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The Impact of Recommendation System on User Satisfaction: A Moderated Mediation Approach

Xinyue He †, Qi Liu † and Sunho Jung *

School of Management, Kyung Hee University, Seoul 02447, Republic of Korea; hexinyue98@khu.ac.kr (X.H.); yangtaoxingzi@khu.ac.kr (Q.L.)
* Correspondence: sunho.jung@khu.ac.kr
† These authors contributed equally to this work.

Abstract: A recommendation system serves as a key factor for improving e-commerce users' satisfaction by providing them with more accurate and diverse suggestions. A significant body of research has examined the accuracy and diversity of a variety of recommendation systems. However, little is known about the psychological mechanisms through which the recommendation system influences the user satisfaction. Thus, the purpose of this study is to contribute to this gap by examining the mediating and moderating processes underlying this relationship. Drawing from the traditional task-technology fit literature, the study developed a moderated mediation model, simultaneously considering the roles of a user's feeling state and shopping goal. We adopted a scenario-based experimental approach to test three hypotheses contained in the model. The results showed that there is an interaction effect between shopping goals and types of recommendation (diversity and accuracy) on user satisfaction. Specifically, when a user's shopping goal aligns with recommendation results in terms of accuracy and diversity, the user satisfaction is enhanced. Furthermore, this study evaluated the mediating role of feeling right and psychological reactance for a better understanding of this interactive relationship. We tested the moderated mediation effect of feeling right and the psychological reactance moderated by the user shopping goal. For goal-directed users, accurate recommendations trigger the activation of feeling right, consequently increasing the user satisfaction. Conversely, when exploratory users face accurate recommendations, they activate psychological reactance, which leads to a reduction in user satisfaction. Finally, we discuss the implications for the study of recommendation systems, and for how marketers/online retailers can implement them to improve online customers' shopping experience.

Keywords: feeling right; moderated mediation; psychological reactance; recommendation system; user shopping goal

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1. Introduction

As Internet technology advances swiftly, the ways in which enterprises meet user needs are undergoing a significant change. Enterprises can leverage recommendation systems to provide personalized recommendations that align with the user preferences or requirements. By collecting extensive transaction data from users, enterprises gain insights into their needs and preferences, and apply this knowledge to inform new product designs and marketing plans [1]. For instance, comprehensive online shopping websites can discern a user's shopping preferences by analysing their transaction data or browsing history, thereby enabling targeted product recommendations. Furthermore, users benefit from recommendation systems not only by accessing a wealth of preferred information, but also by reducing information overload and minimizing the costs associated with data collection and decision-making [2].

Recommendation systems have become indispensable in shopping websites. However, it is essential to recognize that recommendation systems may not universally cater to all users, and in some cases, could evoke resistance, creating a sense of aversion among users [3,4]. Initially, research on recommendation systems was focused on enhancing accuracy to improve user satisfaction. Yet, scholars later argued that accuracy alone is insufficient [5], leading to studies exploring other characteristics such as diversity and novelty [6,7]. However, most of these studies have focused on the recommendation system itself, ignoring the ever-changing needs of users.

There have been numerous studies focusing on recommendation systems and user satisfaction throughout the customer journey. However, thus far, no research has explored both the moderation and mediation mechanism underlying this relationship at the pre-purchase stage. This study makes two major contributions to the literature. First, as indicated by Kim, Choi, and Li [8], the accuracy and diversity of recommendation systems positively affect user satisfaction. However, an accuracy-diversity dilemma for recommendation systems remains unresolved. In our study, we aim to address this dilemma by examining the moderating effect of user shopping goals. We believe that tailored recommendations based on the distinction between different shopping goals can alleviate this dilemma. Second, prior research has primarily attempted to improve the recommendation system performance, which, in turn, may increase user satisfaction, relying on the Technology Acceptance Model (TAM) [9]. In our study, we emphasize the underlying mechanisms of recommendation systems on user satisfaction, and therefore examine two separate mediating processes through emotional pathways (psychological reactance and feeling right) to uncover the psychological factors affecting user satisfaction. We believe that understanding the psychological mechanism can help improve the design of recommendation systems, thereby enhancing user satisfaction.

The purpose of the present study is to evaluate whether the fit between the recommendation type (accuracy versus diversity) and shopping goal can increase user satisfaction. This study sheds light on the moderated mediation effect of feeling right and psychological reactance in explaining the interactive impact of the recommendation system and shopping goal on satisfaction. The remainder of this paper is organized as follows. The conceptual framework and hypotheses are briefly described. The research methodology is presented, with a description of our measures and data collection. Data and statistical analyses were performed using a regression-based path analysis. Finally, we discuss the study's research and managerial implications.

2. Theoretical Background

A recommendation system is widely used in a variety of online shopping environments. When the user enters an online shopping website like Amazon, he or she actively interacts with the system, providing a more convenient and enjoyable shopping experience [10]. There is also strong evidence for its effectiveness in a traditional brick and mortar retail setting [11]. A recommendation system is typically defined as a system that recommends suitable products or services to users based on their preferences and needs, using information filtering techniques to suggest information that users may find interesting [12]. It aims to enhance user satisfaction and experience by reducing the information overload and decision time [13]. The previous research has primarily used accuracy and diversity as key performance indicators to evaluate a variety of recommendation systems [8].

However, there exists a trade-off between accuracy and diversity [14]. Our study aims to find a balance between accuracy and diversity, enabling appropriate recommendations at the right time, rather than sacrificing diversity for accuracy or vice versa. The Task-Technology Fit (TTF) theory refers to the congruence between the characteristics of technology and the task requirements of tasks [15]. The previous research shows that TTF has a positive impact on user satisfaction [16]. Goal specificity is a defining characteristic of user shopping goals [17]. In this study, we consider the user's specific (or ambiguous) shopping goal as the task requirements in TTF, and recommendation accuracy (or diversity) as the characteristics of technology in TTF. When these two elements match, user satisfaction can be enhanced. Therefore, we believe that user shopping goals can serve as a balancing point to moderate the relationship between recommendation systems and user satisfaction. Specifically, a recommender system may enhance user satisfaction, when presenting an accurate (or diversified) recommendation to the user with a specific (or ambiguous) shopping goal.

Previous research has further explored the impact of recommendation systems on users' acceptance or rejection of recommendations. Psychological reactance can be considered one of the main reasons behind the rejection of recommendations, which may arise because users perceive a threat to their freedom of choice [9]. On the other hand, recommendation systems may foster users' engagement when recommendations and shopping goals mutually fit. This subjective experience of engagement is referred to as 'feeling right' [18]. Therefore, we believe that when a set of recommendations and user shopping goals do not match (or match), users will experience psychological reactance (or feeling right).

