The Impact of Algorithmic Recommendation Quality on User Purchase Intentions from a Trust Perspective

——A Case Study of Douyin E-commerce

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Abstract. Smart algorithms are rapidly integrating into people's daily lives, leading to a continuous evolution in consumers' attitudes towards algorithms, shifting from aversion to trust. However, existing research on consumer algorithmic decision-making from a trust perspective remains limited. Against this backdrop, this study selects users who have purchased recommended products on the Douyin platform as the research subjects and employs a questionnaire survey to construct a theoretical model of "information quality - algorithm trust - consumer purchase intentions." The research outcomes not only enrich the academic research in the field of algorithmic recommendations but also provide valuable insights for e-commerce platforms to enhance user experience and purchase conversion rates.

Keywords: Algorithm Attitude; Trust; Information Quality; Purchase Intention

1 Introduction

According to the 54th "China Internet Network Development Status Statistical Report," as of June 2024, short video users accounted for 95.5% of the total internet population, with both user scale and usage duration showing a steady upward trend. In the commercial domain, the monetization efficiency of the "short video + e-commerce" model is continuously increasing. For instance, during the 618 shopping festival, the number of orders and transaction amounts on Douyin's shopping mall increased by 94% and 85% year-on-year, respectively. The core operational mechanism of e-commerce platforms is algorithmic recommendation, which collects user data to construct detailed user profiles and predicts user preferences and behaviors based on this data. By providing personalized products and services to meet users' differentiated needs, it enhances consumer loyalty and platform competitiveness[5](Chellappa & Sin, 2005).

In recent years, consumer attitudes towards algorithms have become an emerging research focus in academia. Early studies indicated that people harbor negative attitudes towards algorithms, known as "algorithm aversion" [8](Dietvorst et al., 2015). This negative attitude may extend to algorithmically recommended products, leading to a reduced willingness to purchase such products[16](Wien & Peluso, 2021). However,

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recent research has shown that under certain conditions, people will accept and even prefer algorithmic recommendations[4](Castelo et al., 2019). For example, as trust in the capabilities of algorithms increases, consumers are more likely to purchase utilitarian products recommended by algorithms[13] [11] (Longoni & Cian, 2022; Jim & Zhang, 2023). Moreover, as users spend more time on platforms, their cognition of algorithms strengthens, making them more likely to accept and appreciate algorithms[10](Filiz et al., 2021). Existing research has also found that the level of algorithmic trust is influenced by situational cues[4] [7] (Castelo et al., 2019; Chen et al., 2024).

Based on this, this study selects users who have purchased recommended products on the Douyin platform as the research subjects and constructs a theoretical model of "information quality – algorithmic trust – consumer purchase intention." The aim is to explore the impact of algorithmic trust as an internal mechanism on consumer behavioral attitudes, as shown in Figure 1.

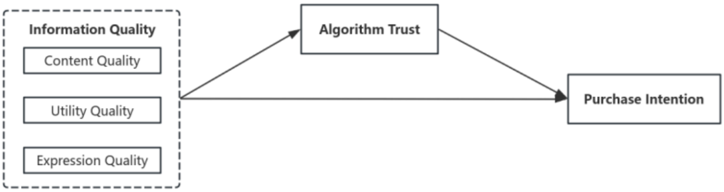

Fig. 1. Theoretical Model Diagram

2 Hypothesis

2.1 Information Quality and Purchase Intention

Cheung et al. (2012) argue that the quality of word-of-mouth information is the force that persuades others to accept one's own views[6]. To have the audience willing to accept one's views, the information provided must be accurate and truthful, with richness and completeness as its notable characteristics. In the context of short video e-commerce platforms, combining Wang and Strong's (1996) types of information quality evaluation, this study adopts content quality (accuracy, completeness, reliability), utility quality (attractiveness, understandability, richness), and expression quality (usefulness, ease of use, and appropriateness) as indicators for evaluating information on short video e-commerce[15]. Albayrak and Ceylan (2021) found that four information characteristics of social media websites—relevance, timeliness, accuracy, and completeness—jointly affect the formation and change of customer attitudes[2]. Addison et al. (2022) noted that the immediacy, relevance, and accuracy of e-commerce platform information have a significant positive relationship with customer satisfaction[3]. These characteristics can also indirectly positively influence customer purchase decisions by enhancing customers' flow experience, satisfaction, and trust. Thus, the following hypotheses are proposed:

H1a: The content quality positively affects consumer purchase intention.

