

The Effects of Personalized Recommendations on Purchasing Intention in Taobao.com: A Study of Customers in Guangxi Province, China

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Abstract

This study aimed to examine the impact of personalized recommendations on user stickiness and purchase intention among customers on Taobao.com in Guangxi Province, China. This research was quantitative research type. Data were collected from 703 consumers who had used personalized recommendations on Taobao.com to purchase goods, using non-probability and purposive sampling methods. Structural equation modeling (SEM) was employed for data analysis.

The theoretical contribution of this study lied in establishing a hypotheses model and conducting empirical testing. The data analysis results indicated that among customers on Taobao.com in Guangxi Province, China, personalized recommendations positively impact purchase intention. The findings showed that the research result of the personalized recommendations had an impact on consumer user stickiness, most of the respondents group gave the highest level of importance to the personalized recommendation accuracy (PRA) factor at ($\bar{x} = 3.47$). The result analysis of purchase intention among customers on Taobao.com in Guangxi Province, China, found that most of the respondents group gave the highest level of importance to the Taobao.com positively affected my decision to buy from the platform (PI5) factor ($\bar{x} = 3.42$). The result analysis of user stickiness had an impact on consumer purchase intention, found that most of the respondents group gave the highest level of importance to the continuous use (CU) factor at ($\bar{x} = 3.41$). The structural equation model developed to assess how personalized recommendations affect purchase intention showed a good fit with the empirical data ($p < 0.001$, Chi-square/df = 1.163, GFI = 0.940, TLI = 0.991, CFI = 0.992, and RMSEA = 0.015). The structural equation model indicates that personalized recommendations predict user stickiness with a coefficient of 0.791 ($p < 0.001$),

and user stickiness impacts purchase intention with a coefficient of 0.434 ($p < 0.001$). Notably, when user stickiness was controlled, the influence of personalized recommendations on purchase intention was significantly with a coefficient of 0.437 ($p < 0.001$).

For Taobao.com, providing personalized recommendations involves comprehensive and specific tracking of consumer preferences, enhancing user stickiness, strengthening consumer relationships, delivering high-quality services that make consumers feel relaxed and happy during the entire shopping process, thereby increasing purchase intention. This research offers valuable insights for e-commerce platforms, highlighting the importance of strategic personalization.

Keyword: Personalized Recommendations, User stickiness, Purchase Intention

Introduction

Entering the 21st century, continuous innovations and breakthroughs in network information technology have driven the development of digitization, networking, and intelligence (Attaran and Mohsen, 2023). Within this technological framework, e-commerce experienced substantial growth, facilitated by the integration of services such as online shopping and online payment systems. (Martasari et al., 2023) These technological advancements have not only greatly enhanced convenience in people's lives but have also significantly altered traditional lifestyles. With the development of the Internet, the online shopping market maintains a rapid growth trend. The China Internet Network Information Center (2022) reported in the "50th Statistical Report on China Internet Development Status" that the number of

Chinese Internet users had reached 1.051 billion. In 2021, Guangxi Province's inter-provincial export bandwidth reached 40.4T, ranking it among the middle to upper tiers in China. In 2022, China's online retail sales reached 1.379 billion yuan. The total population of Guangxi was approximately 50.37 million, with about 30.22 million online shoppers. These figures clearly demonstrate the robust growth of the online shopping market in Guangxi Province (Shi et al., 2023). E-Commerce Department of the Ministry Commerce (2023) indicated in recent years, the role of Guangxi province in the bridgehead had been further highlighted. E-commerce in Guangxi province had played an important role in promoting consumption, expanding domestic demand, stabilizing foreign trade and helping people livelihood.

The surge in e-commerce has been propelled by the broadening reach of

network information technology and an increase in Internet users. The transition from offline to online shopping had rapidly become a dominant trend, significantly influencing consumer purchase intentions. However, these platforms now face challenges such as rising customer acquisition costs and increased market competition. (Ferraro, 2020) The expansion of e-commerce had necessitated more time for customers to find desired products amidst a vast array of options, often leading to information overload. (Li et al., 2019) This issue underscores the critical need for creating effective personalized recommendations. Bai et al. (2019) discovered that research on personalized recommendations originated in the field of computer and information science. Zimmermann et al. (2023) concluded that, through artificial intelligence technology, personalized recommendations could be generated from big data on users' shopping characteristics and behaviors, which could significantly improve customer acquisition and user shopping conversion. Bawack et al. (2021) noted that by enhancing the personalized recommendation shopping assistant program, the overall shopping experience could be improved. It was clear that personalized recommendations that effectively deliver product information tailored to individual consumer needs were

crucial for e-commerce platforms to conduct more efficient online marketing activities. Consumer purchase behavior involved a series of actions taken by consumers in cyberspace to satisfy their own needs. In this process, personalized recommendations played a crucial role in influencing the final purchase decision. In online shopping, the primary method for consumers to obtain product information was through personalized recommendations. The results of keyword searches often list many items that did not accurately meet the consumers' real needs, leading consumers to spend a considerable amount of time searching for the products they need, thereby significantly increasing the time cost of online shopping. Prolonged online browsing also detracts from the overall shopping experience. (Rosário et al., 2021)

