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Research article

The impact of personalized recommendation on purchase intention under the background of big data

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Abstract: In order to address the problem of information overload, numerous solutions have been proposed, among which recommender systems stand out as one of the most effective. By reviewing and organizing existing literature both domestically and internationally, this paper evaluated personalized recommendations on the Internet across six dimensions: information layout, recommendation way, recommendation strength, recommendation precision, recommendation timeliness, and recommendation interactivity. Simultaneously, it considered the customer's mind-flow experience and perceived trust as mediating variables, and consumer purchasing intention as the dependent variable of the study. Furthermore, based on relevant theories, this paper constructed a corresponding research model to explore how personalized recommendations influence customers' intention to purchase by affecting their mind-flow experience and perceived trust through this model.

Keywords: personalized recommendation; mind-flow experience; perceived trust; purchase intention

1. Introduction

With the booming development of information technology and Internet technology as well as the continuous evolution and turnover of new media, we have entered the era of big data with information explosion. In this era, we are exposed to a huge amount of information every minute and every second. The larger the amount of information, the greater the cognitive load of consumers searching for products. Acton and Dabrowski [1] pointed out that a large number of product substitutes and a large amount of information about product attributes lead to information overload, so that consumers need to make more effort to make a purchase decision, and the information overload has a negative impact on the user that reduces consumer satisfaction and loyalty to the brand. In this context, many online platforms are analyzing large amounts of consumer behavioral data to bring consumers a better service experience and increase profitability. As a result, personalized services come into play. Personalized recommendation is one of the main applications of personalized services. Personalized recommendation refers to the use of data mining technology by online platforms to collect behavioral data such as consumers' past search, browsing, or purchase history or related data of similar types of consumers, and use these data to analyze the shopping preferences and needs of the target consumers, so as to recommend the goods or services that the consumers may like.

2. Theoretical background and hypotheses

2.1. Big data and personalized recommendations

How we use and analyze big data efficiently and correctly is the focus of every industry. The huge amount of data in the era of big data has far exceeded the amount of information that an individual or a system can receive. Both the user and the network platform are facing the following problems:

1) Users, in front of a huge amount of information, have difficulty finding their own useful information, and even only in the "information hunger" under the influence of passive to receive a variety of useless information on the network, and cannot correctly realize their core needs.

2) The layout of the network platform restricts the ability of the platform to provide all the information to the users, so the network platform can only filter out part of the useless information in order to provide useful information to different users. In addition, filtering the information is equivalent to giving up a portion of the users of the network platform who rely on those "useless information", which does not improve the economic efficiency of the platform.

3) Personalized recommendation is one of the main tools to solve such problems. Personalized recommendation only began to be researched as an independent concept in the 1990s. Resnick and Varian [2] proposed that recommender systems use e-commerce websites to provide users with product information and suggestions to help them decide what products they should buy, simulating the process of a salesperson assisting a customer in completing a purchase. Today's recommender system is not only used for e-commerce. Various platforms can be filtered through the information technology to recommend the goods to the target user, to provide users with personalized recommendation services. The emergence of big data makes this concept more mature and feasible. Personalized recommendation technology is also the most intuitive feeling for ordinary users of the big data era of technology. Nowadays, users are exposed to every application in the product push, and every web page with the content of the advertisement is a personalized recommendation result. personalized recommendation can help users or even replace users in making choices. A good recommendation system can reach a spiritual unity with the user, establish a good relationship with the user, and improve the efficiency of the user's search for information. It can be said that personalized recommendation has deeply affected every Internet user.

2.2. Dimensions of personalized recommendations

Although personalized recommendation originated in the field of computer science, the personalization and diversification of user needs and the increasing use of online platforms by consumers have prompted personalized recommendation to increasingly reflect the nature of its "people". This paper summarizes the division of recommender system dimensions by scholars in recent years as follows.

Table 1. Dimensions of personalized recommendation.

Scholar	Dimensions
Seddon [3]	Convenience, interface consistency
Xiao and Benbasat [4]	Interpretability
Petter et al. [5]	Flexibility, complexity of recommendation algorithm
Chen and Cai [6]	Recommended information ways, information layout, personalization
Nanou et al. [7]	Information layout
Li and Unger [8]	Interactivity, effectiveness
Bobadilla et al. [9]	Precision, differentiation, novelty
Yang et al. [10]	Interpretability, interactivity, precision
Yang et al. [11]	Novelty, interactivity, interpretability
Kaminskas and Bridge [12]	Comprehensiveness, contingency, diversity
Hong et al. [13]	The ability to process data, the time required for the recommendation process
Xu and Zhu [14]	Recommended way, information layout
Wang [15]	Information layout, recommended way, information value, timeliness, user trust, recommended strength
Chen et al. [16]	Relevance, explainability
Cui [17]	Cross-platformity, cross-platform types
Zou [18]	Perceived personalization

Based on the dimensions of personalized recommendation measurements outlined by the aforementioned scholars, this study first identifies information layout, recommendation way, and recommendation strength as research variables. Second, the primary purpose of personalized recommendation services is to match the recommended products on online platforms with customer needs. Therefore, this study selects recommendation precision and recommendation timeliness as research variables. Finally, the stronger the interaction of the recommendation, the more attractive it is to customers and the more likely it is to generate interest. Therefore, recommendation interactivity is particularly important. Thus, this study will measure personalized recommendation using these six dimensions: information layout, recommendation way, recommendation strength, recommendation precision, recommendation timeliness, and recommendation interactivity. These six output characteristics will be treated as variables in this study to analyze the impact of personalized recommendation on customers' purchase intention in online shopping platforms.

2.3. Research hypothesis

2.3.1. Personalized recommendation and mind-flow experience

Li and Wang [19] argued that diverse recommendation approaches during online shopping can generate consumer interest in recommended products. While traditional pop-up advertisements may trigger consumer defensiveness, many other recommendation approaches have gradually been accepted by consumers. This indicates that well-designed and user-friendly recommended ways can be recognized by consumers, helping them save time and effort in browsing online shopping websites, speeding up their search for desired products, and positively influencing their purchase behavior.

According to Li et al. [20], a product recommendation system can reduce the pressure caused by information overload on consumers. The rationality of information layout in recommendation systems helps to reduce consumers' sensitivity to complex information and lower their perceived risks. Information layout can also affect customers' emotional perception, thereby influencing their initial impression of the webpage. Ouyang and Zhu [21] have confirmed in their research that the reasonable arrangement of recommendation systems significantly affects customer satisfaction and loyalty on shopping websites. One of the main reasons that influence customers' use of recommendation systems during online shopping on e-commerce websites is that their commendation information is not classified and arranged by product categories. Unscientific and unreasonable information layout will reduce customers' perceived usability. A proper visual layout can make previously disordered information appear orderly, adapting to users' reading habits, thus reducing their reading burden and ultimately increasing the readability of interface information. For platform users, complex backend programming languages are difficult to visualize, and what they need is the convenience brought by the frontend interface.

The research by Zhang and Ma [22] indicated that consumers, driven by curiosity and personal preferences, may actively browse recommended information. The level of involvement with the information increases with the recommended strength. When the involvement reaches a certain level, consumers tend to develop a preference for the recommended information, and if the recommendation is for a specific product, consumers are more likely to have the intention to purchase that product. Dai [23] discovered a positive association between recommendation intensity and consumer flow experience. Higher recommendation intensity enhances consumers' cognitive attractiveness of the recommended products, thereby improving their flow experience level. He found that recommendation intensity has a positive influence on consumers' flow experience. High recommendation intensity can alleviate consumers' cognitive load and enhance their flow experience.

