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The Impact of AI-Personalized Recommendations on Clicking Intentions: Evidence from Chinese E-Commerce

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Abstract: AI-personalized recommendation technology offers more accurate and diverse choices to consumers and increases click-through rates and sales on e-commerce platforms. Yet, data on consumers' experiences of AI-personalized recommendations and their impact path on clicking intention are scarce. This article addressed these issues through three studies. In study 1, we adopted the Grounded Theory approach to conduct in-depth interviews with 30 Chinese consumers and constructed a scale to measure the impact of consumer experience on click intention. In study 2, we adopted the empirical research method to conduct reliability and validity tests on 347 valid questionnaires to finalize the scale officially. In study 3, based on the SOR theory, we constructed a model and formulated hypotheses and then conducted empirical analysis using 1097 valid questionnaires. We found that the relevance, inspiration, and insightful experiences of AI-personalized recommendations can significantly promote consumers' clicking intention. Moreover, immersive experience mediates between the former three factors and clicking intention, and technology acceptance mediates between relevance, inspiration, and clicking intention. When consumers perceive a high degree of information privacy infringement, the immersive experience's positive impact on clicking intention will be weakened. Meanwhile, the promoting effect of technology acceptance on clicking intention will also be inhibited. When information quality improves, the positive impact of technology acceptance on clicking intention will be enhanced. This research fills the gap in the literature on consumers' experiences of AI-personalized recommendations and clarifies how these experiences affect the clicking intention. It offers valuable insights for e-commerce platforms to continuously optimize personalized recommendation algorithms and boost the click conversion rate of online shopping.

Keywords: AI-personalized recommendation; consumer experience; scale development; online shopping; clicking intention; SOR

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1. Introduction

The rapid development of global information technology and the emergence of e-commerce platforms have led to an increasingly competitive landscape for e-commerce enterprises in the digital intelligence era. To gain a competitive advantage and provide high-quality services to a wider consumer base, many e-commerce businesses have adopted artificial intelligence (AI) technology [1]. At present, AI technology has facilitated the advancement of e-commerce platforms in several areas, including image recognition, speech recognition, natural language processing, personalized recommendations, and so forth [2]. The evolution of personalized recommendations has progressed from the initial

stages of simple correlation recommendations and list presentation to the current multi-dimensional, multi-featured, and comprehensive AI-personalized recommendations. These recommendations integrate user preference behaviors and scenarios, becoming a crucial merchandising tool for prominent e-commerce platforms, including Taobao, Jingdong, Tmall, Suning.com, and Amazon. The application of AI personalization recommendations has facilitated the expedient identification of goods and services that align with consumer preferences. By leveraging long-term data mining of consumer behaviors, AI-personalized recommendations enable consumers to locate items that resonate with their preferences swiftly. This approach not only enhances the consumer shopping experience but also optimizes shopping efficiency, facilitating the discovery of a diverse range of brands and product types. Consequently, it has proven instrumental in propelling the growth of online shopping platforms [3,4].

1.1. Consumer Experience of Online Shopping

Online consumer experience is defined as consumers' cognitive, emotional, and behavioral responses to the interactions between customers and a company's platforms through digital channels, such as websites, social media, and mobile applications [5]. In a study conducted by Nadeem et al. (2021), it was discovered that consumer experiential values, encompassing cognitive, hedonic, social, and ethical dimensions, positively influence consumer engagement and brand loyalty in the context of social commerce [6]. Zhang and Li (2022) examined the consumer experience of mobile medical consultation (MMC) services, and they identified two key dimensions: service scenario experience, which encompasses perceived telepresence and perceived platform monitoring, and service search experience, which includes perceived diagnosis and perceived serendipity [7]. Kacprzak (2023) defined the online consumer experience as the cognitive, emotional, and behavioral responses of consumers to interactions with a company's digital platform occurring through digital channels (e.g., websites, social media, and mobile apps) [8].

1.2. Consumer Experience of AI-Personalized Recommendations

Artificial intelligence (AI)-personalized recommendations are based on consumers' historical preferences. Technologies such as machine learning and deep learning are employed to construct recommendation models and create lists by collecting and analyzing users' behavioral data and personal information, which enables the identification of items that are highly similar to those favored by consumers to achieve the highest level of consumer satisfaction [9]. Currently, AI-personalized recommendations are widely used in online shopping platforms. Concerning the research on the online consumer experience of AI-personalized recommendations, the current focus is on the relevance, diversity, and insight of the products recommended to them. The relevance of the recommendations reflects the consumer experience of AI-personalized recommendations and is an important manifestation of this experience. In other words, the recommendations are related to products that are centered around the core needs of the consumer [10]. The utilization of intelligent recognition and search facilitates the e-commerce platform marketing engine's deployment of AI technology to identify consumers within a vast repository of data expeditiously. Upon inputting keywords, voice commands, or images into the search bar, AI employs text analytics, speech analytics, and image recognition technology to discern the issue and conduct a search to match pertinent items and prioritize them [11]. The exponential growth in the volume of data has resulted in a concomitant increase in the complexity of individual decision-making processes, rendering the decision-making process an intractable task. Intelligent search engines can assist users in filtering out the noise and directing consumers to goods that are relevant to their search query [12]. The

relevance of AI-personalized recommendations is becoming increasingly evident, with their scope gradually extending to encompass diverse recommendation mechanisms [13]. From the user's perspective, the primary application of AI technology in the marketing field is the formation of on-demand precision marketing for thousands of people. This may take the form of the "Guess Your Favorite" or "Look and See" intelligent push component of online shopping platforms [14]. AI recommendation engines recommend products that users may purchase in the future based on their past purchasing behavior, thereby reducing the cognitive load of consumers. Furthermore, consumers are provided with optimal services through prediction. The accuracy and effect of "intelligent" recommendations using AI technology are more significant than that of traditional retailing, which reflects the insightful experience that AI-personalized recommendations bring [15].

1.3. Scale Development of Consumer Experience and Behavior

In recent years, research on the scale development of consumers' online shopping experiences and behaviors has been categorized into three main types. The first type focuses on the overall online shopping experiences and behavioral decisions. For instance, Sharma et al. (2019) constructed an attribution scale for online shopping behavior, which included brand loyalty, online reputation management, web interactivity, e-WOM, perceived risk, and price [16]. Fernandes et al. (2021) constructed an online susceptibility scale that included evidential online influence, confirmational online influence, and experiential online influence to measure the factors influencing online shopper buying decisions [17]. Pentina I et al. (2022) comprehensively analyzed the online shopping experience, interpreting it from 23 dimensions, including convenience, frugality, diversity, seeking, safety, happiness, fluency, anxiety, anger, heuristics, universality, satisfaction, loyalty, etc. [18]. Also, some scholars measured the factors influencing online shopping addiction [19]. The second type centers on the consumers' experiences and behaviors in specific industries and scenarios. For example, Flacandji et al. (2020) developed the shopping experience memory scale to measure remembering shopping experiences [20]. Nguyen (2022) developed a five-construct model of customer satisfaction in the context of beauty and cosmetic online shopping in the Vietnamese market [21]. Wegmann et al. (2022) developed the "Experience of Gratification Scale" and "Experience of Compensation Scale" to contribute to the experience of gratification and compensation in addictive behaviors, including online shopping [22]. Shin et al. (2022) developed a scale of consumer technology experience in the hospitality and tourism industry, which consists of nine dimensions (sensorial, cognitive, pragmatic, emotional, relational, unique, familiar, controllable, and economical experiences) [23]. Tabaeeian et al. (2023) developed a scale for gamified e-service quality in the e-retailing industry; ease of use, reliability, emotional appeal, interactivity, security, and visual appeal were identified as the dimensions of the GE-SQ scale in online shopping [24]. The third type combines technology with consumers' experiences in specific industries and products. For instance, Wang P et al. (2024) first developed a consumer experience scale for AI-enabled products, including data capture experience, classification experience, delegation experience, social experience, anthropological experience, and interactive experience; it was the beginning of AI-related consumer experience scale research [25].

1.4. AI-Personalized Recommendations and Online Shopping Clicking Intention

The influence of AI-personalized recommendations on consumer behavior, specifically the intention to click online, has inspired a few studies in recent years. From the perspective of click-through rate, AI-personalized recommendations are designed to optimize the user experience by analyzing user behavior and preferences, providing tailored content and products, and increasing the click-through rate of consumers significantly [26–28]. From

the perspective of trust and loyalty, the provision of personalized recommendations has been demonstrated to have a significant impact on user satisfaction and loyalty, which in turn drives click intention [29]. Social trust is positively associated with perceived benefits and perceived algorithmic equity, which are further linked to the intention to click on recommended items and the intention to use them continuously [30]. From the perspective of the technology itself, AI-personalized recommendations increase both the size of consumers' consideration sets and how intensively they are involved with each alternative in consideration [31]. From the perspective of consumer privacy, studies have shown that effective privacy protection measures can significantly enhance users' trust in personalized recommendation systems [32]. From the perspective of information, the study shows that higher-quality Personalized Product Recommendations (PPRs) are associated with greater value derived by consumers from the online product brokering activity in terms of higher decision-making quality, which is positively associated with repurchase intention. Still, no research has paid attention to clicking intention [33].

1.5. Stimulus–Organism–Response Theory

The Stimulus–Organism–Response (SOR) theory was proposed based on the stimulus–response theory [34]. It is a learning theory put forward by cognitivism. This theory refutes the idea that the connection between stimulus (S) and response (R) is direct, mechanical, and passive. It holds that the environment contains various stimuli (S) that can cause changes in the state of the internal cognitive mechanism of the organism (O) and further lead to the response (R) of the behavioral subject. In the field of consumer behavior research, the SOR theory has become the theoretical background for relevant studies on online shopping [35–37].

In the background of e-commerce, the SOR theory has been widely applied to explore the antecedents and paths influencing consumers' online behaviors, such as the characteristics of online brand communities on online shopping attitudes [38] and influencing factors of repurchase intention [39], the impact of online reviews on consumers' online purchase intention [40], the influencing mechanism of impulse purchase behavior in the context of e-commerce live-streaming [41,42], consumer behavior in virtual reality tourism [43], and the inhibiting factors of e-shopping in developing country markets [44]. In terms of commodity and service types, some studies have utilized the SOR theory to study the relationships among personal religious beliefs, shopping values, attitudes, and online purchase intention in the context of halal cosmetic products [45] as well as the impact of augmented reality on e-commerce, especially in the fields of online shopping for fashion, beauty products, and cosmetics, where augmented reality features can significantly enhance the shopping experience [46]. There are also studies that construct an SOR framework for online shopping value and network satisfaction, focusing on the factors that drive consumers to make online purchases [47].

AI-personalized recommendation has transformed consumers' information acquisition, product screening, and decision-making processes in online shopping. The experience it brings is unique and complex, and AI-personalized recommendation technology has become a key factor influencing consumers' shopping experiences and behaviors. Mainstream e-commerce platforms in China leverage AI-personalized recommendations to enhance user experience, increase user stickiness, and promote purchase conversion. Clicking intention is a crucial link in transforming consumers from potential browsers to actual purchasers. Understanding consumers' specific experiences when faced with AI-personalized recommendations and how these experiences further affect their online clicking intention is of great significance for e-commerce enterprises to optimize recommendation algorithms, conduct precision marketing, and improve service quality. In-depth research on its impact on

online clicking intention helps to analyze consumers' psychological and behavioral mechanisms in an intelligent shopping environment from a novel perspective, further enriches and refines our understanding of consumer behavior, and lays a solid foundation for subsequent research and practical applications. Meanwhile, it can provide valuable references for participating entities such as platform operators, merchants, consumers, and regulatory authorities; promote collaborative cooperation among all parties; optimize resource allocation; create a more high-quality, efficient, and consumer-expected online shopping environment; and drive the continuous improvement and maturation of intelligent shopping models.

