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A study on the inverted U-shaped relationship between perceived algorithmic recommendation accuracy and user satisfaction on short video platforms

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Abstract. Clarifying the relationship mechanism between perceived algorithmic recommendation accuracy and user satisfaction helps platforms optimize recommendation algorithms in a targeted manner and guide algorithms to be benevolent. Based on the Stimulus-Organism-Response (S-O-R) theory, this study constructs a theoretical model of how perceived algorithmic recommendation accuracy affects user satisfaction on short video platforms. By analyzing 398 valid questionnaires, the conclusions are drawn as follows: First, there is an inverted U-shaped relationship between perceived algorithmic recommendation accuracy and user satisfaction, which first increases and then decreases; second, algorithm fatigue plays a mediating role in the inverted U-shaped relationship between perceived algorithmic recommendation accuracy and user satisfaction; third, information-seeking motivation moderates the inverted U-shaped relationship between perceived algorithmic recommendation accuracy and user satisfaction.

Keywords: perceived algorithmic recommendation accuracy, user satisfaction, algorithm fatigue, information-seeking motivation

1. Introduction

With the rapid development of digital technology, algorithmic recommendation systems have been widely applied across various platforms. Algorithmic recommendation technology targeting accuracy achieves precise matching between recommended information and user profiles by analyzing user data, recommending products or services that meet users' preferences and needs [1, 2]. Previous studies mostly believed that improving the accuracy of matching between recommended content and user preferences can effectively alleviate information overload, enhance user immersion, and bring positive experiences to users [3]. However, excessive pursuit of accuracy may lead to homogenization of information received by users, trapping their viewpoints and preferences in a self-reinforcing cycle, which is likely to cause cognitive rigidity and arouse concerns about algorithmic recommendation technology targeting accuracy [1, 4-6]. From the perspective of algorithmic recommendation objectives, accuracy measures the degree of matching between the content recommended by the system to users and their existing needs, interests, or preferences [7]. Previous studies have mostly used terms such as "personalization degree", "precision", or "relevance" to describe algorithmic recommendation accuracy [5, 8-10], and this study uniformly adopts the term "algorithmic recommendation accuracy". When exploring the factors that affect users' evaluation of information quality, it is the perceived rather than actual personalization degree that influences users' evaluation of information quality [11, 12]. Therefore, this study focuses on the influence mechanism of perceived rather than actual algorithmic recommendation accuracy on user satisfaction. Excessively low or high matching degree between recommended content and user preferences will affect users' click intention, algorithm resistance behavior, and usage intention. However, users' acceptance intention and resistance behavior cannot fully reflect their true evaluation of recommendation services. For users lacking algorithmic knowledge, they do not know how to make explicit resistance behaviors and can only be forced to accept and continue using the platform's recommendation services. Therefore, this study takes user satisfaction as the outcome variable to fully understand users' subjective and true evaluation of algorithmic recommendation services.

2. Literature review and theoretical framework

2.1. Stimulus-Organism-Response theory

The Stimulus-Organism-Response (S-O-R) theoretical model is used to explain how specific environmental stimuli induce specific attitudinal or behavioral responses by influencing individuals' psychological states [13]. Generally speaking, Stimulus refers to external environmental factors that affect individuals, such as technical condition stimuli perceived by users when using digital platforms, AI tools, etc.; Organism refers to the specific impacts of external environmental stimuli on users' psychology, cognition, and emotions; Response refers to users' reactions based on psychological, cognitive, and emotional impacts, including satisfaction and avoidance behavior [14, 15].