2.1. Online Shopping Recommendation System

A recommendation system is an information filtering system designed to address the issue of information overload by filtering significant information fragments from a vast pool of dynamically generated content, based on user preferences, interests, or browsing history. In other words, a recommendation system can predict whether a user is likely to favor a particular item based on their individual profile [19]. Companies and users can benefit from these recommendation systems. In the context of online shopping, these systems assist users in reducing the costs related to information search, product selection, and final decision-making [19]. As a result, recommendation systems have found widespread application on online shopping websites. Through personalized recommendations, users are aided in decision making, ultimately enhancing user satisfaction [4].

The methods used to analyze user preferences in recommendation systems can be broadly categorized into two main types (Figure 1). One is content-based filtering, which is based on the attributes of products, such as the keywords associated with the products. The content-based (CB) recommendation approach involves recommending products similar to those previously liked by the user. The fundamental principles of content-based recommendation systems are as follows: (1) analyze the product that a specific user prefers, identify the common attributes of these products, and store these preferences in the user's profile; and (2) compare the attributes of each product with the user's profile, recommending products that exhibit a high degree of similarity to the user's profile [20]. However, this type of recommendation approach carries the risk of excessive personalization, meaning that the recommendations received by users are limited to products that are highly similar to their user profiles [2].

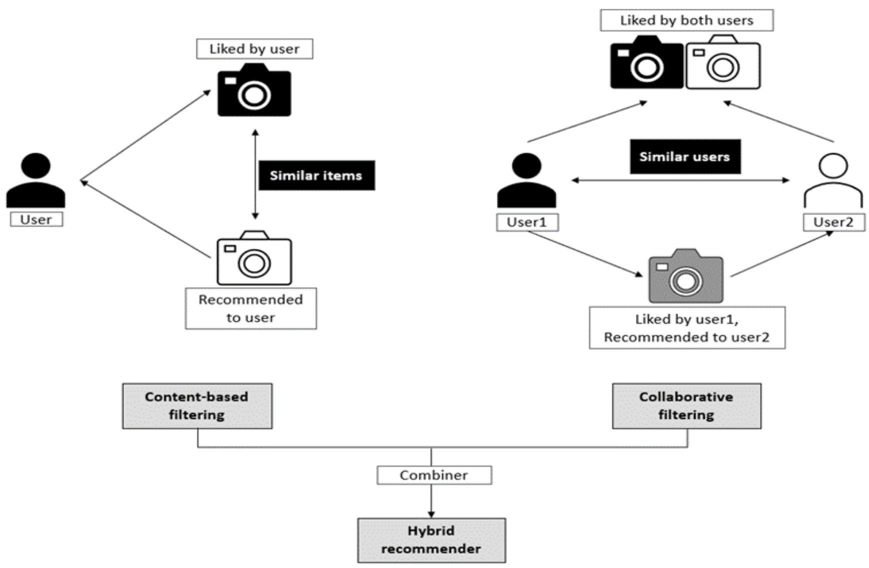

Figure 1. Content-based filtering and collaborative filtering.

The other is collaborative filtering, which relies on user behavior, such as historical purchases [1]. Collaborative filtering (CF) can assist users in decision-making by taking the choices of other users with similar preferences. Collaborative filtering can primarily be categorized into user- and item-based CF. User-based CF involves recommending products preferred by other similar users, whereas item-based CF involves recommending products similar to the user's past preferences [20]. CF is considered one of the most effective recommendation types in recommendation systems and is widely employed [21]. However, owing to its reliance on recommendations based on other users or products with high similarities, CF can potentially lead to repetitive recommendations and a reduced variety of recommended products [22].

2.2. Recommendation System and User Satisfaction

Previous research on recommendation systems has primarily focused on accuracy. However, user satisfaction does not necessarily depend solely on accuracy. In other words, the accuracy alone is insufficient [23]. For example, if a user accidentally clicks on a product on a shopping website, the recommendation system may continuously suggest similar products based on the recommendation principle, even though the user's initial interaction may have been accidental. Such recommendation approaches can lead users into a similarity hole, where they continuously receive high-accuracy recommendations and the suggested products share a high similarity or are already well-known to the user [24].

The concept of filter bubbles was first introduced by Pariser [25]. Websites can provide personalized services to users based on their preferences, actions, and algorithms [25]. Pariser argued that such algorithms create bubbles around users, confining them to a single perspective. This implies that the algorithm excludes diverse perspectives and information outside the bubble. Moreover, because this bubble is crafted using a user's personal information, the filter bubble for each user is unique. This bubble also possesses the characteristics of being invisible as users become trapped within it [25]. In other words, as users become confined within their preference cycle, it becomes increasingly difficult for them to discover alternative viewpoints or domains [26]. However, since user preferences are not permanently fixed, relying solely on high-accuracy recommendations, as mentioned above, is insufficient [5].

Furthermore, from the user's perspective, when shopping, if consumers are uncertain about their preferences, they tend to seek variety before making decisions [27]. Therefore, when evaluating a recommendation system, it is essential to consider not only its accuracy but also its diversity. Additionally, an increase in the diversity of recommendations implies a decrease in the similarity among recommended products, that is, a loss in recommendation accuracy [14]. In other words, there is a trade-off between the accuracy and diversity.

User satisfaction is typically used to evaluate the success of information systems [28]. According to Zipf's principle of least effort, a fundamental principle of human action is to exert the least effort to do things [29]. The contrasting concept of least effort is information overload, which involves providing users with information beyond their processing capabilities within a specified timeframe. Personalized recommendation systems can alleviate information overload by offering users information that aligns with their preferences. In other words, following the principle of least effort, personalized recommendation systems can mitigate users' information overload, thereby enhancing user satisfaction.

However, recommendation systems cannot satisfy all users equally. As mentioned earlier, both accuracy and diversity are criteria for evaluating recommendation systems. Therefore, there are users who prefer systems that prioritize high accuracy and others who favor systems that emphasize diversity. The present study posits that user satisfaction depends not only on recommendation accuracy and diversity but is also influenced by users themselves, specifically their shopping goals. Currently, no study has considered the impact of alignment between user shopping goals and recommendations on user satisfaction.