However, previous scale studies can be mainly divided into three categories. Firstly, some scales are broadly oriented towards online shopping experience and behavior. Secondly, scales have been developed for consumer experiences and behaviors in specific fields, such as the beauty market, the hotel and tourism industries, and addictive behaviors in online shopping. Thirdly, scale developments focus on consumer experiences and behaviors regarding the use of overall AI products. The consumer experience of AI-personalized recommendation falls within the scope of the experience research on personalized technology services. It is difficult for the conventional online shopping experience to measure it accurately. Moreover, AI-personalized recommendation services have the characteristic of customization. Compared with traditional online shopping experiences, they will impact consumers' psychological states and information cognition differently. Therefore, there is an urgent need to study the effects of AI-personalized recommendations on consumers' clicking intentions to fill the gap in the existing literature and deepen our understanding of consumer behavior in the digital age. So, we carried out three studies to solve the above issues:

(1) In study 1, we employed the Grounded Theory method to discover the composition of the AI personalized recommendations consumer experience as well as its influence path on clicking intention. We established a theoretical model framework based on the content of 30 consumer in-depth interviews, aiming to develop an initial scale for the influence of consumers' experiences with AI-personalized recommendations on online clicking intention;
(2) In study 2, we collected 347 valid consumer data through the empirical research method of questionnaire surveys. We then conducted data analysis using SPSS 26.0 and AMOS 23.0 software to verify the reliability and validity of the scale for consumers' experiences of AI-personalized recommendations on clicking intention and form the final scale;
(3) In study 3, we proposed hypotheses and collected 1097 valid questionnaires through the empirical research method of questionnaire surveys and used SPSS 26.0 and AMOS 23.0 software to verify the path of how consumers' experiences of AI-personalized recommendations influence clicking intention through consumer intrinsic perception and external information environment.

2. Study 1: Dimension Construction of the Influence of Consumer Experience of AI Personalized Recommendation on Online Clicking Intention Based on Grounded Theory

2.1. Materials

AI-personalized recommendation technology is widely employed by mainstream e-commerce platforms in China, such as Taobao, JD.com, Pinduoduo, Dangdang, Suning, etc. This study utilized a sample of individuals who have engaged with these AI recommendation services. The interviewees were required to meet the following criteria: (1) participants must have minimum of 5 years of online shopping experience; (2) demographic features—such as age, gender, education level, income range, and region—were balanced to ensure a diverse sample; and (3) participants must comprehend the concept of AI-personalized

recommendations and recognize their impact on the shopping experience. Additionally, the study involved five experts in consumer behavior, e-commerce, psychology, and sociology to conduct interviews, thereby enhancing the richness of the data collected.

This study used semi-structured, in-depth interviews as the primary data collection method. Before the interviews, the research team convened with field experts to discuss and develop an interview outline for exploring the consumer experience of AI-personalized recommendations on online shopping platforms. This outline was finalized through a pre-interview process, during which one background introduction, one basic registration item, and five key topics were confirmed (see Table A1). Subsequently, from 1 June to 30 September 2023, a semi-structured, one-on-one, in-depth interview was conducted with 30 online shopping consumers in China. At the beginning of each in-depth interview, the background and purpose were introduced to the participants, and the interview was conducted with their verbal consent. Each interview lasted approximately 60–90 min. The total duration of the 30 interviews was 40.2 h. All interviews were recorded, generating over 150,000 words of interview data.

2.2. Methods

The study strictly adhered to the principles of procedural Grounded Theory method. The Grounded Theory method is a qualitative research method proposed by Glaser and Strauss in the 1960s. Its core purpose is to construct theories based on empirical data. To generate theoretical frameworks, it extracts concepts, categories, and logical relationships from first-hand data. Data collection employs diverse means such as interviews, observations, etc. The analysis steps include open coding, axial coding, and selective coding. In the open coding stage, the original materials (such as interview transcripts and observation records) are analyzed sentence by sentence, and materials are decomposed to extract and label individual concepts. Based on open coding, the axial coding of clusters integrates related concepts into categories and clarifies their relationships (e.g., causal, chronological, etc.). In the selective coding stage, the core category is selected from numerous categories. Then, other categories are used to build a systematic theoretical framework around it, clarify its logical relationships, and construct a "storyline" centered on it to clearly display the theoretical structure [48]. In this study, we strictly followed the coding processes of the Grounded Theory method. Twenty-three in-depth interviews were chosen for work and seven for theoretical saturation testing.

2.2.1. Open Coding

After collecting all interview contents, this study encoded them line by line and sentence by sentence and then extracted the corresponding concepts. Sixty initial concepts (C1–C60) were extracted, as shown in the open coding example in Table 1.

Table 1. Open coding example.

No.	Open Coding Initial Conceptualization		Original Statement
1	C1 Accurate insight into target products	N4-1	Overall, it looks great and suits my needs. It's pretty accurate. The keywords are on point, and the objectives are clear. The products it advertises seem to be just what I need.
2	C2 Accurate insight into product categories	N7-2	It matches the products I was looking for at that moment or fits into the main categories, such as children's online courses, English, and so on. The recommendations for me are still quite accurate.

Table 1. *Cont.*

No.	Open Coding Initial Conceptualization		Original Statement
3	C3 Accurate insight into consumer behavior	N6-6	I feel like they will analyze my shopping habits and my current concerns and then recommend related products based on these things.
4	C4 Can provide insight into consumers' consumption levels	N12-2	You can clearly see that after you click on a few products, the recommended products on the shopping site are more closely matched to the desired price and style.
5	C5 Can provide insight into consumer personal characteristics	N11-6	The AI-personalized recommendation algorithm is like a perceptive person. It knows my personal characteristics like gender, age, and style. And it uses these to figure out my needs and provide me with information.
6	C6 Can detect the location of consumers.	N14-6	Shopping apps like Meituan will recommend some products based on location. They'll recommend stuff based on where you are. I think it's really cool. Since they know where I am, they can suggest some delicious and well-reviewed restaurants nearby.
7	C7 Can gain insight into consumption trends	N20-5	It can figure out my consumption level and age. It'll recommend products according to your preferences and budget. If I'm looking for inexpensive stuff, it'll show cheaper options. If I'm searching for mid-range items, it'll show more expensive ones.
...	.....	...	.....
60	C60 Privacy leakage infringements between social software and shopping software.	N12-3	It's kind of scary that when you chat with your friends on WeChat about what you want and then when you open a shopping app, you can see relevant recommendations.

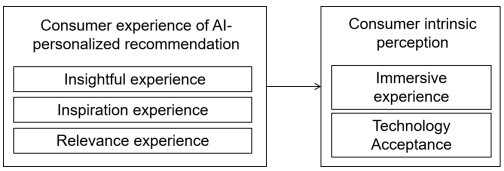
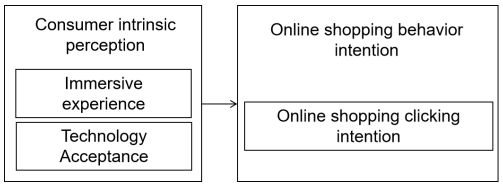
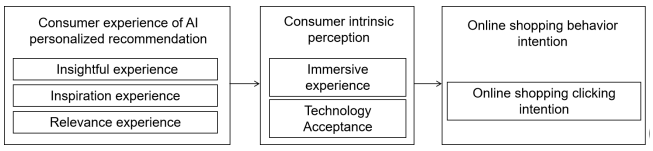
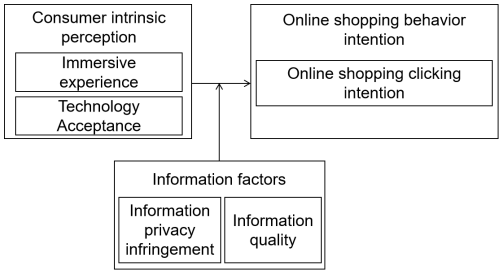
2.2.2. Axial Coding

The open coding process entails screening, merging, and classifying 60 initial concepts, followed by a consistency check after coding. Ultimately, 22 sub-categories that are highly correlated with the consumer experience of AI-personalized recommendations were synthesized and further categorized into eight principal categories. These categories are A1 Functional experience of AI-personalized recommendation, A2 Intrinsic perception, A3 Information factors, and A4 Online shopping behavioral intention (see Table A2).

2.2.3. Selective Coding

This study conducted a synthesis of the existing literature and employed the Grounded Theory process involving repeated induction, summary, and collation. Through this process, a core category, namely "The mechanism of the influence of AI personalized recommendation consumers experience on online shopping clicking intention", was identified. Additionally, it enabled the summarization of the four typical relational structures observed within the four main categories (see Table 2): (1) consumer experience of AI-personalized recommendation (insightful experience, inspiration experience, and relevance experience) has a direct facilitating relationship with consumers' intrinsic perception (immersive experience and technology acceptance); (2) consumers' intrinsic perception of the AI-personalized recommendation system will have a direct facilitating relationship with consumers' online shopping clicking intention; (3) consumers' intrinsic perception of the AI-personalized recommendation system plays a mediating role between consumer experience and online clicking intention; (4) information factors (perceived information privacy infringement and information quality) play a moderating role in the process of consumers' intrinsic perception of AI-personalized recommendation system use on online clicking intention.

Table 2. Analysis of typical relationship structure.

Typical Relationship Structure	The Connotation of Relationship Structure
	Precisely, in the online shopping process, consumers' experience of AI-personalized recommendation consists of insightful experience, inspiration experience, and relevance experience. They can directly promote and bring about consumers' intrinsic perception (immersive experience and technology acceptance).
	In particular, consumers' intrinsic perceptions (perceived immersion experience and technology acceptance) during the process of accepting AI-personalized recommendation services have a direct impact on consumers' clicking intention for online shopping.
	This is evidenced by the fact that consumers' intrinsic perceptions (immersion experience and technology acceptance) during the utilization of AI-personalized recommendation services act as a mediator between the pathways through which the consumer experiences of AI-personalized recommendations (insightful experience, inspiration experience, and relevance experience) exert an influence on online shopping clicking intentions.
	In particular, when an online shopping AI-personalization recommendation system is used, information factors (information privacy infringement and information quality) serve to moderate the influence of consumers' intrinsic perceptions (immersion experience and technology acceptance) on their clicking intention.

Therefore, this study focused on the storyline of the core category "the influence of AI-personalized recommendation consumer experience on clicking intention in online shopping" and determined four main categories: "AI-personalized recommendation function experience", "consumers' intrinsic perception", "information factors", and "online shopping behavior intention".

2.2.4. Test of Theoretical Saturation

This study used the remaining seven interview materials for theoretical saturation testing. No new main categories and relationship structures were found through open coding, axial coding, and selective coding for in-depth excavation and analysis. No new constituent factors were found in the above four main categories. Therefore, the following conclusion can be drawn. The category analysis of this study was already rich enough; therefore, the model of the mechanism of the consumer experience of AI-personalized recommendation on consumers' online clicking intention reached theoretical saturation.

2.2.5. The Initial Scale Design

A total of en individuals were invited to participate in the initial round of item discussion: two professors in business management and marketing, three doctoral students, and five master's degree students in business management. The online shopping consumer experience scale of AI-personalized recommendation was finalized after several rounds of semantic revisions, deletions, and integration. In the 2nd round of item discussion,

10 consumers were invited to evaluate the relevance and accuracy of the questionnaire. Based on their feedback, the scale was revised and subsequently merged, and deleted sentences were removed. The remaining 44 items were categorized into seven groups. The measurement of online shopping clicking intention is possibly available with existing scales [49].

3. Study 2: Scale Development and Conceptual Validation

3.1. Materials

The subjects of this study were Chinese online shopping consumers who had purchased on mainstream Chinese online platforms such as Tmall, Suning, Dangdang, and Taobao. In line with the principle that the number of pre-survey samples should be five times that of question items [50], this questionnaire uses the pre-test scale of 45 items. This study collected the questionnaire through the Questionnaire Star platform from 1 January to 15 January 2024. A total of 400 questionnaires were distributed, and 347 were successfully retrieved, with an effective response rate of 86.8%. The sample included 63.5% female respondents and 36.5% male respondents. Regarding the age distribution of respondents, 36% were under 30 years old, 43.8% were between 31 and 40 years old, 17.9% were between 41 and 60 years old, and 2.3% were over 60 years old. The proportions of respondents with online shopping experience of 5 years or less, 6 to 10 years, 11 to 15 years, and 16 years or more were 10.7%, 48.7%, 32.3%, and 8.4%, respectively.

3.2. Methods

In study 2, we conducted the research using the questionnaire survey method of the empirical research approach. We collected 347 valid questionnaires and then used SPSS 26.0 software to test the reliability and AMOS 23.0 software to test the scale's validity. SPSS 26.0 was used to conduct questionnaire reliability analysis, that is, to assess the scale's stability and consistency. Meanwhile, it is also used to perform Exploratory Factor Analysis (EFA), which aims to extract the underlying common factors that are not directly observable from numerous variables, simplify the data structure, and reveal the internal correlations between variables. AMOS 23.0 was used to perform Confirmatory Factor Analysis (CFA), which is used to check whether the relationships between the observed variables and the latent factors in the scale are as expected.

3.2.1. Exploratory Factor Analysis (EFA)

The initial step was to use SPSS 26.0 to assess data suitability. This study's data's KMO value was 0.944, suggesting appropriate data sampling. Bartlett's test showed the fitness of the variable correlation matrix (χ^2 = 12670.841, p = 0.000), indicating common factors between variables and suitability for factor analysis.

