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Mechanisms of AI-Empowered Social Media in Fostering Sustainable Consumer–Brand Relationships Among Generation Z

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Abstract

As digital transformation accelerates, artificial intelligence (AI) has become a central driver of social media ecosystems. Drawing on Uses and Gratifications Theory (UGT) and Consumer–Brand Relationship Theory, this study employs a quantitative research design based on questionnaire data and Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine how AI-empowered social media functionalities influence the sustainability of consumer–brand relationships among Generation Z. The analysis incorporates key constructs, including AI-empowered functionalities, user engagement behaviors (information seeking, social interaction, and content co-creation), flow experience, user satisfaction, brand loyalty, and brand value co-creation. The results indicate that AI-empowered social media applications significantly enhance user engagement behaviors. However, user engagement does not directly affect consumer–brand relationship outcomes; instead, its influence operates indirectly through flow experience and user satisfaction. Notably, flow experience emerges as a critical mediating mechanism linking AI-empowered user engagement to both brand loyalty and brand value co-creation. This research provides empirical evidence for the development of sustainable consumer–brand relationships in AI-empowered social media environments and offers practical insights for fashion brands to optimize their social media strategies when targeting Generation Z users.

Keywords: AI-empowerment; social media; Generation Z; user engagement; flow experience; sustainable relationships

1. Introduction

In the context of ongoing digital transformation, artificial intelligence (AI) has become a fundamental force shaping social media platforms and user experience design [1]. AI applications—including algorithmic recommendation systems, intelligent interaction interfaces, and generative content tools—continuously shape how users access information, engage with content, and interact within digital environments [2,3]. This transformation fundamentally alters the mechanisms through which consumer–brand relationships are formed and developed [4,5]. Compared with earlier digital technologies that primarily emphasized information efficiency and functional support, contemporary AI technologies exert a deeper and more pervasive influence by continuously shaping users' participation behaviors and experiential processes. This shift creates an important context for understanding the evolving dynamics of consumer–brand relationships in digital environments [6].

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As digital natives raised in highly mediated environments, Generation Z users exhibit higher levels of activity and engagement on social media platforms than other demographic groups, with a strong preference for personalized, interactive, and immersive experiences. Existing research suggests that Generation Z develops brand attitudes and relationships through ongoing interactions and accumulated experiences within brand-related contexts [7–10]. In the fashion industry in particular, brands not only fulfill functional needs but also serve as vehicles for identity expression and symbolic meaning. Engaging with brands thus becomes a primary means through which users construct their identities and lifestyle [7,8]. With the widespread adoption of AI technologies in fashion brands' social media strategies, data-driven recommendations, intelligent interactions, and content generation have further enhanced user engagement [6,11,12]. Against this backdrop, it becomes essential to understand how AI shapes consumer–brand relationships.

Despite growing academic interest in AI applications, flow experience, and consumer–brand relationships, important gaps remain in understanding the underlying mechanisms. Prior research has examined how specific AI features—such as generative content [13] and personalized recommendations [14]—influence user behavior and attitudes. In parallel, flow experiences have been widely employed to explain users' immersive engagement and positive responses in digital environments [15]. Nevertheless, existing research largely adopts fragmented approaches, focusing on isolated technologies or individual psychological mechanisms. As a result, few studies integrate multiple AI-empowered functionalities, diverse forms of user participation, and experiential responses within a unified analytical framework. From the perspective of sustainable consumer–brand relationships, the mechanisms through which AI-empowered social media applications shape relational outcomes among Generation Z—via user participation behaviors and experiential processes—remain insufficiently understood.

To address the aforementioned gaps, this study, situated in the context of fashion brands' social media environments and grounded in Uses and Gratifications Theory and consumer–brand Relationship Theory, focuses on Generation Z users to develop an integrated research framework. The proposed model incorporates AI-empowered social media functionalities, user engagement behaviors, flow experience, and consumer–brand relationship outcomes. The study examines the mechanisms through which AI influences the sustainable development of consumer–brand relationships on social media platforms.

By revealing the sequential mechanisms linking AI-empowered functionalities to user engagement behaviors and subsequent experiential responses, this study offers both theoretical and practical contributions. Theoretically, it advances prior research by integrating AI functionalities, user engagement, and experiential processes into a unified framework, thereby addressing the limitations of fragmented approaches. Practically, it provides actionable insights for multiple stakeholders. For brand managers, it offers guidance on optimizing AI-empowered marketing strategies, enhancing user participation, and facilitating the transition from transactional interactions to sustainable relational co-creation. For social media platform developers, it highlights the importance of designing cohesive and immersive algorithmic ecosystems rather than fragmented technical solutions. For Generation Z consumers, it underscores the value of creating more personalized, engaging, and meaningful digital experiences.

2. Theoretical Background

2.1. AI-Empowered Social Media Functions

The rise of artificial intelligence has significantly transformed social media, shaping how users engage with and experience content on these platforms. Personalized recommendation systems analyze users' behavioral data, interests, and past interactions to predict preferences and respond to individual needs in real time. As a result, these systems improve the accuracy and relevance of information matching [16], thereby supporting users' information-seeking and participatory activities [17]. AI chatbots are capable of delivering instant feedback and personalized interactive experiences [18], which enhance user participation and satisfaction [19]. This dynamic interaction not only strengthens user engagement but also fosters a sense of community within the platform ecosystem. Generative artificial intelligence enables the automatic creation of high-quality text, images, and videos [20], facilitating the production of large-scale and customized creative content [21]. This capability supports more personalized, immediate, and context-aware user experiences. Overall, these AI-empowered functionalities enhance information efficiency, improve interactive responsiveness, and reduce barriers to content creation, thereby providing a technological foundation for user engagement behaviors, including seeking information, social interaction, and co-creating content.

While AI-empowered social media applications encompass diverse functionalities—such as personalized recommendations, interactive chatbots, and generative content tools—this study focuses on their collective impact as a holistic technological ecosystem. For Generation Z users, AI functionalities are not perceived as discrete tools but rather as a seamlessly integrated digital environment that aligns with their identity and problem-solving processes [22]. Accordingly, to capture the systemic influence of algorithmic environments on consumer behavior, this study conceptualizes AI empowerment as an integrated latent construct. This unified approach is further supported by empirical evidence from the subsequent data analysis using Principal Component Analysis (PCA), which enhances the parsimony and explanatory power of the structural model.