Wang and Zhang [24] discovered that interactive personalized recommendation has a positive impact on consumers' flow experience. By offering personalized and interactive recommendations, consumers can better engage in the shopping process, thereby enhancing their shopping experience and satisfaction. Wu et al. [25] investigated the influence of interactive personalized recommendation on consumers' flow experience, with a particular focus on the role of system response time. The research results showed that interactive personalized recommendation, along with shorter system response time, can significantly enhance consumers' flow experience.

Gebeyehu et al. [26] found that the timeliness of recommendations has a positive impact on customers' flow experience. When recommendation information is presented to customers in a timely manner, they are more likely to enter a state of flow and enjoy the shopping process. Priyadarshini et al. [27] revealed that the timeliness of recommendation systems positively influences customers' flow experience. When recommendation information accurately matches customers' needs and is provided at the appropriate time, customers are more likely to experience flow.

Jung [28] found that recommendation precision has a positive impact on customer flow experience. When the recommendation system accurately understands customers' preferences and provides personalized recommendations that meet their needs, customers are more likely to enter a state of flow. Chau et al. [29] demonstrated that recommendation system precision positively affects customer flow experience. When the recommendation system accurately predicts and meets customers' needs, customers are more likely to experience a smooth and enjoyable shopping journey. Zhang and Ma [22] revealed that recommendation precision significantly influences customer flow experience. By precisely matching customers' needs and preferences, the recommendation system can provide more targeted recommendations, enhancing customers' engagement and satisfaction with the shopping process.

These studies indicate that the recommended way, information layout, recommended strength, interactivity, timeliness, precision of personalized recommendation have positive impact on consumers' flow experience, thereby enhancing shopping pleasure and satisfaction. Therefore, this study proposes the following hypotheses:

H1 Recommended way has a positive impact on mind-flow experience.

H2 Information layout has a positive effect on mind-flow experience.

H3 Recommended strength has a positive impact on mind-flow experience.

H4 Interactivity of personalized recommendations has a positive impact on mind-flow experience.

H5 Timeliness of recommendations has a positive impact on mind-flow experience.

H6 Precision has a positive impact on mind-flow experience.

2.3.2. Personalized recommendation and perceived trust

In his study, Cao [30] showed that companies help their customers filter products that match their preferences by deeply mining their personal information, and then choose an appropriate way to push the filtering results to customers, which can improve customers' favorability to the company's recommendation system. Wang [31] argued that diverse recommended ways in the shopping online process are conducive to arousing consumers' interest in recommended products.

Information layout refers to the content structure and typographical organization of the recommended information presented to us on e-commerce websites, and refers to whether the recommended information is well laid out and clearly organized [32]. Li found that as society evolves, information is spreading at an unprecedented rate. The growth and widespread use of the Internet have made accessing vast amounts of information easier than ever. However, this surge in information also brings the challenge of overload, leading to a growing demand for information that is user-friendly and easily manageable [33].

Fu [34] argued that the appropriate amount of information and valuable recommendation information can effectively help consumers in product selection and increase their trust in and willingness to use the recommendation system. The findings of Zhang and Ma [22] show that consumers may actively browse recommendation information due to certain curiosity or influenced by personal preference when faced with recommendation information, and this information involvement degree will increase with the increase of recommendation intensity. When the level of involvement increases to a certain extent, consumers will become more and more attracted to the recommended information, and if the recommended information is about a product, consumers are likely to be willing to buy that product.

Wang [31] believes that recommendation systems can improve the freshness of push services by extracting and timely understanding changes in users' interests and needs based on their historical and real-time online behavior. This study empirically explores the impact of interactivity on consumer trust in e-commerce platforms. The research results indicate that higher interactivity contributes to increased consumer trust in e-commerce platforms, enhancing their willingness to shop and overall satisfaction. In their study, Zhang et al. [35] and Chen et al. [16] pointed out that in recommendation systems, common recommendation rationales include showing similar items to the ones you have collected, items that other customers who bought or viewed this item also bought or viewed, etc. This practice of informing customers about the generated information after interacting with the website increases recommendation transparency, making customers more aware of the reasons behind the recommendations, thus enhancing their trust in the recommendation system.

The impact of timeliness on consumers' perceived trust is an important research topic. Zhu's study [36] have found that timeliness can significantly increase consumers' trust in recommendation systems or e-commerce platforms. When recommendation information is presented to consumers in a timely and accurate manner, they are more likely to perceive the platform as professional and reliable, thus increasing their trust in the platform. In addition, timeliness can also enhance consumers' satisfaction and acceptance of recommendation information, thereby promoting their purchasing behavior.

Yang et al. [37] pointed out that the degree of matching between recommended product information and user needs, i.e. recommended precision, has an important impact on user satisfaction, trust and loyalty. From the user's perspective. Zeng [38] defined information quality as the degree to which the recommended goods satisfy the needs, and that the precision of the recommendation results must be improved in order to enhance the user's recognition of the personalized recommendation system, and that the consumer's willingness to use the recommendation system is influenced by the precision of the recommendation results.

In summary, these studies show that the recommended way, information layout, recommended strength, interactivity, timeliness, precision of personalized recommendation have a positive impact on consumers' perceived trust. Therefore, the following hypothesis is proposed in this study:

H7 Recommended way has a positive impact on consumers' perceived trust.

H8 Information layout has a positive effect on consumers' perceived trust.

H9 Recommended strength has a positive impact on consumers' perceived trust.

H10 Interactivity of personalized recommendations has a positive impact on consumers' perceived trust.

H11 Timeliness of recommendations has a positive impact on consumers' perceived trust.

H12 Precision has a positive impact on the consumers' perceived trust.

2.3.3. Mediating effect of mind-flow experience and perceived trust

Mind-flow experience is a crucial psychological factor that describes an individual's subjective psychological perception of an activity. When a customer has a mind-flow experience, he or she is drawn into the information, ignores the passage of time and automatically skips over irrelevant information around him or her. Customers who experience a mind-flow experience show more positive subjective experiences than those who do not. A good browsing experience is the key to winning customers over and is an important factor in deciding whether to buy a product or service. Customers value the real experience more than the actual value. The stronger the mind-flow experience generated by customers during online shopping, the more positive the cognitive, emotional and behavioral response to the product or website, such as a good brand or website attitude, repeat purchase or willingness to reproduce and spread the word. In addition, the mind-flow experience can attract customers, focus more on the quality and value information of the product itself, improve information processing and decision-making efficiency, reduce price sensitivity, and in turn generate positive buying attitudes and behaviors.

Chen and Cai [6] studied the flow states of customers during shopping, including the feelings of pleasure and time perception, and found that flow significantly affects consumers' purchase intentions. In the same year, Hausman and Siekpe [39] conducted relevant research on online shopping behavior and found that online shopping intentions are significantly positively influenced by mind-flow experience.

Zhang et al. [35] demonstrated through their research that mind-flow experience has a positive impact on customers' purchase intentions. Following that, Wu et al. [25] further confirmed through her study that mind-flow experience positively influences customers' purchase intentions. Then, domestic researchers Wang [15] conducted empirical research and found that users who experience flow are more satisfied with the service provider and more willing to use the service.

Zhao et al. [32] found through relevant research that mind-flow experience has a positive impact on customers' intention to use. Subsequently, Xia et al. [40] approached the study from the opposite perspective and investigated how customers' purchase intentions would change when their attention is disrupted. The results of this study showed that when customers' attention is disturbed, it reduces their positive experience and negatively affects their purchase intention.

Based on the relevant research above, this paper proposes the following hypotheses:

H13: Mind-flow experience has a positive impact on purchase intention.