In the process of users using algorithmic recommendation services on short video platforms, users' attitudes and processing methods towards information are affected by the matching degree between recommended information and their needs. When users perceive that the recommended information meets their preferences, they will devote more attention to the content itself, arouse positive attitudes, reduce the perception that algorithmic recommendation technology threatens personal privacy, alleviate negative psychology such as dissatisfaction, annoyance, and resistance, thereby reducing users' avoidance and resistance behaviors towards recommended information [3]. However, the system's excessive pursuit of precise matching between recommended information and user profiles will lead to repetition and homogenization of recommended content [5], which is likely to arouse users' resistance and psychological refusal, thereby generating the willingness to leave the current information environment [16]. Therefore, based on the S-O-R theoretical framework, this study takes perceived algorithmic recommendation accuracy as the technical condition stimulus, algorithm fatigue as the psychological pressure generated by users after receiving the technical stimulus, and satisfaction as users' response to the stimulus and pressure, aiming to reveal the internal mechanism and boundary conditions of how perceived algorithmic recommendation accuracy affects user satisfaction.

2.2. The inverted U-shaped relationship between perceived algorithmic recommendation accuracy and user satisfaction

User satisfaction refers to the response or emotional state generated by users through short-term or long-term experience in the process of using products or services, reflecting the degree of matching between users' actual usage experience and their expectations [17], and is usually regarded as a response generated by users after being stimulated by the environment [18].

Accuracy is one of the key dimensions to measure information quality, and information quality is an important factor to improve user satisfaction [19]. Algorithmic recommendation systems based on big data analysis technology can depict users' needs and preferences according to observed user data, and recommend content that precisely matches their preferences accordingly, which helps improve users' recognition of recommended information, satisfaction with the platform, and enhance user stickiness [3, 20]; however, blind pursuit of recommendation accuracy will force users to accept highly homogenized goods or services, making them prone to fall into information cocoons and reducing user satisfaction [21]. In other words, different degrees of perceived algorithmic recommendation accuracy have differential impacts on user satisfaction. The sufficiency threshold refers to the amount of information an individual wishes to grasp when addressing specific needs [22]. In the absence of algorithmic filtering mechanisms targeting accuracy, users are forced to browse a large amount of irrelevant information, leading to information overload pressure and poor user experience. At this time, improving the matching degree between recommended information and users' needs can effectively help users save the cost of information screening, alleviate negative emotions [23], and may have a positive impact on user satisfaction. However, when users feel that a certain type of information recommended by the system has met the amount they wish to grasp, they may be more inclined to obtain other types of novel content. If the algorithmic recommendation accuracy is further improved at this time, the homogenized content will instead make users feel bored and reduce user satisfaction. Based on this, Hypothesis H1 is proposed:

H1: There is an inverted U-shaped relationship between perceived algorithmic recommendation accuracy and user satisfaction, which first increases and then decreases.

2.3. The mediating role of algorithm fatigue

Mental fatigue is a subjective feeling experienced by individuals after continuous consumption and loss of their own resources during long-term cognitive activities, and is directly related to negative responses [24, 25]. Algorithm fatigue refers to a psychological state in which users feel overwhelmed and their enthusiasm fades when facing the outputs of algorithmic systems. Its sources include information overload, information hegemony, privacy threats, or the system continuously recommending homogenized content to users [26-28].

Previous studies have believed that recommendation algorithms targeting accuracy can alleviate information overload and improve user experience. When users are faced with a large amount of irrelevant information, they need to consume a lot of cognitive resources to identify and process content that meets their own preferences [26]. At this time, improving the relevance between recommended information and users' preferences can reduce information overload and alleviate algorithm fatigue. However, the recommendation system's excessive pursuit of precise matching between recommended information and users' preferences is likely to trap people in filter bubbles and information cocoons, confining users to a homogenized information environment. At this time, further improving the consistency between recommended information and users' preferences may reduce their interest in recommended information and exacerbate algorithm fatigue. In addition, studies have shown that negative psychological states such as emotional exhaustion, frustration, depression, and anxiety can seriously affect individuals' mental health, well-being, and satisfaction [29]. According to the Stimulus-Organism-Response theory, perceived algorithmic recommendation accuracy, as a technical condition stimulus, may affect user satisfaction by influencing the emotion of algorithm fatigue. In summary, Hypotheses H2-H4 are proposed:

H2: There is a U-shaped relationship between perceived algorithmic recommendation accuracy and algorithm fatigue, which first decreases and then increases.

