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User dissatisfaction and behavioral intention toward personalized advertising recommendation services in Chinese social networking services

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With the advancements in digital advertising, personalized advertising recommendation services are being established as an increasingly important marketing tool. In particular, social networking service (SNS) platforms in China are offering personalized advertising experiences through an extensive user base. However, such services often fail to meet the needs and expectations of Chinese users. Accordingly, this study aimed to explore user dissatisfaction and the resulting negative responses to personalized advertising recommendation services on Chinese SNS platforms. The analysis for this study was conducted using structural equation modeling based on data from 500 Chinese SNS users. The effects of service failure on negative expectation disconfirmation and dissatisfaction as well as how this dissatisfaction affects negative behaviors among users were examined. The results showed that factors related to service failure, such as functional failure, information failure, and system failure, positively affected users' negative expectation disconfirmation, while functional failure, system failure, and negative expectation disconfirmation positively affected dissatisfaction. Moreover, dissatisfaction positively affected negative word-of-mouth and discontinuance intentions. This study identified negative responses to personalized advertising recommendation services on SNS advertising platforms, which can be used by companies to minimize negative outcomes by effectively managing user expectations.

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Introduction

Upon entering the era of digital advertising, advertisers are leveraging personalized targeting to efficiently deliver their messages, which is one of its greatest advantages. Personalized advertising, which uses advanced targeting techniques, provides advertisers with precise marketing opportunities while also providing users with opportunities to receive customized benefits tailored to their interests (Kim and Lee, 2016). Recommendation systems have recently gained increasing popularity, and they are widely applied across online services. With the extensive use of such systems, users can enjoy a variety of personalized recommendations for movies, books, advertisements, restaurants, and hotels. As such, personalized recommendation services have become a highly effective revenue driver for online businesses (Segijn and van Ooijen, 2022).

Global spending on mobile advertising is projected to exceed $400 billion by 2024, with an annual growth rate of 11% (Statista, 2024). Aligning with global trends, China's social networking service (SNS) mobile video advertising market is also experiencing remarkable growth. According to recent data, this market is expected to reach approximately 465 billion CNY (64.2 billion USD) by 2025 (CIW, 2024). Thus, improving the methods for delivering mobile advertisements to Chinese SNS users more effectively is essential.

Personalized advertising recommendation systems in SNS environments reportedly provide adequate content or convenient services based on users' preferences (Chandra et al., 2022); however, scholars have raised concerns about the various potential negative effects of such services (Milano et al., 2020). For example, because such services rely on users' detailed and personal online behavior data, issues concerning personal information, security breaches, and privacy arise (Hanlon and Jones, 2023; Rosário and Dias, 2023; Xie and Huang, 2023). Issues related to information in recommendation systems may cause problems in data quality, affecting the accuracy, reliability, and fairness of algorithmic bias in personalized information recommendations (Xu et al., 2024). Moreover, functional issues exist, especially concerning new users, new products, and niche categories. Without sufficient historical data, providing accurate and relevant recommendations may be difficult; consequently, the user environment may not be optimized (Wang et al., 2022). Due to these negative aspects, consumers reportedly perceive personalized advertising recommendation services as a failure (Tan et al., 2016), leading to dissatisfaction and disappointment (Wu et al., 2022). Therefore, identifying the relationship between service failure and dissatisfaction is important to improve personalized advertising recommendation services on SNS platforms.

Furthermore, negative disconfirmation can lead to negative behavior due to customer dissatisfaction (Engel et al., 1990). Even if the personalized recommendation system has high accuracy, if its use fails to meet users' expectations, the satisfaction derived from it will be lower (Sinha and Swearingen, 2001). The gap between expectations and actual outcomes can significantly affect user satisfaction with SNSs (Tan et al., 2023). To precisely identify the level of satisfaction or dissatisfaction with personalized recommendation services, understating whether the service performance meets user expectations is necessary (Kang and Wang, 2024). Thus, examining the relationship between negative expectation disconfirmation and dissatisfaction with personalized advertising recommendation services on SNS platforms is crucial for managing user experience and retaining users.

Moreover, higher customer dissatisfaction with a service reportedly increases the likelihood of negative word-of-mouth (Mostafa et al., 2024), which can have a greater impact on consumer behavior than positive word-of-mouth (Sheng et al., 2024). Therefore, identifying the relationship between dissatisfaction with personalized recommendation services on SNS platforms and negative word-of-mouth is necessary. User data obtained from service use can help identify determinants of discontinuance decisions (Wang et al., 2017), with dissatisfaction potentially being a key determinant (Wu et al., 2019). Thus, examining the relationships between dissatisfaction with recommendation services on SNS platforms, negative word-of-mouth, and discontinuance intentions is significant.

Several studies on information systems have reported that system usage and the effects of antecedent variables may vary according to demographic factors such as age (Liébana-Cabanillas & Sánchez-Fernández, 2014; Okazak, Mendez (2012)) and gender (Hu and Wise, 2024; Hudders and De Jans, 2022). However, existing research remains inconsistent, and the specific moderating effects of these variables in the context of personalized advertising recommendation services remain unclear. Accordingly, rather than hypothesizing moderating effects on specific paths, this study seeks to explore whether age and gender exert moderating effects across all paths in the research model.

Recently, personalized advertising recommendation services have become a core marketing tool on SNS platforms. They analyze users' past behaviors, interests, and interaction data to deliver customized advertising content (Loureiro et al., 2023). However, despite the increasing sophistication of recommendation algorithms, users are expressing growing dissatisfaction and resistance due to issues such as the repetitiveness of the recommended content, low relevance, and concerns regarding privacy infringement (McNee et al., 2006; Hong et al., 2020). These negative responses not only undermine the advertising effects of the platforms but may also lead to user attrition and long-term erosion of trust.

Existing studies have mainly focused on improving the technical performance of recommendation systems, with limited research systematically analyzing the psychological expectation–disconfirmation mechanism from the perspective of service failure. Especially in the high-context media environment of SNS platforms, not only the accuracy of content but also user perceptions of whether the platform respects user preferences and protects their personal information have become increasingly important criteria for judgment (De Keyzer et al., 2022). Nevertheless, integrated discussions on how different types of personalized service failures—such as functional failure, information failure, and system failure—trigger negative expectation disconfirmation and dissatisfaction are lacking. Moreover, analyses of how such disconfirmation leads to actual behavioral responses (e.g., negative word-of-mouth, service discontinuance intentions) are also limited.

This study is grounded in expectation disconfirmation theory, with the goal of examining the pathways through which service failures in personalized advertising recommendation services on SNS platforms lead to negative expectation disconfirmation, dissatisfaction, and user behavioral responses (i.e., negative word-of-mouth and discontinuance intentions). In particular, by setting demographic factors such as age and gender as potential moderating variables and empirically testing whether moderating effects emerge across all paths in the research model using multi-group structural equation modeling (SEM), this study seeks to bridge the existing research gap in the field of personalized advertising recommendation services. From the consumer perspective, this study expands information and knowledge regarding personalized advertising recommendation services, thereby supporting the rational and efficient use of SNS platforms. From the business perspective, it identifies the causes that generate consumer dissatisfaction and negative behaviors (e.g., complaints, discontinuance). On this basis, this study provides foundational insight for formulating strategies to improve service quality and encourage positive behaviors, thus making practical contributions.

Theoretical background

Definition of personalized advertising recommendation services. Traditional advertising recommendations usually fail to satisfy users' individualized needs, and with the rapid development of the Internet, the implementation of individualized advertising recommendations has already become a means for advertisers to better understand user preferences and increase their advertising revenue (Hong et al., 2020). In this context, personalized recommendation systems have entered the public spotlight (Ha et al., 2022). Huang and Rust (2021) noted that the most powerful marketing tool today is delivering various advertising recommendations through personalized content to customers at the right stage.

SNSs have become an option for marketers, offering advanced targeting options, reliable conversion tracking, and dissemination via mobile devices (Ganguly (2015)). Personalized advertising recommendation services, one of the typical applications of recommendation systems, have emerged as a major form of online advertising. Many e-commerce platforms now utilize personalized advertising to promote their products. In this context, companies such as Alibaba and Amazon have advanced their data mining and algorithmic capabilities to a new level by analyzing users' past data, comparing consumption patterns, and predicting and recommending products likely to attract users' interest and trigger purchasing behavior.

Personalized advertising recommendation services leverage user behavior records, clicks, ratings, and other information to predict individual users' potential demands and preferences for various products. By integrating these data with contextual information, such as location and time, these systems can deliver highly relevant advertisements to users, thereby maximizing advertising effectiveness (Tran et al., 2023). Therefore, based on prior research, this study defined personalized advertising recommendation services as those that analyze the content users like or are interested in on SNS platforms and provide personalized services tailored to individual users.

Service failure. Service failure is defined as the degree to which consumers perceive that the level of services provided falls short of their expectations, similar to the expectancy–disconfirmation paradigm for customer satisfaction (Parasuraman et al., 1993). It can also be defined as a negative consumer experience resulting from various errors that occur in the process of providing a service or when the service promised by a company is not properly fulfilled at the service touchpoint (Lv et al., 2021). Consumers perceiving service failure end up being dissatisfied, and if they perceive the service failure to be caused by the provider, it leads to disappointment, which is expressed as dissatisfaction with the overall service (Janjua, 2017).