In the context of e-commerce live streaming, consumers cannot directly test the quality and suitability of beauty products before purchasing. This lack of ability to try products may negatively affect consumers' perceived trust in merchants and their products, leading to a potential decrease in their purchase intention. Establishing a trust bond between merchants and consumers is crucial, and hosts play a significant role in this process. The professionalism, popularity, and reliability of hosts are important factors influencing consumer trust. Hosts gradually build trust relationships with consumers through daily interactions during live broadcasts, their professional abilities, and positive word-of-mouth reviews from product users.

Du and Xiang [41] while researching the dynamic formation mechanism of online consumers' purchase intention, divided trust propensity into four dimensions: environmental trust propensity, personal trust propensity, online platform trust propensity, and institutional trust propensity. They also confirmed that trust propensity in these dimensions all positively influences consumers' purchase intention.

Zhang et al. [42] proposed that under the influence of trust factors, e-commerce live streaming leads to the Matthew effect. Top anchors, such as Li Jiaqi, have more bargaining power and can often negotiate lower prices with merchants, thereby accumulating more fans. The increasing number of fans also enhances the credibility of anchors, and consumers are more willing to trust products recommended by anchors with a large fan base.

Based on the relevant research above, this paper proposes the following hypotheses:

H14: Perceived Trust has a positive impact on consumer purchase intentions.

Mind-flow experience is a psychological state that requires external stimuli to be generated. It is not an instantaneous process but evolves gradually over time. Once mind-flow is induced, it tends to influence specific desires or behaviors.

Two main factors influencing mind-flow experience are: first, consumer characteristics, and second, characteristics of the live streaming platform. The relationship between mind-flow experience and consumer purchase behavior indicates that the professionalism, authenticity, and interactivity of live streamers can affect the generation of mind-flow experience. The online shopping context is also a significant influencing factor. The more positive the atmosphere in the live streaming room, the more likely consumers are to develop shopping desires. Moreover, higher levels of positive stimuli and attractive content in the live stream can trigger positive mind-flow experiences in consumers.

Animesh et al. [43] found that mind-flow experience can mediate the relationship between social presence and consumers' purchase intention for virtual products. Jiang et al. [44] conducted an empirical study and pointed out that a positive online store image can generate mind-flow experience, which in turn influences customers' purchase intention. In this causal pathway, mind-flow experience acts as a mediator. In the same year, Wu et al. [25] discovered that mind-flow experience can mediate customers' purchase intention. Subsequently, Li [33] conducted research confirming that mind-flow can mediate the relationship between interactivity and customer satisfaction. Liu et al. [24,25] used mind-flow theory to study how mind-flow experience mediates the relationship between recommendation and customer purchase intention. Li and Wang [19] verified that mind-flow experience acts as a mediator in influencing customers' purchase intention.

Based on the above studies, the hypothesis is derived:

H15: Mind-flow experience plays a mediating role between personalized recommendation and purchase intention.

Compared to offline shopping, consumers are more concerned about safety, quality, and after-sales service when shopping online. In the context of e-commerce live streaming, consumers' perceived trust becomes particularly important. In the e-commerce live streaming environment, prices are often more favorable compared to offline and regular online shopping. Additionally, the video format allows consumers to better understand the products, and the visual aspect provides a more intuitive understanding of product information. The authenticity of live streaming showcases real product parameters and information to consumers, while the interactivity enables consumers to receive feedback from other buyers who have already made purchases. Due to the inability to physically touch the products, consumers' trust is lower in online shopping. However, in the context of e-commerce live streaming, the more detailed the product information presented by the hosts, the stronger the consumers' perceived trust. E-commerce live streaming displays products completely to consumers, and the live chat and product review sections allow consumers to directly see the feedback from other buyers. These aspects make consumers perceive the information quality as genuine and reliable, creating a positive impression and increasing their perceived trust. This trust relationship influences consumers' purchase intentions [47].

In a study by Zhou [48] on the impact of the quality of real estate online transaction platforms on users' willingness to transact online, it was demonstrated that platform quality significantly influences consumer satisfaction and trust. There is a strong correlation between consumers' trust and their intention to transact. The higher the service quality and level of the real estate platform, the higher the user trust, leading to a stronger intention to transact. Research conducted by Liu [46] established a theoretical model using emotional attitude as an intermediary between personalized recommendation systems and university students' online shopping behavior. It was confirmed that recommendation systems influence online shopping behavior through trust.

Although the above studies may differ in content, they all indicate the existence of a certain mediating role of user trust between service systems and purchase intention. Given the risks and uncertainties of online shopping, consumer trust is particularly important. The more consumers trust a particular platform, the more willing they are to conduct transactions on that platform. Additionally, higher consumer trust is conducive to maintaining long-term relationships between platforms and users. Based on the above analysis, the following hypothesis is proposed:

H16: Perceived trust plays a mediating role between personalized recommendation and purchase intention.

3. Research design

Personalized product recommendation is crucial for improving the marketing strategies of online shopping platforms. Numerous studies have confirmed that personalized product recommendation in online shopping platforms can enhance the user experience and increase purchase intention. In this chapter, we adopt the stimulus-organism-response (SOR) theory and the mind-flow theory as the foundation. Taking the customer's perspective as the primary focus, we construct the model of this study and propose research hypotheses. Based on existing relevant research, we select measurement indicators for the influencing factors in this study and provide corresponding explanations. The aim is to investigate the impact of personalized product recommendation on customers' purchase intention.

3.1. Research model

Based on relevant theoretical foundations, this study investigates the impact of personalized recommendation on the mind-flow experience and subsequently on customers' purchase intention. The aim is to delve into the underlying mechanisms through which personalized recommendation influences customers' purchase intention. The study constructs a research model of customers' purchase intention based on personalized recommendation, using the SOR framework as its foundation.

In this model, the stimulus variable (dependent variable) is personalized recommendation, the response variable (independent variable) is customers' purchase intention, and the organism variable (mediating variables) are mind-flow experience and perceived trust. Six dimensions are selected to measure the independent variable of personalized recommendation: information layout, recommended way, recommended strength, precision, timeliness, and interactivity.

In this paper, a model is constructed to explore the relationship and impact of different variables that can help us understand the interactions between personalized recommendations, midstream experience, perceived trust, and purchase intention. In this paper, we will verify whether the midstream experience mediates the relationship between personalized recommendations and customers' purchase intentions. This means that we will look at whether the midstream experience partially explains the effect of personalized recommendations on customers' purchase intention. Mediating effect usually refers to the role of a variable in transferring influence between the independent and dependent variables. The research model is as follows in Figure 1.

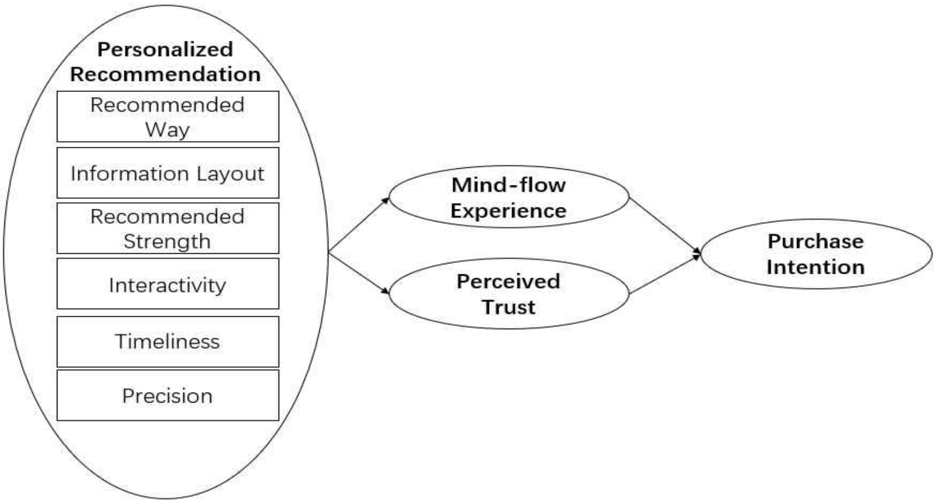

Figure 1. Research model.