H3: Algorithm fatigue negatively affects user satisfaction.

H4: Algorithm fatigue plays a mediating role in the inverted U-shaped relationship between perceived algorithmic recommendation accuracy and user satisfaction.

2.4. The moderating role of information-seeking motivation

The desire for knowledge is one of the inherent pursuits of humans. Information-seeking motivation aims to fill cognitive gaps in specific fields and has a strong goal orientation [30].

There are differences in information-seeking motivation among individuals. First, compared with individuals with low information-seeking motivation, those with high information-seeking motivation are more eager to obtain information in specific fields related to their needs. Since the higher the relevance between information and individuals' preferences, the more willing individuals are to conduct in-depth processing of such information, thereby showing higher immersion [22], with the improvement of perceived algorithmic recommendation accuracy, individuals with high information-seeking motivation may show higher user satisfaction. Second, the purposes of individuals' information seeking include filling cognitive gaps in specific fields, using information to learn new skills, master new environments, correct errors in goal-oriented behaviors, and demonstrate their abilities to the outside world. Compared with individuals with low information-seeking motivation, those with high information-seeking motivation face multiple demand pressures. They not only aspire to efficiently obtain information in a specific field but also hope to quickly switch to new fields, master new knowledge, and continuously improve their abilities after acquiring sufficient information.

It can be inferred that when the perceived algorithmic recommendation accuracy is too low, the information on the platform is difficult to meet users' specific needs. At this time, with the improvement of perceived algorithmic recommendation accuracy, compared with individuals with low information-seeking motivation, those with high information-seeking motivation will show higher user satisfaction. However, the filter bubbles generated by improving accuracy will confine users to existing cognitive frameworks. The narrowed information space is difficult to help users fill cognitive gaps and limits users' opportunities to discover new information, ideas, and knowledge from the recommendation system. Individuals with high information-seeking motivation need to continuously expand their knowledge scope to improve their abilities. Therefore, compared with individuals with low information-seeking motivation, those with high information-seeking motivation may be more sensitive to the reduction in opportunities to obtain new information, ideas, and knowledge, thereby taking the lead in showing reduced satisfaction. Based on this, the following hypothesis is proposed:

H5: Information-seeking motivation moderates the inverted U-shaped relationship between perceived algorithmic recommendation accuracy and user satisfaction. Specifically, compared with individuals with low information-seeking motivation, those with high information-seeking motivation have higher user satisfaction, and with the improvement of perceived algorithmic recommendation accuracy, the inverted U-shaped curve of user satisfaction for individuals with high information-seeking motivation reaches the inflection point earlier.

In summary, the research model is derived based on Hypotheses H1-H5, as shown in Figure 1.

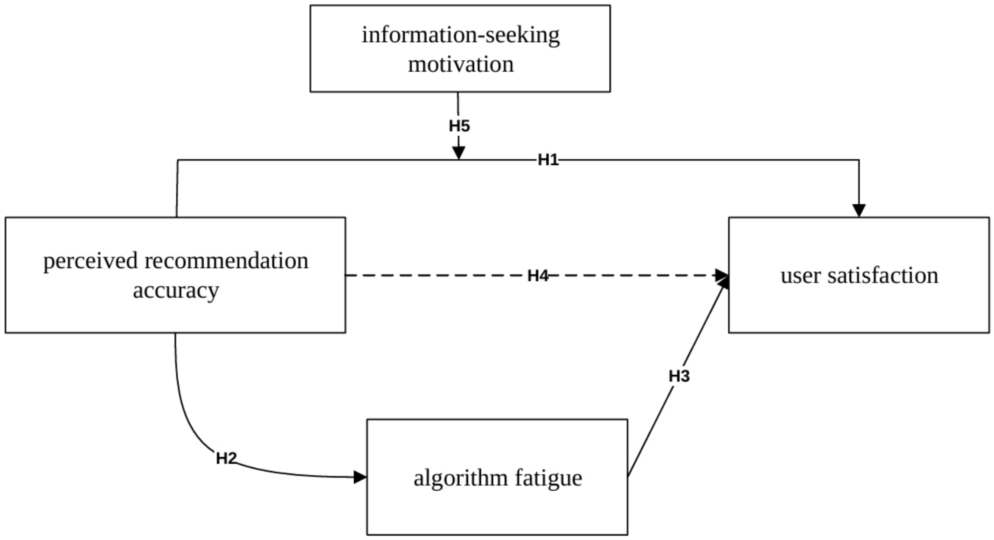

Figure 1. Research model

Note: the dashed line indicates the mediating effect.