2.3. User Shopping Goal

The users have diverse online shopping purposes. Some users have a general or ambiguous concept of the product they are looking for (e.g., "I want to buy the latest newly released smartphone"), while others have very specific purchase goals (e.g., "I want to buy the iPhone 14 Pro 256GB space black"). Based on prior research, shopping behavior can generally be categorized into two types: goal-directed and exploratory. Hoffman and Novak [30] reported that in the online world, users' information processing can be divided into goal-directed and exploratory processes. In other words, goal-directed users have a specific shopping goal before online shopping, whereas exploratory users do not have a goal and must search for information to determine their purchasing objective.

During online shopping, users' behavior varies depending on whether they have a specific shopping goal [31]. Specifically, if there is a specific shopping goal, the search for a goal can be considered a goal-directed behavior. If there is no specific shopping goal, the process of making vague goals more concrete can be viewed as exploratory behavior. When searching for information on shopping websites, users' shopping goals can change instantly, based on the information they find [31]. In summary, the present study categorizes users into goal-directed and exploratory users, based on whether they have a specific shopping goal.

2.4. Feeling Right

Previous research suggests that if these two factors mutually fit, users will experience a subjective experience of engagement. This subjective experience of engagement, which increases based on matching, is referred to as 'feeling right' [18]. Feeling is a form of information that can be utilized when making judgments or decisions [32]. Such a feeling of experience can influence users' evaluations of a product and enhance their assessment of the product in which they are initially interested [18]. Therefore, during online shopping, if a user's shopping goal fits the generated recommendation results, he or she would experience a 'feeling right', which may influence his or her level of satisfaction.

2.5. Psychological Reactance

Psychological reactance theory [33] suggests that individuals have a certain degree of freedom in their behavior. If freedom is diminished or threatened, individuals are motivated to regain it. Psychological reactance consists of three stages: first, perceiving a threat to freedom; second, leading to psychological resistance; ultimately, attempting to restore the threatened freedom [34].

Users need to make judgments and choices from thousands of pieces of information on the internet. Personalized recommendations play an invaluable role in reducing the costs associated with this process. Personalized recommendations can provide users with services or products that match their preferences, helping them reduce the time and effort required for the decision-making process. This convenience enhances the quality of decision-making. Although personalized recommendations can simplify and streamline users' decision-making processes, they also have the potential to undermine their freedom of choice [35]. If personalized recommendations interfere with user autonomy in the decision-making process, they may have a counterproductive effect, leading to psychological reactance.

Users' negative responses to information technology are mainly divided into two types: psychological and behavioral responses [36]. Research has primarily focused on resistance from the perspective of psychological responses. This refers to the actions that individuals take in opposition to situations in which they perceive themselves to be in a compelled condition [37]. Moreover, psychological reactance has been studied in various fields such as advertising [38], artificial intelligence [39], and personalized recommendations [3,36]. Particularly in the field of personalized recommendations, the research results indicate that personalized recommendations can lead to psychological reactance.

More specifically, Youn and Kim [38] conducted research on users' avoidance behaviors toward Facebook ads. They suggest that when using Facebook, if users feel that they have the freedom to avoid ads, their perception of ad intrusion decreases. That is, when ad intrusion or the freedom to avoid ads is threatened, it leads to reactance, and users engage in actions to avoid ads. Pizzi et al. [39] indicated that non-anthropomorphic digital assistants could trigger a psychological reactance and lead to negative evaluations of artificial intelligence.

Fitzsimons and Lehmann [3] showed that when users receive recommendations that do not align with their expectations, a resistance state is activated. In such situations, users not only ignore recommendations from the recommendation system, but may also exhibit resistance. Ma et al. [36] suggested that the greedy recommendation of algorithms, by narrowing the scope of information or recommending repetitive content, can lead to information overload. This, in turn, causes users to feel fatigued, increasing psychological reactance and their intention to interrupt.

3. Conceptual Framework and Hypotheses Development

3.1. Moderating Effect of User Shopping Goal on Recommendation System and User Satisfaction

The present study suggests that approaches for recommendation systems can be divided into two types based on the recommendation results: recommendations with high accuracy (similarity) and those with high diversity. As discussed earlier, we propose that user satisfaction depends not only on recommendation accuracy and diversity but also on the user shopping goal.

When the user is goal-directed, the user already has the desired product and a clear shopping goal before online shopping. When a user searches on a shopping website, he or she usually searches directly for the target product. In a situation where a shopping website recommends products that are highly aligned with its search content (high accuracy), we consider such recommendations to be in line with the user shopping goal. On the other hand, when the user is an exploratory user, the user does not have a clear shopping goal before online shopping or simply wants to browse the website. The user usually first explores the goal in a variety of ranges, and then gradually refines it during the search process. When a shopping website recommends a variety of products to users (with a high diversity), we believe that such recommendations are consistent with the user's shopping goal.

Therefore, we believe that when the recommendation result fits the user shopping goal, the user satisfaction improves. Conversely, in the case of unfitness, the user satisfaction decreases. Specifically, when a user has a clear shopping goal and is goal-directed, highly accurate recommendations will improve user satisfaction compared with diverse recommendations. When a user's shopping goal is mainly exploratory with vague purchase objectives, diverse recommendations will improve user satisfaction compared to accurate recommendations.

H1. *The fit between recommendation type and user shopping goal increases user satisfaction. However, unfitness decreases user satisfaction.*

3.2. Mediating Effect of Feeling Right

According to Westbrook [40], consumers who experience emotions during consumption can be categorized as positive or negative. Positive emotions were associated with satisfaction, whereas negative emotions were associated with dissatisfaction. Emotional responses are often used as mediating variables in research studies. When the type of recommendation (diversity and accuracy) fits the user shopping goal, the user undergoes a subjective experience of engagement, termed 'feeling right' [41]. We predicted that this positive emotional response would positively affect the user satisfaction.

However, our study posits that 'being fit' does not necessarily lead to 'feeling right. According to expectancy disconfirmation theory (EDT), user satisfaction can be assessed by measuring the disparity between users' expectations and their experiences in perceiving a product or service [42]. Expectancy refers to user' expectations regarding the performance of a product or service. The perceived performance relates to users' experiences of using a product or service, which may be better or worse than their expectations. Disconfirmation refers to the difference between users' initial expectations and their actual performance of the product or service they perceive. If the performance of a specific product or service exceeds customer expectations, positive disconfirmation can lead to increased user satisfaction [43].

In the context of the present study, compared to exploratory users, goal-directed users already have specific expectations for the products they want before entering an online shopping site. Therefore, when a shopping website recommends products with high accuracy, these users may experience positive disconfirmation. Consequently, they are more likely to feel right, thereby experiencing increased user satisfaction.

