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RESEARCH ON THE DRIVING PATHS AND MECHANISMS OF USER PURCHASE INTENTIONS IN DOUYIN E-COMMERCE: AN EMPIRICAL ANALYSIS BASED ON REGRESSION MODELS AND STRUCTURAL EQUATION MODELLING

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Abstract

Taking the Douyin e-commerce platform as an example, this paper examines the key factors influencing users' purchase intentions and their underlying mechanisms. Given the diverse platform functionalities and complex user decision-making processes in the current digital consumption environment, this study focuses on four dimensions-algorithmic content, operational convenience, social interactivity, and promotional incentives-and explores how they influence users'overall satisfaction, thereby driving their purchase intentions.

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Based on the "Stimulus-Organism-Response" theoretical framework, data were collected through questionnaire surveys and empirically tested using a combination of regression analysis and structural equation modeling. The results indicate that Douyin's algorithmic content, convenience, interactivity, and incentives significantly enhance user satisfaction and purchase intentions. Among these, the precise recommendations of algorithmic content have the most pronounced impact. More importantly, user satisfaction plays a critical mediating role between these four factors and purchase intentions, suggesting that the emotional resonance generated by optimizing user experience serves as a key bridge in facilitating purchasing behaviour.

This study reveals that, within an integrated e-commerce ecosystem, user satisfaction acts as a core emotional mechanism that consolidates multifaceted platform experiences and ultimately drives consumption. Accordingly, it is recommended that platform operations establish an experience optimization loop centered on satisfaction, promote deep integration between algorithms and social interactions, and implement dynamic marketing strategies based on user segmentation, thereby effectively enhancing user engagement and purchase conversion rates.

Keywords: Douyin E-commerce, user satisfaction, purchase intention, S-O-R theory.

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1. Introduction and Literature Review

With the deep integration of internet technology and social media platforms, the digital marketing landscape has undergone fundamental reshaping. Consumers' decision-making processes are increasingly embedded within a multidimensional ecosystem comprised of algorithms, social interactions, and rich content. In this context, investigating the key factors influencing consumers' purchase intention and their underlying mechanisms holds significant theoretical and practical value for businesses to develop effective marketing strategies and build sustainable competitive advantages [1].

Zhao Dawei and Feng Jiaxin [14], in their study of the Douyin e-commerce platform, pointed out that the interactivity, professionalism, and charisma of e-commerce livestream hosts are crucial factors influencing consumer cognition and decision-making [2]. These characteristics can effectively enhance consumers' purchase intention. Chen Zhiyuan and Cui Lingyu [15] further noted that the professional knowledge and social attributes of e-commerce hosts play an important role in guiding consumers' irrational purchase intention, primarily by enhancing their perceived value [3]. International research provides corroborating evidence. For instance, Lou et al. [16] argued that positive online word-of-mouth can increase consumer trust, perceived quality, and perceived value, thereby simplifying the decision-making process. The empirical study by Jiang et al. [17] confirmed that a host's professional knowledge significantly boosts purchase intention, mediated by online trust and satisfaction.

Chen Caixia et al. [18] and Zhu Yi et al. [19] further analyzed the advantages of such platforms, highlighting that big data capabilities enable precise targeting, while interactive attributes enhance user engagement and cultural adaptability. Research by Chen Qinlan et al. (2023) demonstrated that social media advertising, through a combination of precise targeting, rich content presentation, interactive features, and promotional tactics, can effectively increase consumers' purchase intention. Wang Zongshui et al. [20] also indicated that interactive features on social media, such as likes, comments, and shares, not only deepen brand awareness but can also stimulate purchase desire through the formation of word-of-mouth effects [4].

In summary, existing literature has provided valuable exploration from various contexts and dimensions regarding the stimuli and internal mechanisms through which digital marketing influences consumer purchase intention. It has also proposed practical optimization strategies, laying a solid foundation for understanding digital consumer behaviour.

However, certain limitations and gaps in existing research present opportunities for this study. Firstly, research contexts are often isolated. Most existing studies focus on single scenarios, whereas in reality, consumer decisions frequently occur within integrated platforms like Douyin−an “omnichannel interest-based e-commerce” environment combining short video content, live streaming interaction, algorithmic recommendation, in-app shopping, and social sharing. The compound impact mechanisms of such multi-scenario, multi-stimulus environments on consumer decision-making have not been fully explored. Secondly, there is insufficient focus on a core affective integrative variable. Existing studies often examine specific cognitive variables like trust, value, and risk. However, there is a lack of in-depth empirical investigation into the central mediating role of users' overall affective evaluation-namely, satisfaction-formed after experiencing the platform's complex services, in integrating multiple stimuli and final behavioural intention.