3.2. Date collection and methods

On the basis of previous research assumptions and variable measurement, this study extracts the measurement items related to this study, collects and analyzes the data by means of a questionnaire, and obtains the research results. The questionnaire collection process was divided into two stages: prediction testing, are revision and finalization.

First, the variables related to this study collected in the previous literature were reviewed for screening. Based on the analysis of related literature at home and abroad, this study found that in the existing new research, there are mature measurement scales for variables such as the recommendation method, information layout, recommended strength, and interactivity of personalized recommendation. On this basis, this study chose a measurement scale that is highly recognized and widely used, and modified it based on its own research content, laying the foundation for the preliminary formation of the questionnaire.

Before sending out the questionnaire officially, we selected 239 consumers to conduct a pre-survey, and based on their feedback on the questionnaire, we focused on revising the content of the questionnaire to make the statements accurate. Individual measurement items have been selectively removed to ensure the overall simplicity of the questionnaire, resulting in a formal questionnaire.

The specific research methods are descriptive analysis, reliability test validity analysis, correlation analysis, and regression analysis.

4. Results and analysis

A total of 937 questionnaires were collected, and the questionnaire recovery rate was 100%. The questionnaires were preliminarily screened. Those samples with mistakes of omitted answers or logical inconsistencies were deleted. A total of 127 samples were deleted, leaving 807 samples. Then, 56 extreme samples were further removed based on the principle of three standard deviations. Finally, 751 valid samples were retained. The effective rate of the questionnaire was 80%.

4.1. Demographic analysis

The statistical results of the survey sample in terms of occupation, gender, age, education, years of experience, average monthly household income, and shopping frequency in ecotourism are shown in Table 2.

Table 2. Demographic analysis results (N = 751).

	Option	Frequency	Percent (%)
Gender	Male	319	42.5
	Female	432	57.5
Age	< 18 years	4	0.50
	18–25 years	283	37.7
	26–35years	149	19.8
	36–45 years	183	24.4
	> 45 years	132	17.6
Educational level	Middle school and below	68	9.10
	College	166	22.1
	Bachelor’s degree	373	49.7
	Masters	129	17.2
	PhD	15	2.00
Job	Student	151	20.1
	Government employee	139	18.5
	Employees of state-owned enterprises	100	13.3
	Private sector employees	132	17.6
	Self-employed/Freelance	110	14.6
	Other	119	15.8
Average monthly household income (yuan)	< 3000	206	27.4
	3001–7000	269	35.8
	7001–10,000	152	20.2
	> 10,000	124	16.5
Monthly online purchases times	≤ 3 times	229	30.5
	4–10 times	319	42.5
	≥ 11 times	203	27.0

In terms of gender, the frequency of males was 319, accounting for 42.5%, and females were more numerous than males, occupying 57.5% of the total. In terms of age, the largest number of samples were from 18 to 25 years old, with 37.7%, followed by the 36 to 45 years old group, with a total of 183. The smallest group, 0.5%, was under the age of 18. In terms of education, the majority of respondents were undergraduates, accounting for 49.7%. This was followed by the tertiary level, which accounted for 22.1%. There were only 15 people with a PhD or above, accounting for 2% of the respondents. Overall, the majority of respondents had relatively high levels of education. In terms of occupation, the main group were students, accounting for 20.1% of the total. Next, there were more people working in party and government organizations/institutions and private enterprises, with 18.5% and 17.6%, respectively. State-owned enterprises, on the other hand, had the least, at 13.3%. However, overall, the proportion of groups in each industry was relatively balanced and the differences were not great. In terms of monthly income, the group with income in the range of 3001–7000 yuan had the largest share, with 35.8%, while those with more than 10,000 yuan were relatively few, with only 16.5%. The majority of people's income was below 7000 yuan. In terms of the frequency of online shopping, most of them were 4–10 times/month, occupying 42.5%, indicating that the frequency of online shopping was relatively high among the surveyed group.

4.2. Reliability and validity analysis

Reliability refers to the consistency, stability, and reliability of measurement data. Generally, internal consistency is used to express the reliability of the test. The higher the reliability coefficient is, the more consistent, stable, and reliable the test results are. This study uses multiple questions to measure, so Cronbach alpha is used as an indicator to test the reliability of the questionnaire. Generally speaking, when the Cronbach alpha value of the scale designed by the questionnaire is lower than 0.7, it means that the internal consistency of the variables of the scale is poor, and the scale needs to be recompiled. When the Cronbach alpha value of the equivalence table is higher than 0.7, it means that the internal consistency of several variables constructed by the scale is good. If the Cronbach alpha value of the scale is higher than 0.9, it means that the internal consistency of the variables designed by the scale is excellent.

Table 3 shows that the Cronbach alpha values for recommended way, information layout, recommended strength, recommended interactivity, recommended precision, recommended timeliness, mind-flow experience, perceived trust and purchase intention were 0.927, 0.943, 0.891, 0.908, 0.966, 0.952, 0.948, and 0.922, the Cronbach alpha for each dimension after the deletion of each question item was also greater than 0.7, indicating good internal consistency, i.e. the scale had high reliability and was suitable for subsequent analysis.

This paper will use exploratory factor analysis to test the structural validity of the questionnaire data. Before we formally conduct factor analysis, we first need to conduct the KMO test and Bartlett's spherical test to determine whether the indicators of the variables we select meet the conditions for factor analysis. Kaiser's measurement shows that, in general, when the KMO is greater than 0.7, it can be considered as meeting the conditions for factor analysis.

Table 3 shows that the KMO values of recommended way, information layout, recommended strength, recommended interactivity, recommended precision, recommended timeliness, mind-flow experience, perceived trust and purchase intention are 0.879, 0.881, 0.783, 0.857, 0.874, 0.867, 0.854, 0.875, and 0.876, respectively. For the strength variables, the KMO indicators for all variables were above 0.8. Therefore, the validity level also fully meets the requirements of the study. The explained values of each cumulative variance in Table 3 are all greater than 60%. This means that the information of the research project of the consumer identity feature variable in this paper can be effectively extracted. Combined with the factor load coefficient, it can be seen that the factor dimension obtained by rotating the factor load coefficient matrix matches the corresponding problem item of the consumer identity feature variable defined by the research design, and all the absolute value of the corresponding factor load coefficient are greater than 0.5. Therefore, the consumer identity scale in this paper has good structural validity.

Table 3. Results of confidence analysis and exploratory factor analysis.