2.2. Uses and Gratifications Theory

The uses and gratifications theory (UGT) is a widely adopted framework in communication research, explaining the motivations that drive individuals to interact with mass media [23]. The theory emphasizes the active role of users, suggesting that individuals engage with media technologies to fulfill informational, social, and hedonic needs [12,24]. By conceptualizing users as autonomous actors who actively seek media interactions to achieve specific goals, UGT provides a relevant theoretical lens for understanding user behavior in AI-empowered contexts [25]. Specifically, personalized recommendation systems satisfy users' informational needs by reducing information overload. AI chatbots fulfill social needs through instant responses and human-like interactions, while generative AI technologies address hedonic needs by lowering creative barriers and enhancing enjoyment. From a uses and gratifications perspective, AI-empowered social media enhance users' likelihood of engaging in brand-related interactions, thereby fulfilling informational, social, and hedonic needs. The specific relationships between types of gratification and AI functionalities are summarized in Table 1.

While personalized recommendations, AI chatbots, and generative AI possess distinct technical characteristics, they rarely operate in isolation within modern digital platforms. Instead, they function synergistically to create a holistic AI-empowered environment. Drawing on Beyari and Hashem [26], these applications can be understood as an integrated experiential ecosystem rather than fragmented tools. For Generation Z users, who are digital natives, the boundaries between these functionalities are often blurred in actual platform usage. As a result, they tend to perceive and evaluate the platform "intelligence" as a unified and seamless experience [22]. Accordingly, to capture the holistic impact of algorithmic systems on consumer behavior, this study conceptualizes and empirically operationalizes AI-empowered functionalities as a single integrated latent construct within the structural model, thereby enhancing both theoretical coherence and model parsimony.

Table 1. Principal UGT gratification types and corresponding AI components.

Behavior	Gratification Type	AI Component(s)	Rationale
Information Seeking	Informational	Personalized Recommendation AI Chatbots	AI meets users' informational needs with personalized recommendations and smart conversation.
Social Interaction	Social	AI Chatbots	Chatbots create a strong sense of social presence during interactions, thereby fulfilling users' social needs.
Content Co-creation	Hedonic Social	AIGC	AIGC tools have turned content creation into an essential way to meet users' hedonic needs and their desire for self-expression.

2.3. Flow Experience

The concept of "flow" was first introduced by the psychologist Csikszentmihalyi in 1975 to describe an optimal psychological state characterized by deep concentration, full immersion, and intrinsic enjoyment during task engagement. Hoffman and Novak [27,28] further emphasize that interactivity, information richness, and immediate feedback are essential conditions for facilitating online flow experience. Flow experience has been shown to influence users' learning outcomes, affective responses, and behavioral intentions. Accordingly, it is widely regarded as a key concept for explaining user behavior in online environments, particularly in relation to immersive experiences across digital platforms such as websites and social media [29,30]. In AI-empowered social media contexts, flow experience serves as a critical psychological mechanism linking user engagement behaviors to subsequent attitudes and relational outcomes.

2.4. Consumer–Brand Relationship Outcome Variables

The term "consumer–brand relationship" refers to the emotional, cognitive, and behavioral bonds formed between consumers and brands [31,32]. In this study, sustainable consumer–brand relationships are not solely driven by purchase behavior but are continuously developed through information sharing, interactive engagement, and content co-creation on social media platforms. Accordingly, this study focuses on two key outcome variables. The first is brand loyalty, which reflects users' long-term attitudinal and behavioral commitment to a specific brand [33,34]. The second is brand value co-creation, which involves users and firms jointly creating and enhancing brand value through continuous participation, feedback, and content creation activities [32,35,36]. In social media contexts, both brand loyalty and value co-creation serve as key indicators of the stability and evolution of consumer–brand relationships, making them appropriate outcome variables for assessing sustainable consumer–brand relationships.

3. Hypothesis Development

3.1. AI-Empowered User Engagement Behaviors

This section examines the role of AI-empowered social media applications in shaping user engagement behaviors, including information seeking, social interaction, and content co-creation.

AI-empowered social media applications, including chatbots and personalized recommendation systems, have become increasingly integrated into and significantly influence consumer information-seeking processes. Information seeking is an active process through which customers search for information to support product or service decisions [37]. Liang et al. [38] found that AI-empowered recommendation systems significantly enhance the efficiency and relevance of information acquisition. Similarly, Fayyaz et al. [39] highlight that AI recommendation systems guide consumers toward reliable information by analyzing historical search and browsing data. Nguyen et al. [40] further demonstrate that chatbots reduce cognitive load by providing tailored responses aligned with user preferences. In the context of fashion branding, Grewal et al. [41] show that intelligent agents improve the convenience and efficiency of information acquisition. For example, fashion brands such as Bananain and Uniqlo dynamically adjust content delivery strategies on social media platforms such as TikTok and Reddit based on user interaction data, thereby reducing users' time costs and cognitive effort during the information search process [42,43]. Based on the above discussion, the following hypothesis is proposed:

H1a. *AI-empowered social media applications, including personalized recommendations and chatbots, have a positive effect on users' information seeking*.

Social interaction refers to the behavioral process through which individuals exchange information and develop relational bonds with others within a platform environment, typically through activities such as commenting, liking, sharing, and direct messaging [44]. In contemporary digital marketing environments, fashion brands such as H&M and Sephora have adopted automated response systems across social media and digital communication channels to manage high-frequency inquiries and service requests, thereby improving operational efficiency and service quality [45]. Similarly, brands such as Anta have implemented intelligent agents to enable high-frequency, real-time interactions with users [46]. These AI-empowered interactions enhance users' perceptions of communication quality and engagement, thereby promoting social interaction behaviors [47]. Liu and Sundar [48] further emphasize that AI chatbots fulfill users' social needs—such as companionship, belonging, and understanding—while enhancing perceived social presence. Konya [49] also finds that human-like chatbot design significantly increases users' willingness to engage in social interactions. Based on the above discussion, the following hypothesis is proposed:

H1b. *AI-empowered social media applications, such as AI chatbots, have a positive effect on users' social interaction behaviors*.

Content co-creation refers to the process through which users actively participate in creating, adapting, and reproducing content within a platform environment, thereby jointly generating value with other users or organizations [50]. Research by McKinsey and Company [51] shows that leading fashion brands, including Gucci and Nike, use generative AI to reshape social media content strategies. Basile et al. [52] further demonstrated that user-generated content enhances brand value through co-creation processes. Similarly, Chinese fashion brands such as Cabbeen, Anta, and Bosideng frequently encourage users to utilize AI generation tools on platforms such as TikTok to create and share brand-related content [43,53,54]. This approach enhances user participation, motivation, and sustained engagement [55], while also promoting content secondary creation and adaptation [56]. Based on the above discussion, the following hypothesis is proposed:

H1c. *AI-empowered social media applications, such as AI-generated content, have a positive effect on user content co-creation*.

