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Recommendation algorithm’s influencing factors on college students' continuance use intention—A S-O-R analysis based on Douyin

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Abstract. Nowadays, some applications are having difficulty in retaining users after pulling them in. To enhance user stickiness, algorithms are widely used by major applications due to their advantage of accurate push. Recommendation algorithms have changed the Internet’s business logic and information dissemination modes from pursuing "information bombing" to "precision strike". Based on the S-O-R model, this paper investigates the influence of recommendation algorithm characteristics (recommendation quality, personalization, usability, and user trust) on college students' satisfaction and continuance use intention of Douyin. Structural equation modelling analysis was conducted in this paper with the help of a questionnaire survey and partial least squares (PLS). It was found that personalization positively affects user attitude and user cognition; usability positively affects user cognition and emotional response; and user trust positively affects user attitude, user cognition and emotional response. While none of the stimuli, recommendation quality, has a significant effect on users' psychological emotions. User attitude, cognition, and emotional response all significantly affect user satisfaction, which in turn significantly affects user’ continuance use intention. This study provides a quantitative study for understanding user behaviors on social media platforms, and offers suggestions for the optimization of recommendation systems.

Keywords: Recommendation Algorithm, continuance use intention, Douyin, S-O-R model, structural equation modelling analysis.

1. Introduction

The Internet is reshaping people’s lives, China Internet Network Information Centre (CNNIC) pointed out in the 53rd *Statistical Report on the Development Status of the Internet in China* that as of December 2023, the number of Internet users in China had reached 1.092 billion, with 24.8 million new Internet users added compared to December 2022, and the Internet penetration rate had reached 77.5% [1].

Although the penetration rate of the Internet is increasing year by year, the demographic dividend and time dividend on the Internet are gradually weakening or even disappearing. The Internet is starting a stock competition, that is to say, when the "cake" is no longer large, how to keep or share a larger piece has become the problem that companies need to think about currently. Therefore, the major applications not only need to pull new users in, but the subsequent promotion and retention, user stickiness enhancement should not be underestimated as well. Under these circumstances, algorithms are widely used because of their accuracy and personalization. Recommendation algorithms have changed the Internet's business logic and information dissemination modes from pursuing "information bombing" to "precision strikes".

This paper takes Douyin as the research platform to explore what factors may affect college students' continued willingness to accept Douyin's algorithmic recommendation, and focuses on the characteristics of the algorithmically recommended content and the psychology of the users through quantitative research, which provides data support for the targeted optimization of the algorithmic recommendation system and gives recommendations.

2. Literature review

Recommendation algorithms are used in a wide range of fields, for instance, Kuang and Wang studied the logic of algorithmic recommendation on social media and social responsibility of the platforms [2]. Based on the perspective of digital divide, Fan et al. examined the acceptance of algorithmic recommendation content by social media users [3]. Recommendation algorithms are also used in e-commerce, Jiang pointed out that being widely applied in e-commerce, personalized recommendation algorithms have improved the efficiency of the transaction, but they also break the balance between algorithmic power, individual rights and public space. Furthermore, the algorithmic risk is increasingly prominent [4].

Current research on the association between recommendation algorithms and users is relatively rich, this study analyses from this aspect as well. Through in-depth interviews, Huangfu proposed a term called "algorithmic offence", which is not only a direct expression of users' negative emotions, but also constitutes "transgression" and "usurpation" of the user sovereignty algorithm in the interactive relationship. Due to this, users are increasingly exploring autonomously through mild resistance, self-adaptation, and algorithmic literacy [5]. Recognizing that the result of algorithmic recommendation is actually a direct mapping of users' self-propagation, Wang proposed that in the process of algorithmic recommendation, algorithm certainly disciplines users, but they hold the initiative of controlling algorithm better than those non-users [6]. All in all, there is a wealth of researches on interaction between recommendation algorithms and users, in which a number of scholars are proposing challenges to algorithmic recommendation, including user privacy, data security, algorithmic bias and cold-start. Thus looking ahead, future researches should pay more attention to the logic behind algorithms, as well as focus on their validity, fairness, and transparency [7].