Currently, major large-scale e-commerce platforms in China, such as Taobao.com, jd.com, pinduoduo.com, and TikTok, were offering personalized recommendations to their customers. (Hu et al., 2021) China Report Hall (2022) according to the data at the end of 2021, Taobao.com share of China's e-commerce market was 50%, which was the market share leader. Pinduoduo.com followed with 25% market share, jd.com was 15%, TikTok was 10%. Taobao.com currently had

nearly 500 million registered users, more than 60 million daily regular visitors, and the number of online products had exceeded 800 million per day. The above data strongly illustrate that the current online shopping market in China was showing significant growth in terms of both the number of consumers and the amount of consumption. It could be expected that as mobile payments become more secure, supply channels became more complete, and logistics services became more convenient, the online shopping market would further develop rapidly. Zhou et al. (2023) described how intensified market competition has led e-commerce companies to increasingly demand improvements in the user shopping experience. Despite varying perspectives, there was a consensus among scholars that personalized recommendations serve as an effective tool for aiding consumers in making purchase decisions. These recommendations were targeted based on individual needs, significantly influencing consumers' purchase intentions. Research had significantly progressed toward improving the algorithms and quality of personalized recommendations. The fields of computer and information science primarily focus on developing algorithms and models to achieve greater accuracy. Conversely, marketing and statistics

explore the broader effects of personalized recommendations on consumer purchasing behavior. (Zhang, 2023)

The design of an e-commerce website, encompassing its user-friendly layout, structured arrangement, and responsive search engine, played a crucial role in fulfilling its intended functions and retaining customers (Vila et al., 2021). This had prompted scholars to explore the concept of user stickiness within the framework of consumer behavior and psychology, shifting the focus from mere website design to the users' experience. Further emphasizing the importance of user engagement, Wang et al. (2022) identified that the strategic arrangement and presentation of product information are pivotal. As a result, user stickiness not only reflects the strength of the relationship between users and network services but also highlights the network's capacity to attract and retain users. Wang (2020) developed a framework linking personalized recommendations to user stickiness within an online tourism context. Similarly, Chan et al. (2021) investigated how personalized recommendations affect user stickiness in online hotel services, demonstrating a significant impact on user retention. Li et al. (2021) confirmed that user stickiness could enhance purchase

intentions and significantly increase website traffic and advertisement views.

In summary, personalized recommendations represent a frontier in interdisciplinary research. The field of computer and information science primarily focuses on developing algorithms and models for personalized recommendations. Meanwhile, the fields of marketing and statistics concentrate on examining how personalized recommendations influence consumer purchasing behavior. However, current research on personalized recommendations mainly emphasizes algorithms, technological innovation, and application, with relatively few studies investigating the impact of personalized recommendations on consumer purchase intentions. A robust personalized recommendation system must not only ensure the accuracy of its recommendations but also consider the effects of these recommendations on consumer decision-making processes. Therefore, research should not be confined to the study of algorithms and models in computer science alone but should also deeply explore the impact of personalized recommendations on consumer psychology and purchase intentions from a consumer behavior perspective. Overall, while substantial research has focused on

the technical aspects of personalized recommendations, their practical effects on consumer behavior warrant further exploration. This study aimed to bridge this gap by providing a comprehensive analysis of how personalized recommendations influence consumer purchase intentions and overall business performance.

Objective

Based on the research background described, the main objectives aimed to examine the impact of personalized recommendations on user stickiness, assess the influence of personalized recommendations on purchase intention and explore the relationship between user stickiness and purchase intention among customers on Taobao.com in Guangxi Province, China.

Limitation of studies

This study, while contributing valuable insights into the domain of e-commerce and consumer behavior, acknowledges certain limitations that stem from a variety of subjective and objective factors, including time constraints, resource availability, and the scope of research capabilities. These limitations are elaborated upon as despite these efforts, limitations in resources and technical

constraints led to a sample size of 703 respondents, which may not fully represent the broader consumer population. This limitation was impacted the generalizability of the findings and suggests a need for more expansive future studies that improve upon data collection methods to reduce sampling bias and enhance representativeness.

Literature Review

Research on the “Stimulus - Organism - Response” (SOR) model evolved from the “Stimulus - Response” (SR) model. Watson (1913) first articulated the “Stimulus - Response” theory in his seminal paper, “Psychology as the Behaviorist Views It,” asserting that human psychological activities are complex and profound. Scholars had utilized objective methods to observe external human behaviors to decipher their inner workings. Behavioral psychology focused on these external behaviors, which were influenced by the external environment. This observation led to the formulation of the “Stimulus - Response” model, where a stimulus was applied from the external environment and the response was the psychological or behavioral change that occurs after an individual received this external signal. Subsequent research revealed that the SR model had certain

limitations; it oversimplified the process of investigating human psychological activities, merely addressing external stimuli and outcomes without encapsulating individual inner consciousness and psychological processes. This led Mehrabian and Russell (1974) to propose the SOR model, which incorporated the organism component to represent the internal state of each stimulated individual. Kim et al. (2020) highlighted that the primary goal of psychological research was to identify the stimulus and discern a pattern between the stimulus and response. This model posited that external environmental stimuli affect an individual’s internal state, subsequently influencing their behavior in response to the internal state elicited by the stimulus. The core premise is that individuals respond to environmental features, with their approach or avoidance behavior being mediated by personal emotional states. SOR (stimulus - organism - response) model (refer to Figure 1).