3. Measurement of research variables and data collection

As shown in Table 1, to ensure content validity, the scales adopted in this study are all adapted from mature domestic and foreign scales, and all items are scored using a 7-point Likert scale (1 = Strongly Disagree; 7 = Strongly Agree). In addition, gender, age, educational level, and average daily usage time of short video platforms are taken as control variables. Users who have used algorithmic recommendation functions on short video platforms in the past month are taken as the research objects, and subjects are recruited through the Credamo platform. Subjects are required to answer based on their experience of using algorithmic recommendation functions on short video platforms in the past month, and a total of 400 questionnaires are collected. Subsequently, questionnaires with the same IP address and identical answers, as well as incomplete questionnaires, are excluded, and finally 398 valid questionnaires are obtained, with females accounting for 69.35%.

Table 1. Measurement scales and standardized factor loadings

Latent Variables	Code	Items	Factor Loading
Perceived Algorithmic Recommendation Accuracy	RA01	The content recommended to me by the platform is related to my hobbies.	0.837
	RA02	The content recommended to me by the platform is consistent with my preferences.	0.819
	RA03	The content recommended to me by the platform meets my needs.	0.789

Table 1. Continued

User Satisfaction	US01	I am satisfied with using the algorithmic recommendation function.	0.697
	US02	I am satisfied with the content recommended by the algorithm.	0.694
	US03	I think using the algorithmic recommendation service is wise.	0.705
	US04	Overall, the experience of using algorithmic recommendations makes me feel pleasant.	0.838
Algorithm Fatigue	AF01	Dealing with the recommended information on the platform makes me feel tired of it.	0.872
	AF02	Repeatedly browsing highly similar recommended content makes me feel very tired.	0.902
	AF03	The system continuously recommending content on the same topic makes me feel mentally exhausted.	0.907
	AF04	Using the algorithmic recommendation function makes me feel fatigued.	0.896
	AF05	I think it is very difficult to understand the algorithmic recommendation logic of the platform.	0.658
	AF06	Constantly interacting with the content recommended by the algorithm consumes my energy.	0.868
Information-Seeking Motivation Latent Variables	IS01	My purpose of using the platform's algorithmic recommendation function is to obtain new ideas.	0.758
	IS02	My purpose of using the platform's algorithmic recommendation function is to learn what I need to know.	0.836
	IS03	My purpose of using the platform's algorithmic recommendation function is to acquire knowledge in certain fields.	0.887

4. Data analysis and results

4.1. Reliability and validity analysis

As shown in Table 2, the Cronbach's α values of each latent variable range from 0.817 to 0.940, all greater than the recommended value of 0.7. The Composite Reliability (CR) values of each latent variable are also greater than the recommended value, indicating that the measurement model has good reliability and internal consistency. The scales in this study are all adapted from mature scales in existing domestic and foreign studies, with good content validity. Second, Table 1 and 2 show that the standardized factor loadings of each measurement item are greater than 0.6 and the Average Variance Extracted (AVE) values of each latent variable are greater than 0.5, indicating that the scale has good convergent validity. Finally, the Fornell-Larcker criterion is used to further test discriminant validity. As shown in Table 2, the square root of the AVE value of each latent variable is greater than the absolute value of the correlation coefficient between that variable and other latent variables, indicating that the questionnaire has good discriminant validity. The results of confirmatory factor analysis are shown in Table 3. All fit indices meet the recommended standards, indicating that the observed data of the four-factor model proposed in this study have a good fit with the hypothetical model.

