Additionally, consumers may not perceive these contents as "customized for me" during use, thereby reducing psychological belonging and the motivation to establish trust.

Finally, both PV and TR exhibit significant positive effects on PI. This indicates that when AIGC-generated social media marketing content effectively conveys product advantages and fosters a positive brand image, consumers are more likely to make purchasing decisions. Among the two, PV has the most substantial impact on consumers' purchase intention, which is consistent with the findings of Wu et al. [114] and Chang and Wang [115] Content driven by AIGC facilitates the delivery of high-quality information, enabling consumers to better perceive tangible benefits, thereby reducing perceived risk and stimulating purchase intention. In the future, businesses can leverage AIGC to enhance the practicality and relevance of information, thereby continuously improving consumers' perceived value. Moreover, TR also has a highly significant influence on purchase intention, as supported by the research of Kim et al. [116] and Chiu et al. [117] Consumers' trust in a brand and its marketing content is a critical driver of purchasing decisions. Brands with a high level of trust are more likely to gain consumer support and increase their purchase intention. Therefore, businesses should utilize AIGC to optimize content presentation, incorporate authentic consumer feedback, strengthen word-of-mouth, and establish enduring trust, thereby improving purchase conversion rates.

VI. IMPLICATIONS AND LIMITATIONS

A. IMPLICATIONS

This study constructs a theoretical framework based on the SOR model to explore how AIGC-driven social media marketing influences consumers' purchase intentions by shaping their perceived value and trust. By employing a dual-stage hybrid approach combining PLS-SEM and ANN, the research more accurately captures the complex interrelationships between variables in the context of AIGC. The findings not only provide theoretical support for future studies but also offer practical, actionable insights for businesses and marketing professionals to foster consumer purchase intentions and promote sustainable brand development.

At the theoretical level, this research fills a gap in the current literature concerning the application of AIGC in social media marketing. Moreover, it expands the dimensional framework of social media marketing research—particularly through the introduction of the aesthetics dimension—shedding light on the role of visual and artistic expression in consumer cognition and trust formation. This contributes to a deeper understanding of how consumers respond to different types of marketing stimuli and provides a comprehensive and forward-looking theoretical model for future research. Such a model is of significant value in explaining the cognitive to decisional transformation process of consumer behavior.

At the practical level, the study offers concrete guidance for brand promotion and strategic marketing. In today's highly competitive landscape, brands must go beyond product features and pricing; the quality and sophistication of marketing content have become key differentiators. Therefore, in marketing content creation, companies should consider adopting a "human-machine collaboration" content strategy. It is recommended that in routine promotional scenarios, 70% of the content be generated by AIGC and 30% by human creators to achieve a balance between efficiency and emotional value. In high-sensitivity areas (such as health and finance), the proportion of human created content should be appropriately increased to maintain brand warmth and credibility. Additionally, when publishing AIGC content, companies should proactively disclose the source of content generation, such as by labeling it with a "generated by AI" prompt or icon, to enhance transparency and user trust while avoiding potential misinformation. Furthermore, the distinct dissemination characteristics of different social media platforms dictate differentiated AIGC application strategies. For example, on visually oriented platforms like Xiaohongshu and TikTok, aesthetically appealing AIGC content is more engaging and shareable; whereas on platforms like Weibo and Zhihu, which prioritize interactivity and information density, increased human intervention and semantic review are necessary to minimize misunderstandings and mitigate user trust risks. Therefore, companies should view AIGC as a collaborative tool to enhance creativity and efficiency, rather than a mere replacement for human labor.

In summary, this study not only enriches the theoretical discourse on the relationship between social media marketing and consumer behavior in the era of AIGC but also provides clear guidance and actionable strategies for enterprises to effectively utilize AIGC in enhancing their marketing effectiveness. Therefore, it holds substantial theoretical innovation value and promising practical application potential.

B. LIMITATIONS AND FUTURE RESEARCH

Although this study has achieved certain theoretical contributions and empirical support, it still has several limitations that should be addressed in future research. First, the data collection was based on specific social media platforms within China, which to some extent limits the external generalizability of the findings. Significant differences exist across countries and regions in terms of AI acceptance, content preferences, and social media usage habits. Therefore, the conclusions of this study are primarily applicable within the context of China's digital marketing environment. Future research should expand data sources and sample coverage, conducting comparative studies across different regions and cultural backgrounds to assess the model's applicability in diverse market settings. Second, since all data were collected online, there may be variations in respondents' interpretations of survey items, potentially affecting data accuracy. To enhance the reliability of future findings, subsequent research should consider increasing the proportion of offline data collection. Finally, this study employed cross-sectional data for path analysis, which, while effective in examining the strength of relationships among variables, cannot fully capture causal mechanisms or temporal dynamics. In the future, we will adopt a longitudinal design or experimental research methods to dynamically observe how AIGC content influences consumers' cognitive, emotional, and behavioral changes across different stages, as well as conduct comparative studies with human-generated content. This will enable us to better capture the underlying mechanisms through which AIGC technology impacts marketing content innovation and the consumer purchase decision-making process.