3. Methodology

3.1. Research model and design

3.1.1. Variables and hypotheses. Based on the S-O-R model, four variables are set in the external stimuli dimension(S): recommendation quality (RQ), personalization (PZ), usability (UE), and user trust (UT). Four more variables are set in organism dimension (O), namely user attitude (UA), user cognition (UC), emotional response (ER), and user satisfaction (US). Continuance use intention (CUI) was set as response (R) and the research hypotheses were designed as followed (Table 1).

Table 1. Research hypotheses

Hypotheses	Sub-hypotheses
H1 Algorithm recommendation positively affects user attitude.	H1a Recommendation quality positively affects user attitude. H1b Personalization positively affects user attitude. H1c Usability positively affects user attitude. H1d User trust positively affects user attitude.
H2 Algorithm recommendation positively affects user cognition.	H2a Recommendation quality positively affects user cognition. H2b Personalization positively affects user cognition.

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Table 1. (continued).

	H2c Usability positively affects user cognition. H2d User trust positively affects user cognition.
H3 Algorithm recommendation positively affects emotional response.	H3a Recommendation quality positively affects user cognition. H3b Personalization positively affects user cognition. H3c Usability positively affects user cognition. H3d User trust positively affects user cognition.
H4 User psychology positively affects user satisfaction.	H4a User attitude positively affects user satisfaction. H4b User cognition positively affects user satisfaction. H4c Emotional response positively affects user satisfaction.
H5 User satisfaction positively affects continuance use intention.	

3.1.2. Research model. The S-O-R (stimuli-organism-response) model suggests that human behavior begins with a physical stimulus, then the senses will pick up external stimuli and process them through the nervous system. After that, emotions or perceptions are generated, and finally it will output an action-response [8].

When discussing the impact of algorithmic recommendations on social media on individuals' persistent usage intention, the S-O-R model is also applicable. The system characteristics in the algorithmic recommendation environment (recommendation quality, personalization, usability, and user trust) are the stimuli of the external environment (S), and organism, namely the collective internal psychology (O), which includes user attitude, user cognition, and emotional response, with user satisfaction being the psychology formed by its further integration. Response (R) mainly refers to the user's continuous willingness to use (continuance use intention). This results in a relationship chain: S (RQ, PZ, UE, UT) → O (UA, UC, ER) → O (US) → R (CUI). The paper further develops a research model, as shown in Figure 1.

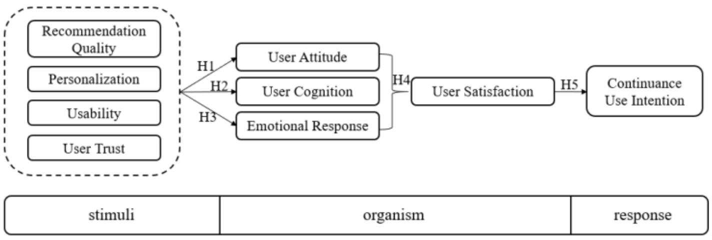

Figure 1. Model of algorithmic recommendation features' effect on personal continuance use intention

3.2. Research process

3.2.1. Research methodology and questionnaire description. In this paper, a questionnaire was used to validate the model, and it included four parts: ① measurement of college students' opinions about the content generated by the algorithm; ② measurement of user attitude, cognition, and emotional response; ③ measurement of user satisfaction and continuance use intention; ④ basic information about interviewees, including users' gender, their usage of Douyin and average use time.

The study measures included content generated by algorithmic recommendations (recommendation quality, personalization, usability, user trust), user attitude, user cognition, emotional response, user satisfaction, and continuance use intention. The questions were based on a 5-point Likert scale, with 1-5 indicating "strongly disagree" to "strongly agree". The final corresponding items for each variable are shown in Table 2.