Table 2. Reliability and validity test results

	Perceived Algorithmic Recommendation Accuracy	User Satisfaction	Algorithm Fatigue	Information-Seeking Motivation
Perceived Algorithmic Recommendation Accuracy	(0.815)			
User Satisfaction	-0.163	(0.736)		
Algorithm Fatigue	-0.174	0.332	(0.855)	
Information-Seeking Motivation	0.131	0.157	-0.013	(0.829)
Cronbach's α	0.852	0.817	0.940	0.865
CR	0.856	0.824	0.942	0.868
AVE	0.664	0.542	0.731	0.687

Note: Values in parentheses on the diagonal are the square roots of the AVE values of each variable.

Table 3. Model fit test results

Fit Indices	CMIN/DF	RMSEA	GFI	TLI	CFI	NFI
Fit Standards	< 3.000	< 0.080	> 0.900	> 0.900	> 0.900	> 0.900
Fit Results	1.406	0.032	0.960	0.987	0.990	0.966

4.2. Common method bias analysis

This study adopts measures such as adapting mature scales from existing domestic and foreign studies and anonymous answering to control the impact of common method bias. Second, the results of Harman's single-factor test show that the unrotated exploratory factor analysis indicates that the first factor accounts for 32.420%, which is less than the threshold of 50%. In addition, the fit indices of the single-factor confirmatory factor analysis are: CMIN/DF = 16.874, RMSEA = 0.200, GFI = 0.626, TLI = 0.510, CFI = 0.576, NFI = 0.562, all of which do not meet the recommended values, indicating that the single-factor model has a poor fit. Furthermore, the Variance Inflation Factor (VIF) statistics show that the VIF values of the model range from 1.024 to 1.103. In summary, there are no serious common method bias and multicollinearity problems in this study.

4.3. Direct effect test

The "three-step test method" is used to test the inverted U-shaped relationship between perceived algorithmic recommendation accuracy and user satisfaction. Perceived algorithmic recommendation accuracy is standardized before regression analysis. First, a regression equation between perceived algorithmic recommendation accuracy and user satisfaction is constructed: $US = \beta_0 + \beta_1 RA + \beta_2 RA^2$. From the regression results of Model 2 in Table 4, compared with Model 1, the regression coefficient of the linear term of perceived algorithmic recommendation accuracy is not significant, while the coefficient of the quadratic term of perceived algorithmic recommendation accuracy is significantly negative (β_2 = -0.094, S.E = 0.045, p < 0.05); second, when β_1 = 0.083 and β_2 = -0.094, the curve slope equation is $k = \beta_1 + 2\beta_2 RA = 0.083 - 0.188RA$. The standardized perceived algorithmic recommendation accuracy ranges from [-4.157,1.681]. When RA = -4.157, the curve slope k_1 = 0.865 > 0; when RA = 1.681, the curve slope k_2 = -0.233 < 0, which meets the curve slope discrimination requirements; as shown in Figure 2, with the increase of perceived algorithmic recommendation accuracy, user satisfaction first increases and then decreases, with the inflection point at $-\beta_1$ /(2 β_2) = 0.441, which is between the original options 5 and 6 and within the range of the independent variable. In summary, the relationship between perceived algorithmic recommendation accuracy and user satisfaction meets the discrimination conditions of an inverted U-shaped curve, supporting Hypothesis H1.

Similarly, a regression equation between perceived algorithmic recommendation accuracy and algorithm fatigue is constructed: $AF = \beta_0 + \beta_1 RA + \beta_2 RA^2$. From the regression results of Model 6 in Table 4, compared with Model 5, the regression coefficient of the linear term of perceived algorithmic recommendation accuracy is not significant, while the coefficient of the quadratic term of perceived algorithmic recommendation accuracy is significantly positive (β_2 = 0.315, S.E = 0.047, p < 0.001); when β_1 =0.138 and β_2 = 0.315, the curve slope equation is $k = \beta_1 + 2\beta_2 RA = 0.138 + 0.630RA$. When RA = -4.157, the curve slope k_1 = -2.481 < 0; when RA = 1.681, the curve slope k_2 = 1.197 > 0; as shown in Figure 3, with the increase of perceived algorithmic recommendation accuracy, algorithm fatigue first decreases and then increases, with the inflection point at $-\beta_1/(2\beta_2)$ = -0.110, which is between the original options 5 and 6 and within the range of the independent variable. In summary, the relationship between perceived algorithmic recommendation accuracy and algorithm fatigue meets the discrimination conditions of a U-shaped curve, supporting Hypothesis H2.