C. ETHICAL REFLECTIONS AND IMPLICATIONS

With the widespread application of AIGC in digital marketing, related ethical issues have also attracted increasing attention from academia and industry. Although this study focuses on the positive impact of AIGC content on consumer behavior, we also recognize that in situations where the source of content is unclear and the authenticity of information is ambiguous, AIGC may pose ethical risks such as consumer misinformation and damage to trust. Therefore, when using AI technology for marketing, businesses should adhere to the principle of "informed consent," proactively disclose content sources, and avoid overly anthropomorphic designs that may mislead consumers [118], [119]; adopt a human-machine collaborative content production strategy to ensure the ethical compliance and brand consistency of content [120]; and establish unified ethical guidelines and regulatory frameworks to define the boundaries and scope of AIGC usage [121]. Finally, future research should also focus on consumers' perceptions and response mechanisms regarding the ethical nature of AIGC, exploring whether the disclosure of AI-generated content's origin affects consumers' credibility assessments, emotional responses, and behavioral decisions. These issues not only hold significant implications for expanding consumer behavior theory but also provide theoretical foundations for formulating public policies and improving platform governance.

VII. CONCLUSION

This study, grounded in the SOR theory, explores how AIGC-driven social media marketing influences consumers' purchase intentions by enhancing their perceived value and trust. A total of 348 valid responses were collected through an online platform, and a hybrid research approach combining PLS-SEM and ANN methods was employed. The results indicate that out of 14 hypotheses, only one was not supported, and the findings from both the PLS-SEM and ANN models were consistent. Notably, ENT and INT had a highly significant impact on perceived value. High levels of entertainment and strong interactivity evoke emotional resonance among consumers, thereby strengthening their recognition of product value. Among all variables, EWOM had the most significant influence on user trust. Positive electronic word-of-mouth generates a favorable social effect that helps reinforce consumers' trust in the brand. In addition, the newly introduced aesthetic dimension was found to significantly affect both perceived value and trust. High-quality visual design conveys professionalism and a sense of premium quality, thereby enhancing the overall effect and appeal of the marketing content, which in turn encourages consumer behavioral intentions. Ultimately, these findings offer valuable insights for the development of AIGC-based social media marketing. Strengthening the six key dimensions can effectively enhance consumers' perceived value and trust, thereby facilitating their decision-making behavior. This not only provides theoretical support and practical guidance for optimizing content strategies and building brand trust in digital marketing but also lays a solid foundation for further exploration of the deep integration of AIGC technology in marketing as well as brand sustainability.

REFERENCES

[1] V. Kumar, J. B. Choi, and M. Greene, ''Synergistic effects of social media and traditional marketing on brand sales: Capturing the time-varying effects,'' *J. Acad. Marketing Sci.*, vol. 45, no. 2, pp. 268–288, Mar. 2017, doi: 10.1007/s11747-016-0484-7.

[2] S.-F. Wang and C.-C. Chen, ''Explore the driving factors of designers' AIGC usage behavior based on SOR framework,'' *Frontiers Comput. Sci.*, vol. 6, Sep. 2024, Art. no. 1417016, doi: 10.3389/fcomp.2024.1417016.

[3] M. Xu, H. Du, D. Niyato, J. Kang, Z. Xiong, S. Mao, Z. Han, A. Jamalipour, D. I. Kim, X. Shen, V. C. M. Leung, and H. V. Poor, ''Unleashing the power of edge-cloud generative AI in mobile networks: A survey of AIGC services,'' *IEEE Commun. Surveys Tuts.*, vol. 26, no. 2, pp. 1127–1170, 2nd Quart., 2024, doi: 10.1109/COMST.2024.3353265.

[4] Y. Cao, S. Li, Y. Liu, Z. Yan, Y. Dai, P. S. Yu, and L. Sun, ''A comprehensive survey of AI-generated content (AIGC): A history of generative AI from GAN to ChatGPT,'' 2023, *arXiv:2303.04226*.

[5] L. Luo, ''The impact and implications of artificial intelligent-generated content (AIGC) on marketing campaigns based on social media,'' in *Proc. SHS Web Conf.*, vol. 207, 2024, p. 2004, doi: 10.1051/shsconf/202420702004.

[6] K. Heinonen, ''Consumer activity in social media: Managerial approaches to consumers' social media behavior,'' *J. Consum. Behav.*, vol. 10, no. 6, pp. 356–364, Nov. 2011, doi: 10.1002/cb.376.

[7] Y. J. Purnomo, ''Digital marketing strategy to increase sales conversion on e-commerce platforms,'' *J. Contemp. Admin. Manage.*, vol. 1, no. 2, pp. 54–62, Aug. 2023, doi: 10.61100/adman.v1i2.23.

[8] G. Tsimonis and S. Dimitriadis, ''Brand strategies in social media,'' *Marketing Intell. Planning*, vol. 32, no. 3, pp. 328–344, Apr. 2014, doi: 10.1108/mip-04-2013-0056.

[9] N. Hong, ''Digital-media-based interaction and dissemination of traditional culture integrating using social media data analytics,'' *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–11, May 2022, doi: 10.1155/2022/5846451.

[10] D. Du, Y. Zhang, and J. Ge, ''Effect of AI generated content advertising on consumer engagement,'' in *Proc. Int. Conf. Hum.-Comput. Interact.*, 2023, pp. 121–129.

[11] A. P. O. Yudhi Ari Wijaya, S. Sulistiyani, J. Pudjowati, T. S. Kartikawati, N. Kurniasih, and A. Purwanto, ''The role of social media marketing, entertainment, customization, trendiness, interaction and word-of-mouth on purchase intention: An empirical study from Indonesian smartphone consume,'' *Int. J. Data Netw. Sci.*, vol. 5, no. 3, p. 3, Jun. 2021.

[12] M. L. Cheung, G. Pires, and P. J. Rosenberger, ''The influence of perceived social media marketing elements on consumer–brand engagement and brand knowledge,'' *Asia Pacific J. Marketing Logistics*, vol. 32, no. 3, pp. 695–720, Mar. 2020, doi: 10.1108/apjml-04-2019-0262.