H1b: The expression quality positively affects consumer purchase intention.

H1c: The utility quality positively affects consumer purchase intention.

2.2 Information Quality and Algorithm Trust

Algorithm trust describes the trust relationship formed between humans and technology[4](Castelo et al., 2019). A review of the technology acceptance field reveals that perceived usefulness and convenience are two key factors affecting users' trust in algorithmic technology[1](Alexander et al., 2018). During the viewing of short video advertisements, high-quality algorithmic recommendations reflect the system's ability to provide valuable and reliable information. High-quality information expression makes it easier for users to understand and accept recommended content, and high utility helps users make better choices. This indicates that the information quality of recommended products significantly positively affects consumers' perceived usefulness and convenience[14] [3](Shin et al., 2020; Addison et al., 2022), thereby influencing consumer algorithm trust. Thus, the following hypotheses are proposed:

H2a: The content quality positively affects algorithm trust.

H2b: The expression quality positively affects algorithm trust.

H2c: The utility quality positively affects algorithm trust.

2.3 Algorithm Trust and Purchase Intention

Trust in an entity can be transferred to other entities associated with it, and the closer the relationship between the two, the more likely the transfer is to occur[12](Lim et al., 2006). On short video e-commerce platforms, algorithmic recommendation systems provide personalized product recommendations by analyzing user data. There is a close relationship between recommended products and the algorithmic system. Shin et al. (2020) constructed an algorithm acceptance model, proving the relationship between consumers' perceived algorithm credibility and reliability and their adoption of recommended suggestions[14]. Wien and Peluso (2021) also found that customers' trust in algorithms can be elevated to their purchase intentions for utility products recommended by algorithms[16]. Thus, the following hypothesis is proposed:

H3: Algorithm trust positively affects purchase intention.

2.4 The Mediating Role of Algorithm Trust

High-quality information can significantly enhance consumers' trust and identification with enterprises and their products, thereby effectively stimulating their online purchase intentions[4] [14] [2](Castelo et al., 2019; Shin et al., 2020; Albayrak and Ceylan, 2021). When watching short videos, consumers perceive the quality of recommended information, which leads to positive evaluations of the algorithmic recommendation system and ultimately results in clicking to purchase products recommended by the algorithm. Thus, the following hypotheses are proposed:

H4a: The mediating role of algorithm trust in the relationship between content quality and purchase intention.

H4b: The mediating role of algorithm trust in the relationship between expressiveness quality and purchase intention.

H4c: The mediating role of algorithm trust in the relationship between utility quality and purchase intention.

3 Methods

3.1 Data Collection and Sample Description

Questionnaires were distributed and collected online, resulting in a total of 193 valid responses, with a retrieval rate of 91.5%. Analysis of the sample data revealed a relatively balanced gender ratio, with 54.4% males and 45.5% females; the age group was predominantly under 50 years old, comprising 185 individuals (95.8%); those with a master's degree or higher education constituted a smaller proportion, at only 15%; the majority of respondents had a monthly income ranging from 4001 to 8000, with 100 individuals (51.6%); the majority were employees of companies or self-employed, totaling 110 individuals (56.7%); only 26 individuals (13.4%) reported making purchases more than 11 times per month; 80 individuals (41.2%) used the Douyin platform more than four days per week; and 64 individuals (33.0%) reported using the platform for over two hours each time.

3.2 Variable Measurement

All scales in this study were adopted from established scales domestically and internationally, adjusted according to the specific context, and measured using a 5-point Likert scale. The measurement of content quality, utility quality, and expression quality of information was based on the scale by Wang and Strong (1996), which included 3 items each. Content quality items included statements like "The introduction of recommended products is accurate and free of errors." Utility quality items included statements like "The product features introduced are useful." Expression quality items included statements like "The plot and presentation of the short video are attractive." [15] Algorithm trust was measured using the scale by Shin (2020), with 3 items, such as "I trust the products recommended by the Douyin platform algorithm." [14] Consumer purchase intention was measured using the scale by Dodds (1991), with 3 items, such as "The likelihood of me purchasing products recommended by the Douyin platform is high." [9] To mitigate the impact of other variables on the study, demographic characteristics (gender, age, education, monthly income, occupation), short video purchase experience, platform usage frequency, and duration of each platform use were included as control variables.