Table 2. Variable test items

Variable	Test items
RQ	RQ1: Usually, it's a good fit for my interests and requirements.
	RQ2: It has various and original content that pleases me.
PZ	PZ1: Its content is highly personalized to my personal preferences.
	PZ2: Douyin effectively understands and reflects my content preference.
UE	UE1: It's easy and convenient for Douyin to find my interest contents.
	UE2: The user interface of Douyin makes it easy for me to navigate and explore contents.
UT	UT1: I trust the accuracy and reliability of Douyin's recommendation algorithms.
	UT2: I believe that Douyin handles personal privacy safely and responsibly.
UA	UA1: I'm positive about Douyin's algorithmic recommendation system.
	UA2: I think Douyin's recommendation system is a valuable tool resource.
UC	UC1: I know how Douyin's recommendation algorithm works.
	UC2: I think Douyin's recommendation algorithm accurately identifies user interests.
ER	ER1: I was entertained and satisfied by the recommended content by Douyin.
	ER2: I hold positive emotions towards Douyin algorithm recommendation.
US	US1: I'm generally satisfied with the content produced by Douyin algorithm recommendation.
	US2: The contents recommended by Douyin can satisfy my needs and expectations.
CUI	CUI1: I intend to use Douyin continuously as my source of information and entertainment.
	CUI2: I'll continue using Douyin even if there's new platforms similar to Douyin.

This paper chose WJX as the platform for questionnaire distribution and collection which started from 27th December 2023 to 31st December 2023, with a total of 143 questionnaires recovered. It is worth mentioning that in the process of questionnaire collection, the number of male samples was relatively low, so this paper launched the supplementary collection of samples for men to narrow the difference between the number of male and female samples. The final proportion of men and women sample was 45.45% and 54.55%, respectively. 124 valid questionnaires were collected in the end with an 86.7% recovery rate of valid samples.

Survey respondents' basic situation and their usage of Douyin are as follows (Table 3). Among college students who use Douyin, 52.42% use it for an average of less than one hour per day, and 47.58% use it for more than one hour.

Table 3. Basic information and statistics of Douyin usage

Variable	Measure term	Frequency	Percentage/%
Gender	Male	65	45.45%
	Female	78	54.55%

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Table 3. (continued).

Usage of Douyin	Previously used	38	26.57%
	Currently in use	86	60.14%
	Never used before	19	13.29%
Average daily length of use	Less than 1 hour	65	52.42%
	1-2 hours	26	20.97%
	2-3 hours	20	16.13%
	Over 3 hours	13	10.48%

3.2.2. Reliability and validity analysis. In this paper, PLS was used for modelling. Before that, the reliability and validity of this model was tested.

Through Cronbach'α and CR, it tested the reliability. The results of indicators for each latent variable were obtained through SmartPLS 4.0 analysis, which is shown in Table 4. All latent variables' Cronbach'α was above 0.8, mostly above 0.9 and generally between 0.8~0.97. This indicates that the design of this model is reasonable and the reliability of this model is relatively high.

Validity tests are divided into convergent and discriminant validity. Convergent validity is usually judged by the factor loading coefficients of the observed variables and the Average Variance Extracted (AVE) of the latent variables. With the help of SmartPLS 4.0 and SPSS 29.0, the results were obtained as shown in Table 4. The factor loading of each coefficients observed variable were above 0.7 and most of them exceeded 0.85, while the AVEs of all the latent variables were above 0.8, which indicates that the model is better aggregated. Discriminant validity was tested by comparing the square root of the AVE values of the latent variables with the correlation coefficients between the other variables, as shown in the results of Table 5. The diagonal elements represent the square root of the mean extracted variance of each latent variable, and the off-diagonal elements are the correlation coefficients of each latent variable. The square root of the mean extracted variance of each latent variable in the model is greater than the correlation coefficients between the latent variables and the other latent variables, indicating that the discriminant validity of the scale is also at an acceptable level.