Second, principal component analysis was used to extract the factors with eigenvalues greater than 1 from 44 items by selecting the orthogonal maximum rotation method. In the first analysis, seven factors were extracted; the cumulative variance explanation was 71.182%, more than 60%; the factor loading of Q_IS3, Q_IP5, Q_RE4, and Q_RE6 was less than 0.5. After eliminating them, 40 items remained. Factor analysis was carried out again, and the analysis results are shown in Table 3 below. The factor loading of all items was between 0.552 and 0.823, which is more significant than 0.5. These indicate that the measurement items to which each variable belongs can effectively converge on their common factors and distinguish them from others.

Table 3. Results of exploratory factor analysis (n = 347).

Items	Factor Load						
	F1	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**
Q_TA1	0.765						
Q_TA2	0.760						
Q_TA3	0.723						
Q_TA4	0.799						
Q_TA5	0.788						
Q_TA6	0.764						
Q_TA7	0.780						
Q_TA8	0.759						
Q_IQ1		0.804					
Q_IQ2		0.779					
Q_IQ3		0.791					
Q_IQ4		0.747					
Q_IQ5		0.728					
Q_IQ6		0.823					
Q_IQ7		0.823					
Q_IS1			0.563				
Q_IS2			0.571				
Q_IS4			0.645				
Q_IS5			0.717				
Q_IS6			0.614				
Q_IS7			0.612				
Q_IS8			0.579				
Q_RE1				0.662			
Q_RE2				0.684			
Q_RE3				0.687			
Q_RE5				0.552			
Q_RE7				0.627			
Q_RE8				0.577			
Q_IE1					0.821		
Q_IE2					0.795		
Q_IE3					0.763		
Q_IE4					0.764		
Q_IPI1						0.783	
Q_IPI2						0.805	
Q_IPI3						0.815	
Q_IPI4						0.756	
Q_IP1							0.743
Q_IP2							0.749
Q_IP3							0.732
Q_IP4							0.516
Cumulative explained variance (%)	39.373	51.892	56.990	61.811	65.380	68.380	71.182

3.2.2. Confirmatory Factor Analysis (CFA)

We used AMOS 23.0 software for CFA. For a newly developed scale, Chin (1998) considered that it is acceptable for the standardized factor loading to be greater than 0.5 or 0.6 [51]. Therefore, the items Q_RE7, Q_RE8, Q_IQ5, and Q_IS6, with a standardized factor loading lower than 0.5, were deleted. After deleting the above four items, CFA for 36 items was performed again with AMOS 23.0. We found that the standardized regression coefficients of the items were higher than 0.5, indicating that the scale items in this study have good quality (see Table 4). The final scale was thus constructed (see Table A3).

Table 4. Confirmatory factor analysis observed variable factor loading (n = 347).

Measurement Items		Belonging Factor	Standardized Regression Coefficients	CR	AVE
Q_RE3	<---	Relevance experience	0.637	0.7530	0.4348
Q_RE1	<---	Relevance experience	0.678		
Q_RE2	<---	Relevance experience	0.747		
Q_RE5	<---	Relevance experience	0.571		
Q_IS1	<---	Insightful experience	0.623	0.8086	0.3769
Q_IS2	<---	Insightful experience	0.662		
Q_IS4	<---	Insightful experience	0.596		
Q_IS5	<---	Insightful experience	0.579		
Q_IS7	<---	Insightful experience	0.599		
Q_IS8	<---	Insightful experience	0.639		
Q_IP1	<---	Inspiration experience	0.643	0.7307	0.4070
Q_IP3	<---	Inspiration experience	0.738		
Q_IP4	<---	Inspiration experience	0.549		
Q_IP2	<---	Inspiration experience	0.607		
Q_IE1	<---	Immersive experience	0.790	0.8046	0.5085
Q_IE2	<---	Immersive experience	0.724		
Q_IE3	<---	Immersive experience	0.667		
Q_IE4	<---	Immersive experience	0.664		
Q_IPI1	<---	Information privacy infringement	0.783	0.8410	0.5700
Q_IPI3	<---	Information privacy infringement	0.796		
Q_IPI4	<---	Information privacy infringement	0.695		
Q_IPI2	<---	Information privacy infringement	0.742		
Q_TA1	<---	Technology acceptance	0.655	0.8491	0.4143
Q_TA2	<---	Technology acceptance	0.693		
Q_TA3	<---	Technology acceptance	0.634		
Q_TA4	<---	Technology acceptance	0.616		
Q_TA5	<---	Technology acceptance	0.694		
Q_TA6	<---	Technology acceptance	0.611		
Q_TA7	<---	Technology acceptance	0.676		
Q_TA8	<---	Technology acceptance	0.557		
Q_IQ1	<---	Information quality	0.779	0.8527	0.4953
Q_IQ2	<---	Information quality	0.726		
Q_IQ3	<---	Information quality	0.771		
Q_IQ4	<---	Information quality	0.766		
Q_IQ6	<---	Information quality	0.607		
Q_IQ7	<---	Information quality	0.537		

In this study, the method proposed by Fornell and Larcker (1981) was used to determine the conceptual validity, aggregate validity, and discriminant validity of the scale through CR and AVE (see Table 4) [52]. The minimum value of CR was 0.7307, which is greater than 0.7, indicating that the composite reliability is good. Standardized loading was consistently above 0.7 and is acceptable between 0.5 and 0.6 (Chin 1998) [27]. This is a new scale, and the standardized loading coefficients of the 36 items in this scale were mostly greater than 0.6 (29 items), with only 7 items more significant than 0.5. Therefore, the AVE calculation results were all above 0.36. Previous works [51,53] have suggested that AVE is acceptable between 0.36 and 0.5 for a newly developed scale, indicating that the convergence of this model is acceptable. Therefore, the internal quality of the model is ideal, with good convergence, and the values on the diagonal line are more significant than

the correlation coefficient under the line, indicating that the discriminant validity of the model is good (see Table 5).

Table 5. Result of discriminant validity (n = 347).

Items	RE	IS	IP	IE	IPI	TA	IQ
RE	0.659	-	-	-	-	-	-
IS	0.622 ***	0.614	-	-	-	-	-
IP	0.624 ***	0.609 ***	0.638	-	-	-	-
IE	0.231 **	0.352 ***	0.272 **	0.713	-	-	-
IPI	0.249 **	0.230 **	0.263 **	0.213 *	0.755	-	-
TA	0.336 ***	0.588 ***	0.466 ***	0.185 *	−0.113 *	0.644	-
IQ	0.209 *	0.175 *	0.321 ***	0.427 ***	0.369 ***	0.135 *	0.703

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

After calculating in AMOS 23.0, the CMIN/DF was 1.455, RMSEA was 0.045, GFI value was 0.838, PGFI value was 0.721, CFI value was 0.909, IFI value was 0.910, and TLI value was 0.900, which mean the model fits well. Thus, a measurement model of seven latent variables was established (see Figure 1).

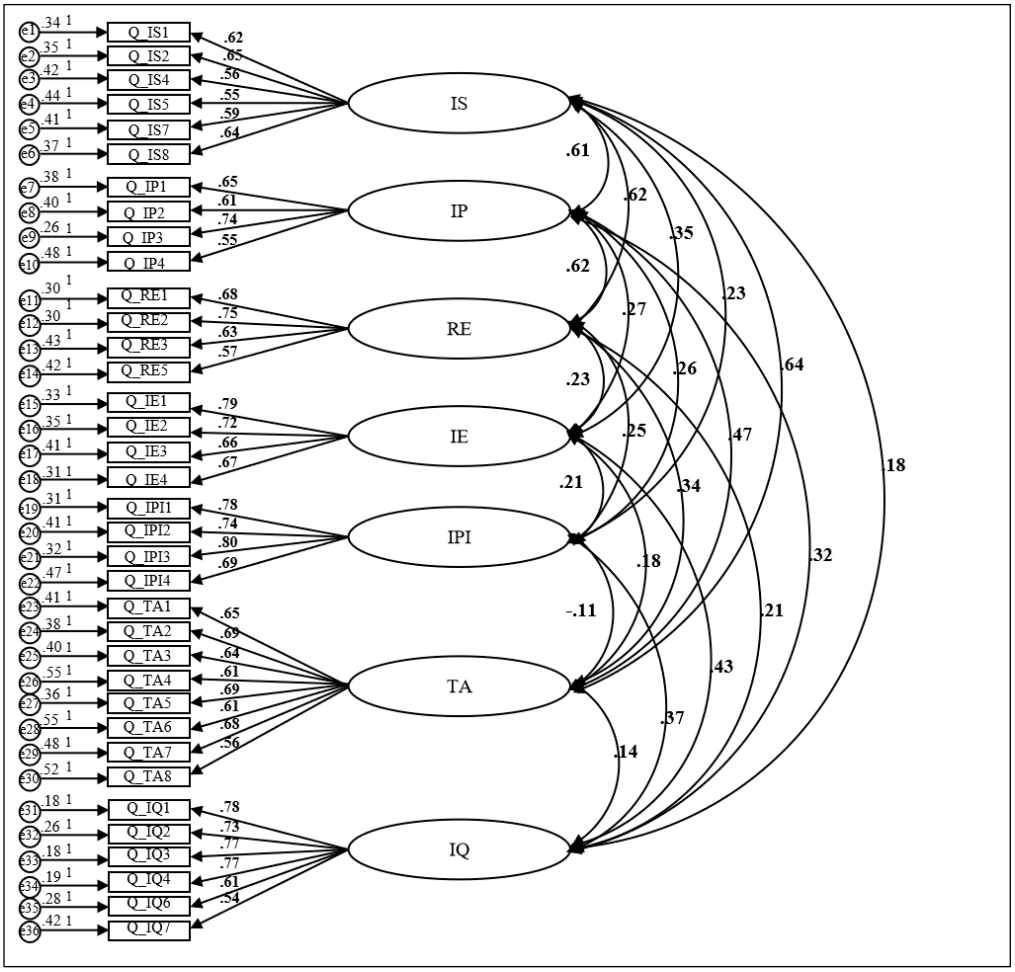


Figure 1. Seven latent variables measurement model.

4. Study 3: Research on the Influence Path of Consumer Experience of AI-Personalized Recommendation on Online Clicking Intention

4.1. Model Establishment and Hypothesis Proposing

Based on the SOR theory, study 1, and study 2, we developed a research model (see Figure 2).

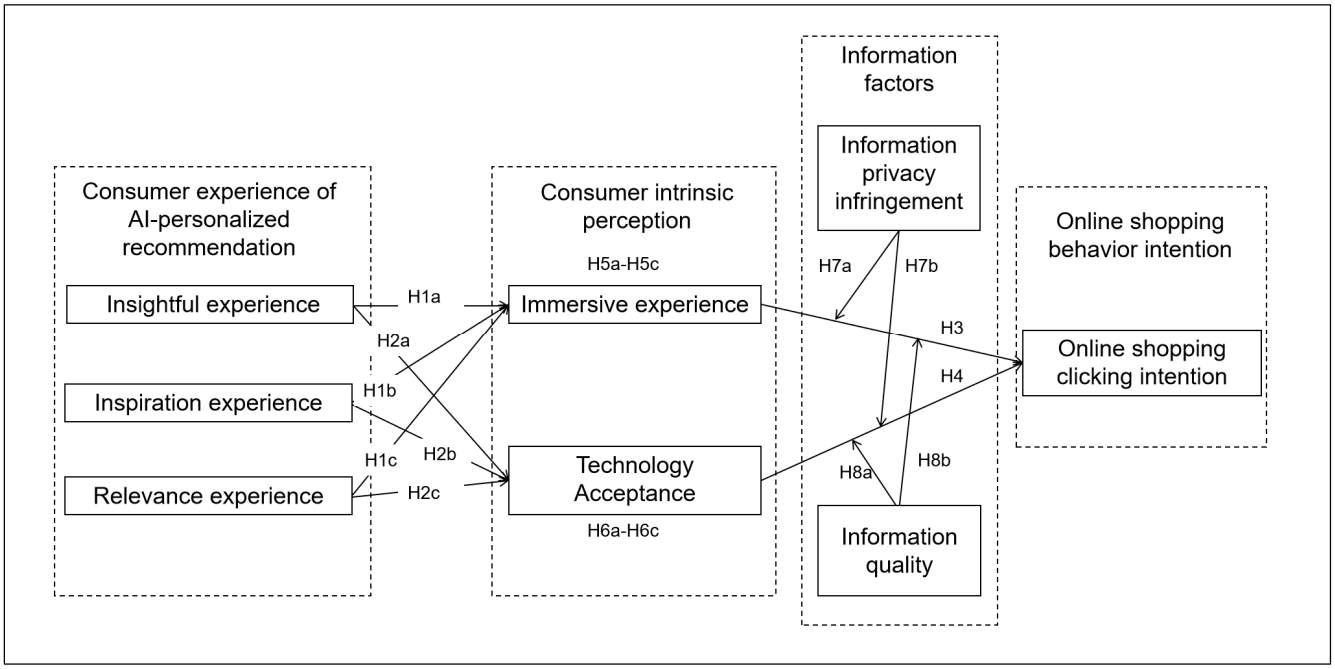


Figure 2. Model construction of the impact of consumer experience of AI-personalized recommendation on online clicking intention.