3.2. The Impact of User Engagement Behaviors on Experiential Responses

This section extends the analysis of AI-empowered user engagement behaviors by examining their effects on users' experiential responses. Specifically, this study investigates how information seeking, social interaction, and content co-creation influence flow experience and user satisfaction.

Intelligent algorithms enhance the accuracy and efficiency of information acquisition, and such effective feedback mechanisms are widely regarded as key factors facilitating the emergence of flow experience. Hoffman and Novak [57] suggest that users are more likely to enter a flow state when they efficiently access brand information that aligns with their interests. Oliver [58] demonstrates that when users perceive brand information as accessible and valuable, their satisfaction increases. Chen et al. [59] further show that AI-empowered information filtering positively influences users' perceived value and overall satisfaction. Based on the above discussion, the following hypotheses are proposed:

H2a. *User information seeking has a positive effect on flow experience.*

H2b. *User information seeking has a positive effect on user satisfaction.*

The rise of AI chatbots has transformed user communication patterns, increasing the likelihood of interactive exchanges [60]. Araujo [61] and Davenport et al. [62] note that AI chatbots enable frequent and real-time interactions, thereby enhancing user engagement. Oliveira et al. [63] argue that instant feedback loops capture users' attention and facilitate the emergence of flow experience. Jeong and Kim [64] further showed that social recognition within interactions significantly enhances users' satisfaction with brand interactions. Based on the above discussion, the following hypotheses are proposed:

H3a. *User social interaction has a positive effect on flow experience.*

H3b. *User social interaction has a positive effect on user satisfaction.*

Content co-creation refers to users' active participation in creating, designing, or modifying content, through which value is collaboratively generated with brands or technological systems [50]. Füller et al. [65] show that users can leverage intelligent tools provided by fashion brands to engage in secondary creation and adaptation, thereby contributing to brand narratives. Hsu and Chen [66] further confirm that co-creation activities significantly enhance flow experiences in digital environments. Cambra-Fierro et al. [67] demonstrated that deeper interactions foster more stable user satisfaction than purely transactional relationships. In addition, emerging technologies make co-creation more intuitive and engaging [68], and this enhanced hedonic value is directly associated with higher levels of user satisfaction [69]. Therefore, the following hypotheses are proposed:

H4a. *User content co-creation has a positive effect on flow experience.*

H4b. *User content co-creation has a positive effect on user satisfaction.*

3.3. The Impact of Flow Experience on User Satisfaction

At the experiential response level, this section examines the relationship between flow experiences and user satisfaction, focusing on how flow serves as a process-oriented psychological mechanism shaping users' overall evaluation of platform and brand interactions. Hoffman and Novak [57], along with Grewal et al. [70], highlight that AI applications enhance users' focus and engagement by improving information matching accuracy, interaction coherence, and experiential immersion, thereby increasing the likelihood of experiencing flow. Rodríguez and Meseguer [71] further integrate the Technology Acceptance Model with Flow Theory, demonstrating that flow experiences positively influences user satisfaction and continuance intentions. Similarly, Zhou [72] shows that

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flow experience in mobile social networks fosters emotional attachment and significantly enhances user satisfaction. Accordingly, the following hypothesis is proposed:

H5. *Flow experience has a positive effect on user satisfaction.*

3.4. The Impact of Experiential Responses on Consumer–Brand Relationship Outcomes

This section examines how experiential responses—specifically flow experience and user satisfaction—translate into consumer–brand relationship outcomes, with a particular focus on brand loyalty and brand value co-creation. In online environments, Novak et al. [27] found that flow experience significantly enhances users' positive attitudes and their intentions to revisit digital platforms. In the context of brand websites, van Noort et al. [73] demonstrated that enhanced interactivity improves online experience, leading to more favorable emotional and behavioral responses toward both the website and the brand. In addition, Nambisan and Baron [74] show that positive interactive experiences in virtual communities promote users' voluntary participation in value co-creation activities. Similarly, France et al. and Iglesias et al. [35,75] indicate that brand experiences characterized by enjoyment, immersion, and interactivity play a critical role in encouraging users to engage in co-creation behaviors. Accordingly, the following hypotheses are proposed:

H6a. *Flow experience has a positive effect on brand loyalty.*

H6b. *Flow experience has a positive effect on brand value co-creation.*

User satisfaction is a well-documented predictor of subsequent loyalty-related behaviors [33]. A substantial body of empirical research demonstrates a positive relationship between satisfaction and users' likelihood of engaging in loyalty behaviors [76–78]. Yi and Gong [36] further show that user participation is positively influenced by prior satisfaction and relationship quality, suggesting a virtuous cycle between satisfaction and co-creation. Similarly, France et al. and Iglesias et al. [35,75] highlight that satisfaction and positive affect play a critical role in driving user-brand co-creation behaviors. Accordingly, the following hypotheses are proposed:

H7a. *User satisfaction has a positive effect on brand loyalty.*

H7b. *User satisfaction has a positive effect on brand value co-creation.*

3.5. Conceptual Model

In line with the hypotheses developed above, this study proposes a conceptual model termed "AI Intervention–User Participation–Experiential Response–Brand Relationship Outcome", as illustrated in Figure 1. This model offers a structured framework for explaining the mechanisms through which AI-empowered social media applications influence consumer–brand relationships. Specifically, AI-empowered applications are conceptualized as the independent variable, whose effects on relationship outcomes—namely brand loyalty and brand value co-creation—are transmitted through two sequential pathways: user engagement behaviors (information seeking, social interaction, and content co-creation) and experiential responses (flow experience and user satisfaction).