Figure 1 SOR model

(Stimulus - Organism - Response)

Source: Mehrabian et al., (1974); Kim et al., (2020)

A review of relevant research both domestically and internationally related to

SOR (stimulus-organism-response), Such as bellows :

Xiao et al. (2019) applied the SOR model to examine the factors influencing consumers' purchase intentions for sustainable cross-border e-commerce, discovering that personalized recommendations directly affect consumer-perceived functional and emotional values, which in turn influence purchase intentions. Liu et al. (2021) developed a research model based on the SOR model to study online purchase intentions and investigated the impact of user stickiness on consumer product interaction, perceived value, and purchase intention. Chopdar et al. (2020) constructed a conceptual model based on the SOR model to assess the impact of consumer responses to mobile commerce applications. Their empirical findings suggested that a satisfying experience enhances the optimization of mobile commerce applications. utilized the SOR model to create a theoretical model of the impact of fashion products on continuous purchase intentions in e-commerce platforms. This model considered social media interactivity as the stimulus, with perceived value and immersive experience as the organism, and purchase intention as the response. Their empirical research

illustrated the dynamics of these relationships.

Wakil et al. (2020) noted that personalized recommendations on e-commerce platforms use the most fitting algorithmic models to help customers manage information overload and provide better options. Zhang et al. (2020) referred to the recommended products that e-commerce platforms actively display to users or push to users via notifications. Based on consumers' personal preferences, personalized recommendations could provide real-time and accurate product suggestions, helping consumers quickly find the products that best meet their needs. This functionality significantly reduces the time cost for consumers and enhances their emotional acceptance and satisfaction with the platform, thereby promoting sales. He noted that on e-commerce platforms, the characteristics of personalized recommendations include information arrangement, interpretability, accuracy, timeliness, and novelty. In the context of modern e-commerce, Zhang et al. (2020) provided a more comprehensive framework. This study adopts his approach, emphasizing personalized recommendation information arrangement, interpretability, accuracy, timeliness, and novelty as key characteristics. Effective

personalized recommendation information arrangement (PRIA) on e-commerce platforms entailed ensuring that product information was organized, reasonable, and standardized. Such an arrangement not only facilitated quick product searches but also enhances the overall shopping experience, thereby improving purchase intentions. Personalized recommendations interpretability (PRI) in provided a rationale for why specific products are suggested by an e-commerce platform rather than others. By clearly articulating the reasons behind these recommendations, an e-commerce platform can demonstrate that these suggestions are well-grounded, thereby increasing customers' trust in the recommended products. The accuracy of personalized recommendations (PRA) referred to the extent to which the suggested products align with individual needs. Accurate information that meets users' specific requirements was more likely to be persuasive and capture their attention. As such, ensuring high relevance in recommendations is crucial, as it significantly increases user engagement and interest. The timeliness of personalized recommendations (PRT) referred to how promptly and appropriately these recommendations are presented relative to user searches and shifts in preferences. E-commerce platforms should provide

immediate product information during searches and dynamically adjust recommendations to align with evolving customer interests and preferences, thereby optimizing user engagement and satisfaction. Personalized recommendation novelty (PRN) referred to how the e-commerce platform introduces customers to product information they have not previously encountered, thus fostering demand for new and suitable items. Such novelty stimulates individuals' intrinsic interest and excitement, enhancing their engagement with the platform.

User stickiness referred to the degree to which a website can capture and retain the attention of its users, encompassing their intentions to revisit or continue using the website. (Zott et al., 2000) Beyond the context of websites, the concept of user stickiness had been extended to various digital platforms, including blogs, mobile applications, and social media platforms, where it denoted prolonged and repeated usage. (Chan et al., 2021) User stickiness was a metric that indicates a platform's capability to attract and maintain user engagement, characterized by the frequency and duration of visits. User stickiness involves the long-term presence and frequent visits of users to e-commerce platforms. This was substantiated by a study that collected 332

valid responses through an online questionnaire and tested the research model using structural equation modeling. (Liu et al., 2023) Lu et al. (2023) aimed to explore the relationship between influencers' characteristics and followers' well-being through followers' stickiness to influencers' channels or posts, gathering data through an online survey of 450 followers. The proposed hypotheses were examined using structural equation modeling, concluding that user stickiness encompasses continued and frequent use. In light of contemporary scholarly perspectives, this study adopts the two dimensions of user stickiness identified by Lu et al. (2023) specifically: continued use and frequent use. Continued use (CU) implied that users who spend substantial time browsing an e-commerce platform are likely to revisit the same site and potentially increase their duration of visit if they find the topics increasingly engaging. Frequent Use (FU) indicated that users frequently revisit websites, consistently returning to the same e-commerce platform, and are expected to maintain these visits over time.