Table 4. Reliability and convergent validity test

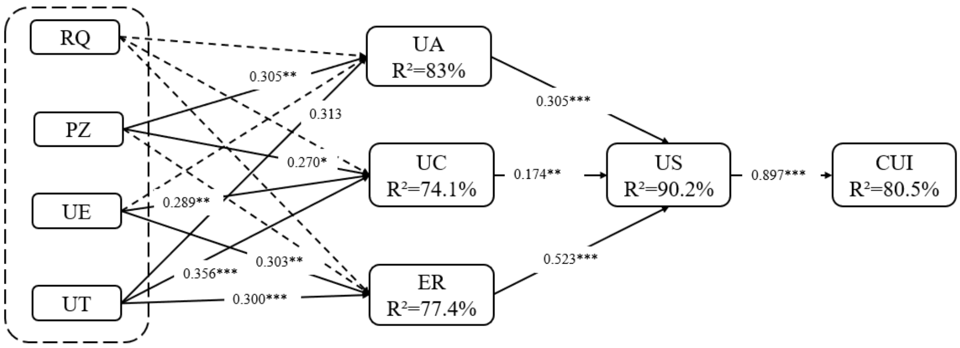
Measurement indicator	Observed variable	Factor loading	Cronbach'α	CR	AVE
RQ	RQ1	0.927	0.901	0.905	0.910
	RQ2	0.879			
PZ	PZ1	0.913	0.954	0.954	0.956
	PZ2	0.905			
UE	UE1	0.938	0.964	0.965	0.965
	UE2	0.910			
UT	UT1	0.884	0.883	0.891	0.895
	UT2	0.791			
UA	UA1	0.911	0.933	0.933	0.937
	UA2	0.906			
UC	UC1	0.744	0.821	0.845	0.847
	UC2	0.878			
ER	ER1	0.912	0.930	0.932	0.935
	ER2	0.886			
US	US1	0.945	0.964	0.964	0.965
	US2	0.944			
CUI	CUI1	0.898	0.933	0.934	0.937
	CUI2	0.855			

Table 5. Correlation coefficient between latent variables

	RQ	PZ	UE	UT	UA	UC	ER	US	CUI
RQ	0.954								
PZ	0.929	0.978							
UE	0.912	0.889	0.982						
UT	0.808	0.777	0.803	0.946					
UA	0.875	0.869	0.855	0.833	0.968				
UC	0.805	0.806	0.817	0.800	0.794	0.920			
ER	0.842	0.818	0.843	0.807	0.866	0.798	0.967		
US	0.889	0.857	0.890	0.809	0.896	0.833	0.926	0.983	
CUI	0.823	0.790	0.817	0.780	0.823	0.773	0.843	0.897	0.968

3.3. Results

Structural equations based on the principle of Partial Least Squares (PLS) were used for validation. Through Smart 4.0, this paper carries out the structural equation analysis for the research model in Figure 1, and obtains the results (Figure 2). Further it demonstrates the Path coefficient, T statistics and the results of the first-order model (Table 6). In terms of the explained variance of endogenous latent variables, the four features of contents recommended by the algorithm, which can be obtained from R^2, can explain more than 50% of the variance of the user's intention to continue to use, and the above analysis results show that the exogenous latent variables have a high explanatory strength for the user's intention to continue to use.



Note:*p<0.05,**p<0.0l,***p<0.001

Figure 2. First-order structural equation modelling and path analysis

Table 6. Path coefficient, T statistics and results

Hypothesis	Variable relationship	Path coefficient	T statistics	P values	Result
H1a	RQ - UA	0.208	1.537	0.062	Disproved
H1b	PZ - UA	0.305**	2.343	0.010	Proved
H1c	UE - UA	0.143*	1.196	0.116	Disproved
H1d	UT - UA	0.313**	4.715	0.000	Proved
H2a	RQ - UC	0.002	0.020	0.492	Disproved
H2b	PZ - UC	0.270**	1.732	0.042	Proved
H2c	UE - UC	0.289***	2.401	0.008	Proved
H2d	UT - UC	0.356***	4.404	0.000	Proved
H3a	RQ - ER	0.220	1.432	0.076	Disproved

Table 6. (continued).