In light of this, this paper takes the “Douyin platform”, a typical integrated digital consumption ecosystem, as the specific research context. It aims to investigate how the platform's four core experiential dimensions-algorithmic content quality, operational process convenience, social interaction atmosphere, and promotional incentive strength-influence users' overall satisfaction and, subsequently, affect their purchase intention.

2. Theoretical Analysis and Research Hypotheses

2.1. SOR theory

The S-O-R theory is a classic theoretical framework in the field of consumer behaviour research. Proposed by Mehrabian and Russell in 1974 based on environmental psychology, it has since been widely applied in marketing, e-commerce, and other fields for analyzing behavioural mechanisms. The core logic of this theory is that stimuli from the external environment affect an individual’s internal psychological state (organism), which in turn triggers corresponding responses. Specifically, stimuli refer to factors in the external environment that can trigger an individual's perception; the organism represents the internal psychological processes generated under the influence of stimuli, serving as the intermediary linking stimuli and responses; and responses refer to the behavioural tendencies or actual behaviours ultimately exhibited by the individual [5].

In the context of marketing and e-commerce, the value of the S-O-R theory lies in its departure from the simplistic linear view that “stimuli directly cause responses.” Instead, it reveals the mediating role of psychological perception in connecting environmental factors and consumption behaviours. This theory provides a clear logical framework for analyzing the internal mechanisms of consumer behaviour and serves as an empirical analytical foundation for businesses to optimize marketing environments and influence consumer decision-making.

2.2. The impact of Douyin platform stimulus factors on user satisfaction

User satisfaction is a core construct that measures users' positive psychological feedback and affective evaluation of their overall experience with a product or service. Within the context of Douyin e-commerce, the diverse functionalities and services provided by the platform constitute external stimuli that directly shape users' experience and cognitive evaluation. Algorithmic content, as Douyin's core competitive advantage, hinges on its accuracy and appeal. When the products, live streams, or short videos recommended by the algorithm are highly aligned with a user's personal interests and latent needs, it not only effectively reduces the user's information search costs but also fosters a sense of "being understood," thereby significantly enhancing satisfaction [6].

Secondly, the convenience of platform operations directly reduces friction and resistance in the transaction process, creating a smooth and efficient shopping journey for the user. This seamless experience serves as a foundational element of user satisfaction. Furthermore, social interactivity fulfills users' needs for social belonging and identity, embedding purchasing behaviour within a network of social relationships, which consequently amplifies the emotional value of the experience and satisfaction. Finally, promotional incentives directly elevate users' perceived value and sense of gain. This economic benefit and feeling of privilege constitute important utilitarian drivers for the formation of satisfaction.

Based on the above theoretical analysis, this study proposes the following hypotheses:

H_1a : Algorithmic content has a significant positive impact on user satisfaction.

H_1b : Convenience has a significant positive impact on user satisfaction.

H_1c : Interactivity has a significant positive impact on user satisfaction.

H_1d : Promotional incentives have a significant positive impact on user satisfaction.

2.3. The Impact of Douyin platform stimulus factors on consumer purchase intention

Purchase intention refers to an individual's subjective probability and inclination to engage in a specific purchasing behaviour. According to the SOR theory, external stimuli can directly trigger behavioural responses. On the Douyin platform, the multi-dimensional functional stimuli drive purchase intention through direct pathways. For instance, precise algorithmic content, by presenting highly relevant product information, can directly stimulate consumer interest and desire, shorten the decision-making process, and foster the formation of impulsive or purpose-driven purchase intentions.

Based on this, this study proposes the following hypotheses:

H_2a : Algorithmic content has a significant positive impact on consumer purchase intention.

H_2b : Convenience has a significant positive impact on consumer purchase intention.

H_2c : Interactivity has a significant positive impact on consumer purchase intention.

H_2d : Promotional incentives have a significant positive impact on consumer purchase intention.

2.4. The impact of consumer satisfaction on purchase intention

Satisfaction, as a comprehensive positive evaluation formed by consumers post-experience, serves as a key antecedent variable for predicting their subsequent behavioural intentions. According to cognitive consistency theory and behavioural intention theory, when users are satisfied with a platform or service, they develop positive attitudes and emotional attachment. This favorable psychological state significantly enhances their future revisit intention, recommendation intention, and willingness to pay. In the context of e-commerce, high satisfaction indicates that users recognize the platform's value and have developed trust in it, thereby substantially reducing their perceived purchase risks. This trust and positive attitude derived from satisfaction directly and powerfully translate into explicit purchase intention. Therefore, this study proposes the following hypothesis:

H_3 : Consumer satisfaction has a significant positive impact on purchase intention.