Originally derived from psychology, the term 'intention' reflects a change in consumers' psychological states. Purchase intention, crucial for behavioral activities, implied that an individual must possess the

willingness to engage in a specific action. This readiness determines the individual's behavioral activities. Dodds et al. (1991) viewed purchase intention as the probability that consumers will purchase a specific commodity or service, asserting that it is the subjective tendency of consumers when buying a specific item. Thus, the formation of consumer purchase intention is inherently subjective, reflecting not only consumers' attitudes toward a particular item or service but also the probability of actual purchase. Al-Ja'afreh et al. (2020) interpreted purchase intention as the likelihood of consumers purchasing a specific product. Kline et al. (2023) differentiated intention from attitude, considering it a motivational force that drives consumer efforts toward purchasing behavior. By examining purchase intention, it was possible to predict the final purchasing behavior of consumers. Compared to traditional offline purchase intention, consumers' online purchase intention is essentially the same. Therefore, this study adopted the concept of purchase intention as defined by Dodds et al. (1991). Purchase intention was defined as the possibility that the consumer is willing to buy goods on the e-commerce platform, representing the subjective tendency of consumers when considering a specific commodity or service.

In recent years, the increasingly widespread application of personalized recommendations in e-commerce has spurred numerous scholarly investigations. Li (2019) noted that personalized recommendations on e-commerce platforms can enhance consumer visits by saving time, thereby boosting consumer stickiness and engagement. Chen et al. (2019) discovered that providing reasons for product recommendations not only captures customer interest during browsing but also reduces concerns about the misuse of information, encouraging greater focus on product selection and quality assessment, which in turn fosters user stickiness. Furthermore, Hu et al. (2021) demonstrated through empirical research that personalized recommendations increase the frequency and duration of visits to stores where consumers have previously made purchases or shown interest, effectively strengthening the relationship between consumers and websites. They found that personalized recommendations with a high degree of novelty not only enhance user stickiness but also reduce the time customers spend searching for information.

The impact of personalized recommendations on consumer decision-making and behavior was a forefront and

prominent issue in the fields of management and marketing research. Research by Yeomans et al. (2019) using experimental methods demonstrated that personalized recommendations could indeed help people make better product choices and improve decision-making quality. Behera et al. (2020) proposed that if the attributes of products recommended align with consumer needs, the success probability of personalized recommendations could be greatly enhanced, thereby increasing the likelihood of consumer purchases. Zhu et al. (2020) indicated that websites capable of providing timely personalized recommendations when consumers are considering a purchase can influence their final decision and increase their willingness to buy. Guo et al. (2022) found that product information arranged according to specific indicator rules is more likely to be favored by consumers than randomly arranged information, directly affecting consumers' purchase intentions.

Research had consistently shown that user stickiness positively influences consumer purchase intention. Friedrich et al. (2021) posited that user stickiness enhances consumers' likelihood of purchasing. Bahtar et al. (2022) demonstrated that social e-commerce platforms with higher community stickiness

foster deeper user engagement, thereby increasing the likelihood of online purchases. Bao et al. (2023) found that a high degree of user stickiness between customers and an e-commerce platform leads to increased website visits and transactions.

In summary, the SOR model had been extensively applied in management disciplines, particularly in studying consumer psychology and behavior. The model provides a robust framework for understanding the stimuli that influence consumers, the resulting internal psychological states, and the consequent behavioral responses. It's high theoretical applicability makes the SOR model well-suited for exploring management disciplines, and it was aptly integrated into the theoretical framework of this study. Personalized recommendations were considered an antecedent stimulus as an external factor that could activate consumers' internal states. User stickiness was viewed as the organism, representing the psychological changed occurring during the online shopping process. Consumer purchase intention was the response,

constituting the final approach behavior reaction of consumers. The external stimulation from personalized recommendations, combined with consumers' adherence to the Taobao.com e-commerce platform, ultimately cultivates consumers' purchase intentions.

Conceptual framework

This study constructed a hypothetical relationship among personalized recommendations, user stickiness and consumer purchase intention. Personalized recommendations were treated as a marketing activity of the e-commerce platform, which facilitates interaction between businesses and consumers. The core objective was to establish and develop positive relationships with consumers to enhance their purchase intentions. From this perspective, it was proposed that user stickiness positively influence the formation of consumers' final purchase intentions. The conceptual framework (refer to Figure 2).

User Stickiness

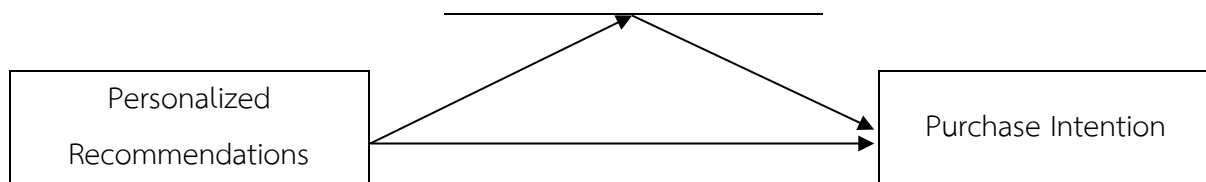


Figure 2 Conceptual framework Diagram

Source: Derived from an extensive examination of relevant theories and pertinent scholarly documents by the author, 2023

Research hypothesis

1. Personalized recommendations had a positive impact on user stickiness among customers on Taobao.com in Guangxi Province, China.

2. Personalized recommendations had a positive impact on consumer purchase intention among customers on Taobao.com in Guangxi Province, China.

3. User stickiness had a positive impact on consumer purchase intention among customers on Taobao.com in Guangxi Province, China.