Various studies have been conducted on the constructs of service failure. Smith et al. (1999) classified service failure in service industries such as retail, hospitality, telecommunications, and finance into behavioral, system, and environmental service failure. Tan et al. (2016) classified service failure into information failure, functional failure, and system failure in a study on e-commerce, while Mustafa et al. (2020) classified it into functional failure, information failure, system failure, and digital service failure in a study on information systems. Mustafa et al. (2020) integrated DeLone, McLean (2003) service quality dimensions into Tan et al., 2016 classification and proposed a more comprehensive concept of 'digital service failure'. However, this classification is more suitable for general digital service contexts such as e-commerce transactions. This study focuses on personalized advertising recommendation services on SNS platforms, which differ from general digital service environments in terms of functional scope and modes of user interaction. Accordingly, Tan et al.'s (2016) original three categories (information failure, functional failure, and system failure) were deemed more appropriate for capturing the core dimensions of failure in the present research context. Based on these previous studies, this study classified service failure in personalized advertising recommendation services into functional failure, information failure, and system failure.

Functional failure refers to a situation in which the function of a digital service is not sufficient in helping users assess alternatives to the services provided or acquire products and services (Mustafa et al., 2020; Tan et al., 2016). In this study, functional failure is defined as the degree to which personalized advertising recommendation services on SNS platforms fail to meet the needs and preferences of users or provide them with services such as information search and diverse advertisements.

Information service failure occurs due to inaccurate, incomplete, irrelevant, and incorrect information (Mustafa et al., 2020). Inaccurate and incomplete information deteriorates information quality, and irrelevant information places a burden on consumers and complicates the system, affecting user experience and trust. Incorrect information leads to service failure (Tan et al., 2016). In this study, information service failure is defined as the degree to which users find it difficult to receive services, including accurate, personalized, and desired information, through personalized advertising recommendation services on SNS platforms.

System failure is caused by security issues within the system (Tan et al., 2016), which significantly affect user experience. In particular, leakage of users' personal information may be perceived as a service failure for the users (Mustafa et al., 2020). Thus, in this study, system failure is defined as the degree to which it is difficult to securely protect personal information while providing personalized advertising recommendation services on SNS platforms.

Negative expectation disconfirmation and dissatisfaction. Expectation disconfirmation theory refers to the discrepancy between consumers' expectations of a product or service and its actual perceived performance (Oliver, 1980). Engel et al. (1990) classified expectation disconfirmation into positive or negative, emphasizing that negative expectation disconfirmation—when actual performance falls short of expectations—has a greater impact on consumer satisfaction than does positive expectation disconfirmation. Tversky and Kahneman (1991) also explained that the impact of losses on preference has a greater influence than the emotions resulting from gains and positivity. Thus, research on negative expectation disconfirmation has significance for service improvements by companies.

Consumers experience dissatisfaction when post-purchase product performance falls short of their pre-purchase expectations, thereby causing negative disconfirmation (Bhattacherjee, 1980). In other words, antecedents are classified into negative expectations, negative perceived performance, and disconfirmation, and the negative disconfirmation paradigm, which employs these variables as antecedent factors, serves as a key to explaining dissatisfaction (Bhattacherjee, 2001). Negative expectation disconfirmation leads to customer dissatisfaction, negative attitudes, and unfavorable behaviors (Zhang et al., 2021). In other words, negative disconfirmation leads to negative results for purchase intentions, prompting customers to explore other competing services (Engel et al., 1990).

Moreover, from the perspective of cognitive evaluation, dissatisfaction is defined as an assessment of the degree to which customer needs are unmet, that is, an assessment of the process determined based on pre-expectations, performance, or the negative experiences of consumers (Cai and Chi, 2021). In one study, when actual performance fell short of expectations, it led to negative expectation disconfirmation and dissatisfaction (Tønnessen Ø et al., (2021)). Thus, dissatisfaction increases the likelihood of service discontinuation (Tan et al., 2023).

Information overload from personalized advertising recommendation services can lead to dissatisfaction in various contexts. Recent research on social media has shown that information overload in advertising has both direct and indirect effects on user dissatisfaction (Zhou et al., 2024). SNS platform users forced to process excessive information from advertisements are more likely to experience dissatisfaction, which, in turn, decreases their engagement with the platform (Fu and Li, 2022). In this study, negative expectation disconfirmation is defined as the degree to which personalized advertising recommendation services on SNS platforms fail to meet user expectations or provide inaccurate recommendations. Furthermore, dissatisfaction is defined as the degree of negative affect experienced by users, such as displeasure, annoyance, and disappointment toward personalized advertising recommendation services on SNS platforms.

Negative word-of-mouth and discontinuance intentions. Negative word-of-mouth regarding a product or service not only deteriorates the satisfaction of other customers but also undermines the negotiation skills companies need to improve service evaluations (Levy et al., 2013). It is well known that negative information is more likely to affect consumer behavior than positive information. In other words, consumers regard negative reviews as more important when seeking information before purchasing a product (Ahluwalia et al., 2000). Consumers who experience displeasure can negatively impact services by spreading negative word-of-mouth and sharing unfavorable information regarding the company (Romaniuk et al., 2007). Negative word-of-mouth has a significant impact on the formation of consumer opinions and behaviors due to negative content (Craciun and Moore, 2019). Thus, it leads to negative consumer reviews related to the product (Doh and Hwang, 2009) and reduces purchase or repurchase intentions, thereby resulting in negative outcomes for the relevant product and company (Nam et al., 2020). In this study, negative word-of-mouth is defined as the degree to which users tend to give negative reviews of personalized advertising recommendation services on SNS platforms to others.

Moreover, discontinuance intentions refer to an individual's willingness or decision to discontinue using a service after temporarily accepting it (Fakhfakh and Bouaziz, 2022). Consumers who feel dissatisfied with the use of new technology tend to exhibit a higher willingness to reduce or discontinue the use of the service (Tan et al., 2023). Thus, retaining existing users, attracting new users, and identifying the reason for discontinuing personalized advertising recommendation services on SNS platforms are necessary (Masood et al., 2020).

Users who experience fatigue, functional overload, and disconfirmation between their needs and available SNSs are likely to discontinue using such services (Gandhi and Kar, 2024). Information service discontinuance arises in terms of multiple aspects, including process, content, and context (Soliman and Rinta-Kahila, 2020). In mobile social media contexts, four types of discontinuance measures can be observed: usage reduction, usage discontinuance, temporary discontinuance, and switching to alternatives (Lin et al., 2020). SNS discontinuance intentions refer to users' intentions to change the context of service use, such as by decreasing the frequency of SNS usage, temporarily or permanently discontinuing the use of services provided by SNS platforms, or switching to another platform (Pang and Ruan, 2023). Thus, in this study, discontinuance intentions are defined as the degree to which users plan to discontinue using personalized advertising recommendation services on SNS platforms.

Moderating effects of demographic characteristics. In the field of social sciences, gender has long been treated as an important topic in relation to consumer behavior (Okazaki and Hirose, 2009). Given that the male–female binary represents one of the most fundamental distinctions in society, gender is often utilized as part of the social and cultural context in developing marketing strategies (Prakash and Flores, 1985). Gender differences also play an important role in SNS services (Chang and Zhu, 2012), influencing both the processing of advertising messages and advertising effectiveness. Men and women exhibit distinct differences in cognitive styles, emotional responses, attention focus, and purchasing decision-making processes (Meyers-Levy and Maheswaran, 1991). Men tend to employ task-oriented information processing, paying greater attention to advertising content that is direct, concise, and functional, whereas women tend to use relationship-oriented and detail-oriented processing and respond more readily to advertising with emotional appeals and plentiful contextual cues (Ahn et al. (2022)). In online advertising contexts, women are also more likely to respond positively to advertisements related to lifestyle or social relationships and to actively engage in ad-related interactions or sharing, whereas men show greater interest in advertisements containing gamification elements, discounts, and technical features (Chatterjee, 2021). In the field of SNS advertising, gender has further been identified as a moderating factor in the relationship between ad relevance and ad attitude, with significant differences in ad acceptance, privacy concerns, and behavioral intentions by gender (Hudders and De Jans, 2022). Overall, men and women differ significantly in cognitive style, information processing, privacy concerns, interaction preferences, and advertising acceptance attitudes, and these differences affect not only their modes of engagement with platform content but also their perceptions, acceptance, and usage behaviors regarding personalized advertising services (Hu and Wise, 2024).

Bhatt and Bhatt (2016) defined consumer demographics in terms of consumer characteristics such as age, income, gender, literacy rate, and education level. Consumer demographics are crucial in service marketing as they influence decision-making and choices (Kamboj and Singh, 2018). Several studies on information systems have considered age a moderating variable affecting user behavior (Liébana-Cabanillas & Sánchez-Fernández, 2014). As new information systems emerge, age has begun to influence whether users accept or continue using them (Kim and Han, 2009). Human physical and psychological activities change with age, which is likely to affect the use of digital products. For example, younger people have been observed to use digital products more frequently (Wang et al., 2009).