Variable	Name	The alpha coefficient of the deleted item	Cronbach's alpha coefficient	Factor loading	Eigen value	Cumulative variance explained	Bartlett's sphericity significance	KMO
RW	RW1	0.941	0.927	0.822	3.413	68.26%	0.000	0.879
	RW2	0.914		0.815				
	RW3	0.928		0.840				
	RW4	0.880		0.837				
	RW5	0.882		0.817				
IL	IL1	0.940	0.943	0.794	3.316	66.32%	0.000	0.881
	IL2	0.942		0.809				
	IL3	0.949		0.840				
	IL4	0.907		0.821				
	IL5	0.908		0.807				
RS	RS1	0.876	0.891	0.785	3.807	66.13%	0.000	0.783
	RS2	0.859		0.782				
	RS3	0.893		0.732				
	RS4	0.881		0.735				
	RS5	0.828		0.709				
I	I1	0.909	0.908	0.792	3.055	61.10%	0.000	0.857
	I2	0.906		0.762				
	I3	0.918		0.806				
	I4	0.849		0.754				
	I5	0.848		0.793				
T	T1	0.967	0.966	0.798	3.232	64.64%	0.000	0.874
	T2	0.961		0.814				
	T3	0.969		0.808				
	T4	0.944		0.802				
	T5	0.945		0.798				
P	P1	0.968	0.952	0.818	3.180	63.61%	0.000	0.867
	P2	0.944		0.808				
	P3	0.942		0.784				
	P4	0.924		0.78				

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Variable	Name	The alpha coefficient of the deleted item	Cronbach's alpha coefficient	Factor loading	Eigen value	Cumulative variance explained	Bartlett's sphericity significance	KMO
	P5	0.924		0.797				
ME	ME1	0.951	0.948	0.776	2.984	69.69%	0.000	0.854
	ME2	0.946		0.765				
	ME3	0.949		0.787				
	ME4	0.916		0.765				
	ME5	0.916		0.770				
PT	PT1	0.937	0.922	0.811	3.270	65.41%	0.000	0.875
	PT2	0.904		0.805				
	PT3	0.927		0.807				
	PT4	0.874		0.827				
	PT5	0.875		0.793				
PIt	PI1	0.885	0.897	0.820	3.221	64.41%	0.000	0.876
	PI2	0.862		0.797				
	PI3	0.856		0.808				
	PI4	0.879		0.798				
	PI5	0.887		0.789				

Note: RW: recommended ways, IL: information layout, RS: recommended strength, I: interactivity, T: timeliness, P: precision, ME: mind-flow experience, PT: perceived trust, PI: purchase intention.

The results of the combined reliability and validity tests showed that the overall reliability of the scales used in this study was good, and the validity of each subscale also passed the tests. They all met the requirements of the study and could be analyzed and hypothesis tested in the follow-up study.

4.3. Correlation analysis

Table 4 shows the correlation analysis among the variables. The correlation coefficients of recommended way, information layout, recommended strength, recommended interactivity, recommended precision, recommended timeliness, and mind-flow experience were 0.268, 0.195, 0.282, 0.320, 0.286, and 0.295, respectively, all significant at the 1% level, indicating that recommended way, information layout, recommended strength, recommended interactivity, recommended precision, and recommended timeliness were positively correlated with mind-flow experience. The correlation coefficients of recommended way, information layout, recommended strength, recommended interactivity, recommended precision, recommended timeliness, and perceived trust were 0.272, 0.101, 0.262, 0.286, 0.297, 0.305, and 0.484, respectively, all significant at the 1% level, indicating that recommended way, information layout, recommended strength, recommended interactivity, recommended precision, recommended timeliness, and perceived trust were significantly correlated at the 1% level, indicating that recommended way, information layout, recommended strength, recommended interactivity, recommended precision, recommended timeliness, and perceived trust were significantly correlated at the 1% level. The relationship between recommended way, information layout, recommended strength, recommended interactivity, recommended precision, recommended timeliness, and perceived trust were all positively correlated. The correlation coefficients between mind-flow experience, perceived trust, and purchase intention were 0.455 and 0.538, respectively, which were significant at the 1% level, indicating that mind-flow experience, perceived trust, and purchase intention were positively correlated. Similarly, the correlation coefficient between mind-flow experience and perceived trust was 0.484, also significant at the 1% level, which initially verified the research content of this paper, but the correlation can only serve as a preliminary test of the relationship between the two.

Table 4. Pearson correlations.

	RW	IL	RS	I	T	P	ME	PT	PI
RW	1								
IL	0.249**	1							
RS	0.154**	0.342**	1						
I	0.286**	0.205**	0.231**	1					
T	0.304**	0.113**	0.160**	0.361**	1				
P	0.336**	0.131**	0.121**	0.360**	0.738**	1			
ME	0.268**	0.195**	0.282**	0.320**	0.286**	0.295**	1		
PT	0.272**	0.101**	0.262**	0.286**	0.297**	0.305**	0.484**	1	
PI	0.245**	0.114**	0.260**	0.305**	0.304**	0.330**	0.455**	0.538**	1

*Note: **The correlation is significant at the 0.01 level (2-tailed). RW: recommended ways, IL: Information layout, RS: recommended strength, I: interactivity, T: timeliness, P: precision, ME: mind-flow experience, PT: perceived trust, PI: purchase intention.*

4.4. Hypothesis testing

4.4.1. Regression analysis

In order to further test the proposed hypotheses, this paper uses SPSS25.0 to analyze and test, and the results are show in Table 5.

Table 5 shows the regression analysis of recommended way, information layout, recommended strength, interactivity, timeliness, and precision on the mind-flow experience. The results show that the adjusted R^2 is 0.194, indicating that recommended way, information layout, recommended strength, interactivity, timeliness, and precision explain 19.4% of the variation in mind-flow experience. The D-W value is 1.949, close to with 2, indicating that the model does not have autocorrelation problems.

The coefficient of recommended way was 0.094, which was significant at the 1% level, indicating that for each unit increase in recommended way, the mind-flow experience increased by 0.094 unit, holding other factors constant. This further supports that recommended way positively affects the mind-flow experience and also shows that hypothesis H1 holds.

The coefficient of information layout is 0.049, and the P value is 0.213, which is greater than 0.05, indicating that information layout cannot significantly affect mind-flow experience. In Ghani and Deshpande [49] , Li [47], Wu et al. [25], Yang et al. [50], Zhao and Shang [51] and other scholars' views: the layout and presentation of recommended information can attract user's attention and enhance users' willingness to use personalized recommendation services, which has not been confirmed in this paper. That is, assumption H2 does not hold.

Table 5. Regression results for personalized recommendations and mind-flow experience.

	Unstandardized coefficients		Standardized coefficients	t	Sig.	R^2	Adjusted R^2	F
	B	Std. Error	Beta					
(Constant)	1.483	0.219		6.784	0.000	0.200	0.194	F (6,750) = 31.077, P = 0.000
Recommended way	0.094	0.028	0.122	3.359	0.001**			
Information layout	0.049	0.040	0.045	1.246	0.213			
Recommended strength	0.236	0.046	0.184	5.166	0.000***			
Interactivity	0.157	0.034	0.168	4.556	0.000***			
Timeliness	0.049	0.034	0.071	1.439	0.151			
Precision	0.086	0.038	0.113	2.266	0.024*			
D-W value: 1.949								

*Note: Dependent variable: mind-flow experience, * refers to p < 0.05; ** refers to p < 0.01; *** refers to p < 0.001.*

The coefficient of recommendation strengths is 0.236, which is significant at the 1% level, indicating that when other factors remain unchanged, the mind-flow experience will increase by 0.236 unit for every unit increase in recommendation intensity. This proves that personalized recommended strength of e-commerce information has a significant positive impact on web page visits, and further proves that the personalized recommended strength has a significant positive impact on mind-flow experience, that is, H3 is established.

The coefficient of interactivity was 0.157, which was significant at the 1% level, indicating that for each unit increase in interactivity, the cardiac mind-flow experience increased by 0.157 unit, holding other factors constant. This proves that the interactivity of personalized recommendations attracts consumers and makes them unconsciously immersed, which proves that the interactivity of personalized recommendations has a positive effect on mind-flow experience which has a positive influence on the relationship, and H4 is established.

The coefficient of timeliness is 0.049, and the P value is 0.151, which is greater than 0.05, indicating that timeliness cannot significantly affect mind-flow experience. This cannot prove that timely information can stimulate customers' inner interest and curiosity. That is, H5 does not hold.

The coefficient of precision is 0.086, which is significant at the 5% level, indicating that when other factors remain unchanged, for every one-unit increase in precision, the mind-flow experience will increase by 0.086 unit. This also proves that the precision of recommendation information will have a positive impact on the behavior and feelings of individuals. The precision of personalized information recommendation positively affects the mind-flow experience, that is, H6 is established.