Research Methodology

The sample was collected using a non-probability sampling method and a purposive sampling technique. This method was chosen to utilize structural equation modeling (SEM) to verify the hypotheses model. For determining the sample size, Alamer et al. (2022) suggested that the number of samples analyzed by SEM should be more than 200. Using the formula of Yamane (1964), a sample size of

400 individuals was initially calculated. Gorsuch (1974) indicated that the ratio of measurement items to the number of samples should be more than 1:5 and ideally reach 1:10. (Ringle et al., 2023) With 77 measurement items in this study's questionnaire, a minimum of 385 samples (at a 1:5 ratio) and ideally 770 samples (at a 1:10 ratio) were necessary.

Comparing the three sample collection methods, to ensure the validity of the significance test, this survey aimed to distribute at least 770 questionnaires. The main target samples were individuals who use personalized recommendations on Taobao.com for daily purchases. Respondents who had not used Taobao.com for online shopping were excluded. Screening items were included in the questionnaire to filter out respondents who did not meet the criteria. Additionally, questionnaires with incomplete answers were considered invalid and excluded from the data analysis.

Sember et al. (2020) showed that the validity mainly included content

validity and construct validity, and content validity was the basis of validity test, which was mainly tested by expert judgment. For the test of content validity, this study used the Item-Object-Consistency (IOC) method and selected five experts to evaluate the content validity of the questionnaire. Experts were responsible for appraising the alignment between the questions and research objectives using the Item-Object-Consistency (IOC) Index for each question. In order for a question to be deemed valid, it was required to have an IOC equal to or exceeding 0.60. Any question falling below the 0.60 IOC thresholds underwent either elimination or revision until the requisite standard was met. (Sganzerla et al., 2021) Construct validity, an advanced form of validity analysis, was used to test whether the scale accurately measured the intended variables. Factor analysis, the basic method for testing construct validity, was employed for this purpose. Reliability referred to the degree to which a measurement tool was free from the impact of errors. During the testing process, the reliability of the scale can be analyzed using Cronbach's α coefficient. According to Nunnally et al. (1994), a Cronbach's α coefficient above 0.7 indicates that the scale has good reliability. (Ekolu et al., 2019)

Before conducting the formal large-sample survey, a pretest involving 30

questionnaires was administered to evaluate the validity of the questions related to the relevant variables and to finalize any necessary modifications. This pretest served as a preparatory step for the formal survey. The pretest questionnaires were distributed over 15 days, distribution primarily occurred online through the author's WeChat and QQ groups. To ensure the scientific validity of the data, participants were encouraged to invite colleagues and friends to complete the survey, thus meeting the differentiation requirements. The pretest results indicated that the scales used were robust, demonstrating good reliability and validity. The items for each variable dimension adhered to standard norms and required no adjustments. The test data confirmed that the questionnaire designed for this study possesses the necessary reliability and stability, making it suitable for a large-scale formal investigation.

For the analysis of data from the questionnaire, descriptive statistics such as frequency, percentage, mean and standard deviation were used to describe the general data. Personalized recommendations, purchase intention, user stickiness and inferential statistics such as the analysis of the structural equation model (SEM) were used to analyze the personalized recommendations have an

impact on user stickiness, personalized recommendations have an impact on consumer purchase intention, and user stickiness has an impact on consumer purchase intention among customers on Taobao.com in Guangxi Province, China.

The main items of the questionnaire were designed using a five point Likert scale, first introduced by Rensis Likert in 1932. The five-point scale was simpler and clearer, making it easier for respondents to complete and saving time. (Taherdoost et al., 2022) To analyzed each variable by finding out the mean and standard deviation. These assigned values were used to rate and assess respondents' opinions based on the Likert scale. The five point Likert scale was commonly employed to inquire about respondents' opinions and attitudes, measuring levels of agreement. The points on the scale, in order, from 1 to 5, were: strongly disagree, highly disagree, somewhat agree, highly agree and strongly agree. The assessment criteria for each class interval can be determined by calculating the width of each class using the following formula: $\text{Class interval} = (\text{Highest Value} - \text{Lowest Value}) / (\text{Number of Classes})$. $\text{Class interval} = (5 - 1) / 5$, $\text{Class interval} = 0.8$. Hence, the class stratification was set at 0.8 and serves the purpose of categorizing the

mean and criterion scores with the following explanations:

Range of Score

4.21 – 5.00	strongly agree with the statement
3.41 – 4.20	highly agree with the statement
2.61 – 3.40	somewhat agree with the statement
1.81 – 2.60	highly disagree with the statement
1.00 – 1.80	strongly disagree with the statement

Data Analysis

To ensure the validity and reliability of the test, this study was employed AMOS software to conduct reliability and validity analyses. Following this, a structural equation model (SEM) was established based on the conceptual model and proposed relational hypotheses to analyze model fit and test the research hypotheses.

Descriptive statistical analysis was employed to statistically describe the data of all variables surveyed to understand the basic characteristics of the sample data. It primarily tested the sample data characteristics and the relationships between variables. This study was required a descriptive statistical analysis to ensure that the sample size is adequate and to

understand the basic characteristics of the sample data. (Mishra et al., 2019) The central tendency of the sample number is primarily grasped through the mean (Mertler et al., 2021), assessing the concentration and dispersion of each variable using the standard deviation and variance.