4.1.1. Hypothesis on the Relationship Between the Functional Experience of AI-Personalized Recommendation and Immersive Experience

Insightful experience describes the capacity of AI-powered recommendation algorithms to observe and analyze a range of consumer behaviors, including registration information, online browsing activity, selections, comparisons, bookmarks, and other actions. This enables the algorithms to identify patterns and conduct a comprehensive analysis of consumer characteristics and preferences. E-commerce platforms collect a range of consumer information, including behavioral patterns, personal identification, feedback on products and services, browsing history, IP address, browser type, telecom operator, and device type, to implement AI-personalized recommendations [54,55]. AI-personalized recommendations are based on consumers' basic information and behavioral data, which can infer consumers' consumption trends and patterns; machine learning provides insights into the outcomes to help consumers reveal the probability of a particular result in the future. Compared with traditional personalized recommendation, AI-personalized recommendations are not limited to what has happened in the past but are used for accurate speculation and prediction of future shopping trends [56]. AI-personalized recommendation can achieve three-dimensional insight into consumer activities, including emotion recognition, potential needs, feelings, and preferences [57]. The deeper the understanding of consumers, the more consumers will inevitably be immersed in the shopping process and find it difficult to extricate.

AI-personalized recommendation systems can accurately identify consumers' preferences by analyzing data such as their browsing histories and purchase records and recommending goods or services that align with their interests [58]. This novel and person-

alized information has the potential to capture consumers' attention, thereby enhancing their engagement in the shopping process. AI-personalized recommendations are not limited to product recommendations, and they can also encompass personalized content, coupons, events, and so forth, offering consumers novel perspectives and solutions [59]. Additionally, an immersive marketing AI-personalized recommendation system, designed through the use of graph neural networks, has the potential to stimulate consumers' creative thinking and desire to explore [60]. When consumers engage in continuous exploration, they become so immersed that they cannot disengage.

The recommendation of relevant products can precisely meet consumers' needs, encouraging consumers to focus on understanding the details of the products in question [61]. This is because the products are selected to match their needs precisely, leading to a sense of immersion in the product. The provision of relevant product recommendations can assist consumers in establishing emotional connections, resulting in a sense of belonging due to the alignment of values and an increased willingness to engage with the product [62]. The recommendation of related products simplifies the decision-making process, while targeted recommendations eliminate the need for consumers to sift through many products, thereby reducing shopping pressure and confusion [63]. It allows consumers to focus on enjoying the evaluation and selection process. It is therefore believed that the relevance experience of AI-personalized recommendations as perceived by consumers can facilitate the immersion experience.

Therefore, H1a, H1b, and H1c are proposed:

H1a. *The insightful experience of AI-personalized recommendation will positively influence consumer immerse experience.*

H1b. *The inspiration experience of AI-personalized recommendation will positively influence consumer immerse experience.*

H1c. *The relevance experience of AI-personalized recommendation will positively influence consumer immerse experience.*

4.1.2. Hypothesis on the Relationship Between the Role of the Functional Experience of AI-Personalized Recommendations on Technology Acceptance

Technology acceptance is composed of consumers' perceived usefulness and ease of use of AI-personalized recommendation technology, based on study 1. AI-personalized recommendations achieve insight and analysis of individual consumer differences through cross-comparison of consumers' multi-dimensional data. Relying on data-driven methods enables e-commerce platforms to process massive amounts of basic consumer information and behavioral data more quickly and effectively. At the same time, it has a relatively high ability for deep learning and self-correction [64]. Furthermore, consumers perceive that they are being perceived in terms of their behavior and intentions during the shopping process. AI-personalized recommendation technology is capable of perceiving consumers' fundamental information and behavioral patterns and is therefore able to predict consumers' preferences and subsequent actions. Consequently, it can provide consumers with products that are more aligned with their demand characteristics and increase sales volume and market conversion rate while raising the average order value [65]. It can thus be surmised that the insightful experience afforded by AI-personalized recommendations to consumers may facilitate their acceptance of AI-personalized recommendation technology.

The provision of AI-personalized recommendations to consumers facilitates access to a vast array of diverse commodity information, thereby enhancing consumers' cognitive abilities [2]. The implementation of AI-personalized recommendations offers consumers a

novel and edifying experience while simultaneously enhancing the value proposition for customers [66]. The inspiration experience can be understood as an external manifestation of the fundamental function of AI-personalized recommendations. This has the potential to expand the consumer's perception and choice space. The advantages and value that enlightenment brings make consumers more amenable to the technology, which in turn increases the technology acceptance of AI-personalized recommendations.

AI-personalized recommendation is based on deep learning technology, which includes algorithms such as multi-layer perception, convolutional neural network, recursive neural network, generative adversarial network, and graph neural network [67–70], and performs potential analysis of characteristics around the consumer's basic information, behavior, socialization, similar groups of people, and recommends goods with relevant attributes according to the degree of importance. The recommendation of highly relevant products will enable consumers to perceive that the AI-personalized recommendation technology is practical, convenient, and easy to use [71]. Consequently, they will adopt it for other consumption activities. That means consumers will accept the AI-personalized recommendation technology due to the recommendation of relevant products.

Therefore, H2a, H2b, and H2c are proposed:

H2a. *The insightful experience of AI-personalized recommendations in online shopping will positively influence consumer technology acceptance.*

H2b. *The inspiration experience of AI-personalized recommendations in online shopping will positively influence consumer technology acceptance.*

H2c. *The relevance experience of AI-personalized recommendations in online shopping will positively influence consumer technology acceptance.*

4.1.3. Hypothesis on the Relationship Between Immersive Experience and Clicking Intention

The intensity of the immersive experience has been found to have a positive correlation with consumers' intention to purchase in online environments [72]. In the context of business services, where AI applications are highly prevalent, immersive experience has also been identified as a key driver of consumer engagement [73]. It can be surmised that AI technology has the potential to enhance the immersive experience of consumers. AI-personalized recommendations continue to play an integral role in consumer shopping decision making. The real-time feedback and continuous intelligent, personalized recommendations AI provides influence consumer behavior, particularly in the shopping environment and the shopping process. This results in a state of forgetfulness, which in turn leads to a constant clicking and browsing pattern. Therefore, hypothesis H3 is proposed:

H3. *The immersive experience of AI-personalized recommendations will positively influence online clicking intention.*

4.1.4. Relationship Hypothesis of Technology Acceptance on Online Shopping Clicking Intention

The perceived usefulness of online shopping platforms positively influences continued use [74]. Online shopping platform service quality, recommended system quality, and information quality affect consumers' intention to adopt recommendations through perceived usefulness and ease of use [75]. The perceived usefulness and ease of use of online shopping have been identified as key factors influencing consumers' intention to purchase products and services [76,77]. Furthermore, the technology acceptance factor comprises perceived usefulness and ease of use. Thus, It can be inferred that consumer

technology acceptance of AI-personalized recommendation is a significant mediator in facilitating consumer clicking intention.

Therefore, hypothesis H4 is proposed:

H4. *Consumer technology acceptance of AI-personalized recommendation will positively influence online clicking intentions.*

4.1.5. Hypothesis of Mediating Relationship

In a network environment, the higher the intensity of the immersive consumption experience, the stronger the consumers' purchase intention [78]. The immersive experience can function as a mediating variable in consumers' purchase intentions when shopping online [79]. Continuous recommendations of related products can easily immerse the consumer in the shopping scenario. It will stimulate purchase intention when consumers enter an immersive state [80]. AI-personalized recommendations enable human–computer interaction with consumers through various techniques, including system interaction, community analysis, and correlation analysis. Recommendations based on predicting consumer behavior and preferences offer a novel and inspiring approach to shopping [81]. Concurrently, it can also anticipate the goods and services that consumers are likely to favor or be interested in as well as the potential for future shopping [56]. Providing continuous recommendations that are relevant, inspiring, and insightful engenders a deeper, more immersive state amongst consumers. During this immersive process, individuals will experience a time distortion, a loss of control over time perception and behavior, and a forgetting of time and space. This, in turn, can promote consumers' purchase intention and behavior.

Therefore, H5a, H5b, and H5c are proposed:

H5a. *Immersive experience plays a mediating role between insightful experience and online clicking intention.*

H5b. *Immersive experience plays a mediating role between inspiration experience and online clicking intention.*

H5c. *Immersive experience plays a mediating role between relevance experience and online clicking intention.*

AI-personalized recommendation technology is a highly sophisticated and effective tool that has gradually gained widespread consumer acceptance. Despite the option to disable personalized recommendations, most consumers tend to opt into these services [82]. According to study 1, relevant experience makes consumers feel that the recommended products are closely connected to their own needs and interests; inspiration experience means expanding the cognitive boundaries of consumers. It brings novelty and supplementation to consumers; insightful experience is when consumers feel that AI has insight into consumption trends and changes in demand, guiding them to broaden their shopping horizons gradually. The diverse functional experiences that users encounter when interacting with AI-personalized recommendation technology demonstrate its usefulness and ease of use, which in turn serve to actively promote specific behaviors such as clicking and browsing [83].

Therefore, H6a, H6b, and H6c are proposed:

H6a. *Technology acceptance plays a mediating role between insightful experience and online clicking intention.*

H6b. *Technology acceptance plays a mediating role between inspiration experience and online clicking intention.*

H6c. *Technology acceptance plays a mediating role between relevance experience and online clicking intention.*

4.1.6. Hypothesis of Moderating Relationship

Since AI-personalized recommendations are primarily based on consumers' private information, the higher the degree of personalization perceived by consumers, the higher the possibility of privacy violations by AI algorithms [84]. This will make consumers feel like they are being spied on and watched. Consumers will want to opt-out if the recommended products and content are too intrusive [1]. Data capture and content extraction technologies increase the frequency with which consumers' privacy is violated. The greater the perceived privacy violation, the more vigilant and defensive consumers will be, and the lower the level of immersion, the more consumers' click intention will be limited.

Technology acceptance involves perceived usefulness and ease of use, which represents the manifestation of the perceived value of AI-personalized recommendation technology from the consumers' perspective [85]. The advancement of AI-personalized recommendation technology hinges on the acquisition of a vast trove of consumer data. Given the pervasive nature of these platforms and the extent of consumer reliance on them, individuals are compelled to divulge personal information, leading to a phenomenon known as "privacy fatigue". This phenomenon can be attributed to two key factors: the compression of digital time and space, which creates a sense of urgency and pressure, and the learned helplessness that arises from consumers' inability to resist the influence of these platforms [86,87]. Concurrently, consumers will comprehensively evaluate the available benefits and risks associated with disclosing their personal information. When consumers perceive that the advantages of revealing their data will outweigh the potential disadvantages, they are highly likely to provide such information despite the inherent risks and potential losses associated with its disclosure [88]. In consumer shopping behavior, it is evident that consumers are aware of the potential of AI personalization to fulfill their desired functions. A clear correlation exists between consumer acceptance of AI-based personalization and the observed behavioral trends in online consumption activities [77]. Concurrently, empirical evidence indicates that when consumers perceive a high level of privacy infringement, their satisfaction with the consumer experience declines, and their trust in the brand is eroded. This can result in consumers developing boredom and avoidance, leading them to close the interface and even deliberately modify their consumer behavior patterns [89,90].

Therefore, H7a and H7b are proposed:

H7a. *Information privacy security invasion exerts a moderating influence on the relationship between immersive experience and online clicking intention.*

H7b. *Information privacy security invasion exerts a moderating influence on the relationship between technology acceptance and online clicking intention.*

A prolonged exposure period to a single information environment can form an information cocoon characterized by a self-circular argumentative structure. Individuals are more inclined to engage in psychological cognitive coordination, whereby inconsistent information is rejected or transformed according to their cognitive framework [91]. The personalized recommendations online shopping platforms provide are analogous to constructing a shopping interface entirely oriented toward consumer preferences. This is

achieved by combining consumer portrait characteristics and behaviors, which ultimately results in the formation of an information cocoon. Due to the increasing dependence on technology, users will become less inclined to take the initiative. They will become more accustomed to accepting the feedback provided by technology and to being indoctrinated, and then, they will make personal choices.