[13] A. Z. Haidar, ''The role of visual design in building brand image to increase consumer loyalty in the digital era,'' *Sci. Develop. J.*, vol. 1, no. 2, p. 2, Oct. 2024.

[14] Q. Liu, X. Wang, X. Xie, W. Wang, and X. Lu, ''Innovative design research on Jiaodong Peninsula's marine folk culture based on AIGC,'' *Int. J. Contemp. Humanities*, vol. 8, no. 1, pp. 17–27, Oct. 2024, doi: 10.62531/14270.2024.32910.723.

[15] P. Strickland, W. Frost, K. M. Williams, and J. Laing, ''The acceptance or rejection of social media: A case study of rochford winery estate in Victoria, Australia,'' *Tourism Culture Commun.*, vol. 13, no. 1, pp. 19–27, Jan. 2013, doi: 10.3727/109830413x13769180530602.

[16] Y.-T. Chang, H. Yu, and H.-P. Lu, ''Persuasive messages, popularity cohesion, and message diffusion in social media marketing,'' *J. Bus. Res.*, vol. 68, no. 4, pp. 777–782, Apr. 2015, doi: 10.1016/j.jbusres.2014.11.027.

[17] R. S. Ebrahim, ''The role of trust in understanding the impact of social media marketing on brand equity and brand loyalty,'' *J. Relationship Marketing*, vol. 19, no. 4, pp. 287–308, Oct. 2020, doi: 10.1080/15332667.2019.1705742.

[18] A. J. Kim and E. Ko, ''Do social media marketing activities enhance customer equity? An empirical study of luxury fashion brand,'' *J. Bus. Res.*, vol. 65, no. 10, pp. 1480–1486, Oct. 2012, doi: 10.1016/j.jbusres.2011.10.014.

[19] A. Wibowo, S.-C. Chen, U. Wiangin, Y. Ma, and A. Ruangkanjanases, ''Customer behavior as an outcome of social media marketing: The role of social media marketing activity and customer experience,'' *Sustainability*, vol. 13, no. 1, p. 189, Dec. 2020, doi: 10.3390/su13010189.

[20] J. R. Hanaysha, ''Impact of social media marketing, price promotion, and corporate social responsibility on customer satisfaction,'' *Jindal J. Bus. Res.*, vol. 6, no. 2, pp. 132–145, Dec. 2017, doi: 10.1177/2278682117715359.

[21] M. L. Cheung, G. D. Pires, P. J. Rosenberger, W. K. S. Leung, and H. Ting, ''Investigating the role of social media marketing on value co-creation and engagement: An empirical study in China and Hong Kong,'' *Australas. Marketing J.*, vol. 29, no. 2, pp. 118–131, May 2021, doi: 10.1016/j.ausmj.2020.03.006.

[22] M. Daya, Y. M. Siagian, and K. Kurniawati, ''Influence social media marketing activities against brand loyalty directly or through consumer satisfaction and brand equity on the largest e-commerce in Indonesia,'' *Jurnal Aplikasi Manajemen*, vol. 20, no. 4, pp. 865–877, Dec. 2022, doi: 10.21776/ub.jam.2022.020.04.09.

[23] E.-J. Seo and J.-W. Park, ''A study on the effects of social media marketing activities on brand equity and customer response in the airline industry,'' *J. Air Transp. Manage.*, vol. 66, pp. 36–41, Jan. 2018, doi: 10.1016/j.jairtraman.2017.09.014.

[24] K. Y. Koay, D. L. T. Ong, K. L. Khoo, and H. J. Yeoh, ''Perceived social media marketing activities and consumer-based brand equity: Testing a moderated mediation model,'' *Asia Pacific J. Marketing Logistics*, vol. 33, no. 1, pp. 53–72, Feb. 2020, doi: 10.1108/apjml-07-2019-0453.

[25] X. Chen and H. Qasim, ''Does E-brand experience matter in the consumer market? Explaining the impact of social media marketing activities on consumer-based brand equity and love,'' *J. Consum. Behav.*, vol. 20, no. 5, pp. 1065–1077, Sep. 2021, doi: 10.1002/cb.1915.

[26] U. Bhandari, K. Chang, and T. Neben, ''Understanding the impact of perceived visual aesthetics on user evaluations: An emotional perspective,'' *Inf. Manage.*, vol. 56, no. 1, pp. 85–93, Jan. 2019, doi: 10.1016/j.im.2018.07.003.

[27] Y.-M. Li and Y.-S. Yeh, ''Increasing trust in mobile commerce through design aesthetics,'' *Comput. Hum. Behav.*, vol. 26, no. 4, pp. 673–684, Jul. 2010, doi: 10.1016/j.chb.2010.01.004.

[28] A. Hussain, D. H. Ting, and M. Mazhar, ''Driving consumer value co-creation and purchase intention by social media advertising value,'' *Frontiers Psychol.*, vol. 13, Feb. 2022, doi: 10.3389/fpsyg.2022.800206.

[29] H. Lv and K. Wang, ''A study of AIGC-enabled international marketing,'' in *Proc. Guangdong-Hong Kong-Macao Greater Bay Area Int. Conf. Digit. Economy Artif. Intell.*, Jul. 2024, pp. 179–191, doi: 10.1145/3675417.3675447.

[30] Y. Cao, S. Li, Y. Liu, Z. Yan, Y. Dai, P. Yu, and L. Sun, ''A survey of AI-generated content (AIGC),'' *ACM Comput. Surveys*, vol. 57, no. 5, pp. 1–38, Jan. 2025, doi: 10.1145/3704262.