Prior to conducting factor analysis, the suitability of the scale for such analysis must be evaluated using Bartlett's sphericity test and the Kaiser-Meyer-Olkin (KMO) test. Kaiser (1974) indicated that KMO values should range from 0 to 1, with specific thresholds suggesting suitability: a KMO less than 0.5 indicates unsuitability for factor analysis, a KMO over 0.6 suggests marginal suitability, a KMO over 0.7 implies adequacy, a KMO over 0.8 denotes suitability, and a KMO over 0.9 signifies excellent suitability for factor analysis. (Noman et al., 2021)

Structural Equation Modeling (SEM) was a well-established research method in management science. Since the 1980s, SEM had rapidly evolved to address the limitations of traditional statistical methods, becoming a crucial tool for multivariate data analysis. (Kline et al., 2023) SEM combines multiple regression, path analysis, and factor analysis to explore complex variable relationships and test theoretical models (Thakkar, 2020). It was

particularly effective for analyzing latent variables, error in variables, mediating effects, and multiple pathways between variables. The primary aim of SEM was to assess the validity of research hypotheses through empirical data analysis and to determine if the observed data fit the theoretical models. (Jak et al., 2020)

The SEM analysis process included model fitting, model correction, and path analysis. Model fitting tests were essential to verify if the empirical data supports the hypothesized model. Commonly used fit indices include the chi-square to degrees of freedom ratio (χ^2/df), the Root Mean Square Error of Approximation (RMSEA), the Goodness-of-Fit Index (GFI), the Adjusted Goodness-of-Fit Index (AGFI), the Normed Fit Index (NFI), and the Comparative Fit Index (CFI). A χ^2/df ratio less than 3, an RMSEA less than 0.08, and GFI and AGFI values greater than 0.8 are indicators of a good model fit. (Tedjakusuma et al., 2023) Scores of 0.9 or higher on NFI and CFI are considered evidence of excellent fit and confirm the model's validity. (Meng, 2022) If the model is empirically supported, the fitting indices will meet statistical standards, allowing for further analysis of the model's path structure. (Sari et al., 2020)

Research Result

The large-scale formal online questionnaire survey was using the Questionnaire Star platform, targeting consumers from Taobao.com. The survey aimed to ensure scientific validity and reliability of the data. Questionnaires that did not meet the sample requirements, those removed automatically by screening items, non-seriously filled, or repeated entries from the same IP address were considered invalid and excluded. After meticulous data screening, a total of 703 valid questionnaires were retained, meeting the minimum requirement of a sample-to-measurement item ratio exceeding 1:5 and far surpassing the threshold of 400 valid responses. The results of general data analysis of the customers on Taobao.com in Guangxi Province, China, it found that most of the customers were male, age between 30-39 years old, with a undergraduate degrees, they were company staff with and average monthly income between 4,001-6,000 yuan, had 9 years and above shopping online years,

monthly shopping frequency were 4-6 times.

The Kaiser-Meyer-Olkin (KMO) measure yielded a result of 0.957, indicating sufficient sampling adequacy for factor analysis ($KMO > 0.6$). Additionally, the Bartlett's Test of Sphericity was significant ($p < 0.05$), confirming correlations among items and justifying the factor analysis. The result analysis of personalized recommendations had positive impact on consumer user stickiness among customers on Taobao.com in Guangxi Province, China, found that most of the respondents gave the highest level of agreement to the Personalized Recommendation Accuracy (PRA) factor at ($\bar{x} = 3.47$), Personalized Recommendation Information Arrangement (PRIA) factor at ($\bar{x} = 3.45$), Personalized Recommendation Interpretability (PRI) factor at ($\bar{x} = 3.43$), Personalized Recommendation Timeliness (PRT) factor at ($\bar{x} = 3.43$), Personalized Recommendation Novelty (PRN) factor at ($\bar{x} = 3.41$), respectively (refer to Table 1).

Table 1 Descriptive Statistical Analysis of Personalized Recommendations

Personalized Recommendations	Mean	Std. Deviation	Level of agreement
Recommendation Information Arrangement	3.45	0.94	highly agree with the statement
Personalized Recommendation Interpretability	3.43	0.97	highly agree with the statement
Personalized Recommendation Accuracy	3.47	0.95	highly agree with the statement
Personalized Recommendation Timeliness	3.43	0.93	highly agree with the statement
Personalized Recommendation Novelty	3.41	0.99	highly agree with the statement
Total	3.44	0.96	highly agree with the statement

The result analysis of purchase intention among customers on Taobao.com in Guangxi Province, China, found that most of the respondents gave the highest level of agreement to the Taobao.com positively affects my decision to buy from the platform (PI5) factor at ($\bar{x} = 3.42$), I am likely to purchase products from Taobao.com in the near future (PI1) factor at ($\bar{x} = 3.40$), Considering my experience with Taobao.com, I plan to buy items from the platform always (PI2) factor

at ($\bar{x} = 3.40$), I see myself as a potential customer for products offered on Taobao.com (PI3) factor at ($\bar{x} = 3.40$), The personalized recommendations on Taobao.com increase my intention to make a purchase (PI4) factor at ($\bar{x} = 3.40$), My frequent use of Taobao.com is an indicator of my intention to buy from the platform (PI7) factor at (Mean= 3.40), and The value I perceive in Taobao.com's offerings enhances my intention to purchase (PI6) factor at ($\bar{x} = 3.39$) (refer to Table 2).