H2a. *Feeling right mediates the effect of fitness of the recommendation type and user shopping goal on user satisfaction.*

H2b. *User shopping goal moderates the mediation effect of the fitness of recommendation type and user shopping goal on user satisfaction. Specifically, when the user shopping goal is specific, feeling right will mediate the effect of the fitness of recommendation type and user shopping goal on user satisfaction (however, such a mediation effect will not occur when the user's shopping goal is ambiguous).*

3.3. Mediating Effect of Psychological Reactance

However, it has often been reported that the recommendation system does not meet a user's shopping goal. When users receive recommendations that do not align with their expectations, resistance is activated. In such cases, users not only ignore recommendations from the recommendation system but may also exhibit resistance [3]. In the present study, we argue that 'being unfit' may not necessarily lead to psychological reactance. Goal-directed users who have a clear shopping goal, even if they receive diverse recommendations, may not experience psychological reactance because of their tendency to purchase products with various attributes or brands while shopping [27]. Conversely, exploratory users who lack specific goals may feel that their freedom of choice is threatened and experience psychological reactance when they receive highly accurate recommendations. This leads to a decrease in the user satisfaction.

H3a. *Psychological reactance mediates the effect of unfitness of the recommendation system and user shopping goal on user satisfaction.*

H3b. *User shopping goals moderate the mediation effect of unfitness of the recommendation system and user shopping goals on user satisfaction. Specifically, when user shopping goals are ambiguous, psychological reactance will mediate the effect of the unfitness of the recommendation system and the user shopping goal on user satisfaction (but such a mediation effect will not occur when the user's shopping goal is specific).*

3.4. Conceptual Framework

We synthesize the three hypotheses (H1–H3) into an integrated model for understanding the psychological mechanisms underlying the relationship between the recommendation system and user satisfaction. The conceptual model for the study is shown in Figure 2, providing a graphical representation of a set of relationships between variables under study. In this conceptual framework, we evaluate the moderating role of the user shopping goal and the mediating role of psychological reactance and feeling right in the relationship between the recommendation system and user satisfaction in an online shopping environment.

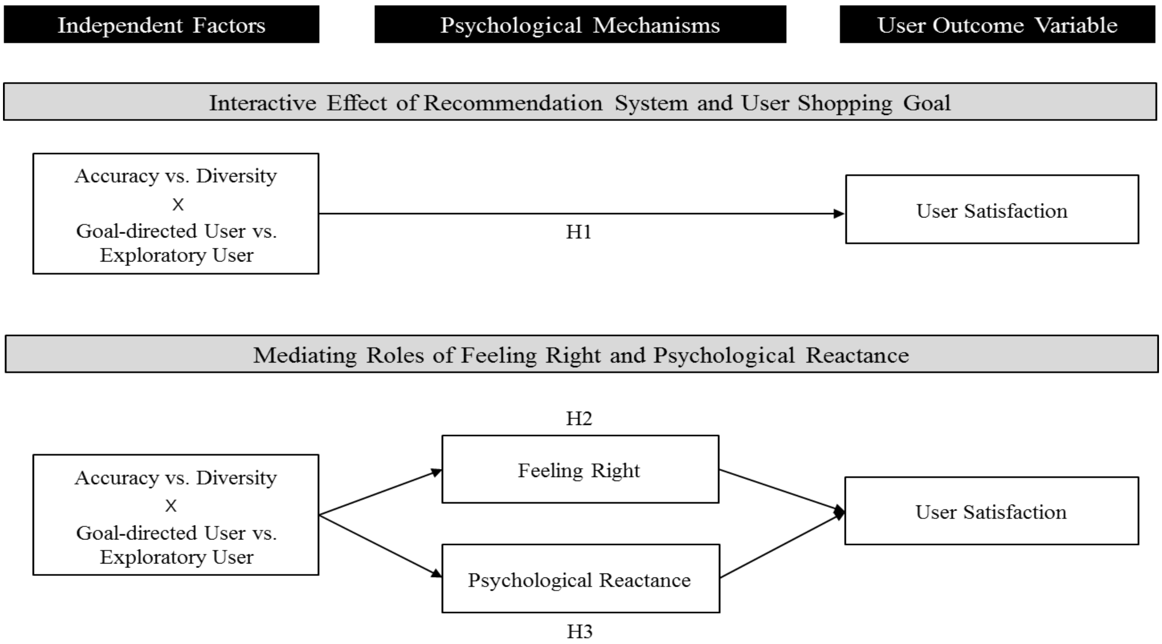

Figure 2. Research model.

As the conceptual model is theoretically framed in terms of a moderated mediation, we present a theoretical description of the methods used in the current study [44]. We employ an analytical framework that was originally developed to test the combined effects of moderation and mediation [45]. Because this framework adopts a hybrid method of a moderated regression analysis and path analysis, the integrated model can be decomposed into three parts: moderation, mediation, and moderated mediation. Comparative analysis deals with a moderation process that involves examining the (dis)similarity between levels of the moderator (shopping goals) of the relationship. Synthesis method is used for a moderated mediation process that incorporates the moderator and mediator into the recommendation system research.

4. Research Design and Methodology

4.1. Sample

A total of 206 university students in South Korea participated in an online survey experiment, and they earned three participation points at the end of the semester. Of these, 22 were excluded from the data analysis due to incomplete and/or careless responses (such as straight-lining). The final sample consisted of 184 individuals (101 males and 83 females, M_{age} = 22.36, SD_{age} = 2.14). The participants were randomly assigned to four experimental conditions. The specific distribution of the participants is presented in Table 1. The demographic characteristics of the participants are as follows. The participants included 101 males (54.9%) and 84 females (45.1%). Most participants were between 20 and 29 years old (97.8%), whereas only three were less than 19 years old (1.6%), and only one was more than 30 years old (0.6%).

Table 1. Goal-directed User: 'SONY ZV series Camera'; exploratory User: 'Camera'.

Combinations		**Recommendation System**	
		Accuracy	**Diversity**
Shopping goal	Goal-directed	Fit (51)	Unfit (47)
	Exploratory	Unfit (36)	Fit (50)

4.2. Experimental Factors

The experimental setup presented in this study was designed based on a hybrid filtering technique [46], which can deliver effective product suggestions to users. For instance, a hybrid collaborative approach produces recommendations using search keywords and the purchase history of user [47]. When a user enters an online shopping website and simply types a keyword into the search bar, this webpage promptly displays a list of recommended products with an emphasis on either accuracy or diversity. Two illustrative webpages of recommendations are shown in Figure 3.