[31] E. Constantinides, ''Foundations of social media marketing,'' *Proc.-Social Behav. Sci.*, vol. 148, pp. 40–57, Aug. 2014, doi: 10.1016/j.sbspro.2014.07.016.

[32] Z. Fang and C. Zhang, ''McDonald's social media marketing strategy in the AIGC era,'' FUDAN, Tech. Rep., Oct. 2024, pp. 1–16, doi: 10.12156/FUDAN.CASE202424007.

[33] J. Wu, W. Gan, Z. Chen, S. Wan, and H. Lin, ''AI-generated content (AIGC): A survey,'' 2023, *arXiv:2304.06632*.

[34] Y. Mu, ''Research on the dissemination effect of AIGC-generated content on new media platforms: A case study of Xiaohongshu,'' *Media Stud.*, vol. 1, no. 2, pp. 1–5, Sep. 2024, doi: 10.70267/22c1r584.

[35] A. Mehrabian and J. A. Russell, ''The basic emotional impact of environments,'' *Perceptual Motor Skills*, vol. 38, no. 1, pp. 283–301, Feb. 1974, doi: 10.2466/pms.1974.38.1.283.

[36] E. Sherman, A. Mathur, and R. B. Smith, ''Store environment and consumer purchase behavior: Mediating role of consumer emotions,'' *Psychol. Marketing*, vol. 14, no. 4, pp. 361–378, Jul. 1997, doi: 10.1002/(SICI)1520-6793(199707)14:4<361::AID-MAR4>3.0.CO;2-7.

[37] M. S. Hossain and M. F. Rahman, ''Detection of potential customers' empathy behavior towards customers' reviews,'' *J. Retailing Consum. Services*, vol. 65, Mar. 2022, Art. no. 102881, doi: 10.1016/j.jretconser.2021.102881.

[38] K. Y. Koay, C. W. Cheah, and S. W.-U. Goon, "How do perceived social media marketing activities foster purchase intentions? A multiple sequential mediation model," *J. Global Marketing*, vol. 36, no. 3, pp. 210–224, May 2023, doi: 10.1080/08911762.2023.2207072.

[39] S. Kumar and J.-K. Hsieh, "How social media marketing activities affect brand loyalty? Mediating role of brand experience," *Asia Pacific J. Marketing Logistics*, vol. 36, no. 10, pp. 2300–2323, Apr. 2024, doi: 10.1108/apjml-09-2023-0900.

[40] A. Sharma, A. Fadahunsi, H. Abbas, and V. K. Pathak, "A multi-analytic approach to predict social media marketing influence on consumer purchase intention," *J. Indian Bus. Res.*, vol. 14, no. 2, pp. 125–149, Jan. 2022, doi: 10.1108/jibr-08-2021-0313.

[41] L. Dessart, C. Veloutsou, and A. Morgan-Thomas, "Consumer engagement in online brand communities: A social media perspective," *J. Product Brand Manage.*, vol. 24, no. 1, pp. 28–42, Mar. 2015, doi: 10.1108/jpbm-06-2014-0635.

[42] C. Ashley and T. Tuten, "Creative strategies in social media marketing: An exploratory study of branded social content and consumer engagement," *Psychol. Marketing*, vol. 32, no. 1, pp. 15–27, Jan. 2015, doi: 10.1002/mar.20761.

[43] M. Moslehpour, A. Dadvari, W. Nugroho, and B.-R. Do, "The dynamic stimulus of social media marketing on purchase intention of Indonesian airline products and services," *Asia Pacific J. Marketing Logistics*, vol. 33, no. 2, pp. 561–583, May 2020, doi: 10.1108/apjml-07-2019-0442.

[44] I. Hidayanti, L. E. Herman, and N. Farida, "Engaging customers through social media to improve industrial product development: The role of customer co-creation value," *J. Relationship Marketing*, vol. 17, no. 1, pp. 17–28, Jan. 2018, doi: 10.1080/15332667.2018.1440137.

[45] J. Bowen, "Trends affecting social media: Implications for practitioners and researchers," *Worldwide Hospitality Tourism Themes*, vol. 7, no. 3, pp. 221–228, Jun. 2015, doi: 10.1108/whatt-04-2015-0021.

[46] R. Algharabat, N. P. Rana, A. A. Alalwan, A. Baabdullah, and A. Gupta, "Investigating the antecedents of customer brand engagement and consumer-based brand equity in social media," *J. Retailing Consum. Services*, vol. 53, Mar. 2020, Art. no. 101767, doi: 10.1016/j.jretconser.2019.01.016.

[47] P. Purwanto and K. Kuswandi, "Effects of flexibility and interactivity on the perceived value of and satisfaction with e-commerce (evidence from Indonesia)," *Market-Tržište*, vol. 29, no. 2, pp. 139–159, Dec. 2017, doi: 10.22598/mt/2017.29.2.139.

[48] M. Naaman, H. Becker, and L. Gravano, "Hip and trendy: Characterizing emerging trends on Twitter," *J. Amer. Soc. Inf. Sci. Technol.*, vol. 62, no. 5, pp. 902–918, May 2011, doi: 10.1002/asi.21489.

[49] B. Godey, A. Manthiou, D. Pederzoli, J. Rokka, G. Aiello, R. Donvito, and R. Singh, "Social media marketing efforts of luxury brands: Influence on brand equity and consumer behavior," *J. Bus. Res.*, vol. 69, no. 12, pp. 5833–5841, Dec. 2016, doi: 10.1016/j.jbusres.2016.04.181.

[50] M. A. A. Z. Chafidon, M. Margono, and S. Sunaryo, "Social media marketing on purchase intention through mediated variables of perceived value and perceived risk," *Interdiscipl. Social Stud.*, vol. 1, no. 9, pp. 1182–1195, Jun. 2022, doi: 10.55324/iss.v1i9.228.