Table 4. Hierarchical regression analysis results with user satisfaction and algorithm fatigue as dependent variables respectively

Variables	User Satisfaction				User Satisfaction	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gender	-0.169	-0.163	-0.195	-0.158	-0.115	-0.135
Age	0.008	0.009	0.006	0.009	-0.007	-0.010
Educational Level	-0.038	-0.023	-0.062	-0.015	-0.115	-0.166
Average Daily Usage Time of Short Video Platforms	0.006	0.010	0.026	0.011	0.080	0.068
Perceived Algorithmic Recommendation Accuracy	0.195**	0.083	0.115	0.123	-0.239**	0.138
Quadratic Term of Perceived Algorithmic Recommendation Accuracy		-0.094*	-0.020	-0.079		0.315***
Algorithm Fatigue			-0.234***			
Perceived Algorithmic Recommendation Accuracy × Information-Seeking Motivation				-0.183*		
Quadratic Term of Perceived Algorithmic Recommendation Accuracy × Information-Seeking Motivation				-0.042		
R^2	0.026	0.037	0.097	0.054	0.038	0.136
Adjusted R^2	0.014	0.023	0.081	0.034	0.026	0.123

Note: Regression coefficients in the table are unstandardized values; * p< 0.05, ** p< 0.01, *** p< 0.001 (two-tailed test)

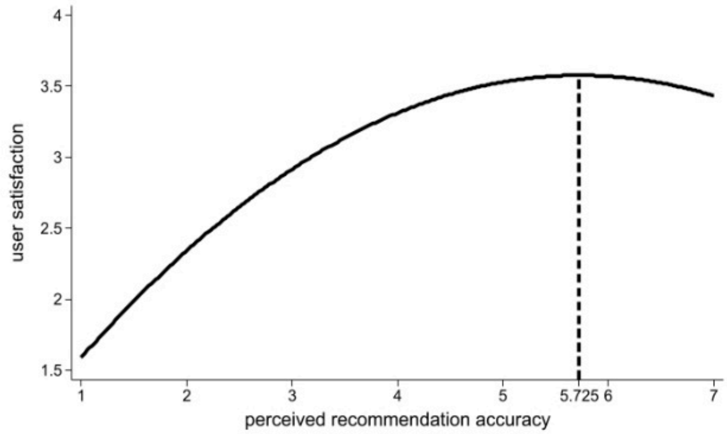

Figure 2. Inverted U-shaped relationship between perceived algorithmic recommendation accuracy and user satisfaction

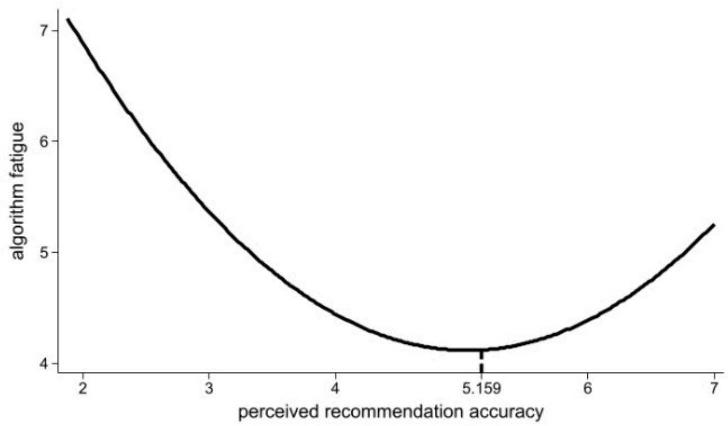

Figure 3. U-shaped relationship between perceived algorithmic recommendation accuracy and algorithm fatigue