Furthermore, the dual influence of the concept of "personal choice" and the phenomenon of "abnormal dependence" will result in users being placed even more firmly within the information cocoon based on their individual user choices [92]. The quality of the information presented in this study comprises three key elements: information homogeneity, information burden, and differences in information quality. The prevalence of homogeneous information, the substantial volume of information, and the inconsistency in information quality indicate the overall quality of the information presented. This phenomenon is an unavoidable consequence of the current era of algorithmic distribution [93]. An excessive information burden may result in a lack of interest in the information in question [94]. A homogeneous and overwhelming amount of information can negatively impact the willingness of network users to remain within the confines of the information cocoon. To a certain extent, the quality of information can make consumers aware and alert and influence the relationship between an immersive experience and online behavioral intention [95].

The higher the degree of consumer acceptance of AI-personalized recommendation technology, the stronger the consumer's willingness to click online [77]. The consolidation of information and the phenomenon of information overload can readily result in an information cocoon. In the context of an abundance of options, consumers may display behaviors indicative of an excess or a lack of choice [96,97]. As consumers become increasingly accustomed to AI-personalized recommendation services, they will be exposed to vast information. The sheer volume of data, the limitations of information quality, and the varying perceptions of information quality will influence consumer perceptions of product quality. While AI-personalized recommendation technology offers value to consumers, it will also impact consumer behavior in subsequent interactions due to the inherent quality of the information provided. Therefore, H8a and H8b are proposed:

H8a. *The information quality exerts a moderating influence on the relationship between technology acceptance and online clicking intention.*

H8b. *The information quality exerts a moderating influence on the relationship between immersive experience and on online clicking intention.*

4.2. Materials

The research consumers of this study were Chinese online shopping consumers with shopping experiences on China's major online platforms like Taobao, JD.com, Tmall, Suning, etc. Based on the principle that the number of pre-test samples is five times the number of question items, this questionnaire used the final scale (Table 5), which contains 36 items and is measured by the Likert 7-level scale (1 = "strongly disagree," 7 = "strongly agree"). In this test, the Credamo Platform in China issued and exported the questionnaire. From 1 February to 31 March 2024, 1368 questionnaires were distributed through Credamo, an online survey platform, and 1097 questionnaires were effectively recovered, with an effective rate of 86.8%. The statistical characteristics of the samples can be found in Table A4.

4.3. Methods

In study 3, we conducted the research using the questionnaire survey method of the empirical research approach. We used SPSS 26.0 software to test the reliability, common

method biases, direct relationship, mediation relationship, and moderation relationship of the scale and AMOS 23.0 software to test the scale's validity.

4.3.1. Reliability and Validity

This study utilized SPSS 26.0 to conduct Bartlett's sphericity test and KMO test on sample data. The KMO value was 0.764, the approximate chi-square value was 1231.648, the significance level was less than 0.000, and the df was 6. Thus, the variables are suitable for factor analysis. Then, we used SPSS 26.0 for EFA (see Table 6). The test results showed good construct validity of the scale, with statistically significant correlations between each dimension and the total scale. Cronbach's α coefficient was used to measure intrinsic consistency between items, and the results were all greater than 0.7, indicating acceptable reliability. We used Amos 23.0 for CFA (see Table 6), and the standardized loading factors for each item greater were than 0.5. A CR value greater than 0.7 indicates good construct reliability of latent variables. The AVE values were all above 0.36. According to Chin (1998) and Purnomo (2017), an AVE between 0.36 and 0.5 is within an acceptable range for a newly developed scale [51,53]. At the same time, the CMIN/DF was 2.139, RMSEA was 0.032, GFI value was 0.941, PGFI value was 0.809, CFI value was 0.957, IFI value was 0.957, and TLI value was 0.953, which means the model fits well.

Table 6. Results of reliability and validity tests (n = 1097).

Variables	Items	Standardized Load Factor	p	AVE	CR	Cronbach's α
IS	IS1	0.719	***	0.400	0.797	0.792
	IS2	0.604	***			
	IS3	0.578	***			
	IS4	0.599	***			
	IS5	0.594	***			
	IS6	0.674	***			
IP	IP1	0.71	***	0.432	0.752	0.751
	IP2	0.646	***			
	IP3	0.616	***			
	IP4	0.653	***			
RE	RE1	0.663	***	0.389	0.718	0.713
	RE2	0.645	***			
	RE3	0.607	***			
	RE4	0.577	***			
IE	IE1	0.734	***	0.443	0.759	0.75
	IE2	0.714	***			
	IE3	0.641	***			
	IE4	0.56	***			
PS	PS1	0.783	***	0.544	0.825	0.819
	PS2	0.799	***			
	PS3	0.733	***			
	PS4	0.622	***			
TA	TA1	0.584	***	0.371	0.824	0.823
	TA2	0.524	***			
	TA3	0.554	***			
	TA4	0.687	***			
	TA5	0.628	***			
	TA6	0.645	***			
	TA7	0.633	***			
	TA8	0.6	***			

Table 6. *Cont.*

Variables	Items	Standardized Load Factor	p	AVE	CR	Cronbach's α
IQ	IQ1	0.795	***	0.645	0.916	0.915
	IQ2	0.804	***			
	IQ3	0.764	***			
	IQ4	0.775	***			
	IQ5	0.816	***			
	IQ6	0.863	***			
CL	CL1	0.781	***	0.596	0.776	0.768
	CL2	0.763	***			

Note: *** $p < 0.001$.

4.3.2. Common Method Biases

To reduce common method bias, this study concealed variable names in the questionnaire design and used the Harman single-factor analysis method. After unrotated factor analysis of all questionnaire items, the highest explanatory factor variance contribution rate was 38.86%, indicating that the common method bias problem in this study is not significant.

5. Result

5.1. Hypothesis Test of Direct Effect Relationship

This study used SPSS 26.0 to conduct a direct relationship test.

When examining the impact of the functional experience of AI-personalized recommendation on consumers' immersive experience, the influence coefficients of insightful experience, inspiration experience, and relevance experience on immersive experience were 0.652 ($p < 0.01$), 0.501 ($p < 0.001$), and 0.441 ($p < 0.001$), respectively. Therefore, hypotheses H1a, H1b, and H1c are supported (see Tables 7–9).

Table 7. Test on the relationships between IS and online clicking intention (n = 1097).

Dependent Variable / Variable		CL M1	IE M2	CL M3	TA M4	CL M5
Control variable	Gender	0.001	−0.023	0.004	−0.044	0.003
	Age	0.003	0.044	−0.002	0.02	0.003
	Shopping experience	−0.056	0.022	−0.059	0.037	−0.057
	Shopping frequency	0.035	0.016	0.033	−0.009	0.036
	Understanding of AI	−0.027	−0.005	−0.027	−0.04	−0.026
	Income	0.019	−0.012	0.02	−0.056	0.021
Independent variable	IS	0.596 ***	0.652 ***	0.521 ***	0.313 ***	0.585 ***
Mediating variable	IE			0.114 ***		
	TA					0.033 *
R^2		0.339	0.227	0.357	0.041	0.342
Adjusted R^2		0.335	0.222	0.352	0.035	0.337
F		79.523 ***	45.586 ***	75.262 ***	6.594 ***	70.37 ***

Note: *** $p < 0.001$; * $p < 0.05$.

In the examination of the impact of AI-personalized recommendations on consumer technology acceptance, the influence coefficients of insightful experience, inspiration experience, and relevance experience concerning technological acceptance were 0.313 ($p < 0.001$), 0.157 ($p < 0.001$), and 0.25 ($p < 0.001$), respectively. Consequently, hypotheses H2a, H2b, and H2c are supported (see Tables 7–9).

The influence coefficient of the immersive experience brought by AI-personalized recommendations on online consumption clicking intention was 0.291 ($p < 0.001$). Thus,

hypothesis H3 is supported. The influence coefficient of the technology acceptance of AI-personalized recommendations on the clicking intention of online consumption was 0.099 ($p < 0.001$). Therefore, hypothesis H4 is supported (see Table 10).

Table 8. Test on the relationships between IP and online clicking intention ($n = 1097$).

Dependent Variable / Variable		CL M6	IE M7	CL M8	TA M9	CL M10
Control variable	Gender	0.039	0.019	0.036	−0.017	0.04
	Age	0.026	0.07	0.015	0.035	0.024
	Shopping experience	−0.059	0.018	−0.062	0.033	−0.061
	Shopping frequency	0.035	0.015	0.033	−0.012	0.036
	Understanding of AI	−0.011	0.012	−0.013	−0.035	−0.008
	Income	0.014	−0.017	0.017	−0.058	0.018
Independent variable	IP	0.482 ***	0.501 ***	0.405 ***	0.157 ***	0.472 ***
Mediating variable	IE			0.154 ***		
	TA					0.064 ***
R^2		0.291	0.176	0.325	0.017	0.301
Adjusted R^2		0.286	0.171	0.32	0.011	0.296
F		63.569 ***	33.217 ***	65.398 ***	2.722 ***	58.45 ***

Note: *** $p < 0.001$.

Table 9. Test on the relationships between RE and online clicking intention ($n = 1097$).

Dependent Variable / Variable		CL M11	IE M12	CL M13	TA M14	CL M15
Control variable	Gender	0.048	0.03	0.042	−0.021	0.049
	Age	0.009	0.053	−0.002	0.022	0.008
	Shopping experience	−0.069	0.008	−0.07	0.031	−0.07
	Shopping frequency	0.029	0.008	0.027	−0.012	0.029
	Understanding of AI	−0.007	0.015	−0.01	−0.028	−0.005
	Income	0.017	−0.014	0.02	−0.057	0.021
Independent variable	RE	0.439 ***	0.441 ***	0.347 ***	0.25 ***	0.424 ***
Mediating variable	IE			0.207 ***		
	TA					0.059 *
R^2		0.191	0.113	0.266	0.029	0.207
Adjusted R^2		0.19	0.107	0.261	0.023	0.201
F		38.262 ***	19.799 ***	49.138 ***	4.669 ***	49.138 ***

Note: *** $p < 0.001$; * $p < 0.05$.

Table 10. Test on the relationships between IE, TA, and online clicking intention ($n = 1097$).

	Dependent Variable	M16	CL M17	M18
Control variable	Gender	0.075	0.058	0.075
	Age	0.04	0.016	0.036
	Shopping experience	−0.071	−0.073	−0.074
	Shopping frequency	0.022	0.021	0.023
	Understanding of AI	−0.032	−0.029	−0.028
	Income	0.02	0.023	0.025
Independent variable	IE		0.291 ***	
	TA			0.099 ***
R^2		0.01	0.171	0.036
Adjusted R^2		0.005	0.164	0.029
F		1.906	27.897 ***	5.738 ***

Note: *** $p < 0.001$.

5.2. Hypothesis Test of Mediating Effect Relationship

Based on the data of direct effects and mediating effects analysis in Tables 7–10, we calculated the mediating effect of immersive experience between insightful experience, inspiring experience, and relevant experience and online clicking behavioral intention, respectively, as 0.074 ($p < 0.001$), 0.077 ($p < 0.001$), and 0.091 ($p < 0.001$). The mediating effects of technology acceptance between insightful experience, inspiring experience, and relevant experience and online clicking behavioral intention were, respectively, 0.01 ($p < 0.001$), 0.01 ($p < 0.001$), and 0.015 ($p < 0.001$). At the same time, bootstrap intervals were tested using the macro PROCESS developed by Hayes to fully validate the mediating role of immersion experience and technology acceptance. The analysis uses a resampling sample size of 5000 with a 95% confidence level. As shown in Table 11 below, it can be observed that only the confidence interval for hypothesis H6a contained 0 and failed to pass the hypothesis test. Therefore, H5a, H5b, H5c, H6b, and H6c are supported.

Table 11. Bootstrap test for the mediating role (n = 1097).

Path	Effect Category	Effect Coefficient	Standard Error	95% Confidence Interval			Result
				Lower	Upper	p	
IS-CL	Direct effect	0.521	0.0285	0.4648	0.5769	***	Supported
IS-IE-CL	Indirect effect	0.074	0.0180	0.0413	0.1118	***	Supported
IP-CL	Direct effect	0.405	0.0249	0.3575	0.4553	***	Supported
IP-IE-CL	Indirect effect	0.077	0.0142	0.0500	0.1065	***	Supported
RE-CL	Direct effect	0.347	0.0278	0.2936	0.4027	***	Supported
RE-IE-CL	Indirect effect	0.091	0.0146	0.0643	0.1213	***	Supported
IS-CL	Direct effect	0.585	0.0259	0.5341	0.6358	***	Supported
IS-TA-CL	Indirect effect	0.010	0.0062	−0.0008	0.0234		Unsupported
IP-CL	Direct effect	0.472	0.0232	0.4281	0.5294	***	Supported
IP-TA-CL	Indirect effect	0.010	0.005	0.0023	0.0216	***	Supported
RE-CL	Direct effect	0.424	0.0276	0.3718	0.4801	***	Supported
RE-TA-CL	Indirect effect	0.015	0.0067	0.0039	0.0298	***	Supported

Note: *** $p < 0.001$.