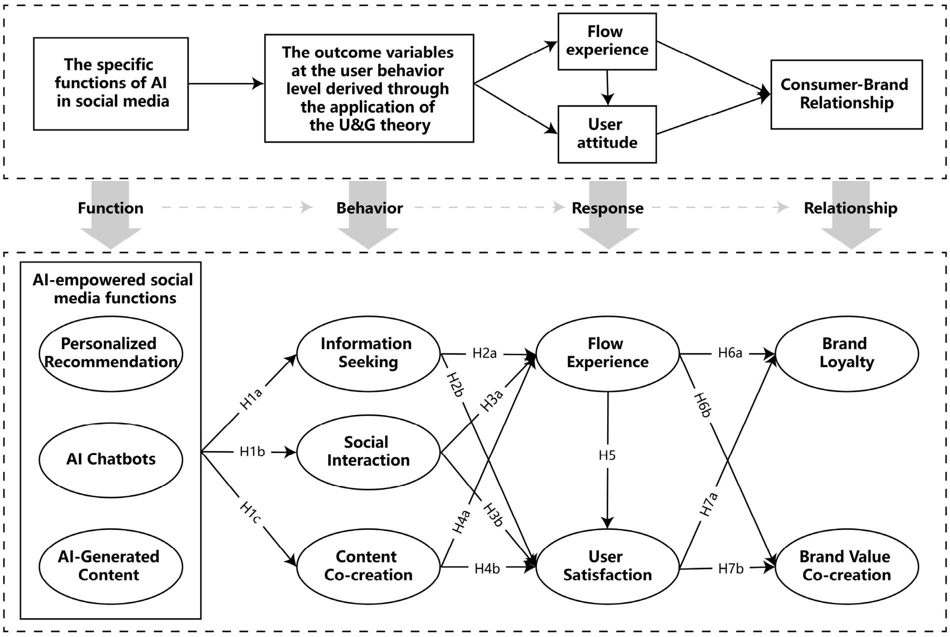

Figure 1. Conceptual model of the study. Note: The upper dashed frame represents the hierarchical stages of the conceptual model (Function–Behavior–Response–Relationship), whereas the lower dashed frames group the corresponding constructs within each stage to enhance analytical clarity.

4. Research Method

4.1. Questionnaire Design

This study employed a structured questionnaire administered via social media platforms using a convenience sampling approach. The instrument consisted of three sections. The first section introduced standardized definitions of common AI applications in social media, including personalized recommendations, chatbots, and AI-generated content (AIGC). To ensure a consistent understanding among respondents, illustrative examples from fashion brands were provided. The second section collected demographic information, including gender, age, education level, and average daily social media usage. The third section measured key constructs related to AI-empowered user behaviors, experiential responses, and consumer–brand relationship outcomes. All measurement items were adapted from validated scales in prior research and contextualized to the AI-empowered social media setting (see Appendix A). All items were measured using a seven-point Likert scale.

4.2. Data Collection

Prior to administering the main survey, the initial questionnaire underwent a systematic review and refinement process. This process was conducted by an academic supervisor and domain experts to ensure content validity and alignment with the study construct. Subsequently, a pilot study was conducted with 34 Generation Z social media users. Based on the feedback obtained, item wording was further refined—for example, technical AI terminology was adapted into more familiar, user-friendly expressions commonly used by Generation Z—to improve clarity and reduce potential cognitive bias. In addition, to minimize response bias associated with monotonous answering patterns, multiple question formats were employed, thereby enhancing the reliability and validity of the responses.

After data screening, 63 invalid responses were removed, resulting in 337 valid questionnaires from 400 distributed surveys, with an effective response rate of 84.25%. According to Hill [79], for multivariate analysis, a sample size of at least ten times the number of measurement items is recommended. Based on this guideline, the sample size in this study is sufficient to meet established social science research standards, demonstrating adequate representativeness and statistical power.

4.3. Sample Profile

The demographic characteristics of the respondents are presented in Table 2. The sample comprised 53.1% females and 46.9% males. The age distribution was predominantly concentrated within the 18–30 range, consistent with the study's focus on Generation Z. Specifically, the 18–21 age group accounted for the largest proportion (55.8%), followed by the 22–25 group (23.7%) and the 26–30 group (20.5%). In terms of educational attainment, the majority of respondents held a bachelor's degree or higher: 73.3% were undergraduates, 14.5% held a master's degree or higher, and 12.2% had a high school education or below.

Table 2. Demographic information (n = 337).

Characteristics	Category	Frequency	Percentages
Gender	Female	179	53.1
	Male	158	46.9
Age	18–21	188	55.8
	22–25	80	23.7
	26–30	69	20.5
Education	High school graduate	41	12.2
	College graduate	247	73.3
	Master graduate	49	14.5
Daily time spent online	<0.5 h	25	7.4
	0.5–1 h	70	20.8
	1–3 h	134	39.8
	>3 h	108	32.0

4.4. Data Analysis

To ensure conceptual parsimony and mitigate potential multicollinearity among highly correlated AI-related dimensions, Principal Component Analysis (PCA) was conducted as a preliminary data reduction step. Although personalized recommendations, AI chatbots, and AI-generated content are conceptually distinct at the functional level, Generation Z users tend to perceive them as a holistic "AI-empowered environment" rather than as isolated features. PCA is particularly suitable for data reduction and enhances the interpretability of factor loadings [80]. Furthermore, this approach is widely adopted across social science disciplines, as it produces underlying factors that are both independent and straightforward to interpret [81].

Following Jebb et al. [82], the suitability of the data for factor analysis was assessed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity. The results (Table 3) indicate that a single factor with an eigenvalue greater than 1 was extracted from items related to AI functionalities, explaining 63.81% of the total variance. Additionally, all item loadings on this factor exceeded 0.70, with no notable cross-loadings. Accordingly, these items were combined into a single construct, which improves model parsimony and reduces multicollinearity among sub-dimensions.

Following this preliminary step, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed as the primary analytical method. PLS-SEM is particularly appropriate for models involving multiple latent structures and complex relationships, as it imposes minimal distributional assumptions and is well suited for predictive research contexts [83]. The analysis followed a two-stage approach. First, the measurement model was evaluated in terms of internal consistency reliability, validity, convergent validity, and discriminant validity. Second, the structural model was assessed to examine the hypothesized relationships among constructs. The significance of path coefficients was tested using a bootstrapping procedure with 5000 resamples. In addition, model explanatory power (R^2), effect sizes (f^2), and predictive relevance (Q^2) were assessed to ensure the robustness of the model.

Table 3. Total Variance Explained.

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.743	63.810	63.810	5.743	63.810	63.810
2	0.628	6.979	70.789			
3	0.588	6.534	77.322			
4	0.423	4.700	82.022			
5	0.379	4.210	86.232			
6	0.350	3.889	90.121			
7	0.326	3.623	93.744			
8	0.282	3.135	96.879			
9	0.281	3.121	100.000			

5. Results

5.1. Measurement Model Evaluation

Following the guidelines proposed by Hair et al. [84], the measurement model was evaluated in terms of internal consistency reliability, convergent validity, and discriminant validity. These criteria are essential for ensuring the reliability and validity of the constructs. Specifically, convergent validity assesses the extent to which indicators of a construct converge to represent the same underlying concepts, while discriminant validity examines the extent to which constructs are empirically distinct from one another.