Table 6. Regression results of personalized recommendations on perceived trust.

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	R^2	Adjusted R^2	F
	B	Std. Error	Beta					
(Constant)	1.461	0.226		6.454	0.000	0.189	0.183	F (6,750) = 31.077, P = 0.000
Recommended way	0.118	0.029	0.149	4.074	0.000***			
Information layout	–0.065	0.041	–0.057	–1.583	0.114			
Recommended strength	0.263	0.047	0.199	5.568	0.000***			
Interactivity	0.127	0.036	0.132	3.567	0.000***			
Timeliness	0.059	0.035	0.083	1.672	0.095			
Precision	0.101	0.039	0.130	2.590	0.01*			
D-W value: 2.122								

*Note: Dependent variable: perceived trust, * refers to p < 0.05; ** refers to p < 0.01; *** refers to p < 0.001.*

Table 6 shows the regression analysis of perceived trust by recommended way, information layout, recommended strength, interactivity, timeliness, and precision. The results show that the adjusted R^2 is 0.189, indicating that recommended way, information layout, recommended strength interactivity, timeliness and precision explain 18.9% of the change in perceived trust. The D-W value is 2.122, which is close to 2, indicating that the model does not have autocorrelation problems.

The coefficient of recommended way is 0.118, which is significant at the 1% level, indicating that for each unit increase in recommended way, perceived trust increases by 0.118 unit, holding other factors constant. This proves that appropriate recommended way can enhance consumer' shopping experience and improve consumer satisfaction, and the higher the consumer satisfaction, the easier it is to trust the recommended service, and the recommended way has a positive influence relationship on perceived trust, i.e., H7 holds.

The coefficient of information layout is –0.065, with a P value of 0.114, which is greater than 0.05. This indicates that information layout does not significantly affect perceived trust, and thus H8 does not hold. The rationality of the information layout of the recommendation system lies in its ability to weaken consumers' sensitivity to complex information, reduce customers' perceived risk, and enhance customers' perceived trust. This viewpoint has not been confirmed in this article, meaning that H8 is not established.

The coefficient of recommended strength is 0.236, which is significant at the 1% level. This indicates that, holding other factors constant, for each unit increase in recommended strength, perceived trust increases by 0.236 unit. This proves that recommendation strength has an impact on consumers' psychology or emotions when shopping, and that an increase in recommendation strength is beneficial to the dissemination of recommendation information. It enhances consumers' more comprehensive understanding of a product, reduces consumers' perceived risk, and increases trust in the recommended information. That is, recommended strength positively affects perceived trust, and H9 holds.

The coefficient of interactivity is 0.127, which is significant at the 1% level. This indicates that, with other factors held constant, for each unit increase in interactivity, perceived trust increases by

0.127 unit. This proves that the practice of informing customers of the information generated after interacting with them clarifies why they are being recommended, improves the transparency and precision of the recommendation, and is a means of enhancing users' trust in the recommendation system. That is, the interactivity of personalized recommendations positively affects consumer perceived trust, and H10 holds.

The coefficient of timeliness is 0.059, with a p-value of 0.095. Since this p-value is greater than 0.05, it indicates that timeliness does not significantly influence perceived trust, and therefore H11 does not hold.

The coefficient of precision is 0.101, which is significant at the 5% level. This indicates that, holding other factors constant, for each unit increase in precision, perceived trust increases by 0.101 unit. This supports the view that the more the recommended goods meet the needs of consumers, the more likely consumers are to develop trust. Therefore, the precision of personalized recommendations positively affects perceived trust, and H12 holds.

Table 7. Regression results of mediator and dependent variables.

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	R^2	Adjusted R^2	F
	B	Std. Error	Beta					
(Constant)	1.129	0.142		7.963	0.000	0.339	0.337	F(2,750) = 191.759, P = 0.000
Mind-flow experience	0.267	0.036	0.254	7.481	0.000***			
Perceived trust	0.425	0.035	0.415	12.22	0.000***			
D-W value: 1.716								

*Note: Dependent: purchase intention, * refers to p < 0.05; ** refers to p < 0.01; *** refers to p < 0.001.*

Table 7 shows the regression analysis of mind-flow experience and perceived trust on purchase intention. The results show that the adjusted R^2 is 0.339, indicating that mind-flow experience and perceived trust explain 33.9% of the change in purchase intention. The F-value is 191.759, which is significant at the 1% level, indicating the overall validity of the model coefficients. The D-W value is 1.716, which is close to 2, indicating that the model does not have autocorrelation problems.

The coefficient of mind-flow experience is 0.267, which is significant at the 1% level, indicating that for each unit increase in mind-flow experience, purchase intention increases by 0.267 mind-flow experience units, holding other factors constant. This proves that the mind-flow experience significantly and positively affects purchase intention and mediates between personalized recommendation and purchase intention, and H13 holds.

The coefficient of perceived trust is 0.425, which is significant at the 1% level, indicating that for each unit increase in perceived trust, purchase intention increases by 0.425 units, holding other factors constant. This proves the view of Ouyang [27] that the important role of perceived trust between online store impressions and purchase intention positively affects purchase intention, and H14 holds.

4.4.2. The mediating effect analysis

Table 8. Results of mediating effect test (PW and ME, PT).

Outcome variable	Predict variable	R	R^2	F	Coeff	t	P
Purchase Intention		0.245	0.06	47.84			
	Constant				3.098	29.59	0.000
	Recommended way				0.200	6.917	0.000
Mind-flow experience		0.268	0.072	58.15			
	Constant				3.329	33.69	0.000
	Recommended way				0.208	7.625	0.000
Perceived trust		0.272	0.074	59.66			
	Constant				2.974	29.3	0.000
	Recommended way				0.217	7.724	0.000
Purchase intention		0.586	0.344	130.3			
	Constant				1.029	6.944	0.000
	Recommended way				0.058	2.276	0.023
	Mind-flow experience				0.254	7.032	0.000
	Perceived trust				0.412	11.7	0.000

Note: Refers to P < 0.05, the regression results are significant.

We validate the test of mediating effect of mind-flow experience and perceived trust in the relationship between recommended way and purchase intention, the results are shown in Table 8. The effect of recommended way on purchase intention is positively significant (B = 0.200, t = 6.917, p < 0.05), and the effect of recommended way on mind-flow experience and perceived trust is also positively significant (B = 0.208, t = 7.625, p < 0.05; B = 0.217, t = 7.724, p < 0. 05). When the mediating variables were put in, the recommended way remained positively significant on purchase intention (B = 0.058, t = 2.276, p <0. 05), indicating a significant mediating effect of mind-flow experience and perceived trust.

Table 9. Total, direct, and indirect effects (PW and ME, PT).

	Effect	LLCI	ULCI	Relative effect value
Total	0.200	0.143	0.257	
Direct	0.058	0.008	0.108	29.00%
Indirect (Mind-flow experience)	0.053	0.031	0.077	26.50%
Indirect (Perceived trust)	0.089	0.061	0.120	44.50%

In addition, in Table 9, the upper and lower bounds of the bootstrap 95% confidence interval for the mediating effect of mind-flow experience and perceived trust between recommended way and purchase intention do not contain 0, indicating that recommended way can positively influence purchase intention not only directly, but also indirectly through the mediating effect of mind-flow experience and perceived trust. The direct effect (0.058) and the mediating effect (0.142) accounted for 29% and 71% of the total effect, respectively. The mediating effects of mind-flow experience and perceived trust between recommended way and purchase intention were partially significant.

Table 10. Results of the mediating effect test (IL and ME, PT).