[51] R. A. Kakar, S. Shahzad, and L. Khoso, "The impact of social media marketing dimensions: Interaction, entertainment, customization, trendiness, and word of mouth on purchase intention with the mediating role of brand image and brand trust for smartphone users in Quetta city," *Int. J. Contemp. Issues Social Sci.*, vol. 2, no. 4, pp. 1249–1260, 2023.

[52] Y.-Q. Zhu and H.-G. Chen, "Social media and human need satisfaction: Implications for social media marketing," *Bus. Horizons*, vol. 58, no. 3, pp. 335–345, May 2015, doi: 10.1016/j.bushor.2015.01.006.

[53] S.-C. Chen and C.-P. Lin, "Understanding the effect of social media marketing activities: The mediation of social identification, perceived value, and satisfaction," *Technological Forecasting Social Change*, vol. 140, pp. 22–32, Mar. 2019, doi: 10.1016/j.techfore.2018.11.025.

[54] D. Shin, J. H. Song, and A. Biswas, "Electronic word-of-mouth (eWOM) generation in new media platforms: The role of regulatory focus and collective dissonance," *Marketing Lett.*, vol. 25, no. 2, pp. 153–165, Jun. 2014, doi: 10.1007/s11002-013-9248-z.

[55] F. A. Buttle, "Word of mouth: Understanding and managing referral marketing," *J. Strategic Marketing*, vol. 6, no. 3, pp. 241–254, Jan. 1998, doi: 10.1080/096525498346658.

[56] W. Duan, B. Gu, and A. Whinston, "The dynamics of online word-of-mouth and product sales—An empirical investigation of the movie industry," *J. Retailing*, vol. 84, no. 2, pp. 233–242, Jun. 2008, doi: 10.1016/j.jretai.2008.04.005.

[57] N. F. Awad and A. Ragowsky, "Establishing trust in electronic commerce through online word of mouth: An examination across genders," *J. Manage. Inf. Syst.*, vol. 24, no. 4, pp. 101–121, Apr. 2008, doi: 10.2753/mis0742-1222240404.

[58] A. J. Kim and E. Ko, "Impacts of luxury fashion brand's social media marketing on customer relationship and purchase intention," *J. Global Fashion Marketing*, vol. 1, no. 3, pp. 164–171, Aug. 2010, doi: 10.1080/20932685.2010.10593068.

[59] C. Liu, Z. Bao, and C. Zheng, "Exploring consumers' purchase intention in social commerce: An empirical study based on trust, argument quality, and social presence," *Asia Pacific J. Marketing Logistics*, vol. 31, no. 2, pp. 378–397, Mar. 2019, doi: 10.1108/apjml-05-2018-0170.

[60] V. A. Zeithaml, "Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence," *J. Marketing*, vol. 52, no. 3, pp. 2–22, Jul. 1988, doi: 10.1177/002224298805200302.

[61] B. Chan, E. Purwanto, and T. Hendratono, "Social media marketing, perceived service quality, consumer trust and online purchase intentions," *Technol. Rep. Kansai Univ.*, vol. 62, no. 10, pp. 6265–6272, 2020.

[62] V. A. Nasir, A. C. Keserel, O. E. Surgit, and M. Nalbant, "Segmenting consumers based on social media advertising perceptions: How does purchase intention differ across segments?" *Telematics Informat.*, vol. 64, Nov. 2021, Art. no. 101687, doi: 10.1016/j.tele.2021.101687.

[63] A. A. Alalwan, "Investigating the impact of social media advertising features on customer purchase intention," *Int. J. Inf. Manage.*, vol. 42, pp. 65–77, Oct. 2018, doi: 10.1016/j.ijinfomgt.2018.06.001.

[64] R. S. Algharabat, "Linking social media marketing activities with brand love: The mediating role of self-expressive brands," *Kybernetes*, vol. 46, no. 10, pp. 1801–1819, Nov. 2017, doi: 10.1108/k-04-2017-0130.

[65] M. L. Cheung, G. Pires, P. J. Rosenberger, W. K. S. Leung, and M. K. Chang, "The role of social media elements in driving co-creation and engagement," *Asia Pacific J. Marketing Logistics*, vol. 33, no. 10, pp. 1994–2018, Mar. 2021, doi: 10.1108/apjml-03-2020-0176.

[66] M. S. Balaji and S. K. Roy, "Value co-creation with Internet of Things technology in the retail industry," *J. Marketing Manage.*, vol. 33, nos. 1–2, pp. 7–31, Jan. 2017, doi: 10.1080/0267257x.2016.1217914.

[67] H. O'Brien and P. Cairns, "An empirical evaluation of the user engagement scale (UES) in online news environments," *Inf. Process. Manage.*, vol. 51, no. 4, pp. 413–427, Jul. 2015, doi: 10.1016/j.ipm.2015.03.003.

[68] Y. Yang, Z. Khan, and Y. Zhang, "The influence of social media marketing on apparel brands' customers' satisfaction: The mediation of perceived value," *Asian Acad. Manage. J.*, vol. 25, no. 2, Dec. 2020, Art. no. 2, doi: 10.21315/aamj2020.25.2.7.

[69] Z. B. Ramadan, I. Abosag, and V. Zabkar, "All in the value: The impact of brand and social network relationships on the perceived value of customer endorsed Facebook advertising," *Eur. J. Marketing*, vol. 52, nos. 7–8, pp. 1704–1726, Jun. 2018, doi: 10.1108/ejm-03-2017-0189.