4.4. Mediating effect test

The product method is used to test the mediating role of algorithm fatigue. As shown in Model 3 of Table 4, the negative relationship between algorithm fatigue and user satisfaction is significant (β = -0.234, S.E = 0.046, p < 0.001). After controlling for algorithm fatigue, the impact of the quadratic term of perceived algorithmic recommendation accuracy on user satisfaction is no longer significant (β = -0.020, S.E = 0.046, p > 0.05). Combined with Model 6, the quadratic term of perceived algorithmic recommendation accuracy has a significant positive impact on algorithm fatigue (β = 0.315, S.E = 0.047, p < 0.001). The U-shaped mediating effect of perceived algorithmic recommendation accuracy on user satisfaction through algorithm fatigue is significant (β = -0.074, S.E = 0.018, p < 0.001), with a 95% confidence interval of [-0.109, -0.038], supporting Hypotheses H3 and H4.

4.5. Moderating effect test

As shown in Model 4 of Table 4, the interaction term between perceived algorithmic recommendation accuracy and information-seeking motivation is significantly negative (β = -0.183, S.E = 0.071, p < 0.05), but the interaction term between the quadratic term of perceived algorithmic recommendation accuracy and information-seeking motivation is not significant (β = -0.042, S.E = 0.030, $p > 0.05$). This indicates that the moderating role of information-seeking motivation only changes the position of the inflection point of the inverted U-shaped curve between perceived algorithmic recommendation accuracy and user satisfaction, but not the slope of the curve. As shown in Figure 4, with the mean of information-seeking motivation as the center, the moderating effect diagrams of the high-value group (M+1SD) and low-value group (M-1SD) of information-seeking motivation are drawn separately. The inflection point of the inverted U-shaped curve for users with high information-seeking motivation is located to the left of that for users with low information-seeking motivation; in addition, between the values 5 and 6 of the independent variable, a "scissors difference" appears, that is, the inverted U-shaped curve of users with high information-seeking motivation intersects with that of users with low information-seeking motivation. On the left side of the intersection point, with the improvement of perceived algorithmic recommendation accuracy, the user satisfaction of users with high information-seeking motivation is higher than that of users with low information-seeking motivation; on the right side of the intersection point, with the improvement of perceived algorithmic recommendation accuracy, the user satisfaction of users with high information-seeking motivation is lower than that of users with low information-seeking motivation. Hypothesis H5 is partially supported.

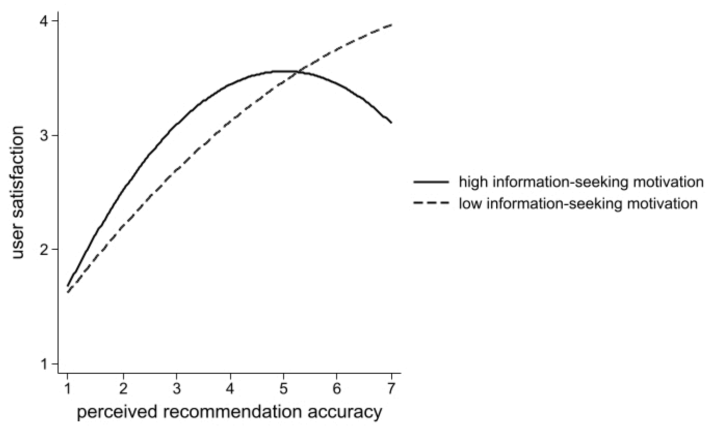

Figure 4. Moderating role of information-seeking motivation between perceived algorithmic recommendation accuracy and user satisfaction