5.1.1. Internal Consistency Reliability

Internal consistency reliability was assessed using Cronbach's alpha (α), Dijkstra-Henseler's rho-A and Composite Reliability (CR). As shown in Table 4, all CR values exceed the recommended threshold of 0.7 [85], indicating satisfactory internal consistency. In addition, Cronbach's alpha values for all constructs also exceed the acceptable threshold, further confirming the reliability of the measurement model.

Table 4. Reliability and AVE of the outer model.

Construct	Cronbach's Alpha	Rho-A	Composite Reliability	AVE
AI	0.929	0.930	0.941	0.638
IS	0.803	0.803	0.884	0.717
SI	0.879	0.881	0.925	0.805
CC	0.846	0.849	0.896	0.684
FL	0.837	0.838	0.891	0.672
SAT	0.849	0.850	0.908	0.768
BL	0.830	0.832	0.887	0.662
BVC	0.845	0.848	0.896	0.683

5.1.2. Convergent Validity

Convergent validity was assessed using standardized factor loadings and Average Variance Extracted (AVE). The results indicate that all item loadings exceeded the recommended threshold of 0.70. In addition, all AVE values are above 0.50, indicating that the constructs explain a substantial proportion of the variance in their indicators [86]. Therefore, the measurement model demonstrates adequate convergent validity.

5.1.3. Discriminant Validity

Discriminant validity was assessed using the Heterotrait–Monotrait ratio of correlations (HTMT), as recommended by Henseler et al. [87]. All HTMT values are below the conservative threshold of 0.90 [86], indicating adequate discriminant validity (see Table 5). As an additional assessment, cross-loadings were examined. As shown in Table 6, each indicator loads higher on its corresponding construct than on any other construct, satisfying the recommended criterion for discriminant validity [84]. These results further confirm that the constructs are empirically distinct from one another.

Table 5. Results of discriminant validity by HTMT.

Factors	AI	IS	SI	CC	FL	SAT	BL	BVC
AI								
IS	0.828							
SI	0.786	0.696						
CC	0.840	0.754	0.719					
FL	0.818	0.756	0.681	0.744				
SAT	0.856	0.763	0.734	0.759	0.807			
BL	0.898	0.786	0.744	0.765	0.787	0.771		
BVC	0.861	0.764	0.741	0.774	0.751	0.788	0.825	

Table 6. Standardized factor loadings and cross-loadings of the outer model.

	AI	IS	SI	CC	FL	SAT	BL	BVC
PR1	**0.769**	0.561	0.506	0.573	0.603	0.578	0.611	0.560
PR2	**0.799**	0.539	0.572	0.589	0.605	0.597	0.638	0.574
PR3	**0.807**	0.556	0.560	0.595	0.570	0.623	0.642	0.626
CB1	**0.846**	0.613	0.618	0.633	0.614	0.674	0.685	0.678
CB2	**0.779**	0.521	0.515	0.603	0.551	0.584	0.637	0.619
CB3	**0.770**	0.532	0.541	0.598	0.561	0.601	0.591	0.621
AI1	**0.781**	0.564	0.604	0.528	0.539	0.572	0.597	0.578
AI2	**0.813**	0.606	0.582	0.614	0.564	0.639	0.616	0.612
AI3	**0.822**	0.649	0.611	0.629	0.579	0.593	0.656	0.627
IS1	0.585	**0.842**	0.481	0.492	0.518	0.543	0.533	0.525
IS2	0.624	**0.857**	0.508	0.561	0.510	0.532	0.555	0.556
IS3	0.611	**0.840**	0.497	0.508	0.545	0.525	0.505	0.526
SI1	0.634	0.511	**0.905**	0.585	0.512	0.587	0.566	0.574
SI2	0.663	0.543	**0.899**	0.562	0.571	0.576	0.591	0.596
SI3	0.619	0.520	**0.888**	0.525	0.492	0.544	0.553	0.554
CC1	0.636	0.509	0.528	**0.833**	0.532	0.565	0.542	0.562
CC2	0.578	0.470	0.492	**0.823**	0.483	0.508	0.465	0.479
CC3	0.657	0.531	0.560	**0.857**	0.559	0.562	0.581	0.604
CC4	0.594	0.521	0.473	**0.795**	0.499	0.494	0.535	0.522
FL1	0.554	0.526	0.476	0.507	**0.806**	0.563	0.516	0.451
FL2	0.596	0.507	0.451	0.509	**0.814**	0.526	0.535	0.517
FL3	0.610	0.504	0.485	0.525	**0.841**	0.555	0.541	0.558
FL4	0.603	0.496	0.507	0.517	**0.817**	0.591	0.560	0.551
SAT1	0.671	0.534	0.551	0.580	0.640	**0.882**	0.602	0.609
SAT2	0.657	0.581	0.555	0.572	0.598	**0.879**	0.557	0.588
SAT3	0.670	0.540	0.562	0.543	0.552	**0.867**	0.546	0.562
BL1	0.599	0.479	0.508	0.489	0.508	0.468	**0.789**	0.542
BL2	0.636	0.534	0.489	0.557	0.534	0.553	**0.829**	0.580

Table 6. *Cont.*

	AI	IS	SI	CC	FL	SAT	BL	BVC
BL3	0.654	0.521	0.544	0.489	0.556	0.520	**0.821**	0.536
BL4	0.677	0.505	0.528	0.557	0.538	0.567	**0.815**	0.599
BVC1	0.654	0.565	0.593	0.601	0.558	0.563	0.636	**0.851**
BVC2	0.575	0.416	0.464	0.502	0.477	0.489	0.486	**0.784**
BVC3	0.622	0.544	0.530	0.534	0.514	0.574	0.561	**0.849**
BVC4	0.672	0.555	0.525	0.533	0.544	0.582	0.602	**0.820**

Note: Bold values indicate the highest loading of each indicator on its corresponding construct, demonstrating adequate discriminant validity.

5.2. Structural Model and Hypothesis Testing

To address common method bias (CMB), both procedural and statistical remedies were applied. Procedurally, respondent anonymity was ensured and the order of questionnaire items was randomized. Statistically, a full collinearity assessment approach was conducted following Kock [88]. All variance inflation factors (VIFs) values were below the conservative threshold of 3.3, indicating that common method bias is unlikely to pose a serious concern in this study.

The structural model was assessed using a bootstrapping procedure with 5000 resamples to evaluate the significance of path coefficients. As shown in Table 7 and Figure 2, all hypothesized relationships were statistically significant ($p < 0.05$).