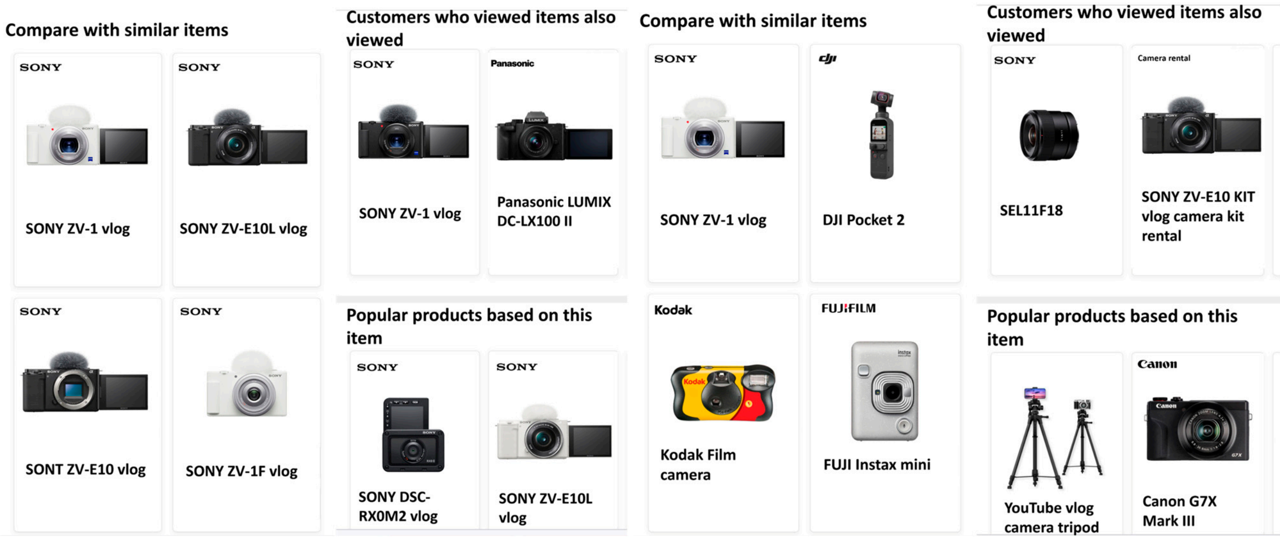

Figure 3. Accurate recommendation type (**left**); diverse recommendation type (**right**).

At the beginning of the experiment, the participants were presented with a scenario in which they needed to buy a camera online. Participants assigned to the Goal-directed User condition were given the scenario: "Due to recent interest in VLOGs, combining recommendations from friends and online reviews, you decided to buy a SONY ZV series Vlog camera". Participants assigned to the Exploratory User condition were given the following scenario: "You are planning a trip recently, and you want to buy a camera". Subsequently, two pre-made recommendation pages on online shopping websites were displayed, each containing eight products.

The high-accuracy (high similarity) recommendation page includes seven SONY cameras, six of which belong to the SONY ZV series and one Panasonic Vlog camera. This design reflects the characteristics of a high accuracy (similarity). In addition, the diverse recommendation page, which emphasizes product diversity and reduces recommendation accuracy (similarity), includes six cameras from different brands, featuring Vlog cameras, disposable film cameras, camera lenses, camera rentals, and so on.

After the participants were randomly assigned to four different conditions to verify the success of our manipulation (accuracy/diversity) of the recommendation system, they were required to answer two manipulation check items after browsing the recommended page on the shopping website. A single-item, seven-point scale was used to assess the participants' perceived differences in the various recommendation types. Participants were asked, 'How do you perceive the products recommended by the shopping site?' (1 = very accurate; 7 = very diverse).

The results indicated that our manipulation was successful: Participants assigned to different recommendation types (accuracy/diversity) showed significant differences in their perception of the accuracy and diversity of the recommended products (M_accuracy = 3.23, t(87) = −7.58, $p < 0.001$; M_diversity = 4.84, t(97) = −7.52, $p < 0.001$). Another single-item, seven-point scale was used to assess the participants' perceived differences in the scenarios. Participants were asked, 'What do you think of your shopping goal?' (1 = not specific;

7 = very specific). The results indicate that our manipulation was also successful: Participants assigned to different scenarios showed significant differences in their perception of the specificity of their shopping goals (M_goal-directed = 5.13, t(98) = 12.31, $p < 0.001$; M_exploratory = 2.88, t(86) = 12.32, $p < 0.001$). The details are presented in Table 1.

4.3. Measures

After answering the two manipulation check questions, participants assigned to the four different scenarios responded to the same set of questions to measure "Feeling right", "Psychological reactance", and "User satisfaction". After presenting the participants with the scenario conditions and pre-made shopping site recommendation pages, they were asked to evaluate their feelings toward the presented products on the recommendation pages.

A single-item, seven-point scale was used to check 'feeling right' toward the fit of recommendation type and user shopping goal by asking participants to indicate "how right" or "how wrong" they felt about the recommendation (1—feeling wrong to 7—feeling right), based on Cesario and Higgins [48] (Mfit = 5.10, t(101) = 3.43, $p = 0.01$; Munfit = 4.42, t(83) = 3.40, $p = 0.01$). To measure the extent to which users felt that their freedom of choice was threatened after seeing the shopping site's recommendation page, we used the scale developed by Bleier and Eisenbeiss [49] with appropriate modifications for this experiment. To measure user satisfaction with the recommendation page after viewing the shopping site, we employed the scale developed by Liang [1] with appropriate modifications for this experiment. The final scale comprised eight items. (e.g., "whether the recommendation finds the item that the user wants to view", $\alpha = 0.928$; M = 4.96; SD = 1.00). Table 2 shows the reliability of measurement instruments used in this study.

Table 2. Reliability.

Construct	Item	Mean (S.D.)	Cronbach's Alpha
Psychological reactance (PR)	PR1	2.37 (1.381)	0.930
	PR2	2.79 (1.699)	
	PR3	2.51 (1.515)	
	PR4	2.44 (1.567)	
	PR5	2.63 (1.641)	
	PR6	2.42 (1.499)	
User satisfaction (US)	US1	4.67 (1.261)	0.928
	US2	4.85 (1.212)	
	US3	5.18 (1.114)	
	US4	4.78 (1.304)	
	Us5	5.02 (1.199)	
	Us6	4.89 (1.311)	
	Us7	5.26 (1.084)	
	Us8	5.01 (1.310)	

4.4. Procedure

The purpose of this experiment was to explore the psychological reactions of users with different shopping goals when exposed to different types of recommendations during online shopping as well as their impact on their satisfaction. After presenting participants with scenarios containing a shopping goal, pre-made recommendation pages with either a high accuracy or diversity were shown. Subsequently, the participants answered two manipulation check questions and provided subjective feedback on the recommendation system, including "Feeling Right", "Psychological Reactance", and "User Satisfaction". Finally, the participants answered demographic questions, including gender, age, and occupation.