H3b	PZ - ER	0.111	0.760	0.224	Disproved
H3c	UE - ER	0.303***	2.474	0.007	Proved
H3d	UT - ER	0.300***	3.872	0.000	Proved
H4a	UA - US	0.305***	3.399	0.000	Proved
H4b	UC - US	0.174***	2.806	0.003	Proved
H4c	ER - US	0.523***	5.237	0.000	Proved
H5	US - CUI	0.897**	42.172	0.000	Proved

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

Based on the structural model analysis, a simple modification of the hypothetical model in Figure 1 was made, as shown in Figure 3.

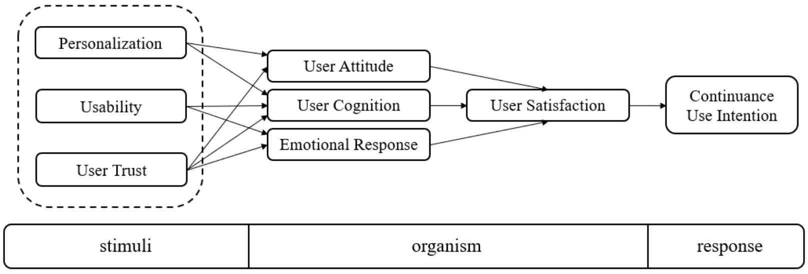


Figure 3. Revised model

4. Conclusion

According to the analysis above, it can be concluded that the quality of content generated by Douyin's algorithmic recommendation has no significant impact on user emotions or psychology. Whether on user attitude, user cognition, or user emotional responses, the quality of Douyin algorithmic recommendations did not show a significant impact. For one, this could mean that personalization, usability and user trust have a more direct and significant impact. Secondly, nowadays, with highly developed digitalization and continuous development of algorithmic technology, users are gradually adapting to the recommendation algorithms, and without taking into account the fact that users have different expectations of the recommended content, it can be assumed that high-quality personalized recommendations have now become a basic need for users, and are no longer able to have a significant impact on their satisfaction. Thirdly, in the setting of question items, only two aspects are set about interests and needs, diversity and novelty, and there may be various evaluation criteria for recommendation quality, such as accuracy and coverage. The impact of recommendation content can be further investigated through in-depth interviews.

User trust has a significant impact on all three dimensions of individuals' psychological emotions. This is the same as the findings of current research, which Huangfu calls "algorithmic offence" [9]. In response to "algorithmic offence", users will take the initiative to resist, which, in this study, is reflected in college students' emotional responses and attitudinal perceptions of Douyin algorithm, which will further affect their continuance use intention. College students' distrust of the current algorithm reflects their desire to ensure that their personal data are not abused while enjoying personalized content, which should be a key concern of Douyin platform in its algorithmic refinement.

The selection of variables in the study design is mainly based on past literature, which means there are still limitations in the field of vision. This paper also wants to make supplements, which can be explored in depth in future research. First, there is a "desire fulfilment" behind Douyin algorithm [10].

The reason why users can't stop using Douyin, that is, continuance use intention, is because Douyin makes use of instantaneous and immediate linking of user-preferred content, and for college students, the exposure to and use of short videos can better satisfy their visual desire, which is conducive to releasing the psychological pressure of college students, relieving negative emotions such as anxiety, tension, depression, etc., and obtaining positive emotions, meeting diversified and diversified emotional needs. Compared with Weibo, which plays the role of "living room" for celebrities, Douyin is more like a bedroom, which satisfies the public's more down-to-earth desires. Secondly, there is a view that Douyin has the dilemma of "information cocoon" in its algorithmic recommendation, and Douyin has made algorithmic improvements to address this issue: on the one hand, Douyin will choose a certain percentage of the content categories that users have not often watched in the past to recommend each time it is recommended. On the other hand, Douyin also adds a random content to ensure the diversity of content visible to users [11]. Although this was considered in the variable design of this study, the results of the study show that the research on multiple recommendations is weak and lacks a separate systematic study. In addition, it is also possible to consider the internal characteristics of the algorithm, focusing on its internal structural features.

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