5.3. Hypothesis Test of Moderating Effect Relationship

After adding the interaction term between immersive experience and perceived information privacy security infringement to regression equation M8, the R^2 value of M9 increased by 0.005, indicating enhanced explanatory power and supporting hypothesis H7a. The regression coefficient of the interaction term between immersive experience and information privacy security infringement on online clicking intention was −0.054 ($p = 0.003 < 0.01$); thereby, hypothesis H7a is supported (see Table 12). After adding the interaction term between technology acceptance and information privacy security infringement to regression equation M11, the R^2 value of M12 increased by 0.06, supporting hypothesis H7b. The regression coefficient of the interaction term between technology acceptance and information privacy security invasion on online clicking intention was −0.053 ($p < 0.01$), which signifies that H7b is supported (see Table 12).

After adding the interaction term between immersive experience and information quality to regression equation M14, the R^2 value of M15 remained unchanged; thus, hypothesis H8a is not supported (see Table 13). After adding the interaction term between technology acceptance and information quality to regression equation M17, the R^2 value of M18 increased by 0.012. The regression coefficient of the interaction term between technology acceptance and information quality on online clicking intention was 0.047 ($p < 0.01$). Consequently, H8b is supported (see Table 13). Moderation effect diagrams are presented in Figure 3.

Table 12. Test for the moderating effects of information privacy infringement (n = 1097).

Variable	Dependent Variable: CL			Variable	Dependent Variable: CL		
	M7	M8	M9		M10	M11	M12
Constant	5.811 **	5.666 **	5.700 **	Constant	5.713 ***	5.608 ***	5.651 ***
Gender	0.058	0.029	0.032	Gender	0.075	0.033	0.033
Age	0.016	0.029	0.03	Age	0.036	0.039	0.036
Shopping experience	−0.073 *	−0.034	−0.031	Shopping experience	−0.074 *	−0.031	−0.032
Shopping frequency	0.021	0.025	0.024	Shopping frequency	0.023	0.027	0.024
Understanding of AI	−0.029	−0.006	−0.013	Understanding of AI	−0.028	−0.002	−0.007
Income	0.023	0.012	0.011	Income	0.025	0.013	0.012
IE	0.291 ***	0.137 ***	0.132 ***	TA	0.099 ***	0.051 **	0.053 ***
IPI		0.584 ***	0.570 ***	IPI		0.648 ***	0.633 ***
IE × IPI			−0.054 **	TA × IPI			−0.053 **
R^2	0.161	0.412	0.416	R^2	0.036	0.389	0.395
Adjusted R^2	0.156	0.407	0.411	Adjusted R^2	0.029	0.385	0.39
F	F (7, 1086) = 29.798 ***	F (8, 1085) = 94.835 ***	F (9, 1084) = 85.854 ***	F	F (7, 1086) = 5.738 ***	F (8, 1085) = 86.521 ***	F (9, 1084) = 78.649 ***

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

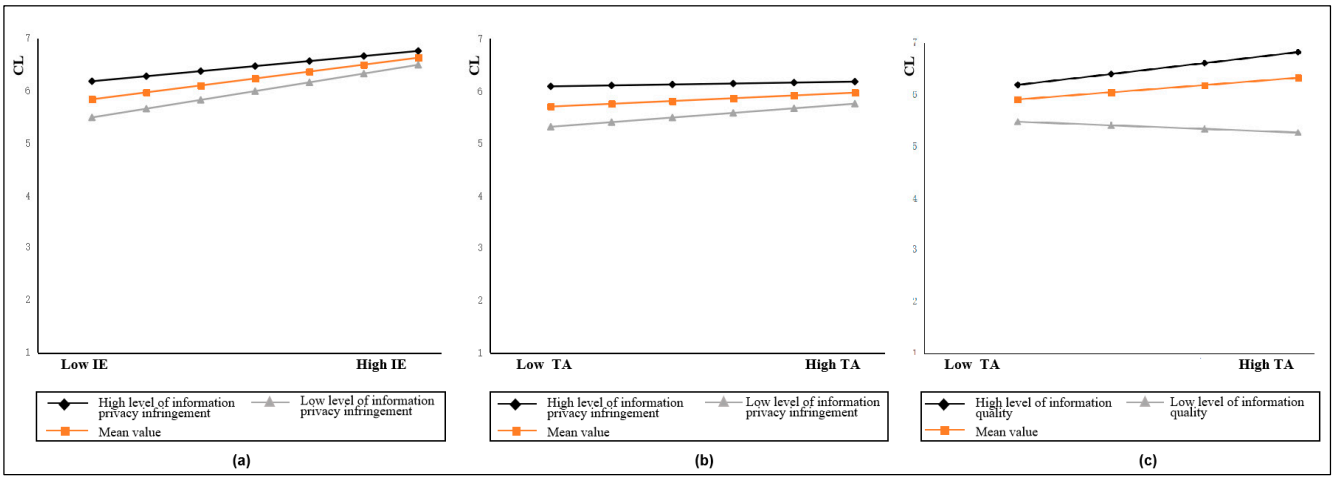


Figure 3. Moderating effect of information factors on (**a**) IE and (**b**,**c**) TA.

Table 13. Test for the moderating effects of information quality (n = 1097).

Variable	Dependent Variable: CL			Variable	Dependent Variable: CL		
	M13	M14	M15		M16	M17	M18
Constant	5.811 **	5.806 **	5.809 **	Constant	5.713 **	5.709 **	5.755 **
Gender	0.058	0.043	0.042	Gender	0.075	0.055	0.046
Age	0.016	0.025	0.025	Age	0.036	0.046	0.040
Shopping experience	−0.073 **	−0.079 *	−0.079 *	Shopping experience	−0.074 *	−0.083 *	−0.082 *
Shopping frequency	0.021	0.021	0.021	Shopping frequency	0.023	0.023	0.022
Understanding of AI	−0.029	−0.021	−0.020	Understanding of AI	−0.028	−0.016	−0.022
Income	0.023	0.018	0.018	Income	0.025	0.021	0.020
IE	0.291 **	0.274 **	0.273 **	TA	0.099 **	0.120 **	0.139 **
IQ		−0.104 **	−0.105 **	IQ		−0.135 **	−0.144 **
IE × IQ			0.006	TA × IQ			0.047 **

Table 13. *Cont.*

Variable	Dependent Variable: CL			Variable	Dependent Variable: CL		
	M13	M14	M15		M16	M17	M18
R^2	0.161	0.207	0.207	R^2	0.036	0.112	0.124
Adjusted R^2	0.156	0.201	0.2	Adjusted R^2	0.029	0.105	0.117
F	F (7, 1086) = 29.798 ***	F (8, 1085) = 35.299 ***	F (9, 1084) = 31.376 ***	F	F (7, 1086) = 5.738 ***	F (8, 1085) = 17.045 ***	F (9, 1084) = 17.046 ***

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

5.4. Construction of a Theoretical Model

Based on the above data analysis, the theoretical model for the AI-personalized recommendation functional experience and online clicking intention is presented in Figure 4 below.

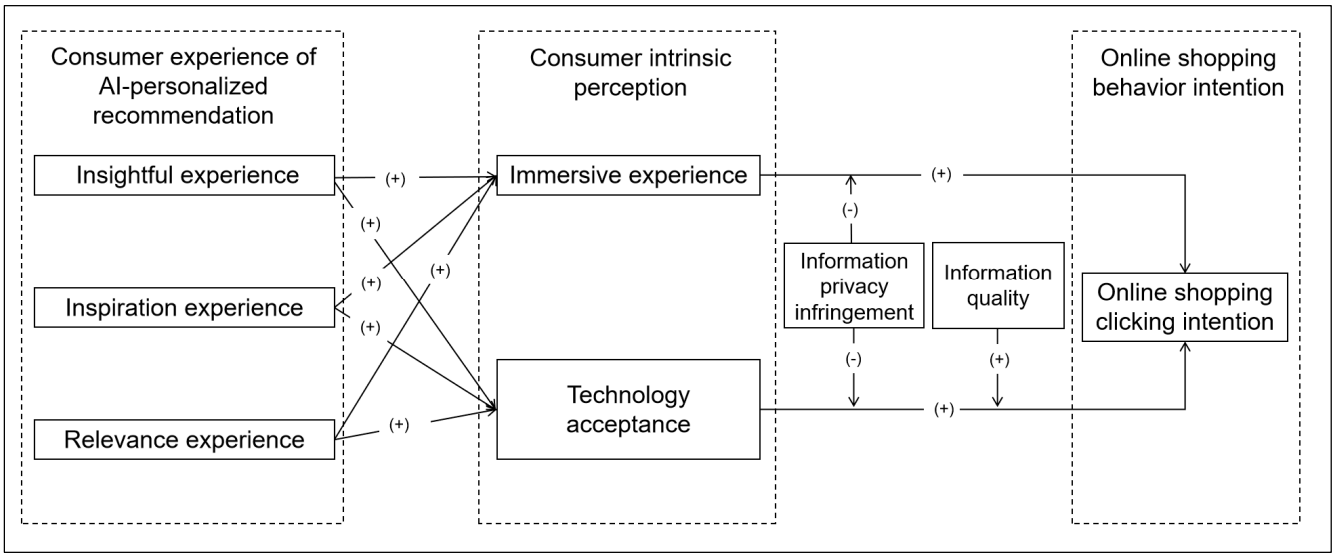


Figure 4. Impact path of consumer experience of AI-personalized recommendations on online clicking intentions.

6. Discussion

This research focused on Chinese consumers on mainstream Chinese e-commerce platforms like JD.com, Taobao, Dangdang, etc., and the research's findings may not apply to research on AI-personalized recommendations in other countries and cultures. It is limited to AI-personalized recommendations on online shopping platforms, excluding rapidly developing short-video e-commerce with great potential for AI integration. Future research should give more attention to this. Regarding information acquisition, although this study used a qualitative method, the limited sample size of the in-depth interviews prohibited covering all consumers' viewpoints. Also, during interviews, memory bias and expression ability can affect consumers' answers, likewise affecting information quality. However, this study offers some innovations and contributions in studying the impact of Chinese consumers' experiences of AI-personalized recommendations on clicking intention on mainstream Chinese e-commerce platforms.

6.1. Enriched Scales of Consumer Experience–Behavior Relationship in AI-Personalized Recommendation

In this study, we conducted interviews with 30 consumers to gain insight into their actual experiences with the AI-personalized recommendation system in an online shopping context. The interviews were conducted with the objective of further developing four

dimensions and eight variables, including (1) the functional experiences of AI-personalized recommendations, which encompass relevance experience, inspiration experience, and insightful experience; (2) consumers' intrinsic perceptions, which include immersive experience and technology acceptance; (3) information factors, such as information privacy security infringement and information quality; and (4) online shopping clicking intention. We constructed a scale for measuring the impact of consumers' functional experiences of AI-personalized recommendations on clicking intention. This study is consistent with the existing research in some aspects. Firstly, some of the literature on scale development has focused on online shopping behaviors toward products or services in different industries by using the qualitative research method of Grounded Theory [16–25]. Secondly, the SOR theory has been utilized to construct a theoretical framework with the experience as the stimulating factor, consumers' internal perception as the internal organism [40–42,98–100], and the intention of online shopping as the response [39,40], with subsequent verification of this framework.

From the perspective of variable measurement, the relevance experience, inspiration experience, and insightful experience developed in this paper do not have existing scales. Previous studies have mainly focused on describing phenomena but lacked measurement [101,102]. Immersive experience, although it is similar to the flow experience, was measured in the past by nine dimensions [103]. However, different from previous studies on immersive experience, during the use of the AI-personalized recommendation system, through in-depth interviews, we learned that consumers mainly focus on four dimensions: continuous immersion, concentration, loss of sense of time, and forgetting the original intention of shopping. We found that, unlike previous research, which treated the usefulness and ease of use of technologies or information systems as independent variables, in AI-personalized recommendation applications, consumers' technology acceptance has blurred the boundaries between usefulness and ease of use, completely breaking the boundaries between them [104,105]. Research on information privacy infringement mainly focuses on the illegal exploitation of users' private data on social networking sites, contactless payment methods, and tracking applications [106–108], but the information privacy violations in AI-personalized recommendation mainly focus on privacy violations across social platforms and the connection between the communication of hardware devices and the data of shopping platforms, showing significant differences. Previous research has focused on the information quality of information service platforms, social reviews, and online learning. Our measurement placed more emphasis on the quality of the information content itself. However, the information quality of AI-personalized recommendation is measured in terms of information homogenization, information overload, and quality characteristics differences of information, thus expanding the research scope of information quality [109–111].