[70] C.-F. Chen and F.-S. Chen, "Experience quality, perceived value, satisfaction and behavioral intentions for heritage tourists," *Tourism Manage.*, vol. 31, no. 1, pp. 29–35, Feb. 2010, doi: 10.1016/j.tourman.2009.02.008.

[71] I. B. Hong and H. S. Cha, "The mediating role of consumer trust in an online merchant in predicting purchase intention," *Int. J. Inf. Manage.*, vol. 33, no. 6, pp. 927–939, Dec. 2013, doi: 10.1016/j.ijinfomgt.2013.08.007.

[72] P. A. Pavlou, "Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model," *Int. J. Electron. Commerce*, vol. 7, no. 3, pp. 101–134, Apr. 2003, doi: 10.1080/10864415.2003.11044275.

[73] R. G. Duffett, "Influence of social media marketing communications on young consumers' attitudes," *Young Consumers*, vol. 18, no. 1, pp. 19–39, Apr. 2017, doi: 10.1108/yc-07-2016-00622.

[74] A. Chrisniyanti and C. T. Fah, "The impact of social media marketing on purchase intention of skincare products among Indonesian young adults," *Eurasian J. Social Sci.*, vol. 10, no. 2, pp. 68–90, 2022, doi: 10.15604/ejss.2022.10.02.001.

[75] A. Emini and J. Zeqiri, "Social media marketing and purchase intention: Evidence from Kosovo," *Ekonomska misao i praksa*, vol. 30, no. 2, pp. 475–492, Dec. 2021, doi: 10.17818/emip/2021/2.8.

[76] M. Naderifar, H. Goli, and F. Ghaljaie, "Snowball sampling: A purposeful method of sampling in qualitative research," *Strides Develop. Med. Educ.*, vol. 14, no. 3, Sep. 2017, doi: 10.5812/sdme.67670.

[77] R. W. Emerson, "Convenience sampling, random sampling, and snowball sampling: How does sampling affect the validity of research?" *J. Vis. Impairment Blindness*, vol. 109, no. 2, pp. 164–168, Mar. 2015, doi: 10.1177/0145482x1510900215.

[78] R. Hill and W. P. Hamilton. (1998). *Wht Sample Size is 'Enough' in Internet Survey Research?*. Accessed: Dec. 12, 2024. [Online]. Available: https://www.semanticscholar.org/paper/WHAT-SAMPLE-SIZE-is-%22ENOUGH%22-in-INTERNET-SURVEY-Hill-Hamilton/8813 4689f8eb30296cd67bf8f11c0a0856927ee6

[79] A. Alwosheel, S. van Cranenburgh, and C. G. Chorus, "Is your dataset big enough? Sample size requirements when using artificial neural networks for discrete choice analysis," *J. Choice Model.*, vol. 28, pp. 167–182, Sep. 2018, doi: 10.1016/j.jocm.2018.07.002.

[80] L.-W. Wong, L.-Y. Leong, J.-J. Hew, G. W.-H. Tan, and K.-B. Ooi, "Time to seize the digital evolution: Adoption of blockchain in operations and supply chain management among Malaysian SMEs," *Int. J. Inf. Manage.*, vol. 52, Jun. 2020, Art. no. 101997, doi: 10.1016/j.ijinfomgt.2019.08.005.

[81] A. Almufarreh, "Determinants of students' satisfaction with AI tools in education: A PLS-SEM-ANN approach," *Sustainability*, vol. 16, no. 13, p. 5354, Jun. 2024, doi: 10.3390/su16135354.

[82] X.-M. Loh, V.-H. Lee, and L.-Y. Leong, "Mobile-lizing continuance intention with the mobile expectation-confirmation model: An SEM-ANN-NCA approach," *Expert Syst. Appl.*, vol. 205, Nov. 2022, Art. no. 117659, doi: 10.1016/j.eswa.2022.117659.

[83] T. Dang Quan, G. Wei-Han Tan, E. C.-X. Aw, T.-H. Cham, S. Basu, and K.-B. Ooi, "Can you resist the virtual temptations? Unveiling impulsive buying in metaverse retail," *Asia Pacific J. Marketing Logistics*, vol. 36, no. 10, pp. 2259–2280, Mar. 2024, doi: 10.1108/apjml-09-2023-0911.

[84] L.-T. Nguyen, Y. K. Dwivedi, G. W.-H. Tan, E. C.-X. Aw, P.-S. Lo, and K.-B. Ooi, "Unlocking pathways to mobile payment satisfaction and commitment," *J. Comput. Inf. Syst.*, vol. 63, no. 4, pp. 998–1015, Jul. 2023, doi: 10.1080/08874417.2022.2119444.

[85] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to use and how to report the results of PLS-SEM," *Eur. Bus. Rev.*, vol. 31, no. 1, pp. 2–24, Jan. 2019, doi: 10.1108/ebr-11-2018-0203.

[86] K. Akram, A. Saeed, S. Bresciani, S. U. Rehman, and A. Ferraris, "Factors affecting environmental performance during the COVID-19 period in the leather industry: A moderated-mediation approach," *J. Competitiveness*, vol. 14, no. 1, pp. 5–22, Mar. 2022, doi: 10.7441/joc.2022.01.01.

[87] P. M. Podsakoff, S. B. MacKenzie, J.-Y. Lee, and N. P. Podsakoff, "Common method biases in behavioral research: A critical review of the literature and recommended remedies," *J. Appl. Psychol.*, vol. 88, no. 5, pp. 879–903, 2003, doi: 10.1037/0021-9010.88.5.879.