Table 2 Descriptive Statistical Analysis of Purchase intention

Purchase Intention	Mean	Std. Deviation	Level of agreement
P11	3.40	1.17	somewhat agree with the statement
P12	3.40	1.14	somewhat agree with the statement
P13	3.40	1.13	somewhat agree with the statement
P14	3.40	1.15	somewhat agree with the statement
P15	3.42	1.14	highly agree with the statement
P16	3.39	1.13	somewhat agree with the statement
P17	3.40	1.15	somewhat agree with the statement
Total	3.40	0.94	somewhat agree with the statement

The result analysis of user stickiness had an impact on consumer purchase intention among customers on Taobao.com in Guangxi Province, China, found that most of the respondents gave

the highest level of agreement to the Continuous use (CU) factor at ($\bar{x} = 3.41$), Frequency use (FU) factor at ($\bar{x} = 3.33$) (refer to Table 3).

Table 3 Descriptive Statistical Analysis of User Stickiness

User Stickiness	Mean	Std. Deviation	Level of agreement
Continuous Use	3.41	0.99	highly agree with the statement
Frequency Use	3.33	0.99	somewhat agree with the statement
Total	3.37	0.99	somewhat agree with the statement

The structural equation model indicated the Chi-square to degrees of freedom ratio of the model was 1.163, with GFI, TLI, and CFI all greater than 0.9, and

RMSEA at 0.015, below 0.08, indicating that the model fitting effect is relatively good (refer to Table 4).

Table 4 Path coefficient value

Fit indicators	χ^2/df	GFI	TLI	CFI	RMSEA
	1.163	0.940	0.991	0.992	0.015

That personalized recommendations predict user stickiness with a coefficient of 0.791 ($p < 0.001$), and user stickiness impacts purchase intention with a coefficient of 0.434 ($p < 0.001$). Notably,

when user stickiness was controlled, the influence of personalized recommendations on purchase intention was significantly with a coefficient of 0.437 ($p < 0.001$) (refer to Table 5, Figure 3).

Table 5 Path Coefficient Value

			Estimate	P
User Stickiness	<---	Personalized Recommendations	0.791	***
Purchase Intention	<---	User Stickiness	0.434	***
Purchase Intention	<---	Personalized Recommendations	0.437	***

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

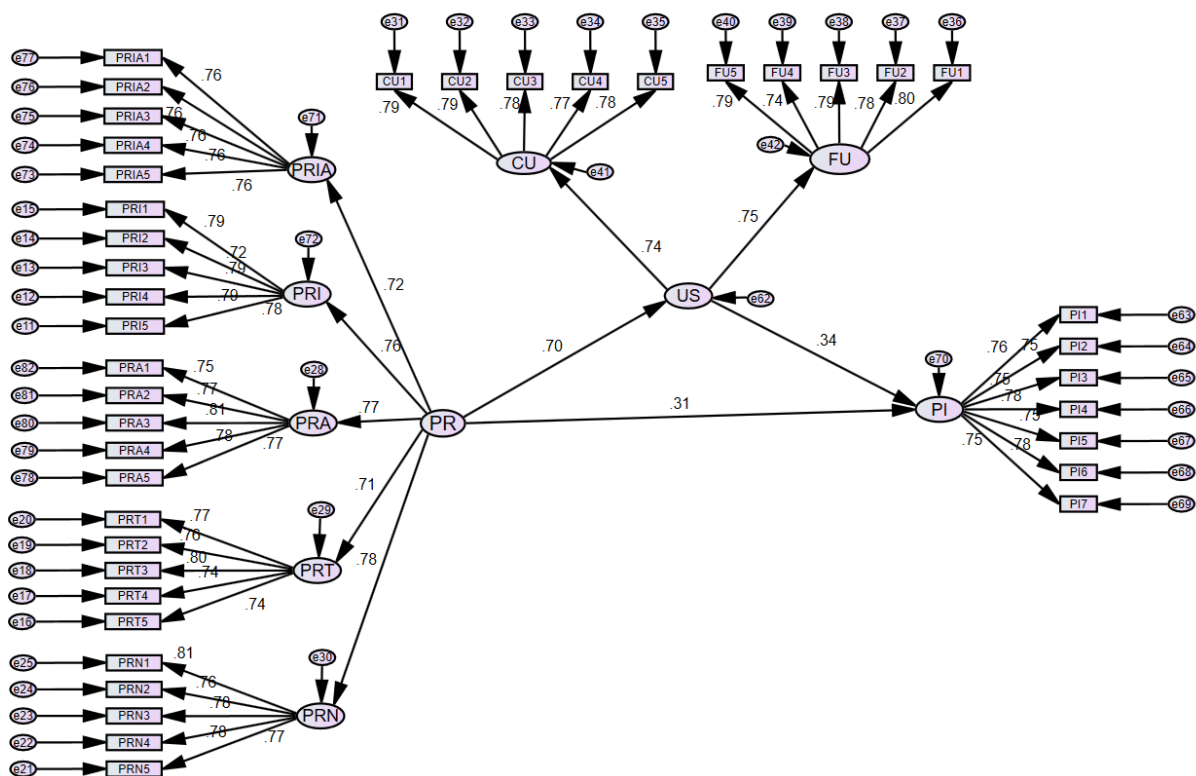


Figure 3 Path Coefficient Diagram

Conclusion and Discussion

The survey using Questionnaire Star, garnered 703 valid responses from Taobao.com consumers. Screening excluded incomplete and invalid questionnaires. The participants were diverse, with a near-even split between males (51.4%) and females (48.6%). The age distribution was primarily between 30 to 39 years (37.3%), with the majority holding undergraduate degrees (44.9%) and working as company staff (41.8%). Income levels varied, with most earning between 4,001 and 6,000 yuan monthly. This varied demographic ensures a robust basis for further analysis.