Recently, the moderating effect of demographic characteristics, particularly age, has been receiving attention in explaining user responses to personalized advertising. According to a study by Horgby and Galizzi (2024), the impact of the type of ad creator (artificial intelligence [AI] vs. human) on consumer responses such as ad evaluation, purchase intention, and word-of-mouth did not show statistically significant moderating effects by age, but a weak trend was observed. The authors noted that younger users tend to respond more positively to AI-generated content, while older users are more likely to exhibit distrust toward AI ads.

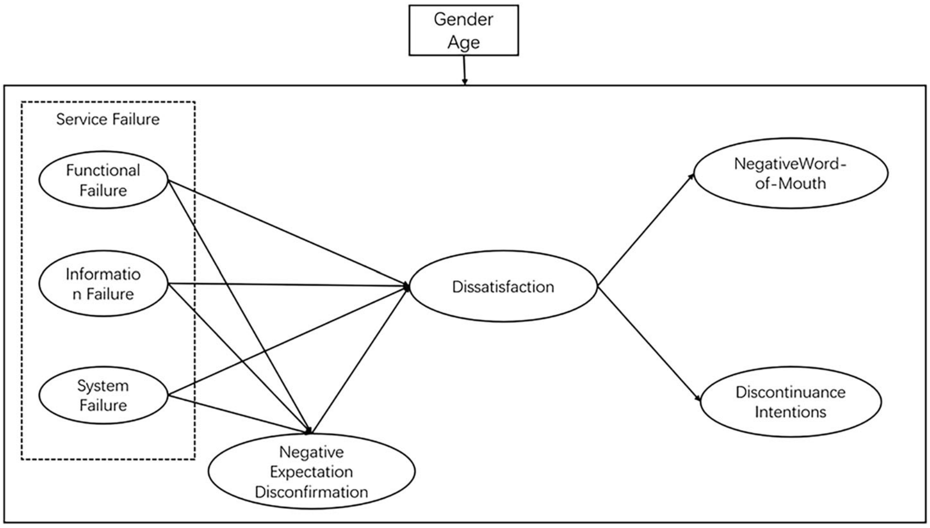

Fig. 1 Research model.

Moreover, Janavi et al. (2021) analyzed the impact of social media use on online purchasing behavior by conducting a permutation test and found that individuals aged 20 to 50 years were most strongly influenced by social media-based advertising. This suggests that digital service experiences and response patterns may differ by age and that considering age as a moderating variable provides theoretical validity for a more detailed analysis of user responses to personalized advertising recommendation systems.

Existing research findings are inconsistent and vary depending on context. Accordingly, this study does not restrict the analysis to specific paths; instead, it seeks to explore whether age and gender demonstrate moderating effects across all paths in the research model.

Research Question 1 (RQ1): In which paths of the proposed research model does gender demonstrate moderating effects? Research Question 2 (RQ2): In which paths of the proposed research model does age demonstrate moderating effects?

Research model and hypotheses. This study verified the effects of service failure in personalized advertising recommendation services on SNS platforms on negative expectation disconfirmation, the effects of service failure and negative expectation disconfirmation on dissatisfaction, and, ultimately, the effects of dissatisfaction on negative word-of-mouth and discontinuance intentions (Fig. 1).

Relationship between service failure and negative expectation disconfirmation. As social media is widely used in marketing, platforms now recommend personalized advertisements based on information users voluntarily disclose on SNSs. However, these data have limitations in terms of accuracy and diversity due to the presence of false information, bot accounts, and malicious user interference. Hong et al. (2020) noted that while user-generated text content (e.g., tweets) is utilized for personalized advertising, the use of image data remains limited. Such information discrepancies negatively influence the judgment of recommendation algorithms, leading users to experience services that fall short of the expected level of personalization accuracy. This results in negative expectation disconfirmation, which becomes one of the major causes of service failure. Moreover, as Barnard (2014) explained, personalized messages can raise privacy concerns, leading consumers to distrust the marketing activities of platforms altogether.

Previous studies on service failure have proposed various classification systems. For example, Tan et al. (2016) classified service failure into three sub-factors: functional failure, informational failure, and system failure. This system was adopted by Mustafa et al. (2020), who further added digital service failure as a distinct category. Such classifications are frequently applied in digital services or technology-based platforms. Moreover, Hien et al. (2024) conducted a study focusing on airline services and confirmed the impact of service failure severity on negative expectation disconfirmation. As such, service failure is classified differently depending on the context and serves as an important analytical criterion in studies on consumer expectation disconfirmation.

Functional failure refers to a state in which personalized recommendation services fail to meet user needs or preferences or are perceived as lacking in content diversity and relevance (Peng et al., 2024). According to Tan et al. (2016), functional failure occurs when users' outcome expectations are not met, making it a core source of psychological dissonance, as described in expectation disconfirmation theory. Thus, when recommendation services do not align with users' intentions, users may have experiences that deviate from their expectations, resulting in negative expectation disconfirmation.

Information failure refers to a state in which the advertising content delivered to users is perceived as inaccurate, irrelevant, or inconsistent (Peng et al., 2024). The qualitative limitations of the recommended content fail to meet users' information expectations, which can lead to a gap between expected and actual information experiences. Hong et al. (2020) claimed that data bias on social media and algorithmic errors hinder the suitability of recommended content, resulting in information failure. This can lead to negative expectation disconfirmation, in which users' expectations regarding the accuracy of personalization are undermined.

System failure refers to a state in which trust in users' privacy protection is damaged or when expectations regarding system reliability are not met due to security concerns and technical defects during the service usage process (Do and Bowden, 2025; Tan et al., 2023). As personalized advertising services are based on sensitive data, users may exhibit strong psychological dissonance, along with resistance, when security expectations are violated. Therefore, system failure can serve as a major cause of the collapse of both cognitive and emotional user expectations. Based on this, the following hypotheses were proposed:

H1: Service failure in personalized advertising recommendation services on SNS platforms influences negative expectation disconfirmation. H1-1: Functional failure is positively associated with negative expectation disconfirmation. H1-2: Information failure is positively associated with negative expectation disconfirmation. H1-3: System failure is positively associated with negative expectation disconfirmation.

Relationship between service failure and dissatisfaction. In recent years, user satisfaction with recommendation systems has been on the decline due to the widespread application of personalized recommendation technologies. This decline is primarily driven by dissatisfaction with the overall services, as the recommended content often fails to align with users' preferences for personalization (McNee et al., 2006). Zhao et al. (2017) noted that many recommendation algorithms tend to recommend projects that users have already seen or clicked on. This significantly reduces the novelty and perceived value of the recommendations, leading users to feel that the information lacks relevance and accuracy because they have already seen such ads, thereby intensifying dissatisfaction. In addition, Kim et al. (2022) stated that excessive use of consumer privacy in personalized recommendation systems can lead to dissatisfaction among users and prompt negative measures.

Weun et al. (2004) revealed that higher severity of service failure leads to lower customer satisfaction and more negative subsequent behavior. Tan et al. (2016) studied electronic services and discovered that service failure (functional failure, information failure, and system failure) negatively affected customer satisfaction. A meta-analysis by Orsingher et al. (2022) showed that service failure causes negative emotions in customers, which directly affects customer dissatisfaction. Janjua (2017) confirmed that service failure positively affects consumer dissatisfaction and complaint intentions. In summary, these prior studies suggest that service failure in personalized recommendation services deepens the cognitive and emotional gap between users' expectations and their actual experiences, which is likely to lead to strong dissatisfaction. Therefore, the following hypotheses were proposed:

H2: Service failure in personalized advertising recommendation services on SNS platforms influences dissatisfaction. H2-1: Functional failure is positively associated with dissatisfaction. H2-2: Information failure is positively associated with dissatisfaction. H2-3: System failure is positively associated with dissatisfaction.

Relationship between negative expectation disconfirmation and dissatisfaction. Personalized recommendation services provided by SNS platforms generally push advertising content based on users' historical behavior, interest preferences, and click records. However, many users have found that, during actual use, such recommendations are often highly repetitive, weakly correlated, and misaligned with their expectations, leading to disappointment (Singh and Adhikari, 2023; Wu, Jing Wen (2021)). According to expectation disconfirmation theory (Oliver, 1980), negative expectation disconfirmation, which is a psychological gap, occurs when users' actual experiences fail to meet their initial service expectations. Huang and Ma (2024) reported that when consumers perceive a gap between expectations and reality in a service, it generally triggers negative emotional responses, which manifest as overall dissatisfaction with the service.

Che et al. (2022) analyzed the effect of expectation disconfirmation on consumer dissatisfaction in online-to-offline (O2O) websites and revealed that negative expectation disconfirmation in both the website and offline service positively affected consumer dissatisfaction. Huang and Ma (2024) found that in live streaming commerce, negative expectation disconfirmation positively affected dissatisfaction. Therefore, the following hypothesis was proposed:

H3: Negative expectation disconfirmation in personalized advertising recommendation services on SNS platforms is positively associated with dissatisfaction.