[88] W.-L. Shiau and M. M. Luo, "Factors affecting online group buying intention and satisfaction: A social exchange theory perspective," *Comput. Hum. Behav.*, vol. 28, no. 6, pp. 2431–2444, Nov. 2012, doi: 10.1016/j.chb.2012.07.030.

[89] S. Tehseen, T. Ramayah, and S. Sajilan, "Testing and controlling for common method variance: A review of available methods," *J. Manage. Sci.*, vol. 4, no. 2, pp. 142–168, Mar. 2017, doi: 10.20547/jms.2014.1704202.

[90] A. Leguina, "A primer on partial least squares structural equation modeling (PLS-SEM)," *Int. J. Res. Method Educ.*, vol. 38, no. 2, pp. 220–221, Apr. 2015. [Online]. Available: https://www.tandfonline.com/doi/abs/10.1080/1743727X.2015.1005806

[91] H. Taherdoost, "Validity and reliability of the research instrument; how to test the validation of a questionnaire/survey in a research," *Int. J. Academic Res. Manag.*, vol. 5, pp. 28–36, 2016. Accessed: Sep. 3, 2024. [Online]. Available: https://hal.science/hal-02546799

[92] O. Bolarinwa, "Principles and methods of validity and reliability testing of questionnaires used in social and health science researches," *Nigerian Postgraduate Med. J.*, vol. 22, no. 4, p. 195, Dec. 2015, doi: 10.4103/1117-1936.173959.

[93] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *J. Marketing Res.*, vol. 18, no. 1, pp. 39–50, Feb. 1981, doi: 10.1177/002224378101800104.

[94] R. P. Bagozzi and Y. Yi, "On the evaluation of structural equation models," *J. Acad. Marketing Sci.*, vol. 16, no. 1, pp. 74–94, Mar. 1988, doi: 10.1007/bf02723327.

[95] D. Child, *The Essentials of Factor Analysis*. London, U.K.: A. & C. Black, 2006.

[96] K. Lee, K. Y. Lee, and L. Sheehan, "Hey alexa! A magic spell of social glue: Sharing a smart voice assistant speaker and its impact on users' perception of group harmony," *Inf. Syst. Frontiers*, vol. 22, no. 3, pp. 563–583, Jun. 2020, doi: 10.1007/s10796-019-09975-1.

[97] J. F. Hair, Jr., G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. P. Danks, and S. Ray, *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*. Cham, Switzerland: Springer, 2021, doi: 10.1007/978-3-030-80519-7.

[98] M. Sharma, S. Joshi, S. Luthra, and A. Kumar, "Impact of digital assistant attributes on millennials' purchasing intentions: A multi-group analysis using PLS-SEM, artificial neural network and fsQCA," *Inf. Syst. Frontiers*, vol. 26, no. 3, pp. 943–966, Jun. 2024, doi: 10.1007/s10796-022-10339-5.

[99] K. Berahmand, F. Saberi-Movahed, R. Sheikhpour, Y. Li, and M. Jalili, "A comprehensive survey on spectral clustering with graph structure learning," 2025, *arXiv:2501.13597*.

[100] K. Berahmand, F. Daneshfar, E. S. Salehi, Y. Li, and Y. Xu, "Autoencoders and their applications in machine learning: A survey," *Artif. Intell. Rev.*, vol. 57, no. 2, p. 28, Feb. 2024, doi: 10.1007/s10462-023-10662-6.

[101] L.-Y. Leong, T.-S. Hew, K.-B. Ooi, and J. Wei, "Predicting mobile wallet resistance: A two-staged structural equation modeling-artificial neural network approach," *Int. J. Inf. Manage.*, vol. 51, Apr. 2020, Art. no. 102047, doi: 10.1016/j.ijinfomgt.2019.102047.

[102] A.-F. Lim, V.-H. Lee, P.-Y. Foo, K.-B. Ooi, and G. Wei-Han Tan, "Unfolding the impact of supply chain quality management practices on sustainability performance: An artificial neural network approach," *Supply Chain Management: Int. J.*, vol. 27, no. 5, pp. 611–624, Jun. 2021, doi: 10.1108/scm-03-2021-0129.

[103] A. Sharma, Y. K. Dwivedi, V. Arya, and M. Q. Siddiqui, "Does SMS advertising still have relevance to increase consumer purchase intention? A hybrid PLS-SEM-neural network modelling approach," *Comput. Hum. Behav.*, vol. 124, Nov. 2021, Art. no. 106919, doi: 10.1016/j.chb.2021.106919.

[104] M. S. Talukder, G. Sorwar, Y. Bao, J. U. Ahmed, and M. A. S. Palash, "Predicting antecedents of wearable healthcare technology acceptance by elderly: A combined SEM-neural network approach," *Technological Forecasting Social Change*, vol. 150, Jan. 2020, Art. no. 119793, doi: 10.1016/j.techfore.2019.119793.

[105] G. A.-M. Taufiq-Hail, A. Sarea, and I. T. Hawaldar, "The impact of self-efficacy on feelings and task performance of academic and teaching staff in Bahrain during COVID-19: Analysis by SEM and ANN," *J. Open Innov., Technol., Market, Complex.*, vol. 7, no. 4, p. 224, Dec. 2021, doi: 10.3390/joitmc7040224.

[106] L.-W. Wong, G. W.-H. Tan, V.-H. Lee, K.-B. Ooi, and A. Sohal, "Unearthing the determinants of blockchain adoption in supply chain management," *Int. J. Prod. Res.*, vol. 58, no. 7, pp. 2100–2123, Apr. 2020, doi: 10.1080/00207543.2020.1730463.