To test the proposed hypotheses on moderation, mediation, and conditional indirect effects, we employed the SPSS PROCESS macro [50] using a regression-based approach. To test the mediation effect [51], we first examined the interaction effect of the type of recommendation (1 = accurate recommendation; −1 = diverse recommendation) and users' shopping goals (1 = goal-directed user; −1 = exploratory user) on their satisfaction. The indirect effect of the interaction term on user satisfaction through feeling right or psychological reactance was tested using bootstrapping [52].

5. Results

5.1. Moderation Effect

To test H1, we examined whether the interaction effect between recommendation type and shopping goal on user satisfaction is statistically significant. The results (Table 3) support this hypothesis. More specifically, there was a significant interaction between the recommendation type and user-shopping goals (b = 0.31, $t = 4.47$, $p < 0.001$). The main effect of the recommendation type was not significant (b = 0.46, $t = 0.66$, $p = 0.51$). The main effect of the user-shopping goal was significant (b = 0.22, $t = 3.19$, $p < 0.01$). To decompose the significant interactions, we plotted the predicted values at two different levels of shopping goals [53]. Figure 4 shows the interaction patterns.

Table 3. Moderation analyses.

Predictor	B	SE	*t*	*p*
		User satisfaction		
Constant	4.9141	0.0696	70.6449	0.0000
Recommendation system (X)	0.0457	0.0696	0.6576	0.5116
Shopping goal (Mo)	0.2218	0.0696	3.1890	0.0017
X × Mo	0.3110	0.0696	4.4702	0.0000

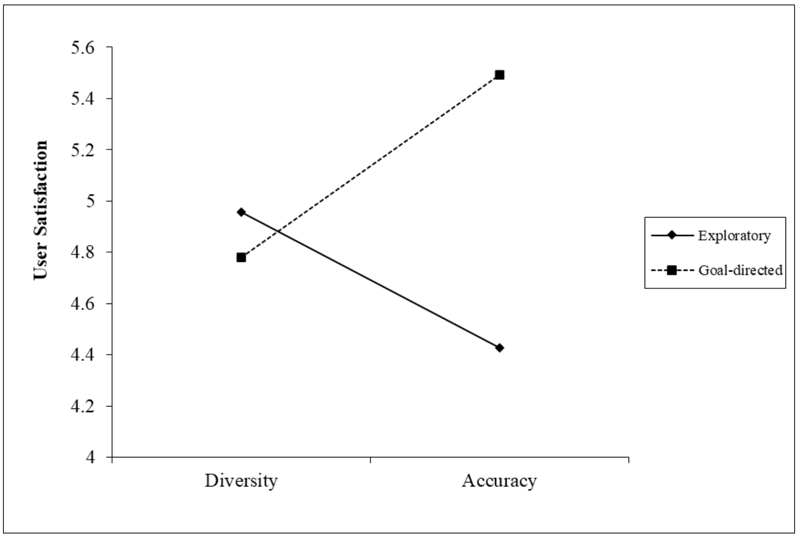

Figure 4. Moderating role of shopping goal.

Simple effects analyses [54] further supported our hypotheses: for goal-directed users, recommendation system (diversity = −1; accuracy = 1) had a significant and positive influence on user satisfaction (b = 0.36, t = 3.78, and $p < 0.001$). In contrast, for exploratory users, recommendation system (diversity = −1; accuracy = 1) had a significant negative influence on user satisfaction (b = −0.27, t = −2.60, and $p < 0.05$).

The results were consistent with H1: higher satisfaction is achieved when accurate recommendations are provided to goal-directed users versus to exploratory users. Likewise, exploratory users were more satisfied with diverse recommendations than goal-directed users were.

5.2. The Mediating Role of Feeling Right and Psychological Reactance

To test H2a, we analyzed the impact of the fit of the recommendation type and user shopping goal on the user's feeling of being right. The results (see Table 4) are consistent with the hypothesis that when the recommendation type fits the user shopping goal, the user's feeling of being right is stronger (b = 0.34, t = 3.63, and $p < 0.001$). Next, we examined whether a user's feeling of right affected their satisfaction. The results showed that feeling right was positively associated with user satisfaction (b = 0.39, t = 11.14, and $p < 0.001$). The indirect effect was positive and significant (b = 0.13, 95% CI [0.06, 0.22]). Thus, the mediating effect was significant and Hypothesis 2a was supported.

Table 4. Mediation analyses. Independent variable: fit (recommendation type × shopping goal); mediator variable: feeling right/psychological reactance.

Variable	**B**	**SE**	***t***	***p***
		Direct effects		
Fit → Feeling right	0.3426	0.0944	3.6311	0.0004
Feeling right → User satisfaction	0.3921	0.0352	11.1449	0.0000
Unfit → Psychological reactance	−0.2765	0.0978	−2.8284	0.0052
Psychological reactance → User satisfaction	−0.3385	0.0340	−9.9680	0.0000
	M	SE	LL 95% CI	UL 95% CI
		Indirect effect Bootstrap results for indirect effect		
Feeling right	0.1343	0.0424	0.0585	0.2240
Psychological reactance	0.0936	0.0372	0.0258	0.1698

To test H3a, we analyzed the impact of the unfit recommendation type and the user shopping goal on the user's psychological reactance. The results (see Table 4) were consistent with the hypothesis that when the recommendation type did not fit the user shopping goal, the user's psychological reactance is stronger (b = −0.28, t = −2.83, and $p = 0.0052$). Next, we examined whether the users' psychological reactance affected their satisfaction. The results showed that psychological reactance was negatively associated with user satisfaction (b = −0.34, t = −9.97, and $p < 0.001$). The indirect effect was positive and significant (b = 0.09, 95% CI [0.03, 0.17]). Thus, the mediating effect was significant, and Hypotheses 3a was supported.