Relationship between dissatisfaction and negative word-of-mouth. After experiencing dissatisfaction due to a service failure, consumers may directly discuss or share the issue with acquaintances such as family and friends (Anderson, 1998; Mittal et al., 2021). Yadav et al. (2025) noted that when personalized recommendation services on a platform fail to meet users' expectations, they can trigger cognitive disengagement and feelings of dissatisfaction, which may further lead to negative word-of-mouth regarding the platform.

Mostafa et al. (2024) found that higher dissatisfaction with services related to virtual agents leads to higher levels of negative word-of-mouth among users. Nam et al. (2020) analyzed negative word-of-mouth data from Tripadvisor users and confirmed that experience-based dissatisfaction was a major cause of creating negative electronic word-of-mouth. Dissatisfaction had a direct positive effect on the likelihood of writing negative reviews. Based on prior studies, the following hypothesis was proposed:

H4: Dissatisfaction with personalized advertising recommendation services on SNS platforms is positively associated with negative word-of-mouth.

Relationship between dissatisfaction and discontinuance intentions. Users often express dissatisfaction when they experience service disruptions due to poor experiences. This stems from distrust in AI technologies and service delivery (Chen et al., 2022). AI service failures can evoke disappointment or negative emotions from consumers, ultimately reducing their intentions to continue using the service (Sun et al., 2022). Moreover, service failure has been shown to significantly influence users' reuse intentions through experience and satisfaction (Masorgo et al., 2022). In a study on short video platforms, Gan (2024) revealed that dissatisfaction positively affected discontinuance intentions. Fakhfakh and Bouaziz (2022) found that communication overload led to dissatisfaction with SNSs, which, in turn, resulted in discontinuance intentions. Tan et al. (2023) also confirmed that consumer dissatisfaction is positively related to discontinuance intentions on social media platforms. Therefore, the following hypothesis was proposed:

H5: Dissatisfaction with personalized advertising recommendation services on SNS platforms is positively associated with discontinuance intentions.

Measurements. The measurement items used in this study to measure service failure (functional failure, information failure, and system failure), negative expectation disconfirmation, dissatisfaction, negative word-of-mouth, and discontinuance intentions were all modified based on the conceptual definitions and measurement logic from prior research. Most existing scales are primarily focused on traditional services or e-commerce platforms, due to which they are not fully applicable to personalized advertising recommendation services on SNS platforms. Thus, the expression was adjusted within the scope, ensuring that the core meaning of the original concept remains unchanged while aligning with the service context of this study. The scale construction of the measurement variables used in this study is presented in Table 1. Service failure (functional, information, and system) in personalized advertising recommendation services on SNS platforms was developed based on prior research (Mustafa et al., 2020; Peng et al., 2024; Tan et al., 2016). Moreover, the

Table 1 Scale construction.

Variable		Measurement item	Prior research
Service Failure (SF)	Functional Failure (FF)	1. I have not received support for my needs and preferences through personalized advertising recommendation services on SNS platforms. 2. It is difficult to receive diverse advertisement content through personalized advertising recommendation services on SNS platforms. 3. I did not receive help when searching for information through personalized advertising recommendation services on SNS platforms.	Adapted from: Mustafa et al. (2020); Peng et al. (2024); Tan et al. (2016)
	Information Failure (IF)	1. It is difficult to receive accurate information through personalized advertising recommendation services on SNS platforms. 2. It is difficult to receive relevant information through personalized advertising recommendation services on SNS platforms. 3. It is difficult to receive consistent information through personalized advertising recommendation services on SNS platforms.	
	System Failure (SyF)	1. I do not feel that my personal information is safe while using personalized advertising recommendation services on SNS platforms. 2. It is difficult to securely protect my personal information while using personalized advertising recommendation services on SNS platforms.	
Negative Expectation Disconfirmation (NED)		1. The experience of using personalized advertising recommendation services on SNS platforms did not meet my expectations. 2. Personalized advertising recommendation services on SNS platforms cannot meet my expectations. 3. Most of my expectations for personalized advertising recommendation services on SNS platforms were not met.	Adapted from: Fan and Suh (2014); Tan et al. (2023); Wang et al., (2023)
Dissatisfaction(DS)		1. I feel dissatisfied when using personalized advertising recommendation services on SNS platforms. 2. I feel displeased when using personalized advertising recommendation services on SNS platforms. 3. I often feel annoyed by personalized advertising recommendation services on SNS platforms.	Adapted from: Tan et al. (2023); Zhou et al. (2024)
Negative Word-of-Mouth (NWOM)		1. I would speak negatively to others about personalized advertising recommendation services on SNS platforms. 2. I would express my distrust of personalized advertising recommendation services on SNS platforms to others. 3. I would tell others not to receive product recommendations through personalized advertising recommendation services on SNS platforms.	Adapted from: Mostafa et al. (2024); Nam et al. (2020)
Discontinuance Intentions (DI)		1. I plan to discontinue personalized advertising recommendation services on SNS platforms. 2. I intend to temporarily discontinue personalized advertising recommendation services on SNS platforms. 3. I intend to stop personalized advertising recommendation services on SNS platforms. 4. I intend not to use personalized advertising recommendation services on SNS platforms.	Adapted from: Lin et al. (2020); Tan et al. (2023)

items were adapted and refined to fit the context of this study, with reference to prior research on negative expectation disconfirmation (Fan and Suh, 2014; Tan et al., 2023, Wang et al., 2023), dissatisfaction (Tan et al., 2023; Zhou et al., 2024), negative word-of-mouth (Mostafa et al., 2024; Nam et al., 2020), and discontinuance intentions (Lin et al., 2020; Tan et al., 2023). All measurement items were rated on a five-point Likert scale.

Data collection. The survey was conducted with Chinese users with experience in encountering personalized advertising recommendation services on Chinese SNS platforms. First, bilingual researchers with experience in marketing and survey design translated the English items into Chinese. Then, independent bilingual translators, who had not been exposed to the original items, retranslated the Chinese items back into English. The two English versions were compared to examine semantic discrepancies, and any differences found were resolved through discussions with two experts in translation and consumer behavior. Finally, the wording was refined to ensure that the survey items were easily understood by actual Chinese social media users while maintaining conceptual equivalence. Moreover, prior to the

Table 2 Demographic characteristics.

N (%) = 500 (100)

Variable	Group	N (%)	Variable	Group	N (%)
Sex	Male	248 (49.6)	Average monthly income	Less than 3000 CNY	30 (6.0)
	Female	252 (50.4)		3000–less than 6000 CNY	96 (19.2)
Age	20–29	169 (33.8)		6000–less than 9000 CNY	148 (29.6)
	30–39	163 (32.6)		9000–less than 12,000 CNY	135 (27.0)
	40–49	168 (33.6)		12,000 CNY or more	91 (18.2)
Education level	High school graduate or lower	16 (3.2)	Occupation	Professional /clerical/government posts	405 (81.0)
	College student or bachelor's degree holder	431 (86.2)		Self-employed/sales, service/ technical posts	63 (12.6)
	Graduate student or postgraduate degree holder	53 (10.6)		Student or other	32 (6.4)

CNY 7.13 = US$1 (August 25, 2024).

Table 3 Descriptive statistics of each measurement item (mean and standard deviation).

	N	Mean	SD
FF1	500	2.60	1.046
FF2	500	2.88	1.239
FF3	500	2.42	1.219
IF1	500	2.70	1.224
IF2	500	2.73	1.254
IF3	500	2.74	1.214
SyF1	500	3.22	1.312
SyF2	500	3.21	1.312
NED1	500	3.04	1.162
NED2	500	2.90	1.210
NED3	500	2.79	1.233
DS1	500	2.71	1.164
DS2	500	2.60	1.199
DS3	500	2.65	1.240
NWOM1	500	2.61	1.045
NWOM2	500	2.57	1.131
NWOM3	500	2.26	1.134
DI1	500	2.56	1.177
DI2	500	2.60	1.223
DI3	500	2.53	1.248
DI4	500	2.49	1.233

main survey, a pilot test was conducted with 50 participants to assess the clarity of item wording, structural consistency, and potential redundancy among items. Consequently, the word order and vocabulary of some items were revised to enhance the integrity of the measurement tool. Then, a preliminary survey was conducted with 40 copies of the questionnaire, following which the main survey was conducted through the famous Chinese survey company WJX (www.wjx.cn) from August 1 to August 10, 2024, using 528 copies of the online survey. A total of 500 valid responses were used in the final analysis after eliminating responses with false entries or missing values. Before the survey began, the definition of personalized advertising recommendation services was provided along with visual examples to ensure that the participants fully understood the context of the items. The examples included personalized ads inserted into WeChat Moments and customized recommendation ads displayed in WeChat videos.

Moreover, the participants were prompted to recall whether they had ever received such ads while using SNS platforms, encouraging pre-awareness of the concept being surveyed. The survey was specifically designed with a screening question to ensure that only individuals with actual experience participated. The screening question was as follows: 'Have you ever experienced personalized advertising recommendation services on an SNS platform?' Yes (→ Proceed with the survey), No (→ End the survey). This step ensured that data were collected from only participants who had actual experience, thereby obtaining a sample capable of evaluating the failure of personalized advertising recommendation services.