3.3 Reliability and Validity Testing

To test the reliability and validity of the questionnaire, reliability analysis was conducted using SPSS 23.0. The data in Table 1 show that the Cronbach's α for all variables was greater than 0.7, indicating good reliability of the questionnaire. Confirmatory factor analysis was also performed on the questionnaire data using AMOS 26.0, and the results showed that the model fit indices were $\chi^2/df=1.351<3$, RMSEA=0.043<0.05, TLI=0.971>0.9, CFI=0.978>0.9, NFI=0.920>0.9, all of which met the ideal values, indicating good model fit. Additionally, as shown in Table 1, the standardized factor loadings (λ) in the confirmatory factor analysis were >0.7, CR>0.6, and AVE>0.5, all of which met the standards, indicating good convergent validity of the questionnaire.

Table 1. Reliability Test Results

Variables	Item	Sta FC	Cronbach's α	C.R.	AVE
Content Quality (CQ)	CQ1	0.711	0.814	0.759	0.512
	CQ2	0.732			
	CQ3	0.704			
Utility Quality(UQ)	UQ1	0.716	0.811	0.772	0.530
	UQ2	0.760			
	UQ3	0.707			
Expression Quality(EQ)	EQ1	0.715	0.804	0.758	0.511
	EQ2	0.704			
	EQ3	0.726			
Algorithm Trust(AT)	AT1	0.818	0.848	0.848	0.651
	AT2	0.793			
	AT3	0.809			
Purchase Intention(PI)	PI1	0.737	0.828	0.831	0.622
	PI2	0.816			
	PI3	0.810			

To compare the internal consistency of the dimensions with their inter-dimensional correlations, Table 2 shows that the internal correlations are greater than the inter-dimensional correlations, indicating good discriminant validity of the data. In summary, the data has good reliability and validity, making it suitable for further analysis.

Table 2. Discriminant Validity Table

	CQ	UQ	EQ	AT	PI
CQ	0.716				
UQ	0.469	0.728			
EQ	0.396	0.411	0.715		
AT	0.389	0.412	0.353	0.807	
PI	0.437	0.441	0.413	0．388	0.788

3.4 Hypothesis Testing

3.4.1 Direct Effect Testing.

Direct effects were examined using multiple linear regression, and the results are presented in Tables 3 and 4. The findings indicate that, with the exception of usage duration, no other control variables have a significant relationship with algorithm trust.

Content quality positively affects purchase intention (β=0.435, p<0.001), confirming hypothesis H1a; it also positively affects algorithm trust (β=0.390, p<0.001), confirming hypothesis H2a. Utility quality positively affects purchase intention (β=0.449, p<0.001), confirming hypothesis H1b; it positively affects algorithm trust (β=0.411, p<0.001), confirming hypothesis H2b. Expressiveness quality positively affects purchase intention (β=0.422, p<0.001), confirming hypothesis H1c; it positively affects algorithm trust (β=0.368, p<0.001), confirming hypothesis H2c. Algorithm trust positively affects purchase intention (β=0.394, p<0.001), confirming hypothesis H3.

Table 3. Hierarchical Regression Results of Information Quality and Algorithm Trust

Variables	Dependent Variable: Algorithm Trust			
	M1	M2	M3	M4
Gender	0.084	0.068	0.079	0.077
Age	-0.047	-0.054	-0.025	-0.073
Education	-0.008	0.004	0.011	0.019
Income	-0.035	-0.033	-0.042	-0.057
Occupation	0.179	0.147	0.115	0.173
Purchase Frequency	0.086	0.099	0.039	0.005
Usage Frequency	0.060	0.081	0.12	0.172
Usage Duration	-0.158	-0.200^{*}	-0.196^{*}	-0.181
Content Quality		0.390^{***}		
Utility Quality			0.411^{***}	
Expression Quality				0.368^{***}
R^2	0.037	0.186	0.200	0.162
ΔR^2	-0.005	0.146	0.161	0.121
F	0.885	4.660^{***}	5.091^{***}	3.939^{***}