Table 7. Hypothesized relationships.

Hypothesis	Path Coefficient	t-Statistics	*p*-Values	f^2	Result
H1a AI → IS	0.717	25.789	0.000	1.056	Supported
H1b AI → SI	0.712	24.023	0.000	1.030	Supported
H1c AI → CC	0.746	30.409	0.000	1.258	Supported
H2a IS → FL	0.304	5.308	0.000	0.104	Supported
H2b IS → SAT	0.185	3.105	0.002	0.043	Supported
H3a SI → FL	0.218	3.193	0.001	0.053	Supported
H3b SI → SAT	0.218	3.487	0.000	0.062	Supported
H4a CC → FL	0.305	4.710	0.000	0.098	Supported
H4b CC → SAT	0.198	3.193	0.001	0.046	Supported
H5 FL → SAT	0.316	5.530	0.000	0.122	Supported
H6a FL → BL	0.400	6.824	0.000	0.174	Supported
H6b FL → BVC	0.332	5.460	0.000	0.120	Supported
H7a SAT → BL	0.377	6.506	0.000	0.154	Supported
H7b SAT → BVC	0.443	8.029	0.000	0.213	Supported

Note: f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively [83].

In addition to path significance, the model's explanatory power and predictive relevance were evaluated in accordance with established PLS-SEM guidelines [83]. Specifically, the coefficient of determination (R^2) was used to assess explanatory power, while predictive relevance was evaluated using the blindfolding procedure to obtain the cross-validated redundancy measure (Q^2).

As presented in Table 8, the coefficient of determination (R^2) values for all endogenous constructs exceed the recommended threshold of 0.50 (ranging from 0.507 to 0.598), indicating moderate explanatory power. Furthermore, the blindfolding procedure yielded Q^2 values ranging from 0.329 to 0.450, all greater than zero, confirming the model's strong predictive relevance.

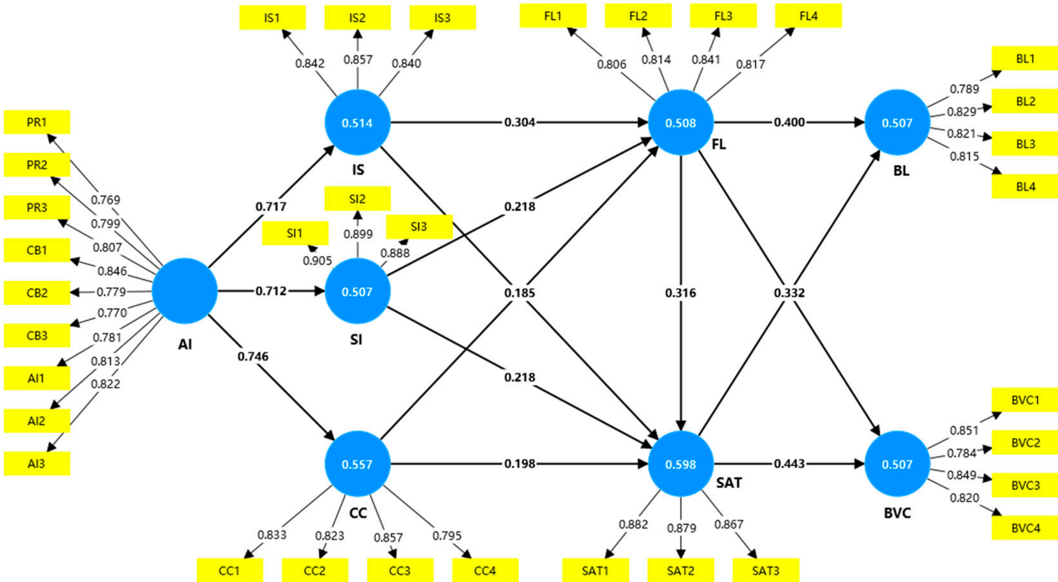

Figure 2. Path analysis.

Table 8. Explanatory power and predictive relevance of the endogenous constructs.

Construct	R^2	Explanatory Power	Q^2	Predictive Relevance
IS	0.514	Moderate	0.364	Supported
SI	0.507	Moderate	0.403	Supported
CC	0.557	Moderate	0.377	Supported
FL	0.508	Moderate	0.337	Supported
SAT	0.598	Moderate	0.450	Supported
BL	0.507	Moderate	0.329	Supported
BVC	0.507	Moderate	0.342	Supported

The effect size analysis (f^2) (Table 7) indicates large effect sizes of AI-empowered applications on user engagement behaviors (f^2 = 1.056 for IS, 1.030 for SI, and 1.258 for CC). In contrast, the subsequent experiential and relational pathways exhibit small to moderate effect sizes (ranging from 0.043 to 0.213), which are consistent with expectations for complex multi-step mediation models.

Taken together, these results confirm the robustness of the structural model and support the validity of the proposed framework.

5.3. Mediation Analysis

Mediation effects were tested using a bias-corrected bootstrapping procedure with 5000 resamples. As shown in Table 9, the results provide statistical support for the hypothesized indirect effects. Specifically, the findings indicate that AI-empowered social media applications have significant indirect effects on relational outcomes, which are sequentially mediated by user engagement behaviors (i.e., social interaction, information seeking, and content co-creation) and subsequently by flow experience.

Table 9. Mediation effects testing.

Relationships	Original Sample	STD	t-Statistics	*p*-Values	BC 95% CI Lower	Upper
Indirect 1: AI → SI → FL → BL	0.062	0.023	2.646	0.008	0.021	0.113
Indirect 2: AI → SI → FL → BVC	0.052	0.021	2.507	0.012	0.017	0.097
Indirect 3: AI → SI → FL → SAT → BL	0.018	0.007	2.529	0.011	0.006	0.035

Table 9. *Cont.*

Relationships	Original Sample	STD	t-Statistics	*p*-Values	BC 95% CI Lower	Upper
Indirect 4: AI → SI → FL → SAT → BVC	0.022	0.008	2.656	0.008	0.008	0.040
Indirect 5: AI → IS → FL → BL	0.087	0.020	4.292	0.000	0.052	0.131
Indirect 6: AI → IS → FL → BVC	0.072	0.018	4.037	0.000	0.040	0.110
Indirect 7: AI → IS → FL → SAT → BL	0.026	0.009	2.971	0.003	0.012	0.046
Indirect 8: AI → IS → FL → SAT → BVC	0.030	0.01	3.097	0.002	0.015	0.053
Indirect 9: AI → CC → FL → BL	0.091	0.025	3.593	0.000	0.046	0.145
Indirect 10: AI → CC → FL → BVC	0.076	0.023	3.268	0.001	0.035	0.125
Indirect 11: AI → CC → FL → SAT → BL	0.027	0.008	3.432	0.001	0.014	0.044
Indirect 12: AI → CC → FL → SAT → BVC	0.032	0.009	3.647	0.000	0.016	0.051

6. Discussion

This study examines the mechanisms through which AI-empowered social media applications foster sustainable consumer–brand relationships among Generation Z. The findings provide important insights that both align with and extend prior research.