5.3. Testing Conditional Indirect Effects

To gain a deeper understanding of the impact of the recommendation system on user satisfaction, we further investigated the conditional indirect effect of the former on the latter through feeling the right and the psychological reactance across levels of shopping goals. Table 5 presents the results for Hypothesis 2b. With regard to H2b, we predicted that the positive relationship between recommendation type and user feeling right would be stronger for users with specific shopping goals. The results indicate that the cross-product term between the recommendation type and user shopping goal on the user feeling right was significant (b = 0.34, t = 3.63, and $p < 0.001$). To fully support H2b, we applied conventional procedures to plot the simple slopes (Figure 5). The results are consistent with our expectations (and supporting H2b), where specific shopping goals had a significant and positive influence on users' feeling right (simple slope = 0.58, t = 4.51, and $p < 0.001$). In contrast, exploratory shopping goals did not have a significant influence on users' feeling right (simple slope = −0.11, t = −0.77, and p = 0.44).

Table 5. Moderated mediation: Feeling right.

Predictor	B	SE	t	p
		Feeling right		
Constant	4.7507	0.0944	50.3488	0.0000
Recommendation system (X)	0.2354	0.0944	2.4948	0.0135
Shopping goal (Mo)	0.3379	0.0944	3.5815	0.0004
X × Mo	0.3426	0.0944	3.6311	0.0004
User shopping goal	Boot indirect effect	Boot SE	Boot LLCI	Boot ULCI
		Conditional indirect effect at the type of user shopping goal		
Exploratory	−0.0457	0.0635	−0.1791	0.0749
Goal-directed	0.2465	0.0578	0.1373	0.3647

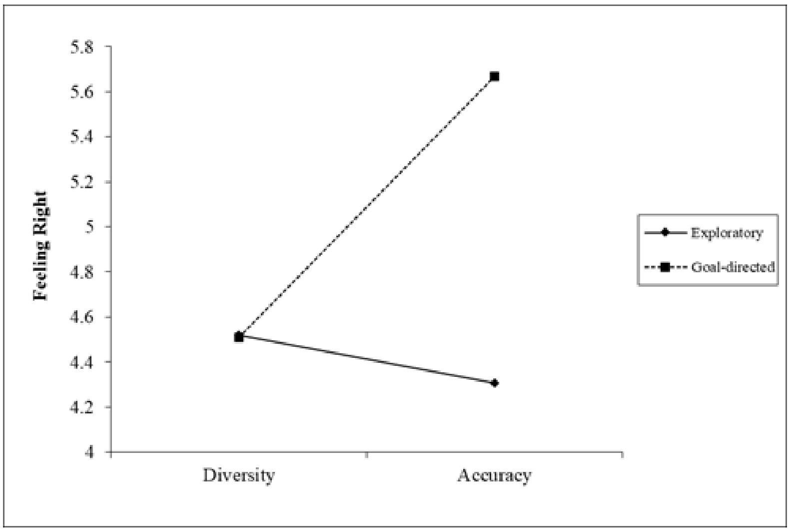

Figure 5. The moderating role of shopping goal on the relationship between recommendation type and feeling right.

Although the results showed that user shopping goals interacted with the recommendation type to influence the user feeling right, they did not directly assess the conditional indirect effects. Therefore, we analyzed the conditional indirect effects (Table 5). The results supported H2b by showing that the indirect and positive effect of accurate recommendations on user satisfaction was significant (b = 0.25, 95%, and CI [0.14, 0.36]) when the user was goal-directed; however, the indirect and positive effect of diverse recommendations on user satisfaction was not significant (b = −0.05, 95%, and CI [−0.18, 0.07]) when the user was an exploratory user.

Table 6 presents the results for Hypothesis 3b. Regarding H3b, we predicted that there is a positive relationship between the recommendation type and user psychological reactance for users with exploratory shopping goals. The results indicate that the cross-product term between the recommendation type and user shopping goal on the user psychological reactance is significant (b = −0.28, t = −2.83, and p < 0.01). To fully support H3b, we applied conventional procedures to plot the simple slopes (Figure 6). These results are consistent with our expectations (and supporting H3b). For ambiguous shopping goals, the recommendation system (diversity = −1; accuracy = 1) had a significant and positive influence on users' psychological reactance (simple slope = 0.37, t = 2.56, and $p < 0.05$). On the contrary, for specific shopping goals, the recommendation system did not have a significant impact on users' reactance (simple slope = −0.19, t = −1.40, and $p = 0.16$).

Table 6. Moderated mediation: Psychological reactance.

Predictor	B	SE	*t*	*p*
		Psychological reactance		
Constant	2.5554	0.0978	26.1386	0.0000
Recommendation system (X)	0.0911	0.0978	0.9316	0.3528
Shopping goal (Mo)	0.0712	0.0978	0.7281	0.4675
X × Mo	−0.2765	0.0978	−2.8284	0.0052
User shopping goal	Boot indirect effect	Boot SE	Boot LLCI	Boot ULCI
		Conditional indirect effect at the type of user shopping goal		
Exploratory	−0.1243	0.0549	−0.2379	−0.0250
Goal-directed	0.0627	0.0466	−0.0235	0.1600

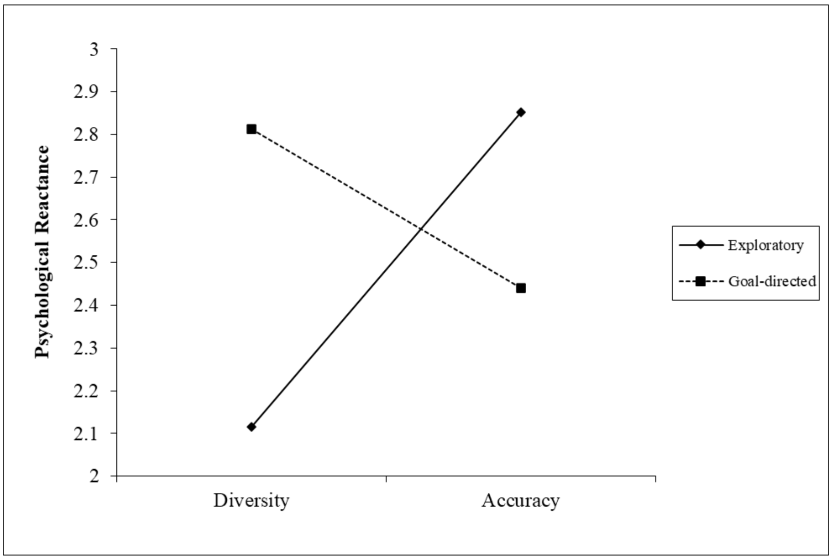

Figure 6. The moderating role of shopping goal on the relationship between recommendation type and psychological reactance.