6.2. Validating the Path of the Consumer Experience of AI-Personalized Recommendations on Clicking Intention Online

Firstly, as hypothesized by H1a–c, we took the relevance experience, the inspiration experience, and the insightful experience as stimulating factors. The research findings indicate that they have a significant positive impact on the immersive experience. This is consistent with previous research on the application of AI-related technologies in other shopping fields, such as AR and VR, which all mention that AI-related technologies can facilitate an immersive experience [112–114]. With the continuous upgrading of artificial intelligence machine-learning technologies and recommendation algorithms, e-commerce platforms can deeply capture the correlations among commodities [115]. The stronger the correlations among commodities are, the more they will meet consumers' current consumption goals [116]. AI-personalized recommendations have the function of inspiring

consumers in terms of inspiration and creativity. When consumers have no clear goals and feel confused or hesitant, these intelligent, personalized recommendations can provide valuable information assistance [117]. AI-personalized recommendations gain insights into consumers' characteristics by analyzing various aspects of users, including browsing history, essential characteristics, social labels, and location [104,105,118–120]. This enables users to access content that aligns with their own characteristics and interests more conveniently, thus continuously immersing themselves in the process.

Secondly, as hypothesized in H2a–c, we considered the relevance experience, inspiration experience, and insightful experience as stimulating factors. Our research findings indicate that they have a positive and facilitating effect on technology acceptance. Some research has utilized perceived usefulness and perceived ease of use to analyze users' acceptance of technology [104,105]. Intriguingly, our study discovered that, in the context of accepting AI-personalized recommendation technology, these two dimensions converge into one, which we termed technology acceptance. The various related products recommended by AI-personalized recommendation can broaden consumers' consideration sets, satisfying their need for more information [121]. Consumers can derive new consumption ideas and novel marketing recommendations from these recommendations and uncover novel products or solutions they to which had never previously paid attention. This leads them to perceive this technology more positively [122]. When the system can accurately analyze and determine consumers' characteristics and preferences, the recommended products will be more tailored to consumers' needs. As a result, consumers can genuinely experience the benefits of this technology, thereby enhancing their acceptance of it [123].

Thirdly, as hypothesized in H3–H4, immersive experience and technology acceptance can promote the formation of online clicking intention. This finding is consistent with previous research. In an online shopping context, the stronger the consumers' immersive experience, the more likely it is that they will be thoroughly engrossed and find it hard to disengage [124]. The environment of AI-personalized recommendations is distinct from traditional recommendations. Faced with diverse and dynamically adjusted recommendations, an individual's thoughts and consciousness will fully integrate into the shopping environment [125], resulting in a more pronounced immersive state [126]. Simultaneously, the greater the consumers' recognition and acceptance of the AI-personalized recommendation application, the more likely they will be to click on the recommended products. With the rapid advancement of modern technology, consumers have gradually become accustomed to and dependent on the conveniences brought to their lives by various intelligent technologies [127]. When they accept the AI-personalized recommendation technology, they place more trust in the recommended products and interact more actively with the recommendation system by clicking [128].

Fourthly, as indicated by the verification of hypotheses H5a–c, the immersive experience plays a mediating role between the relevance experience, inspiration experience, insightful experience, and clicking intention. This is consistent with the mediating role of the immersive experience found in some previous online shopping research [129–131]. The relevance experience is typically defined as the degree of fit between the information presented to users (such as web page content, product introductions, etc.) and their personal needs and interests [17]. A higher perceived relevance makes it more likely for users to explore the recommended content further, thus entering an immersive state. The inspiration experience enables consumers to experience AI-personalized recommendations that offer new product categories (substitutes or complements) or solutions beyond their cognitive scope [132]. By breaking through the limitations of human cognition, these recommendations not only match consumers' needs but also provide targeted suggestions in combination with merchants' marketing hotspots. Such content often exhibits

interestingness and novelty. The insightful experience makes consumers perceive that they are being observed, analyzed, and strategized by an independent AI system based on their basic information, consumption behaviors, personality preferences, and other characteristics [133]. This kind of service has a higher degree of fit with consumers, which can enhance consumers' loyalty and satisfaction more effectively [134]. The presentation of a large amount of commodity information that is relevant, inspiring, and insightful into consumers' behavior patterns enables consumers to enter an immersive state. Consumers will perceive a sense of self-forgetfulness, vitality, and complete integration of shopping behavior and brain consciousness [135]. Their attention will be highly concentrated, thus effectively promoting the generation of online click intention. As verified by hypotheses H6a–b, consumers form an acceptance of the technology based on their perception of the relevance of the recommended products, and this acceptance will be further transformed into actual online click intention. Once consumers accept the AI-personalized recommendation technology, they are more likely to click to view the recommended products, increasing the likelihood of subsequent interactions and potential purchases [136]. When consumers are inspired by the products recommended by AI personalization and encounter products or shopping solutions that they have never seen before but find valuable, they will accept it more positively. Consequently, they are more inclined to click further to explore those products or content that may inspire them [137]. This is crucial for promoting consumers' in-depth participation and interaction online. However, analyzing consumer behavior by AI recommendation often implies a privacy invasion, making consumers feel spied on and causing privacy concerns [64,138]. As a result, technology acceptance cannot act as a mediator to promote the next-step clicking intention (H6c unsupported).

Finally, the results indicate that information privacy infringement negatively moderates the interaction between immersive experience, technology acceptance, and click intention (H7a and H7b supported). Through interviews with 30 consumers and analysis of the related literature, it was found that in online shopping, information privacy infringement most frequently occurs in identifying information obtained from mobile phone calls and WeChat as well as in the cross-platform dissemination of data [139]. This makes consumers feel a lack of privacy, thus weakening the positive relationship between immersive experience and the intention of online clicking. When consumers have a strong perception of privacy infringement, they may exhibit behaviors of evasion and boredom towards AI-personalized recommendation technology, which weakens the promoting effect of technology acceptance on click intention. H8b is supported, confirming that information quality positively moderates technology acceptance and click intention. This means that the higher the information quality provided by e-commerce platforms, the greater the promoting effect of technology acceptance on clicking intention. However, no moderating effect of information quality was observed between immersive experience and online click intention (H8a not supported). The main reason may be that there are differences in users' subjective experiences and levels of concentration during the browsing process. Factors affecting users' immersive experience involve page design, content presentation effects, content fluency, and the degree of fit between consumers' interests and the content. These factors are rich and complex [140]. Since information quality is only one aspect of content presentation, the level of information quality does not change the impact of immersive experience on clicking intention.

6.3. Practical Implication

Firstly, in optimizing the AI-personalized recommendation system, it is possible to focus on the promotion of consumers' insightful, inspiration, and relevance experience. It is essential to pursue continuous improvement of the AI-personalized recommendation

algorithm, optimize the recommendation model, and accurately capture the correlation between commodities and the degree of match with consumers' needs with the help of big data. This may be achieved, for example, by accurately analyzing the user's browsing history. The recommended products must align with the consumer's current consumption goals to ensure a high degree of fit, enhancing the consumer's relevance experience. This results in a more relevant consumer experience, which fosters greater immersion, technology acceptance, and an increased likelihood of the consumer clicking through to subsequent purchases. Concurrently, it is imperative to enhance the system's insight capacity. The AI-personalized recommendation system must prioritize improving its insight into consumer behavioral characteristics, user preferences, and consumption trends. By precisely identifying these elements, the recommended products will become more aligned with consumer needs, thereby enhancing consumer acceptance of the technology. Furthermore, the design of AI-personalized recommendation models should focus on providing consumers with multi-dimensional inspiration, such as new consumption ideas, products, or shopping solutions. This will stimulate consumers' interest in shopping and their positive views on this technology.

Secondly, to enhance the immersive experience, it is essential to concentrate on the e-commerce platform page and content design in addition to the feedback rhythm of the match. The page design and recommended content coordination should be the primary focus. The immersive experience primarily concerns the consumer's subjective perceptions of the browsing experience and concentration level. Consequently, the page design, content presentation (including image quality and the use of short videos), and the alignment between user interest and content fit, among other factors, are closely interrelated. It is essential for e-commerce platforms to meticulously devise many recommended formats, such as the "Guess Your Favorite" option, to enhance consumer engagement and facilitate deeper immersion, thereby optimizing the click-through conversion rate. At the same time, the recommendations should be dynamically adjusted according to user feedback. This is because the products recommended by AI have a certain degree of variability, and the recommended content will be adjusted according to the changes in the process of consumer clicks. Therefore, the platform must continue to pay attention to the user. According to the user's behavioral performance in the immersive experience, feedback should be employed to optimize the recommended content in real time. This will reinforce the immersive experience and establish a virtuous cycle, encouraging consumers to continue to click on the relevant product information.

Thirdly, it is paramount to safeguard consumer information privacy and enhance the quality of information on online shopping platforms. E-commerce platforms must accord the protection of consumer information privacy a high degree of importance; adhere strictly to the relevant laws and regulations throughout the entire process of data collection, processing, and dissemination; provide consumers with clear and comprehensive privacy consent instructions; take all necessary measures to avoid any disturbance caused by privacy leakage to consumers in the areas of voice collection, mobile phone calls, WeChat chat information identification, and cross-platform data dissemination; and take all possible steps to avoid any reduction in consumer trust and weakening of clicking willingness due to information privacy infringement. In terms of ensuring reliable information quality, while there is no moderating effect of information quality between immersion experience and online click intention, there is a positive moderating effect between technology acceptance and online click intention. It is, therefore, imperative that the AI-personalized recommendations provided by the platform are of the highest quality, accurate, comprehensive, pertinent, and timely. This will ensure that consumers are receptive to the technology

and that their intention to click on the website with high-quality information is further enhanced, thus promoting online click-to-purchase conversions.

7. Conclusions

In the digital era, AI-personalized recommendation has been deeply applied in e-commerce. It has a remarkable promoting effect on consumers' purchasing behavior and effectively increases the sales volume of e-commerce platforms. As a crucial link in promoting consumption conversion, the intention of click-through behavior has drawn extensive attention. Although there is relatively abundant research on consumer experience, significant differences in experience exist across different consumer industries, scenarios, and products, and the research dimensions are also quite diverse. Regarding the consumer experience of using AI-personalized recommendation technology and how these experiences influence consumers' clicking intention through internal mechanisms, it is impossible to conduct research using existing scales, thus leaving a particular research gap. Based on this, this paper aimed to explore the specific experiences that AI-personalized recommendation technology brings to consumers and the internal mechanisms by which these experiences affect clicking intention. This study comprehensively employed the Grounded Theory method in qualitative research and the questionnaire research method in empirical research. With the help of the Grounded Theory, potential influencing factors and dimensions were determined through in-depth interviews with consumers. At the same time, the empirical research method was utilized to design and distribute questionnaires for data collection. In the data analysis stage, SPSS and AMOS software were used to conduct reliability and validity analysis and hypothesis testing on the data, ensuring the reliability and validity of the research results.

The main conclusions are as follows: Firstly, a scale was developed via interviews with 30 consumers to measure the impact of AI-personalized recommendations on online clicking intention. Four dimensions and related variables were identified, including functional experience (insightful, inspiration, and relevance experience), consumers' intrinsic perceptions (flow experience and technology acceptance), information factors (information privacy infringement and information quality), and online shopping clicking intention. Secondly, the scale's reliability was verified through the consumer data of 347 questionnaires. Thirdly, a model was constructed to examine the impact of consumers' experience with AI-personalized recommendations on their online clicking intention. The path relationships among the identified factors were verified by analyzing 1097 questionnaires: (1) The experiences of relevance, inspiration, and insightful significantly and positively promote the immersive experience and technology acceptance. (2) It can be posited that consumers' immersive experience and technology acceptance of AI personalized recommendations can promote online clicking intention. Consequently, e-commerce platforms may utilize this to enhance shopping conversion rates, and the recommendation function's convenience can also drive clicking intention. (3) The mediating roles were confirmed. With the AI-personalized recommendation system, consumers' experiences (relevance, inspiration, and insightful experience) can trigger an immersive experience, which induces a clicking intention. Furthermore, technology acceptance acts as a mediator between relevance, inspiration experiences, and click intention. (4) The more substantial the consumer perception of information privacy infringement, the more significant the weakening of the relationships between immersive experience and click intention as well as between technology acceptance and click intention. Conversely, the higher the information quality, the more significant the strengthening of the relationship between technology acceptance and click intention. However, this has no moderating effect on the relationship between immersive experience and clicking intention. This study focused on e-commerce platforms in China

that are used by Chinese consumers. Given the differences in consumers' behaviors and preferences across different cultural backgrounds, the conclusions drawn from this study may have limited applicability in other cultural contexts. Additionally, this study used the Grounded Theory to conduct one-on-one consumer research interviews. This process may be restricted by consumers' shopping experiences and expressive abilities, which somewhat affects the research questions' comprehensiveness and depth of understanding.