First, the results are consistent with prior research emphasizing the efficiency and functional advantages of AI technologies (e.g., algorithmic accuracy and chatbot responsiveness) [62]. However, rather than exerting direct effects, the findings indicate that the impact of AI on consumer–brand relationships is primarily indirect, operating through user engagement behaviors. This result supports and extends the perspective of Hollebeek et al. [55] by demonstrating that technological interventions require active behavioral participation as a prerequisite for relationship development in AI-empowered social media context.

Second, in contrast to traditional relationship marketing literature, which emphasizes user satisfaction as the primary driver of brand outcomes [33], this study finds that flow experience plays a more prominent mediating role, particularly in driving brand value co-creation. This finding extends Flow Theory [57] into AI-empowered environments, suggesting that for digital natives, immersive and hedonic experiences may outweigh utilitarian satisfaction in fostering sustainable co-creation behaviors.

Third, this study contributes to the literature by integrating multiple AI functionalities into a unified analytical framework. While prior studies have often examined AI technologies in isolation [61], the present findings indicate that Generation Z users perceive AI-empowered social media as a synergistic ecosystem. This provides empirical support for conceptualizing AI empowerment as a higher-order latent construct, thereby addressing recent calls for a more integrated perspective on AI-empowered environments.

Finally, regarding generalizability, although this study focuses on Chinese Generation Z fashion consumers, the proposed "AI Intervention—User Participation—Experiential Response" framework demonstrates potential applicability across diverse cultural and industry contexts. While cultural differences may influence the strength of observed effects, the underlying psychological mechanism—from need fulfillment to flow experience—appears to be broadly applicable. Furthermore, while the fashion industry is highly experiential, the model may also be transferable to other experience-intensive sectors such as tourism and digital entertainment, although its adaptation to more utilitarian contexts may require further investigation.

7. Conclusions and Implications

7.1. Research Conclusions

This study draws upon the theoretical frameworks of Uses and Gratifications Theory (UGT) and Consumer–Brand Relationship Theory. To examine how AI-empowered social media applications influence the sustainability of consumer–brand relationships among Generation Z, the study employed a questionnaire survey and Partial Least Squares Structural Equation Modeling (PLS-SEM). The main conclusions are summarized as follows:

The findings indicate that the impact of artificial intelligence (AI) on consumer–brand relationships is primarily indirect rather than direct, operating through a sequence of interconnected mechanisms: "AI Intervention—User Participation—Experiential Response—Brand Relationship Outcome." AI-empowered social media applications are positively associated with user engagement behaviors, including information seeking, social interaction, and content co-creation. Furthermore, these effects are indirectly transmitted through flow experience and user satisfaction. Among these pathways, flow experience emerges as a key mediating mechanism linking AI-empowered user participation to both brand loyalty and brand value co-creation. In this way, AI-empowered social media applications facilitate the development of consumer–brand relationships by promoting active user participation.

Second, user engagement behaviors alone are insufficient to directly generate stable consumer–brand relationships, as their effects depend on underlying psychological mechanisms. The results indicate that user engagement exerts an indirect influence on brand loyalty and value co-creation through flow experience and user satisfaction. This finding highlights the critical role of experiential mechanisms in transforming behavioral engagement into relational outcomes.

Within these multiple mediation pathways, flow experience serves as the primary mediating mechanism. Compared with user satisfaction, flow experience demonstrates stronger explanatory power in linking AI-empowered user engagement to both brand loyalty and brand value co-creation. This finding suggests that flow experience is particularly critical for fostering sustainable consumer–brand relationships in AI-empowered social media environments.

7.2. Theoretical Implications

First, this study moves beyond the prevailing focus on individual AI technologies in prior research. By empirically capturing users' overall perception of AI, it demonstrates that, within a brand context, AI can be conceptualized as a unified experiential environment rather than as discrete technological functions. This finding extends existing theoretical perspectives by reconceptualizing the role of intelligent technologies in shaping consumer–brand relationships.

Second, by incorporating Flow Theory into the AI-empowered consumer–brand relationship model, this study empirically validates the central mediating role of flow experience between technological stimuli and relational outcomes. This finding extends the applicability of Flow Theory to highly algorithmic and platform-based environments, thereby highlighting its relevance in AI-empowered digital contexts.

Third, from the perspective of relationship sustainability, this study systematically elucidates the mechanisms linking AI, user engagement behaviors, and experiential responses. The proposed framework offers a process-oriented explanation for the long-term development of consumer–brand relationships in digital platform environments, emphasizing the sequential pathway from technological intervention to relational outcomes.

7.3. Practical Implications

First, as users perceive AI as a holistic system, brands undergoing digital transformation should not treat individual AI technologies in isolation. Instead, they should develop a unified and coherent intelligent ecosystem centered on the overall user experience, thereby avoiding fragmentation that may negatively affect brand perception.

Second, the findings indicate that the value of AI extends beyond improving service efficiency to enhancing flow experience. When deploying AI technologies, brands should prioritize experiential design, leveraging personalization, interactivity, and instant feedback to strengthen users' sense of immersion. To translate these insights into practical strategies, fashion brands can transform conventional customer service chatbots into intelligent styling assistants. Rather than merely addressing logistical queries (e.g., shipping or sizing), these systems can engage users through interactive, real-time styling quizzes or provide gamified and personalized outfit recommendations. Such interactive and empathetic experiences can increase user dwell time and enhance psychological immersion.

Third, content co-creation appears to be more effective than passive information consumption or simple interaction in fostering flow experiences and enhancing brand value. Therefore, fashion brands should actively develop AIGC-based co-creation tools that lower barriers to user participation. One practical strategy is to launch "AI Co-Design Challenges" on highly interactive platforms such as TikTok. Brands can provide Gen Z users with proprietary AIGC templates—such as virtual try-on filters or AI-empowered pattern generators—enabling them to easily create and share personalized content. By transforming passive followers into active co-creators through low-barrier algorithmic tools, brands can expand their reach while strengthening long-term user loyalty.