5. Conclusions and discussions

5.1. Research conclusions

The study finds that: (1) There is an inverted U-shaped relationship between perceived algorithmic recommendation accuracy and user satisfaction; (2) Algorithm fatigue plays a mediating role in the inverted U-shaped relationship between perceived algorithmic recommendation accuracy and user satisfaction; (3) Users' information-seeking motivation moderates the inverted U-shaped relationship between perceived algorithmic recommendation accuracy and user satisfaction. Specifically, compared with users with low information-seeking motivation, the inverted U-shaped curve of perceived algorithmic recommendation accuracy and user satisfaction for users with high information-seeking motivation reaches the inflection point earlier. In addition, the inverted U-shaped curves of the two groups intersect, resulting in a "scissors difference". This study argues that the "scissors difference" is caused by the interaction of multiple needs inherent in information-seeking motivation. Driven by information-seeking motivation, users first need to fill cognitive gaps in specific fields, and after fully mastering the information, they will turn to other fields to learn new knowledge. When the perceived algorithmic recommendation accuracy is low, compared with users with low information-seeking motivation, users with high information-seeking motivation are more eager to obtain specific information related to their needs to fill cognitive gaps. At this time, improving perceived algorithmic recommendation accuracy can make users with high information-seeking motivation have higher satisfaction. However, when users with high information-seeking motivation believe they have fully mastered the information in that field, obtaining new information to broaden their knowledge scope becomes the main demand. At this time, further improving perceived algorithmic recommendation accuracy makes users with high information-seeking motivation acutely aware that the opportunities to expand their knowledge and improve their abilities are limited, leading to lower user satisfaction than users with low information-seeking motivation.

5.2. Theoretical contributions

First, the divergence in previous research conclusions lies in that some studies believe that improving the matching degree between recommended content and user preferences has a positive impact on users' behavioral intentions, while others argue that pursuing recommendation accuracy is likely to limit users to homogenized information content, trap them in information cocoons, and reduce user satisfaction [21]. This study holds that the root cause of the above divergence is that different degrees of perceived algorithmic recommendation accuracy have differential impacts on user experience. Therefore, the study comprehensively tests the inverted U-shaped relationship between perceived algorithmic recommendation accuracy and user satisfaction in the context of short video platforms. Second, it reveals the internal psychological mechanism in the context of short video platforms, where users' perceived algorithmic recommendation accuracy, as a technical characteristic stimulus, affects users' psychological state of algorithm fatigue and then acts on user satisfaction, further expanding the applicable context of the Stimulus-Organism-Response theory. Finally, although existing studies have explored the moderating roles of variables such as content type and privacy concerns [1, 5], they have ignored that obtaining needed information, as one of the important motivations for users to use short video platforms, also affects users' evaluation of the platform's algorithmic recommendation services. Therefore, this study also explores the differential effects of different intensities of information-seeking motivation on the relationship mechanism between perceived algorithmic recommendation accuracy and user satisfaction, supplementing new insights.

5.3. Practical implications

First, short video platforms should avoid taking accuracy as the sole recommendation goal, and can try to construct algorithm models by integrating novelty, serendipity, or diversity goals on the basis of accuracy to meet users' real-time and diverse needs. Second, short video platforms should provide users with content management channels, allowing users to adjust the recommendation style according to changes in their needs. In addition, short video platforms can establish user emotional feedback and response mechanisms, as well as demand feedback and response mechanisms. Based on users' algorithm fatigue levels and their causes, as well as the intensity of information-seeking motivation, user groups can be further segmented, and the weights of accuracy, novelty, and diversity can be adjusted according to the needs and characteristics of different groups to optimize user experience.

5.4. Limitations and prospects

First, the study only asked subjects to recall their recent experiences of using algorithmic recommendation services on short video platforms for the questionnaire survey. Future research can adopt mixed methods such as experimental methods and interviews to improve the robustness of the research conclusions. Second, this study only focuses on the context of short video platforms to draw conclusions. However, user satisfaction is affected by different environmental characteristics, and future research can be further extended to other contexts. Finally, this study only discusses the moderating role of user motivation. However, users' sense of autonomy and different types of autonomy (choice autonomy vs. decision-making autonomy) may also have an impact on the relationship between algorithmic recommendation technology and user experience, which is worthy of further exploration.

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