The demographic characteristics of the participants are presented in Table 2. In terms of sex, there were slightly more female respondents (50.4%) than male respondents (49.6%). Most respondents were aged 20–29 years (33.8%), followed by 40–49 years (33.6%) and 30–39 years (32.6%). Concerning education level, most respondents (86.2%) were college students or graduates. In terms of average monthly income, most earned 6,000 to less than 9,000 CNY (29.6%). In addition, most respondents worked in professional, clerical, or government posts (81.0%). 'Professional/clerical/government posts' respectively refer to occupations requiring professional qualifications (e.g., lawyer, professor, doctor), general clerical positions, and posts in public institutions.

Furthermore, descriptive statistical analyses were conducted for each measurement item to calculate the mean and standard deviation (see Table 3). The results showed that the mean values for items related to Functional Failure (FF) and Information Failure (IF) were generally in the range of 2.42–2.88, suggesting that respondents held somewhat negative perceptions of the functional and informational aspects of personalized advertising recommendation services. The mean values for System Failure (SyF1 and SyF2) were 3.22 and 3.21, respectively, which were relatively higher than those for the other types of failure. The mean values for Negative Expectation Disconfirmation (NED) items ranged from 2.79 to 3.04, while those for Dissatisfaction (DS) items ranged from 2.60 to 2.71. In addition, the mean values for Negative Word-of-Mouth (NWOM) items ranged from 2.26 to 2.61, and those for Discontinuance Intention (DI) items ranged from 2.49 to 2.60. The standard deviations for all items ranged from 1.046 to 1.312, indicating that the variability among responses remained relatively stable.

Data analysis. This study conducted Harman's single-factor test to assess the presence of common method bias (CMB). According to Podsakoff et al. (2003, p. 889), if the single factor accounts for less than 50% of the total variance, CMB is at an acceptable level. The analysis revealed that the first factor explained 47.523% of the total variance, confirming no issues with CMB. Statistical analysis was conducted using SPSS 26 and AMOS 24 to analyze

Table 4 Validity and reliability testing of the measurement tool.

Variable	Factor	Std. factor loadings	SMC	t-value	Cronbach's α	AVE	CR
FF	FF1	0.827	0.683	18.213	0.803	0.594	0.814
	FF2	0.700	0.490	15.406			
	FF3	0,779	0.607				
IF	IF1	0.778	0.606	16.844	0.822	0.607	0.822
	IF2	0.784	0.615	16.958			
	IF3	0.775	0.600				
SyF	SyF1	0.837	0.701	16.900	0.835	0.717	0.835
	SyF2	0.856	0.733				
NED	NED1	0.820	0.673	18.623	0.836	0.632	0.837
	NED2	0.780	0.608	17.682			
	NED3	0.784	0.614				
DS	DS1	0.804	0.646	17.565	0.826	0.614	0.827
	DS2	0.800	0.640	17.481			
	DS3	0.746	0.556				
NWOM	NWOM1	0.713	0.508	15.237	0.805	0.582	0.806
	NWOM2	0.820	0.672	17.406			
	NWOM3	0.713	0.565				
DI	DI1	0.825	0.680	22.312	0.910	0.717	0.910
	DI2	0.867	0.752	24.145			
	DI3	0.854	0.729	23.565			
	DI4	0.841	0.708				

Goodness-of-fit: x^2=239.787, df=168, p = .000, CMIN/df=1.427, GFI = 0.956, RMR = 0.038, NFI = 0.963, IFI = 0.989 TLI = 0.986, CFI = 0.988, and RMSEA = 0.029

the survey data in this study. Descriptive statistics were analyzed for demographic characteristics, and the reliability of the measurement items (Cronbach's α values) was verified. In addition, confirmatory factor analysis was conducted to verify the internal consistency and convergent validity of the items. Discriminant validity was identified through correlation analysis. Moreover, SEM was conducted to test the research hypotheses in this study.

Results

Confirmatory factor analysis. Confirmatory factor analysis was conducted to examine the internal consistency and reliability of the measurement items in this study Table 4. The reliability testing results showed that Cronbach's α for all measurement variables ranged from 0.803 to 0.910, ensuring reliability. In addition, based on the confirmatory factor analysis, the model fit indices were as follows: $x^2 = 239.787$, degrees of freedom (df) = 168, p-value = 0.000, CMIN/df = 1.427, GFI = 0.956, RMR = 0.038, NFI = 0.963, IFI = 0.989, TLI = 0.986, CFI = 0.988, and RMSEA = 0.029. In model fit indices, CMIN/df between 1 and 3 is considered acceptable (Muthén and Kaplan, 1985), while TLI above 0.9, GFI, CFI, and NFI above 0.9 and RMR below 0.05 indicate a good model fit. RMSEA below 0.05 also indicates a good model fit (Browne and Cudeck, 1992). Based on these criteria, the overall fit of the model in this study was deemed adequate. Moreover, the average variance extracted (AVE) and construct reliability (CR) were verified according to the results of the confirmatory factor analysis, which showed AVE between 0.582 and 0.717 and CR between 0.806 and 0.837, confirming the convergent validity of the latent variables. According to the correlation analysis among variables in this study (Table 5), when applying the Φ ± 2SE method proposed by Anderson and Gerbing (1988) and Bagozzi and Yi (1988), the 95% confidence intervals of all correlation coefficients did not include 1, thereby confirming discriminant validity. In addition, for a more conservative test, the Heterotrait–Monotrait (HTMT) ratio (Henseler et al., 2015) was analyzed, and all constructs were below the recommended threshold of 0.90 (Hair et al., 2021), further confirming discriminant validity. However, in the Fornell–Larcker discriminant validity test, the square root of the AVE for the three constructs—FF, NWOM, and DS—was lower than their corresponding correlation coefficients, showing values at the boundary of the traditional criterion. Nevertheless, upon considering the results of the Φ ± 2SE method (Anderson and Gerbing, 1988) and the HTMT analysis together, it was determined that there were no substantive issues with the discriminant validity of this study.

Hypothesis testing. Before conducting the SEM analysis, univariate normality was assessed by examining skewness and kurtosis. The skewness values ranged from −0.264 to 0.745 and the kurtosis values ranged from −1.121 to −0.182. According to the criteria proposed by West et al. (1995), with skewness values below 2 and kurtosis values below 7, all items met the acceptable thresholds, indicating no substantial deviation from normality. The skewness and kurtosis values for all constructs in this study were within these thresholds, confirming that the data did not deviate substantially from a normal distribution. This study employed SEM to verify the effects of service failure in personalized advertising recommendation services on SNS platforms on negative expectation disconfirmation, the effects of service failure and negative expectation disconfirmation on dissatisfaction, and, ultimately, the effects of dissatisfaction on negative word-of-mouth and discontinuance intentions. The fit indices of the structural equation model were as follows: $x^2 = 276.231$, df = 177, p = 0.000, CMIN/df = 1.561, GFI = 0.950, RMR = 0.044, NFI = 0.957, IFI = 0.984, TLI = 0.981, CFI = 0.984, and RMSEA = 0.034. The analysis results are presented in Table 6.

The hypothesis testing results were fourfold. First, functional failure (β = 0.355, $P < 0.001$), information failure (β = 0.220, $P < 0.01$), and system failure (β = 0.333, $P < 0.001$) in personalized advertising recommendation services on SNS platforms all had a significant positive effect on negative expectation disconfirmation. Therefore, hypotheses H1-1, H1-2, and H1-3 were accepted. In other words, functional, information, and system failures in personalized advertising recommendation

Table 5 Correlations of the measurement variables.

Variable	FF	IF	SyF	NED	DS	NWOM	DI
FF	0.771						
IF	0.784 (0.067)	0.780					
SyF	0.519 (0.067)	0.491 (0.066)	0.847				
NED	0.700 (0.065)	0.662 (0.063)	0.626 (0.072)	0.795			
DS	0.685 (0.062)	0.644 (0.061)	0.676 (0.072)	0.790 (0.067)	0.784		
NWOM	0.687 (0.058)	0.595 (0.054)	0.564 (0.062)	0.711 (0.059)	0.793 (0.061)	0.763	
DI	0.613 (0.063)	0.535 (0.060)	0.582 (0.072)	0.647 (0.065)	0.786 (0.069)	0.775 (0.063)	0.847
Means	2.64	2.72	3.22	2.91	2.65	2.48	2.54
SD	0.99	1.05	1.21	1.04	1.03	0.93	1.08

()SE, diagonal elements are the square root of AVE.

Table 6 Hypothesis testing.

Hypothesis	β	S.E.	C.R.	p-value	Result
H1-1: FF- > NED	0.355	0.087	4.159	0.000***	Accept
H1-2: IF - > NED	0.220	0.084	2.675	0.007**	Accept
H1-3: SyF -> NED	0.333	0.045	6.421	0.000***	Accept
H2-1: FF- > DS	0.249	0.071	3.317	0.000***	Accept
H2-2: IF - > DS	0.050	0.066	0.721	0.471	Reject
H2-3: SyF -> DS	0.261	0.039	5.349	0.000***	Accept
H3: NED - > DS	0.437	0.061	6.600	0.000***	Accept
H4: DS - > NWOM	0.854	0.057	13.825	0.000***	Accept
H5: DS - > DI	0.827	0.062	15.434	0.000***	Accept

Goodness-of-fit: x^2=276.231, df=177, p = .000, CMIN/df=1.561, GFI = 0.950, RMR = 0.044, NFI = 0.957, IFI = 0.984, TLI = 0.981., CFI = 0.984, and RMSEA = 0.034
**p < 0.01, ***p < 0.001

services on SNS platforms increase negative expectation disconfirmation among users.