The study of personalized recommendations had positive impact on consumer user stickiness among customers on Taobao.com in Guangxi Province, China, found that the majority of consumer pay attention to the personalized recommendation accuracy factor. Personalized recommendations had a direct impact on purchase intention among customers on Taobao.com in Guangxi Province of China. And the user stickiness had an impact on purchase intention among customers on Taobao.com in Guangxi Province of China, found that most of the respondents pay attention to the continuous use factor. This was in line with

the research of Yeomans et al. (2019) conducted research through experimental methods, and the results showed that personalized recommendations could indeed help consumers make better goods choices and improve decision-making quality. Gupta et al. (2020) suggested that the recommendations by providing people with information that highly matches their needs, people were more likely to be persuaded and can focus on it. If the matching degree between this recommendation and personal needs was very low, this would reduce customers' trust, thus causing customers to be suspicious of personalized recommendations. Indicated by analyzing the browsing time of users on each topic, one can infer the level of interest and corresponding preferences of users. If the browsing time is longer than usual, it can be estimated that users have a higher preference level for that topic.

The influence of personalized recommendations on consumer purchase intention is corroborated by a collection of recent studies. This research aligned with the current study's findings that personalized recommendations significantly improve purchase intention. The systematic literature review by Zhou et al. (2020) commented the recommendation of highly relevant products was, to a certain

extent, a response to the customer's hidden needs which can then transform the customer's implicit purchase intention into actual customer purchase behavior. Behera et al. (2020) proposed that if the attributes of products recommended align with consumer needs, the success probability of personalized recommendations can be greatly enhanced, thereby increasing the likelihood of consumer purchases. The collective insights from these studies provide empirical support for the positive impact of personalized recommendations on purchase intention. This pattern was evident across various contexts and methodologies emphasizing the role of make the personalized recommendations with users' needs and preferences and arouse users' shopping interest. By enriching the presentation of personalized recommendations, consumers can be more satisfied with the personalized recommendations provided by taobao.com e-commerce platform, thereby effectively increasing consumers' purchase intention.

The relationship between user stickiness and purchase intention was a critical focus in recent literature, highlighting how user stickiness served as a fundamental driver of purchase intention. This was in line with the research of Belhadi et al. (2023), if customers had consumption

needs, they uses the platform's personalized recommendations service based on their past behavior habits. The consumers' increased loyalty to the platform largely lead to the customer's continuous purchasing behavior. Qu et al. (2023) found a high degree of user stickiness between customers and social commerce, online interactions generate significant effects on consumer behavior. These studies collectively illuminate how user stickiness is instrumental in enhancing consumer purchase intention. They provided empirical evidence that if the stickiness between a user and an e-commerce platform is high, it means that the user would frequently visit the e-commerce platform to obtain and browse relevant information. Once this long-term relationship is established, it would continue to carrying out marketing activities as effectively increase consumers, willingness to purchase goods on the e-commerce platform.

Research Suggestions

1. When providing personalized recommendations, Taobao.com needs to conduct comprehensive and specific tracking of relevant preference of customers. Comprehensively and carefully analyze these interest and preference of

customers, understand the products that customers need, and then realize accurate recommendation to customers, and improve the probability of customers buying products on the platform. Rationalize the personalized recommendation information arrangement and enhance the image of the platform. When giving the content of recommendation interpretability, the platform must ensure its authenticity and reliability, and through reasonable recommendation explanation, customers can better recognize the recommended goods, so as to make better consumption decisions. Detect changes in consumer preferences in a timely manner, so that the personalized recommendations do not meet the new needs of users.

2. Enhance the user stickiness between consumers and websites. For Taobao.com, which has already used personalized recommendation system, to make the recommendation effect better, it is necessary to cultivate the customer relationship between consumers and websites, such as: provide a reliable and complete description of personalized recommendations, explain the reasons for personalized recommendations to consumers, personalize recommendation information arrangement according to consumers' needs and habits, simplify the

operation process, and improve users' willingness to visit and purchase for the website.

Recommendations for Future Research

1. Advanced Data Collection Techniques: Employing more sophisticated data collection methods, such as web tracking and machine learning algorithms, could improve the accuracy and depth of data regarding consumer interactions with personalized recommendations. Such data could provide deeper insights into the decision-making processes underlying purchase intentions.

2. Integration of Qualitative Methods: Incorporating qualitative research methods, such as interviews or focus groups, could provide deeper insights into the subjective experiences and perceptions of consumers regarding personalized recommendations. This approach would add a rich, narrative dimension to the understanding of quantitative findings.

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