Based on the research findings, this study urges all industry stakeholders to collaborate and take practical measures for the e-commerce platform's sustainable development. E-commerce platforms should use large-model AI to optimize recommendation algorithms. By better matching recommended content to consumer needs, they can enhance their relevance. Exploring new products and shopping solutions to strengthen inspiration and updating the consumer-portrait model boosts insight. These actions aim to foster immersion, increase acceptance of AI-personalized recommendations, and heighten click-through intent. Moreover, they must optimize algorithms to relieve information-cocoon pressure, rigorously review recommended information quality, and prioritize consumer privacy protection by reducing call and social software data monitoring, thus reducing consumers' repulsion and improving service. Regulatory authorities must intensify supervision of e-commerce platforms' acquisition of consumer privacy information to ensure the fairness and transparency of recommendation algorithms, prevent unfair competition and rights infringement, and safeguard the healthy and orderly development of the e-commerce market.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of the Business Administration Department, School of Economics and Management, Beijing Jiaotong University (No. 20230506, 6 May 2023).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original contributions presented in the study are included in the article, and further inquiries can be directed to the corresponding authors.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Consumer Experience Interview Outline of AI-Personalized Recommendation in Online Shopping.

NO	Interview Topic	Specific Questions
1	Explain the research background and purpose to the interviewees.	Explain the research background and provide an ethical statement for this research topic.
2	Acquire the basic information of the interviewees.	Age, gender, marital status, educational level, current occupation, income level, online shopping frequency, and frequently used online shopping platforms.
3	Whether consumers are aware of AI-personalized recommendation services.	Have you experienced personalized recommendation services during the online shopping process? Have you noticed that the platform recommends products that match your characteristics based on your search behavior, historical browsing behavior, and consumption behavior? Please elaborate.

Table A1. *Cont.*

NO	Interview Topic	Specific Questions
4	What specific experiences do consumers have with AI-personalized recommendation services?	What is your experience with the platform's AI-personalized recommendation service when shopping online? What are the specific experiences? What is the most important experience? Can you describe it in detail and rank the experiences according to their profundity? Do you think personalized recommendations are helpful for your shopping?
5	The intrinsic feelings about using AI-personalized recommendation services.	When receiving AI-personalized recommendation services, what are your internal feelings? Will these feelings affect online shopping click behavior? How?
6	How do consumers feel about the information provided by AI-personalized recommendations?	When receiving AI-personalized recommendation services, how do you feel about the recommended information provided by the platform? For example, will information overload, information cocoons, information quality, privacy violations, etc., influence online clicking intention?
7	How does the experience of AI-personalized recommendations influence the intention of online click behavior?	Through which internal feelings and information factors does the service experience of AI-personalized recommendations influence the intention of online shopping clicking intention?

Table A2. The process of categorization in axial coding.

Main Category	Subcategory	Scope
A1: Consumer experience of AI-personalized recommendation	B1 Insightful experience	Consumer-targeting insights: AI-personalized recommendations of online shopping platforms are more accurate in terms of the category and range of goods recommended based on the keywords retrieved by the consumer.
		Consumer-portrait insights: AI-personalized recommendations can provide insights into consumers' behavioral habits, consumption levels, personal characteristics, and location.
		Consumption trend insight: AI-personalized recommendation can be based on the consumer's browsing history insight into consumer shopping demand trends, such as price trends, product trends, demand mining, and upgrading.
	B2 Inspiration experiences	Enlightenment when the target is specific and when the consumer's online shopping goal is very clear: AI-personalized recommendation of goods can expand the consumer's knowledge of the function, scope, and cost effectiveness of the target goods.
		Enlightenment when the goal is vague and when the consumer's online shopping goal is not too clear: AI-personalized recommendation can bring inspiration and hints of novelty goods.
		The inspirational nature of goal-related complements: AI-personalized recommendations can bring unexpected shopping inspiration and complements to the consumer's shopping process.
	B3 Relevance experience	Behavioral relevance: AI-personalized recommendations of goods are related to the consumer's search behavior, browsing behavior, and buying behavior.
		Target relevance: AI-personalized recommendations are similar, related, peripheral, and equally priced to the target item that the consumer wants to buy.
		Marketing relevance: AI-personalized recommendation of goods related to the platform's marketing and promotion strategy so that consumers perceive obvious merchandising of merchants participating in the platform's marketing activities related to the target goods.

Table A2. *Cont.*

Main Category	Subcategory	Scope
A2: Intrinsic perception	B4 Immersion experience	Deeply immersed in it and cannot be extricated: AI-personalized recommendation of this function is more and more in line with the characteristics of consumer demand and the fission of information so that consumers continue to click and then are immersed in it and cannot be extricated.
		Forget about time: AI-personalized recommendations keep consumers drilling down and clicking, with a plethora of informative recommendations that make consumers forget about the concept of time and become immersed in it.
		Ignore the original intention of shopping: AI-personalized recommendation of rich and diverse goods and all kinds of information consumers will want to click to see so that consumers very easily forget the original intention of shopping in the shopping process.
	B5 Technology acceptance	Useful for shopping comparison: AI-personalized recommendation can facilitate consumers to make comparisons of similar products among different merchants, making it easier for consumers to make shopping decisions.
		Useful for the shopping process: AI-personalized recommendations can optimize the shopping process and help consumers initially screen products.
		The features are easier to use: AI-personalized recommendations, a feature that is easy to use, can help provide consumers with well-matched items.
		The access to information is more convenient: AI-personalized recommendation can provide consumers with a more convenient, fast, and efficient online shopping experience and can provide consumers with promotional information, and access to information is faster and more convenient.
A3: Information factors	B6 Information quality	Information homogenization: AI-personalized recommendations give consumers information about products that are similar and homogenized, and consumers feel wrapped up in homogenized information.
		Information overload: AI-personalized recommendations give consumers too many types of information, too much information, and too much information burden.
		AI-personalized recommended information content varies in brand, authenticity, and quality.
	B7 Information privacy infringement	It can sense that consumers have had discussions about the products in their browsers, social software, and entertainment software, and when they open the shopping platform again, there will be relevant recommendations.
		The shopping software listens to the consumer's conversations and chats, and the shopping software search bar will appear correspondingly.
		The AI-personalized recommendation backend calculates and analyzes consumer habits and behaviors in depth based on algorithms, and consumers have concerns about excessive privacy invasion and leakage.
A4: Behavioral intention to shop online	B8 Online clicking intentions	AI-personalized recommendations will influence consumers' behavior to go and click on targeted and related items.

Table A3. Scale for the Impact of AI-Personalized Recommendation Experience on the Online Shopping Clicking Intention.

Dimension	Coding	Item
Insightful experience (IS)	IS1	AI-personalized recommendations system help me find the products I'm looking for more accurately.
	IS2	The category of products it recommended to me is accurate.
	IS3	AI-personalized recommendations system can analyze my consumption level.

Table A3. *Cont.*

Dimension	Coding	Item
Insightful experience (IS)	IS4	AI-personalized recommendations system can analyze my personal characteristics (gender, age group, preferred style, etc.).
	IS5	AI-personalized recommendations system can facilitate the identification of products with enhanced specifications and quality, thereby directing consumers towards a higher level of demand.
	IS6	AI-personalized recommendation system is capable of identifying the characteristics of my shopping habits and suggesting items that it believes may be of interest or necessity to me.
Inspiration experience (IP)	IP1	AI-personalized recommendations system can give me inspiration during shopping.
	IP2	It is easy for me to discover novelty shops with the help of AI-personalized recommendations.
	IP3	AI-personalized recommendations give me shopping insights.
	IP4	AI-personalized recommendations will easily surprise me with unexpected purchases.
Relevance experience (RE)	RE1	The products it recommended to me are consistent with those I have previously searched for.
	RE2	The products it recommended to me are consistent with those I have browsed.
	RE3	The products it recommended to me are consistent with those I have previously purchased online.
	RE4	The product it recommended to me is consistent with the product category I searched for (substitute).
Immersive experience (IE)	IE1	AI-personalized recommendation makes me immersed in the page with constant recommendations.
	IE2	I find that AI-personalized recommendations draw me in and keep me engaged on the page.
	IE3	The recommendation made me feel like I had only been shopping for a short time, but in fact, I had been shopping for a long time.
	IE4	The constant recommendation kept me immersed, and I often forgot the original intention of shopping.
Information privacy infringement (IPI)	IPI1	I get the feeling that the shopping and entertainment platforms (Douban, Zhihu, Xiaohongshu, etc.) are connected.
	IPI2	It seems like the shopping and tool-related platforms (like 360/Baidu/Google browser, Tencent News, etc.) are all connected.
	IPI3	I get the feeling that the shopping platform and social platforms (like WeChat and Weibo) are connected.
	IPI4	I get the feeling that the shopping platform and mobile phone communication data are connected and that the shopping search bar will appear for the products mentioned in the phone chat.
Technology acceptance (TA)	TA1	It helps me easily compare different stores/merchants on the e-commerce platform.
	TA2	It is convenient for me to compare similar products.
	TA3	It is really helpful for me when I am shopping online, especially for the initial screening.
	TA4	It helps me optimize my online shopping process.
	TA5	It makes me feel that online shopping is very convenient and easy to use.
	TA6	It makes my online shopping more efficient.

Table A3. *Cont.*

Dimension	Coding	Item
Technology acceptance (TA)	TA7	The products that were recommended to me made it really easy for me to choose the right products.
	TA8	The discount promotion info I was given was really useful and basically served as a shopping guide.
Information quality (IQ)	IQ1	The product info I was given is exactly what I was looking for, so I think it is pretty spot on.
	IQ2	It keeps a lot of similar information in my field of vision for a short time, and it is slow to update unless you change keywords (or search/click on new products).
	IQ3	The sheer volume and complexity of the information I was presented with was overwhelming.
	IQ4	The product they suggested is a bit too detailed for my needs.
	IQ5	It is tricky for me to tell which products are the real deal when I see all these recommended ones.
	IQ6	There are differences in the quality of recommended products, which needs to be identified and compared repeatedly.
Online clicking intention (CL)	CL1	I will click on my target products (I have searched in the search bar) recommended to me by AI-personalized recommendations
	CL2	I will click on the products related to the ones I searched for that are recommended by AI-personalized recommendations.

Table A4. Statistical Characteristics of Samples (n = 1097).

Characteristic	Item	Sample Size	Proportion
Gender	Male	376	34.28%
	Female	721	65.72%
Age group	Below 20	49	4.47%
	20–30	472	43.03%
	31–40	458	41.75%
	41–50	66	6.02%
	51–60	36	3.28%
	Above 60	16	1.46%
Online shopping experience time	Below 5 years	128	11.67%
	5–10 years	683	62.26%
	11–15 years	236	21.51%
	Above 16 years	50	4.56%
Online shopping frequency	1–2 times a week	98	8.93%
	2–4 times a week	526	47.95%
	Once a day	99	9.02%
	2–4 times a day	287	26.16%
	More than 5 times a day	87	7.93%
Education	Less than a Bachelor's degree	143	13.04%
	Bachelor's degree	795	72.47%
	Master's degree or above	159	14.49%
Understanding of Artificial Intelligence	Very unfamiliar	3	0.27%
	Unfamiliar	60	5.47%
	Generally familiar	232	21.15%
	More familiar	668	60.89%
	Very familiar	134	12.22%

Table A4. *Cont.*

Characteristic	Item	Sample Size	Proportion
Current family's annual disposable income (CNY)	0–100 thousand	213	19.42%
	100–200 thousand	328	29.90%
	200–300 thousand	277	25.25%
	300–400 thousand	158	14.40%
	400–500 thousand	63	5.74%
	Above 500 thousand	58	5.29%
Frequency of use of large-scale integrated shopping platforms	Taobao	1039	94.70%
	JD.com	961	87.60%
	Tmall	798	72.70%
	Pinduoduo	742	67.60%
	Suning.com	270	24.60%
	Amazon	130	11.90%
	Dangdang	100	9.10%
	Other	59	5.40%
Total		1097	100%

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