Second, functional failure ($\beta = 0.249$, $P < 0.001$) and system failure ($\beta = 0.261$, $P < 0.001$) had a significant positive effect on dissatisfaction with personalized advertising recommendation services on SNS platforms, while information failure ($\beta = 0.050$, $P > 0.05$) did not have such an effect. Therefore, hypotheses H2-1 and H2-3 were accepted, while hypothesis H2-2 was rejected. These results demonstrate that functional and system failures are key factors in dissatisfaction with personalized recommendation services on SNS platforms. However, information failure did not affect dissatisfaction with personalized recommendation services on SNS platforms. Moreover, negative expectation disconfirmation ($\beta = 0.437$, $P < 0.001$) had a significant positive effect on dissatisfaction; thus, hypothesis H3 was accepted. In other words, higher negative expectation disconfirmation regarding the use of personalized advertising services on SNS platforms leads to higher dissatisfaction.

Third, dissatisfaction with personalized advertising recommendation services on SNS platforms had a positive effect on negative word-of-mouth ($\beta = 0.854$, $P < 0.001$); thus, hypothesis H4 was accepted. These results confirm that higher user dissatisfaction with personalized advertising services on SNS platforms leads to higher levels of negative word-of-mouth.

Fourth, dissatisfaction with personalized advertising recommendation services on SNS platforms had a positive effect on discontinuance intentions ($\beta = 0.827$, $P < 0.001$); thus, hypothesis H5 was accepted. These results confirm that dissatisfaction is the cause of higher discontinuance intentions for personalized advertising services on SNS platforms.

Moderating effect. Before conducting the moderating effect analysis, this study described in detail the sociodemographic characteristics of each subsample by gender and age (see Tables 7 and 8). This was done to ensure comparability of characteristics across subsamples in model comparisons and to provide the background information necessary for interpreting the results of group-specific analyses.

To test the moderating effects of Research Question 1 (RQ1: sex) and Research Question 2 (RQ2: age), multi-group SEM analysis was conducted (see Tables 9 and 10).

First, for RQ1 (sex), respondents were divided into male ($n = 248$) and female ($n = 252$) groups. The results showed that the differences in path coefficients between males and females were not statistically significant across all paths ($p > 0.05$).

Next, for RQ2 (age), following Wu (2019), respondents were divided into three groups: 20–29 years ($n = 169$), 30–39 years ($n = 163$), and 40–49 years ($n = 168$). The results indicated a statistically significant difference across age groups in the 'DS → NWOM' path ($\Delta\chi^2(df{=}2) = 8.251$, $p < 0.05$). The effect was strongest in the 30 s group ($\beta = 0.911$, $CR = 9.714$), followed by the 40 s group ($\beta = 0.812$, $CR = 7.247$) and the 20 s group ($\beta = 0.809$, $CR = 7.357$). A significant difference across age groups was also observed in the DS → DI path

Table 7 Sociodemographic characteristics of subsamples for moderating effect analysis (Sex).

Sex		Male (N = 248)	Female (N = 252)
Variable	Group	N (%)	N (%)
Age	20–29	81 (32.7)	88 (34.9)
	30–39	85 (34.3)	78 (31.0)
	40–49	82 (33.1)	86 (34.1)
Education level	High school graduate or lower	6 (2.4)	10 (4.0)
	College student or bachelor's degree holder	213 (85.9)	218 (86.5)
	Graduate student or postgraduate degree holder	29 (11.7)	24 (9.5)
Average monthly income	Less than 3,000 CNY	14 (5.6)	16 (6.3)
	3,000–less than 6,000 CNY	43 (17.3)	53 (21.0)
	6,000–less than 9,000 CNY	79 (31.9)	69 (27.4)
	9,000–less than 12,000 CNY	63 (25.4)	72 (28.6)
	12,000 CNY or more	49 (19.8)	42 (16.7)
Occupation	Professional /clerical/government posts	194 (78.2)	211 (83.7)
	Self-employed/sales, service/technical posts	38 (15.3)	25 (9.9)
	Students or other	16 (6.5)	16 (6.3)

Table 8 Sociodemographic characteristics of subsamples for moderating effect analysis (age).

Age		20–29 (N = 169)	30–39 (N = 163)	40–49 (N = 252)
Variable	**Group**	**N (%)**	**N (%)**	**N (%)**
Sex	Male	81 (47.9)	85 (52.1)	82 (48.8)
	Female	88 (52.1)	78 (47.9)	86 (51.2)
Education level	High school graduate or lower	3 (1.8)	1 (0.6)	12 (7.1)
	College student or bachelor's degree holder	156 (92.3)	143 (87.7)	132 (78.6)
	Graduate student or postgraduate degree holder	10 (5.9)	19 (11.7)	24 (14.3)
Average monthly income	Less than 3,000 CNY	29 (17.2)	0	1 (0.6)
	3,000–less than 6,000 CNY	41 (24.3)	15 (9.2)	40 (23.8)
	6,000–less than 9,000 CNY	58 (34.3)	54 (33.1)	36 (21.4)
	9,000–less than 12,000 CNY	24 (14.1)	54 (33.1)	57 (33.9)
	12,000 CNY or more	17 (10.1)	40 (24.5)	34 (20.2)
Occupation	Professional /clerical/government posts	114 (67.5)	145 (88.9)	146 (57.9)
	Self-employed/sales, service/technical posts	24 (14.2)	17 (10.4)	22 (8.7)
	Students or other	31 (18.3)	1 (0.6)	0

Table 9 Multi-group analysis results (RQ1: Sex).

Path	$\Delta\chi^2$, Δdf	Male		Female		Significant Difference
		(N = 248)		(N = 252)		
		β	CR	β	CR	
FF- > NED	$\Delta\chi^2$ (df = 1) = 1.222	0.452	2.497	0.294	2.546	No
IF - > NED	$\Delta\chi^2$ (df = 1) = 0.368	0.175	2.438	0.247	2.046	No
SyF -> NED	$\Delta\chi^2$ (df = 1) = 1.679	0.273	3.362	0.375	5.156	No
FF- > DS	$\Delta\chi^2$ (df = 1) = 0.180	0.168	1.462	0.306	3.017	No
IF - > DS	$\Delta\chi^2$ (df = 1) = 0.730	0.061	0.243	0.024	0.239	No
SyF -> DS	$\Delta\chi^2$ (df = 1) = 1.360	0.320	3.541	0.227	3.278	No
NED - > DS	$\Delta\chi^2$ (df = 1) = 0.406	0.447	3.547	0.446	4.813	No
DS - > NWOM	$\Delta\chi^2$ (df = 1) = 0.025	0.879	7.357	0.827	9.300	No
DS - > DI	$\Delta\chi^2$ (df = 1) = 0.344	0.838	9.318	0.819	11.250	No

Table 10 Multi-group analysis results (RQ2: Age).

Path	$\Delta\chi^2$, Δdf	20 s (N = 169)		30 s (N = 163)		40 s (N = 168)		Significant Difference
		β	CR	Β	CR	β	CR	
FF- > NED	$\Delta\chi^2$ (df = 2) = 0.319	0.315	2.497	0.398	2.381	0.226	1.325	No
IF - > NED	$\Delta\chi^2$ (df = 2) = 0.728	0.289	2.438	0.142	0.937	0.321	1.755	No
SyF -> NED	$\Delta\chi^2$ (df = 2) = 0.955	0.316	3.362	0.361	3.984	0.349	3.814	No
FF- > DS	$\Delta\chi^2$ (df = 2) = 0.983	0.167	1.462	0.186	1.487	0.308	2.037	No
IF - > DS	$\Delta\chi^2$ (df = 2) = 0.207	0.026	0.243	0.103	0.953	0.060	0.372	No
SyF -> DS	$\Delta\chi^2$ (df = 2) = 2.000	0.324	3.541	0.318	4.245	0.149	1.720	No
NED - > DS	$\Delta\chi^2$ (df = 2) = 0.351	0.442	3.547	0.442	4.719	0.453	3.841	No
DS - > NWOM	$\Delta\chi^2$ (df = 2) = 8.251*	0.809 ***	7.357	0.911 ***	9.714	0.812 ***	7.247	Yes
DS - > DI	$\Delta\chi^2$ (df = 2) = 9.630**	0.796 ***	9.318	0.921***	12.133	0.730***	8.086	Yes

***$p < 0.001$.

($\Delta\chi^2$(df=2) = 9.630, $p < 0.01$). The effect was highest in the 30 s group (β = 0.921, CR = 12.133), followed by the 20 s group (β = 0.796, CR = 9.318) and the 40 s group (β = 0.730, CR = 8.086).