Outcome variable	Predict variable	R	R^2	F	Coeff	t	P
Purchase intention		0.114	0.013	9.807			
	Constant				3.244	17.948	0.000
	Information layout				0.132	3.132	0.002
Mind-flow experience		0.195	0.038	29.562			
	Constant				3.151	18.588	0.000
	Information layout				0.215	5.437	0.000
Perceived trust		0.101	0.010	7.788			
	Constant				3.250	18.386	0.000
	Information layout				0.115	2.791	0.005
Purchase intention		0.583	0.339	127.957			
	Constant				1.035	5.496	0.000
	Information layout				0.027	0.756	0.450
	Mind-flow experience				0.263	7.246	0.000
	Perceived trust				0.425	12.210	0.000

Note: Refers to P < 0.05, and the regression results are significant.

We verified the mediation effect of mind-flow experience and perceived trust in the relationship between information layout and purchase intention, and the results are shown in Table 10. The effect of information layout on purchase intention is positively significant ($B = 0.132$, $t = 3.132$, $p < 0.05$) and the effect of information layout on mind-flow experience and perceived trust is also positively significant ($B = 0.215$, $t = 5.437$, $p < 0.05$; $B = 0.115$, $t = 2.791$, $p < 0.05$). When the mediating variables were put in, information layout was not significant on purchase intention ($B = 0.027$, $t = 0.756$, $p > 0.05$). The mediating effects of mind-flow experience and perceived trust between information layout and purchase intention were partially significant.

Table 11. Total, direct, and indirect effects (IL and ME, PT).

	Effect	LLCI	ULCI	Relative effect value
Total	0.132	0.049	0.215	
Direct	0.027	–0.043	0.096	
Indirect (mind-flow experience)	0.057	0.029	0.089	
Indirect (perceived trust)	0.049	0.000	0.094	

To further verify the mediating effect, in addition, in Table 11, the upper and lower bounds of bootstrap 95% confidence intervals for the mediating effect of mind-flow experience and perceived trust between information layout and purchase intention do not contain 0, but the upper and lower bounds of bootstrap 95% confidence intervals on direct contain 0. This indicates that the information layout is fully mediated by the mind-flow experience and perceived trust to influence the purchase intention, i.e., a full mediation effect.

Table 12. Results of the mediating effect test (RS and ME, PT).

Outcome variable	Predict variable	R	R^2	F	Coeff	t	P
Purchase intention		0.261	0.068	54.514			
	Constant				2.301	11.219	0.000
	Recommended strength				0.352	7.383	0.000
Mind-flow experience		0.282	0.079	64.470			
	Constant				2.520	13.015	0.000
	Recommended strength				0.361	8.029	0.000
Perceived trust		0.262	0.069	55.368			
	Constant				2.259	11.284	0.000
	Recommended strength				0.346	7.441	0.000
Purchase intention		0.588	0.346	131.767			
	Constant				0.748	3.849	0.000
	Recommended strength				0.120	2.851	0.005
	Mind-flow experience				0.249	6.867	0.000
	Perceived trust				0.410	11.711	0.000

Note: Refers to $P < 0.05$, and the regression results are significant.

We verified the mediating effect of mind-flow experience and perceived trust in the relationship between recommendation strength and purchase intention, and the results are shown in Table 12. The effect of recommended strength on purchase intention is positively significant ($B = 0.352$, $t = 7.383$, $p < 0.05$), and the effect of recommended strength on mind-flow experience and perceived trust is also positively significant ($B = 0.361$, $t = 8.029$, $p < 0.05$; $B = 0.346$, $t = 7.441$, $p < 0.05$). When the mediating variables were put in, recommended strength remained positively significant on purchase intention ($B = 0.748$, $t = 3.849$, $p < 0.05$), indicating a significant mediating effect of mind-flow experience and perceived trust.

Table 13. Total, direct, and indirect effects (RS and ME, PT).

	Effect	LLCI	ULCI	Relative effect value
Total	0.352	0.258	0.445	
Direct	0.120	0.037	0.203	34.09%
Indirect (mind-flow experience)	0.090	0.049	0.138	25.57%
Indirect (perceived trust)	0.142	0.084	0.205	40.34%

In addition, in Table 13, the upper and lower bounds of the bootstrap 95% confidence interval for the mediating effect of mind-flow experience and perceived trust between recommended strength and purchase intention do not contain 0, indicating that recommended strength can not only positively affect purchase intention directly, but also positively affect purchase intention indirectly through the mediating effect of mind-flow experience and perceived trust. The direct effect (0.120) and the mediating effect (0.232) accounted for 34.09% and 65.91% of the total effect, respectively. The mediating effect of mind-flow experience and perceived trust between recommended strength and purchase intention was partially mediated.

Table 14. Results of the mediating effect test (I and ME, PT).

Outcome variable	Predict variable	R	R^2	F	Coeff	t	P
Purchase intention		0.305	0.093	76.709			
	Constant				2.715	21.455	0.000
	Interactivity				0.300	8.758	0.000
Mind-flow experience		0.320	0.103	85.697			
	Constant				2.976	24.890	0.000
	Interactivity				0.299	9.257	0.000
Perceived trust		0.286	0.082	66.692			
	Constant				2.740	22.036	0.000
	Interactivity				0.275	8.167	0.000
Purchase intention		0.593	0.352	134.942			
	Constant				0.901	5.892	0.000
	Interactivity				0.118	3.798	0.000
	Mind-flow experience				0.238	6.543	0.000
	Perceived trust				0.404	11.575	0.000

Note: Refers to P < 0.05, and the regression results are significant.

We verified the mediating effect of mind-flow experience and perceived trust in the relationship between interactivity and purchase intention, and the results are shown in Table 14. The effect of interactivity on purchase intention is positively significant (B = 0.300, t = 8.758, $p < 0.05$), and the effect of interactivity on mind-flow experience and perceived trust is also positively significant (B = 0.299, t = 9.257, $p < 0.05$; B = 0.275, t = 8.167, $p < 0.05$). When the mediating variables were put in, interactivity remained positively significant on purchase intention (B = 0.118, t = 3.798, $p < 0.05$), indicating a significant mediating effect of mind-flow experience and perceived trust.

Table 15. Total, direct, and indirect effects (I and ME, PT).

	Effect	LLCI	ULCI	Relative effect value
Total	0.300	0.233	0.367	
Direct	0.118	0.057	0.179	39.33%
Indirect (mind-flow experience)	0.071	0.041	0.104	23.67%
Indirect (perceived trust)	0.111	0.072	0.153	37.00%

In addition, in Table 15, the upper and lower bounds of the bootstrap 95% confidence interval for the mediating effect of mind-flow experience and perceived trust between interactivity and purchase intention do not contain 0, indicating that the inferred interactivity can positively influence purchase intention not only directly but also indirectly through the mediating effect of mind-flow experience and perceived trust. The direct effect (0.118) and the mediating effect (0.182) accounted for 23.67% and 37% of the total effect, respectively. Mind-flow experience and perceived trust partially mediated the relationship between interactivity and purchase intention.

Table 16. Results of the mediating effect test (T and ME, PT).

Outcome variable	Predict variable	R	R^2	F	Coeff	t	P
Purchase intention		0.304	0.092	76.084			
	Constant				3.069	35.151	0.000
	Timeliness				0.221	8.723	0.000
Mind-flow experience		0.286	0.082	66.932			
	Constant				3.405	40.828	0.000
	Timeliness				0.198	8.181	0.000
Perceived trust		0.297	0.089	72.689			
	Constant				3.035	35.516	0.000
	Timeliness				0.212	8.526	0.000
Purchase intention		0.593	0.352	135.248			
	Constant				1.027	7.190	0.000
	Timeliness				0.088	3.877	0.000
	Mind-flow experience				0.244	6.779	0.000
Outcome variable	Perceived trust				0.399	11.376	0.000

Note: Refers to P < 0.05, and the regression results are significant.