Although the results showed that user shopping goals interacted with the recommendation type to influence users' psychological reactance, they did not directly assess the conditional indirect effects. Therefore, we analyzed the conditional indirect effects (see Table 6). The results supported H3b by showing that the indirect and negative effects of accurate recommendations on user satisfaction through psychological reactance were significant (b = −0.12, 95%, and CI [−0.24, −0.03]) when the user has an exploratory shopping goal, but not when the user was goal-directed (b = 0.06, 95%, and CI [−0.02, 0.16]).

In sum, user shopping goals would moderate the indirect effect of the recommendation type on user satisfaction through feeling right or psychological reactance. Specifically, for users with specific shopping goals, an accurate recommendation would make them feel right and increase their satisfaction. For users who do not have a specific shopping goal, an accurate recommendation activates their psychological reactance and decreases their satisfaction.

6. Discussion

This study investigated user satisfaction from the perspective of matching user shopping goals with recommendation types. We also aimed to understand the psychological mechanisms underlying the relationship between the recommendation system and user satisfaction. This study found that the user shopping goal moderates the relationship between types of recommendation and user satisfaction. When the user-shopping goal fits the type of recommendation, user satisfaction is expected to increase (H1). Second, we investigated the mediating role of feeling right and psychological reactance on the interaction effect between shopping goals and recommendation types on user satisfaction. When the user shopping goal matches the type of recommendation (fit), it leads to a feeling of right, thereby enhancing the user satisfaction. Conversely, when the user shopping goal and type of recommendation do not match (are unfit), it may lead to psychological reactance, thus reducing user satisfaction (H2a, H3a). Third, we examined the conditional indirect effect of the type of recommendation on user satisfaction through feeling right and psychological reactance at different levels of user shopping goals. Because of the alignment of recommendations with initial expectations, goal-directed users who experience accurate recommendations are expected to feel right, thereby increasing user satisfaction. By contrast, as exploratory users inherently seek diversity, accurate recommendations may activate psychological reactance, leading to a decrease in user satisfaction (H2b, H3b). These results offer new insights for e-commerce websites regarding how to enhance user satisfaction when designing recommendation systems.

6.1. Theoretical Implications

This study makes several important theoretical contributions to the literature on recommendation systems. First, this study uniquely combines the user shopping goal with the type of recommendation, and investigates the interactive effects of both factors on user satisfaction. Building on previous research, which primarily examined the accuracy and diversity of recommendation systems [5,6,24], we took a step further by incorporating user shopping goals. Earlier studies initially emphasized the accuracy of recommendation systems and later recognized the need for diversity; however, they were confined to recommendation systems, overlooking the diverse shopping needs of users. When users shop online, they have different needs based on various factors (products, purchase timing, etc.). Recommendation systems should dynamically adapt to meet the changing needs of users in order to enhance their satisfaction. Based on the results of our study, depending on whether users have specific shopping goals, a recommendation system should provide different approaches to satisfy their shopping needs. Second, it is also found that the mediating process between the recommendation system type and user satisfaction differs depending on the user shopping goals. Users with specific shopping goal are associated with the process of feeling right, whereas those with an exploratory goal are related to the process of psychological reactance.

6.2. Managerial Implications

The practical implications of this study are as follows: First, when designing a recommendation system, e-commerce websites should consider a user's shopping goal. Websites can classify users based on their search routine. Goal-directed users typically search for a specific product using precise keywords, whereas exploratory users are more likely to explore the product using product categories or general keywords. An e-commerce website may provide recommendations that best fit a user's shopping goal, potentially enhancing user satisfaction. Second, because feeling right is activated only when goal-directed users encounter accurate recommendations, it should strive to provide highly accurate information to users with specific shopping goals, thereby enhancing their satisfaction.

Conversely, psychological reactance is activated only when exploratory users encounter accurate recommendations, and websites should avoid recommending highly accurate information to users without specific shopping goals. Third, managers may support the continuous development of recommendation systems in a way to maximize marketing performance. They can benefit from implementing recommendation systems by providing users with an enjoyable and useful experience in an online shopping environment. However, these systems have faced a variety of critical challenges, including privacy concerns and ethical issues [55]. Therefore, managers need to maintain a healthy balance between privacy protection and personalization.

6.3. Limitations

This study has several limitations. First, in our experiment, the generated recommendation was divided into two separate categories: diversity and accuracy. However, the recommendation systems may generate a list of recommendation, which simultaneously balances both accuracy and diversity [56]. They can also take other forms such as novelty recommendations [57]. The two pre-made recommendation pages in our study do not represent mutually exclusive recommendation results. In addition, because the recommendation system itself is built on a large amount of user data and algorithms, our pre-made recommendation pages can only reflect the surface features presented by the recommendation system (accuracy/diversity) and cannot fully represent the recommendation approaches that users encounter during online shopping.

Second, the participants only provided evaluations of the recommendation pages as soon as they browsed them, and this process did not involve comparison, selection, decision making, or other aspects. Therefore, the participants' evaluations of the recommended pages may differ from their actual feelings during real-life shopping activities. Thus, we suggest that future research should attempt to make the recommendation pages more realistic by involving participants in the entire online shopping process (including comparison, selection, and decision-making) before assessing the recommendation pages.

Third, previous studies have suggested that product involvement is closely linked to pre-purchase information search [58]. This is because users with high product involvement tend to evaluate products more carefully, which requires extensive information search. In addition, Amarnath and Jaidev [59] have recently emphasized the critical role of product involvement (high involvement/low involvement) in the broader context of consumer reactance. Kwon and Chung [60] examined the interaction between product involvement and recommendations in e-commerce. Therefore, future research would examine the moderating role of product involvement on recommendation systems and its impact on user satisfaction.

7. Conclusions

The recommendation system is evidently an indispensable component of the online shopping website. Because designing the recommendation system is indeed a strategic activity, we should not only focus on enhancing its performance but also pay attention to the ever-changing needs of users, striving to avoid the occurrence of negative emotions and ensuring that users have a better shopping experience. Our empirical results show that online recommendation, when properly aligned with a user's shopping goal, positively influences his/her satisfaction in the online e-commerce context. Furthermore, when targeting the user who has a specific shopping goal, more accurate recommendations may help him/her feel right. This in turn leads to a higher user satisfaction. By contrast, when targeting the user with ambiguous shopping goal, more accurate recommendations decrease user satisfaction owing to the activation of psychological reactance.

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Informed Consent Statement: We conducted the research after obtaining the consent of the participants.

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