Discussion

This study examined the effects of service failure in personalized advertising recommendation services on SNS platforms on negative expectation disconfirmation among Chinese consumers and confirmed the effects of service failure and negative expectation disconfirmation on dissatisfaction, negative word-of-mouth, and discontinuance intentions. Based on the results, functional failure, information failure, and system failure in personalized advertising recommendation services on SNS platforms had a significant positive effect on negative expectation disconfirmation. Furthermore, functional failure, system failure, and negative expectation disconfirmation in personalized advertising recommendation services on SNS platforms positively affected dissatisfaction. Finally, dissatisfaction with personalized advertising recommendation services positively affected negative word-of-mouth and discontinuance intentions. Finally, dissatisfaction with personalized advertising recommendation services positively influenced negative word-of-mouth and discontinuance intentions, and these relationships differed by age (see Fig. 2 Structural Model for details).

Theoretical implications. First, this study provides theoretical implications in that it comprehensively considered the constructs of service failure—functional failure, information failure, and system failure—and confirmed their effects on negative expectation disconfirmation in personalized advertising recommendation services on SNS platforms. The application of functional failure, information failure, and system failure to identify users' negative expectation disconfirmation regarding personalized advertising recommendation services on SNS platforms is theoretically significant. Moreover, service failure was classified into functional failure, information failure, and system failure to analyze the relationship with dissatisfaction. The empirical findings revealed that functional and system failures are crucial factors contributing to dissatisfaction and partially supported the relevant hypotheses, thereby demonstrating theoretical significance.

Furthermore, this study applied negative expectation disconfirmation based on the expectation disconfirmation theory to analyze its relationship with dissatisfaction, and through empirical analysis, it revealed that negative expectation disconfirmation is a crucial factor contributing to dissatisfaction. The model analyzing the relationship between negative expectation disconfirmation and dissatisfaction can serve as a theoretical foundation for future research. This study provides a new perspective for understanding the mechanisms that determine dissatisfaction with personalized advertising recommendation services on SNS platforms and further expands the scope of factors contributing to dissatisfaction. In addition, it investigated the relationship between dissatisfaction, negative word-of-mouth, and discontinuance intentions. It also examined the effect of dissatisfaction with personalized advertising recommendation services on SNS platforms on negative word-of-mouth and discontinuance intentions, which can provide foundational data for future research on dissatisfaction, negative word-of-mouth, and discontinuance intentions.

Finally, this study observed the moderating effect of age in the relationships between dissatisfaction and negative word-of-mouth and between dissatisfaction and service discontinuance intentions. Notably, a significant difference in these pathways was found among users in their 30 s (aged 30–39 years) compared to other age groups. This finding expands the research on negative emotional responses by linking them to negative behavioral responses, indicating that user heterogeneity plays a role in the acceptance of personalized advertising recommendation services. The results support the incorporation of age as a key moderating variable in digital advertising acceptance models and contribute to a deeper understanding of how dissatisfaction is perceived and acted upon across different lifecycle stages. Based on this, further exploration of the moderating effects of other demographic characteristics (e.g., education level, digital literacy) could serve as foundational data for providing valuable theoretical implications.

Practical implications. Based on the results of this study, several practical implications and suggestions can be made. First, the

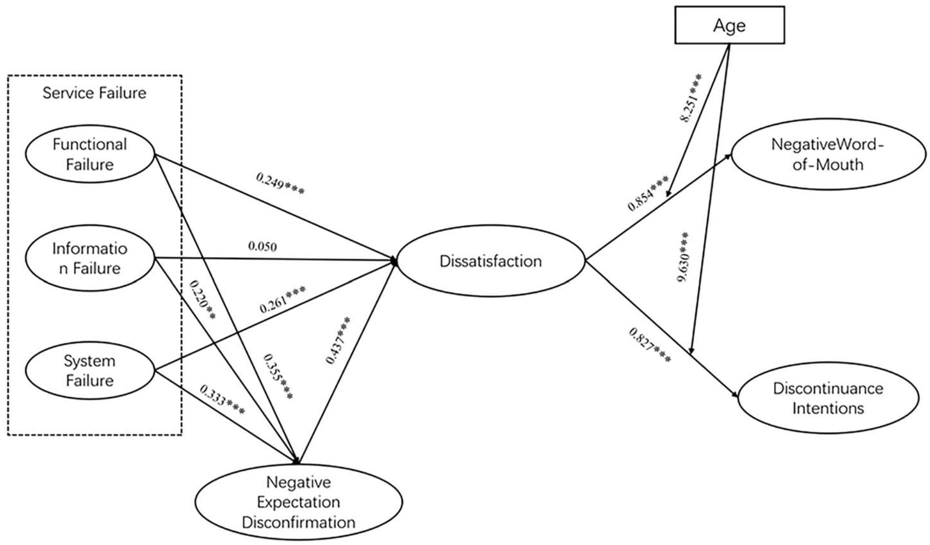

Fig. 2 Structural model.

study confirmed that service failures in personalized recommendation services on SNS platforms, such as functional failure and system failure, are critical factors contributing to negative expectation disconfirmation and dissatisfaction. These findings support the results obtained by Mustafa et al. (2020), which showed that functional and system failures in digital services positively affected negative expectation disconfirmation. They also support the results obtained by Tan et al. (2016), which showed that service failures such as functional and system failures in e-commerce services positively affected dissatisfaction. Thus, companies operating SNS platforms must focus on addressing issues such as functional and system failures and carefully improve their services to reduce dissatisfaction among users. Enabling users to perceive that they can use excellent features when experiencing the recommendation service is important (Chandra and Verma, 2023). Therefore, conducting an in-depth analysis of user behavior, searches, inputs, and clicks is necessary to accurately provide recommendations and, in particular, assist users in exploring personalized advertising information. In addition, perceiving that SNS platforms can protect their personal information when they use personalized recommendation services is crucial for users (Xie and Huang, 2023). Therefore, providing transparent and easy-to-understand privacy policies is necessary so that users can clearly understand how their personal information is collected, processed, and protected. Moreover, the results, which demonstrated the positive effect of information failure on negative expectation disconfirmation, support the findings of Mustafa et al. (2020), who examined digital services. Receiving accurate and high-quality information when using recommendation services is important for users (Leszczynska and Baltag, 2024). Thus, SNS platform operators should collaborate with advertisers to improve the accuracy and relevance of personalized advertising recommendation services in real time through big data analysis and user feedback, and they must utilize recommendation systems to provide users with recommendations. However, information failure did not appear to have a significant effect, despite being an important factor influencing dissatisfaction. Consumers are aware that recommendation systems are not perfect and may be tolerant of some errors or inaccuracies (Knees et al., 2024). Nonetheless, because the accuracy, relevance, and consistency of personalized recommendation services are highly critical, highlighting the importance of information and providing education for consumers to emphasize the value of information are necessary.

Based on the findings, several specific suggestions can be proposed. First, platforms should clearly indicate the reasons behind each recommended advertisement and encourage users to participate in feedback and evaluation. This can enhance users' sense of control and understanding, thereby fundamentally reducing expectation gaps caused by functional failure. Second, to address information failure, platforms should enhance users' trust in recommendation accuracy through labeling interpretation and traceable data logic. Additionally, the personal data management interface must be improved for users to clearly understand the scope of their data usage and to provide them with the authority to adjust personalized data to mitigate personal information-related concerns arising from system failure. In addition, platforms should implement buffering mechanisms to address negative experiences and identify user dissatisfaction behaviors (e.g., pop-up avoidance, ad blocking/reporting, ad concealment). This could involve promptly adjusting the frequency of recommendations and initiating user feedback inquiries, thereby taking active measures to recover users' trust. These strategies can not only help reduce the psychological gap caused by service failure but also contribute to restoring users' trust in the platform's recommendation system, ultimately enhancing overall satisfaction and encouraging continued usage intentions.

Second, negative expectation disconfirmation in personalized advertising recommendation services on SNS platforms was identified as an important variable explaining dissatisfaction. This supports the findings of Huang and Ma (2024) regarding live streaming commerce. Dissatisfaction may increase when users' perceptions of their personalized recommendation service experiences or their expectations when using SNS platforms are lower than what they had anticipated. This may lead to negative emotions such as dissatisfaction, displeasure, and annoyance, thereby resulting in dissatisfaction. Thus, providing users with appropriate expectations is important. In other words, negative expectations and dissatisfaction can be prevented by clearly explaining the functions and limitations of personalized advertising recommendation services to users and by setting realistic expectations (Seo and Park, 2024). Furthermore, negative expectation disconfirmation and dissatisfaction can be reduced by accurately analyzing user data and providing tailored recommendations that meet their expectations. Therefore, providing diverse and positive personalized advertising recommendation service experiences for SNS platform users, fulfilling users' expectations through interaction with services, and reducing dissatisfaction will ultimately enhance service quality.