Note: $p^{*}<0.05$;$p^{**}<0.01$;$p^{***}<0.001$

3.4.2 Mediation Effect Testing.

Table 4 presents the analysis of the mediating effect. The results indicate that after including the mediating variable algorithm trust, the positive impact of content quality on purchase intention decreases (β=0.333, p<0.001); the positive impact of utility quality on purchase intention decreases (β=0.346, p<0.001); and the positive impact of expressiveness quality on purchase intention decreases (β=0.318, p<0.001). Therefore, algorithm trust plays a partial mediating role between information quality and purchase intention, confirming hypotheses H4a, H4b, and H4c.

Using the Process procedure to test the mediating role of algorithm trust with 5000 bootstrap samples, the results show that at the 95% confidence interval, the mediating effect of content quality through algorithm trust on purchase intention is 0.104, with an asymmetric interval of [0.041,0.177]; the mediating effect of utility quality is 0.108, with an asymmetric interval of [0.046,0.188]; and the mediating effect of expressiveness quality is 0.105, with an asymmetric interval of [0.048,0.170]. All asymmetric intervals do not include 0, further confirming hypotheses.

Table 4. Hierarchical Regression Results of Information Quality and Purchase Intention

Variables	Dependent Variable: Purchase Intention							
	M1	M2	M3	M4	M5	M6	M7	M8
Gender	0.044	0.011	0.026	0.008	0.039	0.019	0.036	0.015
Age	0.114	0.132	0.105	0.119	0.137	0.143	0.083	0.104
Education	0.028	0.031	0.041	0.040	0.049	0.046	0.060	0.054
Income	-0.095	-0.081	-0.092	-0.084	-0.102	0.092	-0.120	-0.104
Occupation	0.008	-0.062	-0.026	-0.065	-0.061	0.090	0.002	-0.047
Purchase	-0.032	-0.066	-0.017	-0.043	-0.083	0.093	-0.124	-0.126
Usage	-0.110	-0.133	-0.086	-0.107	-0.044	0.074	0.019	-0.030
Duration	0.002	0.065	-0.045	0.008	-0.039	0.010	-0.025	0.026
Content			0.435^{***}	0.333^{***}				
Utility					0.449^{***}	0.346^{***}		
Expression							0.422^{***}	0.318^{***}
Trust		0.394^{***}		0.262^{***}		0.251^{***}		0.281^{***}
R^2	0.034	0.183	0.220	0.275	0.229	0.280	0.199	0.265
ΔR^2	-0.008	0.143	0.181	0.235	0.191	0.240	0.159	0.225
F	0.810	4.566^{***}	5.719^{***}	6.909^{***}	6.049^{***}	7.066^{***}	5.043^{***}	6.562^{***}

Note: $p^{*}<0.05$;$p^{**}<0.01$;$p^{***}<0.001$

4 Conclusions

This study, utilizing questionnaire surveys and data analysis, delved into the impact of the quality of algorithmic recommendations on the purchase intentions of users on the Douyin e-commerce platform, with a particular focus on the intricate relationships among information quality, trust in algorithms, and purchase intentions. The findings reveal that the quality of product recommendations on Douyin e-commerce platform significantly strengthens users' trust in the platform's algorithmic technology, encompassing content quality, utility quality, and expressiveness quality, which in turn affects their willingness to purchase products recommended by the platform. The research outcomes not only contribute to the academic discourse on algorithmic recommendations but also offer valuable insights for e-commerce platforms aiming to enhance user experience and boost purchase conversion rates.

However, this study has several limitations that should be acknowledged: (1) The research primarily focuses on the Douyin e-commerce platform. While this platform is highly representative, the conclusions may not be generalizable to other e-commerce or social media platforms. (2) The data were collected exclusively through questionnaire surveys, which could introduce biases, such as respondents' answers being influenced by the survey design or personal biases. Future studies could employ a variety of data collection methods, including user behavior logs and purchase records, to enhance the accuracy and objectivity of the data. (3) The model did not incorporate variables such as perceived risk and personal values, and analyze their complex relationships with algorithmic recommendations and purchase intentions.

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