[107] V.-H. Lee, J.-J. Hew, L.-Y. Leong, G. W.-H. Tan, and K.-B. Ooi, "Wearable payment: A deep learning-based dual-stage SEM-ANN analysis," *Expert Syst. Appl.*, vol. 157, Nov. 2020, Art. no. 113477, doi: 10.1016/j.eswa.2020.113477.

[108] D. Firat, "YouTube advertising value and its effects on purchase intention," *J. Global Bus. Insights*, vol. 4, no. 2, pp. 141–155, 2019, doi: 10.5038/2640-6489.4.2.1097.

[109] Y. L. Lee and S. Song, "An empirical investigation of electronic word-of-mouth: Informational motive and corporate response strategy," *Comput. Hum. Behav.*, vol. 26, no. 5, pp. 1073–1080, Sep. 2010, doi: 10.1016/j.chb.2010.03.009.

[110] E. Y. Putra, W. Gamelia, and H. H. Ariyanto, "Analysis of local fashion competition readiness through consumer shopping intention: A media and brand authenticity approach," *Jurnal Manajemen dan Kewirausahaan*, vol. 12, no. 2, pp. 207–221, Feb. 2025, doi: 10.26905/jmdk.v12i2.14083.

[111] K. Karvonen, "The beauty of simplicity," in *Proc. Conf. Universal Usability-CUU*, Nov. 2000, pp. 85–90, doi: 10.1145/355460.355478.

[112] Y. P. Chang and X. B. Dong, "Research on the impact of consumer interaction behaviour on purchase intention in an SNS environment: Evidence from China," *Inf. Develop.*, vol. 32, no. 3, pp. 496–508, Jun. 2016, doi: 10.1177/0266666914556821.

[113] A. Jakic, M. O. Wagner, and A. Meyer, "The impact of language style accommodation during social media interactions on brand trust," *J. Service Manage.*, vol. 28, no. 3, pp. 418–441, Jun. 2017, doi: 10.1108/josm-12-2016-0325.

[114] L.-Y. Wu, K.-Y. Chen, P.-Y. Chen, and S.-L. Cheng, "Perceived value, transaction cost, and repurchase-intention in online shopping: A relational exchange perspective," *J. Bus. Res.*, vol. 67, no. 1, pp. 2768–2776, Jan. 2014, doi: 10.1016/j.jbusres.2012.09.007.

[115] H. Hsin Chang and H.-W. Wang, "The moderating effect of customer perceived value on online shopping behaviour," *Online Inf. Rev.*, vol. 35, no. 3, pp. 333–359, Jun. 2011, doi: 10.1108/14684521111151414.

[116] H.-W. Kim, Y. Xu, and S. Gupta, "Which is more important in Internet shopping, perceived price or trust?" *Electron. Commerce Res. Appl.*, vol. 11, no. 3, pp. 241–252, May 2012, doi: 10.1016/j.elerap.2011.06.003.

[117] C.-M. Chiu, M.-H. Hsu, H. Lai, and C.-M. Chang, "Re-examining the influence of trust on online repeat purchase intention: The moderating role of habit and its antecedents," *Decis. Support Syst.*, vol. 53, no. 4, pp. 835–845, Nov. 2012, doi: 10.1016/j.dss.2012.05.021.

[118] C. P. Kirk and J. Givi, "The AI-authorship effect: Understanding authenticity, moral disgust, and consumer responses to AI-generated marketing communications," *J. Bus. Res.*, vol. 186, Jan. 2025, Art. no. 114984, doi: 10.1016/j.jbusres.2024.114984.

[119] U. Paschen, C. Pitt, and J. Kietzmann, "Artificial intelligence: Building blocks and an innovation typology," *Bus. Horizons*, vol. 63, no. 2, pp. 147–155, Mar. 2020, doi: 10.1016/j.bushor.2019.10.004.

[120] D. Gursoy, O. H. Chi, L. Lu, and R. Nunkoo, "Consumers acceptance of artificially intelligent (AI) device use in service delivery," *Int. J. Inf. Manage.*, vol. 49, pp. 157–169, Dec. 2019, doi: 10.1016/j.ijinfomgt.2019.03.008.

[121] R. Vinuesa, H. Azizpour, I. Leite, M. Balaam, V. Dignum, S. Domisch, A. Felländer, S. D. Langhans, M. Tegmark, and F. F. Nerini, "The role of artificial intelligence in achieving the sustainable development goals," *Nature Commun.*, vol. 11, no. 1, p. 233, Jan. 2020, doi: 10.1038/s41467-019-14108-y.

JIACHENG LUO was born in Changsha, Hunan, in 1998. She received the B.A. degree in environmental design from Hunan University of Science and Technology, in 2019, and the M.A. degree in product design from Kunming University of Science and Technology, in 2022. She is currently pursuing the Ph.D. degree in interaction design with Kookmin University, Seoul, South Korea. She has published several papers in journals and conference proceedings. Her current research interests include AIGC, artificial intelligence, service design, and smart health care.

KEWEI ZHANG was born in Kunming, Yunnan, in 1998. He received the B.A. degree from Shanghai University of Engineering Science, in 2019, and the M.A. degree in product and service design from the Nuova Accademia di Belle Arti, Italy, in 2022. He is currently pursuing the Ph.D. degree in interaction design with Kookmin University, Seoul, South Korea. He has published several papers in journals and conference proceedings. His current research interests include digital heritage, artificial intelligence, user experience design, and interaction design.

JIANG DU received the Ph.D. degree from Wuhan University of Technology, China. He is currently an Associate Professor with the Department of Product Design, Faculty of Art and Communication, Kunming University of Science and Technology. His main research interests include intelligent experience design, human–computer interaction, and interaction design.