Third, dissatisfaction with personalized advertising recommendation services on SNS platforms was observed to have a positive effect on negative word-of-mouth. This result is consistent with the findings of Mostafa et al. (2024), which demonstrated the effect of dissatisfaction in services related to virtual agents on negative word-of-mouth. Thus, efforts must be made to reduce dissatisfaction and, in turn, reduce negative word-of-mouth among users regarding personalized advertising recommendation services on SNS platforms. In other words, dissatisfaction with personalized recommendation services naturally generates negative word-of-mouth in conversations with others, which ultimately leads to a negative effect on the reputation of the SNS platform and reduces the inflow of potential new users. To reduce user dissatisfaction and negative reputation associated with personalized advertising recommendation services, SNS platforms should enhance users' perceived sense of control and autonomy. On one hand, the relevance of recommendations can be improved by enabling a user-defined ad preference labeling feature so that users can clearly indicate their interests or exclude certain content. On the other hand, users' engagement with and trust in the platform must be enhanced by providing options to block and adjust ad content or end personalized ad recommendations. In addition, a word-of-mouth alert system must be established to monitor users' negative emotional feedback on ad content in real time and take prompt measures, such as content optimization or promotional interventions. This can help mitigate the spread of user dissatisfaction and protect the platform's reputation.

Fourth, dissatisfaction with personalized advertising recommendation services on SNS platforms was observed to have a positive effect on discontinuance intentions. This result aligns with the findings of Tan et al. (2023), which demonstrated that consumer dissatisfaction with social media platforms affects discontinuance intentions. The analysis revealed that user dissatisfaction with personalized recommendation services on SNS platforms strongly triggers discontinuance intentions. Therefore, discontinuance intentions must be effectively reduced by taking immediate and practical measures to reduce dissatisfaction with personalized advertising recommendation services. To effectively reduce service discontinuance intentions resulting from dissatisfaction, platforms must accurately identify the specific points of user dissatisfaction and establish a structured intervention mechanism. First, platforms should consistently display optional feedback items such as 'irrelevant' or 'overly repetitive' for all advertisements to collect immediate user dissatisfaction feedback and reflect it in the recommendation algorithm in real time. Second, they must operate a personalization settings center through which users can directly control ad types, recommendation frequency, and whether to block specific ads, thereby empowering users with control. Third, regular satisfaction surveys should be sent to users who consistently express dissatisfaction to identify the key sources of dissatisfaction, classifying these users as high-risk for churn and using the information as an early warning signal. Finally, for users who express strong dissatisfaction, an intervention system should be implemented for churn prevention, offering corrective measures such as guidance on resetting advertising recommendations, point rewards, or temporary suspension of ad exposure. Only by clearly articulating dissatisfaction, visualizing response pathways, and establishing a system that responds immediately to feedback can platforms effectively suppress user discontinuance intentions and foster long-term trust and loyalty.

The finding that the moderating effect of sex was not statistically significant in this study may be due to recent changes in the environment of SNS-based personalized advertising recommendation services. Such services are now routinely exposed to both males and females, and patterns of use and response have become increasingly homogenized (Xie and Huang, 2023). In particular, in mobile-based platform environments, advertising messages and recommendation algorithms are applied uniformly, which may have reduced cognitive and emotional differences by sex compared with the past (Zhu and Kanjanamekanant, 2021). These changes may have weakened differences in the process by which perceptions of service failure or negative expectation disconfirmation—and the resulting dissatisfaction—lead to negative word-of-mouth or discontinuance intentions across sexes. Consequently, the role of sex as a moderating variable in the research model was limited, suggesting that other demographic characteristics, such as age, may be more effective in explaining user responses to personalized advertising recommendation services. The moderating effect of age (20–29, 30–39, and 40–49 years) on the relationship between dissatisfaction with personalized advertising recommendation services on SNS platforms and its impact on negative word-of-mouth and discontinuance intentions showed statistically significant differences. While some studies have pointed out that younger users are more likely to spread negative word-of-mouth when dissatisfied, this study empirically found that users in their 30 s react more strongly to the pathway between dissatisfaction and negative behavioral intentions. This finding aligns with the report by Yiva Digital (2021). It appears that consumers in their 30 s or older have higher usage frequencies on SNS platforms, higher expectations regarding the practicality of recommended content, and higher sensitivity to algorithmic errors. Shin (2020) conducted a study comparing age-based differences in perceptions of algorithmic recommendation systems, reporting that users in their 30 s or older are more sensitive to errors or unfairness in algorithms. This result aligns with some of the findings obtained in this study, which confirmed the need for platforms to pay special attention to the behavioral characteristics and satisfaction management of users in their 30 s when implementing personalized recommendation strategies. Moreover, platforms should first provide a feature to users in their 30 s for adjusting ad preference tags, allowing them to independently set and control ad types, frequencies, and areas of interest. Second, when the system detects feedback from users regarding content repetition, lack of relevance, or other similar aspects, the freshness of the user experience must be restored by quickly providing new content through resetting users' recommendation history and re-learning their interests. Third, by establishing a churn prediction and retention notification mechanism, platforms can intervene when a user's usage rate declines, using reminder messages or incentives to reduce the likelihood of discontinuation. Finally, they should conduct simple monthly surveys targeting a small group of users in their 30 s to collect feedback on satisfaction with the recommendation strategy and improvement needs, regularly adjusting the recommendation algorithm based on this feedback.

Limitations and future research. This study has certain limitations and offers suggestions for future research. First, it was conducted with Chinese users. Considering that personalized advertising recommendation services on SNS platforms may vary by region or culture, a broader sample is necessary. Second, the age range of the participants was limited to those in their 20 s to

40 s, which may limit the generalizability of the findings to other age groups or diverse user groups. Thus, a more diverse range of user groups and age cohorts must be considered in future research. Third, this study investigated the effects of service failure in personalized advertising recommendation services on SNS platforms on dissatisfaction but did not explore the severity of service failure and the service recovery process. Thus, future research must examine recovery measures for failures in personalized advertising recommendation services on SNS platforms and explore how user satisfaction varies depending on the severity of service failure. Fourth, because this study collected data based on a cross-sectional design, the relationships among variables derived through SEM should be interpreted as correlations rather than strict causal relationships. While the study provided meaningful insight into the relationships between the variables, future research should aim to demonstrate causality more clearly through longitudinal data or experimental designs. The study was conducted through 'WJX (Wenjuanxing, www.wjx.cn)', a leading online survey platform in China. This approach offers advantages in terms of sample collection efficiency and speed but also comes with limitations, such as a lack of sample representativeness and heterogeneity in response quality. Individuals using such platforms may differ from the general SNS user population in certain characteristics, which can affect the external validity of the results. Therefore, future studies should consider using more representative sampling methods, such as stratified sampling or probability sampling. Fifth, the high correlations observed among functional failure, NWOM, and DS can be interpreted as resulting from the fact that these constructs were all measured within the same consumer experience flow of service failure and the resulting negative evaluations. This conceptual proximity may lead to conservative results under the traditional Fornell–Larcker criterion. However, the supplementary validation results indicated that there were no substantive problems with discriminant validity. Future research should more clearly distinguish the measurement items of each construct or adopt alternative validation methods in parallel with a research design that reflects the structural separation of service failure, dissatisfaction, and negative word-of-mouth as distinct stages. Sixth, the scale development process in this study was closer to item development than to a typical scale development procedure, which limited the comprehensiveness of the validation process. In addition, the wording and phrasing of certain items may have introduced interpretive differences among respondents, potentially affecting the validity and reliability of the measurement instrument. These points suggest the need for future studies to adopt more rigorous and systematic scale development procedures. For example, conducting repeated factor analyses with diverse samples, long-term reliability testing, and cross-cultural validity assessments would enhance the generalizability and consistency of interpretation of the measurement instrument.

Data availability

The raw data supporting the conclusions of this article will be made available by the authors on request.

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Author contributions
Conceptualization and methodology: LJ and MHR; formal analysis, investigation, data curation, and writing—original draft: LJ; writing—review and editing, supervision: MHR. All authors have read and agreed to the published version of the manuscript.

Competing interests
The authors declare no competing interests.

Ethical approval
This study was conducted in accordance with the ethical principles of the Declaration of Helsinki. According to Article 13 of the Enforcement Regulations of the Bioethics and Safety Act of Korea, social science research that does not collect sensitive personal information from participants is not subject to institutional review (official text available at the Korean National Law Information Center: link, https://www.nhis.or.kr/lm/lmxsrv/law/lawFullContent.do?SEQ_HISTORY=23147). In addition, according to the Measures for Science and Technology Ethics Reviews issued by the Ministry of Science and Technology of China in September 2023, ethics review is also not required for this type of study. Article 2 of the Measures stipulates that ethics review is required for science and technology activities involving human participants (including testing, surveys, and observations) that collect personal information or biological data; however, social science research that does not involve personal privacy, biological or medical intervention, or national security does not require ethics review (The official Chinese government URL: https://www.gov.cn/zhengce/zhengceku/202310/content_6908045.htm). Therefore, under both Korean and Chinese regulations, this study did not require institutional ethics review or approval. All participants were adult SNS users who voluntarily completed the survey, and all responses were collected anonymously, kept strictly confidential, and used solely for academic research purposes.

Informed consent
Informed consent was obtained from all respondents included in the study. During the data collection period from August 1 to August 10, 2024, the respondents were presented with an informed consent form outlining the research purpose, the confidentiality and anonymity of information, voluntary participation, and the right to withdraw from the study at any time. On the first page of the online questionnaire, participants were required to actively confirm their consent by selecting the option "I want to participate in the research" before proceeding to the main survey. This process ensured that all participants were fully informed and voluntarily agreed to participate and have their data processed.

Additional information
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