We verified the mediating effect of mind-flow experience and perceived trust in the relationship between timeliness and purchase intention, and the results are shown in Table 16. The effect of timeliness on purchase intention is positively significant ($B = 0.221$, $t = 8.723$, $p < 0.05$) and the effect of timeliness on mind-flow experience and perceived trust is also positively significant ($B = 0.198$, $t = 8.181$, $p < 0.05$; $B = 0.212$, $t = 8.526$, $p < 0.05$). When the mediating variables were put in, timeliness remained positively significant on purchase intention ($B = 0.088$, $t = 3.877$, $p < 0.05$), indicating a significant mediating effect of mind-flow experience and perceived trust.

Table 17. Total, direct, and indirect effects (T and ME, PT).

	Effect	LLCI	ULCI	Relative effect value
Total	0.221	0.172	0.271	
Direct	0.088	0.044	0.133	39.82%
Indirect (mind-flow experience)	0.048	0.028	0.073	21.72%
Indirect (perceived trust)	0.085	0.055	0.118	38.46%

In addition, in Table 17, the upper and lower bounds of the bootstrap 95% confidence interval for the mediating effect of mind-flow experience and perceived trust between timeliness and purchase intention do not contain 0, indicating that pushing timeliness can positively affect purchase intention not only directly but also indirectly through the mediating effect of mind-flow experience and perceived trust. The direct effect (0.088) and the mediating effect (0.143) account for 39.82% and 60.18% of the total effect, respectively. Mind-flow experience and perceived trust partially mediated the relationship between timeliness and purchase intention.

Table 18. Results of the mediating effect (P and ME, PT).

Outcome variable	Predict variable	R	R^2	F	Coeff	t	P
Purchase intention		0.330	0.109	91.512			
	Constant				2.895	29.647	0.000
	Precision				0.264	9.566	0.000
Mind-flow experience		0.295	0.087	71.163			
	Constant				3.293	35.065	0.000
	Precision				0.224	8.436	0.000
Perceived trust		0.305	0.093	77.045			
	Constant				2.916	30.313	0.000
	Precision				0.238	8.778	0.000
Purchase intention		0.598	0.358	138.662			
	Constant				0.965	6.688	0.000
	Precision				0.117	4.669	0.000
	Mind-flow experience				0.238	6.643	0.000
Outcome variable	Perceived trust				0.393	11.242	0.000

Note: Refers to $P < 0.05$, and the regression results are significant.

We verified the mediating effect of mind-flow experience and perceived trust in the relationship between precision and purchase intention, and the results are shown in Table 18. The effect of precision on purchase intention is positively significant ($B = 0.264$, $t = 9.566$, $p < 0.05$) and the effect of precision on mind-flow experience and perceived trust is also positively significant ($B = 0.224$, $t = 8.436$, $p < 0.05$; $B = 0.238$, $t = 8.778$, $p < 0.05$). When the mediating variables were put in, precision remained positively significant on purchase intention ($B = 0.117$, $t = 4.669$, $p < 0.05$), indicating a significant mediating effect of mind-flow experience and perceived trust.

Table 19. Total, direct and indirect effects (P and ME, PT).

	Effect	LLCI	ULCI	Relative effect value
Total	0.264	0.210	0.318	
Direct	0.117	0.068	0.166	44.32%
Indirect (mind-flow experience)	0.053	0.030	0.080	20.08%
Indirect (perceived trust)	0.094	0.063	0.129	35.61%

In addition, in Table 19, the upper and lower bounds of the bootstrap 95% confidence interval for the mediating effect of mind-flow experience and perceived trust between precision and purchase intention do not contain 0, indicating that the inferred precision can positively influence purchase intention not only directly but also indirectly through the mediating effect of mind-flow experience and perceived trust. The direct effect (0.117) and the mediating effect (0.147) account for 44.32% and 55.68% of the total effect, respectively. mind-flow experience and perceived trust partially mediated the relationship between precision and purchase intention.

This is demonstrated by the above analysis: Mind-flow experience plays a mediating role between personalized recommendation and purchase intention, and H15 holds.

Perceived trust plays a mediating role between personalized recommendation and purchase intention, and H16 holds.

On the basis of theoretical analysis and literature reading, this paper builds a model of the impact of personalized recommendation services on purchase intentions, and puts forward 14 hypotheses: H1, H3, H4, H6, H7, H9, H10, H12, H13, H14, H15, and H16 have been established, and H2, H5, H8, and H11 have not been established. That is, information layout cannot have a significant impact on mind-flow experience and perceived trust, and the timeliness of personalized recommendations cannot have a significant impact on flow experience and perceived trust. Other dimensions of personalized recommendation can have a significant impact on mind-flow experience and perceived trust. mind-flow experience and perceived trust play a mediating role between personalized recommendation and purchase intention.

5. Conclusions

This paper explores six dimensions of personalized recommendation: recommended way, information layout, recommended strength, precision, timeliness, and interactivity. The study analyzes how these dimensions affect purchase intention through mind-flow experience and perceived trust. The findings indicate that the recommended way, strength, precision, and interactivity positively impact purchase intention. However, information layout and timeliness do not significantly affect purchase intention in this model.

The reasons for the non-significant impact of information layout on purchase intention are attributed to the combined effects of interference factors, the precision of personalized recommendations, diverse shopping objectives, and the uncertainty of the online shopping environment. To enhance the effectiveness of information layout, online shopping platforms need to pay more attention to consumers' personalized needs, reduce interference, improve recommendation precision, clarify shopping objectives, and a strengthen the sense of security.

Similarly, timeliness cannot create a positive impact on purchase intention due to the combined effects of consumer context, difficulty in information retrieval, online shopping uncertainty, network environment factors, and competition and advertising interference. To enhance the impact of timeliness, online shopping platforms need to provide fast and stable network environments, optimize information presentation, reduce advertising interference, and address online shopping uncertainty by enhancing consumer trust and sense of security.

Overall, the study highlights the importance of considering various factors when designing personalized recommendation systems to effectively influence purchase intention. By focusing on consumers' personalized needs, improving recommendation precision, reducing interference, and enhancing trust and security, online shopping platforms can enhance the flow experience and positively impact purchase intention.

The paper delves into the implications of personalized recommendation in the realm of online shopping, enriching the research perspective by examining its influence on customers' purchase intention from six dimensions: information layout, recommendation method, recommended strength, recommended precision, recommended timeliness, and recommended interactivity. It introduces the concept of mind-flow experience from psychological research, designing it as an intermediary variable between personalized recommendation and customer purchase intention, thereby constructing a research model and proving its feasibility. This approach realizes innovations in understanding the mechanism of personalized recommendation on customer purchase intention.

From a practical standpoint, the research holds significance for online shopping platforms, offering targeted suggestions for system improvement and enhancing personalized service quality to boost competitiveness and customer retention. By focusing on optimizing related services accessible to customers, the paper aims to provide the best personalized recommendation service, reducing time spent on online shopping and improving decision-making efficiency during purchases.

However, the study acknowledges limitations, including issues with the questionnaire content and data quality, which may have impacted the reliability and validity of the research findings. To address these, future research is suggested to involve more rigorous data collection methods, consider multi-platform data, and incorporate additional factors such as product type and price to further explore their impact on customers' purchase intention.

Furthermore, recognizing the trend of social shopping in China, where customers' online shopping behavior is easily influenced by acquaintances on social networking platforms, the paper suggests that future research on personalized product recommendation could be conducted from the perspective of social shopping, offering a new direction for exploration in this field.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare no conflict of interest.

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