8. Limitations and Future Research

This study focuses on Chinese Generation Z users within the context of fashion brand social media. The broader applicability of the findings to other cultures, age groups, or industries requires further empirical validation. Future research should conduct cross-cultural comparisons and include more diverse age groups and industry contexts to verify the model's generalizability.

Second, the reliance on single-source, cross-sectional survey data limits the ability to establish causal relationships and fully capture mediation mechanisms. Although the PLS-SEM bootstrapping results provide statistical support for the hypothesized indirect pathways, the temporal sequence among AI intervention, user participation, experiential responses, and relationship outcomes cannot be definitively established. Therefore, the identified indirect effects should be interpreted as robust associations rather than causal relationships. Future research should employ longitudinal or experimental designs to more rigorously examine these causal pathways and capture the dynamic evolution of AI-empowered consumer–brand relationships. For example, longitudinal studies could track Generation Z users' interactions with AI-empowered brand features over time to observe how initial flow experiences develop into sustained brand loyalty. Alternatively, experimental designs could isolate the causal effects of specific AI functionalities by comparing user responses to personalized AI-generated content and non-personalized brand content.

Third, although this study identifies flow experience and satisfaction as key experiential variables, AI may influence user responses through a broader range of psychological and social mechanisms. Future research could incorporate additional variables, such as trust, perceived authenticity, anthropomorphism, and algorithmic transparency, to develop a more comprehensive understanding of user experience and relationship formation in AI-empowered environments.

Given the rapid development of AI technologies, users' understanding of their functions and roles is likely to evolve alongside technological progress and societal acceptance. Future research should continuously monitor these changes and refine theoretical models accordingly to better explain how consumer–brand relationships emerge and evolve within increasingly sophisticated human–AI interaction contexts.

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Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

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Abbreviations

The following abbreviations are used in this manuscript:

UGT	Uses and gratifications theory
AI	Artificial intelligence
AIGC	Artificial Intelligence Generated Content
PR	Personalized Recommendation
CB	Chatbots
IS	Information Seeking
SI	Social Interaction
CC	Content Co-creation
FL	Flow Experience
SAT	User Satisfaction
BL	Brand Loyalty
BVC	Brand Value Co-creation

Appendix A

Table A1. Questionnaire items.

Construct	Item		Sources
Personalized Recommendation	PR1	The platform's AI recommendation algorithm suggests brand content that closely matches my interests.	Tam & Ho [89]; Bleier et al. [90]
	PR2	The brand content recommended by the AI system is usually relevant and useful to me.	
	PR3	The platform's personalized algorithm helps me find brand information more efficiently than before.	
AI Chatbots	CB1	When I inquire about a brand on the platform, the AI Chatbots can respond to my questions instantly.	Araujo [61]; Ashfaq et al. [91]
	CB2	The responses provided by the AI Chatbots help me solve problems related to this brand.	

Table A1. *Cont.*

Construct		Item	Sources
AI Chatbots	CB3	Interacting with the brand's AI Chatbots makes me feel more relaxed than interacting with traditional customer service, and I am more willing to further learn about the brand.	Araujo [61]; Ashfaq et al. [91]
AI-Generated Content	AI1	The AI tools related to the brand provided by the platform (such as AI filters, effects, and virtual try-on features) are rich in functionality.	Hofacker et al. [92]; Davenport et al. [62]
	AI2	Using these AI-assisted features to create brand-related content is very simple and enjoyable for me.	
	AI3	The AI-generated content released by the brand (such as virtual idols, AI posters, and AI short videos) is highly visually appealing to me.	
Information Seeking	IS1	Through AI recommendations, I can more easily find relevant brand information on the platform.	Tam & Ho [89]; Häubl & Trifts [93]
	IS2	AI personalized recommendations help me save time when searching for brand-related information.	
	IS3	The content recommended by AI enables me to discover brand information that aligns more closely with my interests.	
Social Interaction	SI1	With the support of the platform's algorithm-based matching, I often discover and interact with other users who follow the same brand.	Ellison et al. [94]; Hajli [95]; Dessart et al. [96]
	SI2	The platform's AI recommendation system helps me connect with more like-minded users who are interested in the brand.	
	SI3	Under AI-recommended brand-related topics, I enjoy sharing my opinions or interacting with others in the comment sections.	
Content Co-creation	CC1	I am very willing to use the AI creation tools provided by the platform (such as AI filters, templates, and editing features) to publish original content related to the brand.	Yi & Gong [36]; Nambisan & Baron [74]; France et al. [35]
	CC2	I am willing to proactively help refine and spread brand-related content through comments, supplementary information, or reposts.	
	CC3	I am happy to participate in AI-powered brand challenges initiated by the platform.	
	CC4	With the assistance of the platform's AI technology, I can create higher-quality brand-related content.	
Flow Experience	FL1	When I browse or use AI-recommended or AI-generated brand content on the platform, I often become fully immersed in it.	Novak et al. [27]; Hoffman & Novak [57]
	FL2	When interacting with brands using the platform's AI features, I feel that time passes very quickly.	
	FL3	When experiencing brand-related AI content or services, I feel a sense of enjoyable immersion.	

Table A1. *Cont.*

Construct		Item	Sources
Flow Experience	FL4	The AI-empowered interactive experience on the platform is very interesting and makes me completely immersed in the brand content.	Novak et al. [27]; Hoffman & Novak [57]
User Satisfaction	SAT1	Overall, I am very satisfied with my overall brand-related experience on social media platforms.	Oliver [33]; Bhattacherjee [97]
	SAT2	The brand-related content and services provided by the platform meet my expectations.	
	SAT3	If I had to choose again, I would still choose to follow and use this brand's content or services on this social media platform.	
Brand Loyalty	BL1	For this brand that uses AI in its marketing, I will continue to purchase or support its products in the future.	Chaudhuri & Holbrook [98]; Yoo & Donthu [99]
	BL2	Even if there are other competing brands, I still consider this brand as my first choice.	
	BL3	I am willing to recommend this brand to people around me.	
	BL4	I consider myself a loyal user of this brand.	
Brand Value Co-creation	BVC1	I am willing to provide feedback to this brand to help improve its AI-powered services or AI features.	Yi & Gong [36]; Ranjan & Read [100]
	BVC2	I am willing to participate in testing and providing suggestions for new AI features or experiences developed by this brand.	
	BVC3	Even if it requires investing time, I am still willing to contribute to improving this brand's digital and AI-powered services.	
	BVC4	I feel that I am co-creating valuable experiences together with this brand.	

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