2.5. The mediating effect of consumer satisfaction

Based on the overall framework of SOR theory, external environmental stimuli (S) can not only directly trigger behavioural responses (R) but may also indirectly influence behaviour by affecting an individual's internal cognitive and affective states (O). In this study, while the various functional stimuli of the Douyin platform (algorithmic content, convenience, interactivity, and promotional incentives) directly affect purchase intention, their impact is likely partially or fully mediated through the key psychological state of "user satisfaction." Therefore, this study proposes the following hypotheses:

H_4a : Satisfaction plays a mediating role in the relationship between algorithmic content and purchase intention.

H_4b : Satisfaction plays a mediating role in the relationship between convenience and purchase intention.

H_4c : Satisfaction plays a mediating role in the relationship between interactivity and purchase intention.

H_4d : Satisfaction plays a mediating role in the relationship between promotional incentives and purchase intention.

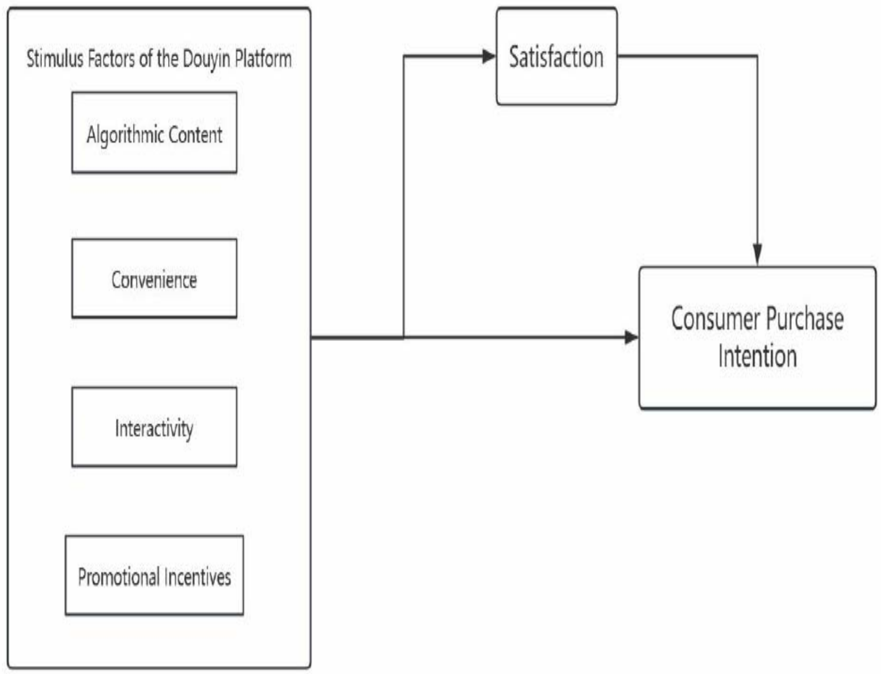

Figure 1. Research model.

3. Empirical Analysis of Users' Purchase Intention in Douyin E-Commerce

3.1. Model construction

This study constructs a theoretical model based on the S-O-R (Stimulus-Organism-Response) framework, aiming to explore how four dimensions of the Douyin platform-algorithmic recommendation content, platform convenience, social interactivity, and promotional incentives-affect purchase intention through consumer satisfaction. Specifically, S represents the various functionalities and services provided by the platform (stimulus factors), O represents the internal psychological state formed by consumers during usage (organism response), and R represents the ultimate behavioural intention (response outcome).

In the context of Douyin shopping, the accuracy of algorithmic content, the convenience of the interface and processes, the functions enabling social interaction, and promotional incentive activities serve as external stimulus factors. They directly influence consumers' usage experience and psychological perceptions, subsequently enhancing satisfaction as an internal psychological state, which ultimately affects purchase intention.

3.2. Variable measurement

Table 1. Measurement items

Algorithmic Content	Recommendation-Interest Match	Q6
	Purchase Impulse from Host's Presentation	Q7
	Persuasion of Host's Outfit	Q8
Convenience	Convenience of Product Links	Q9
	Convenience of Payment Process	Q10
Interactivity	Trust in Recommendations from Friends	Q11
	Influence of Positive Comments	Q12
Incentives	Incentive of Limited-time Discounts	Q13
	Exclusive Benefits for Followers	Q14
Purchase Intention	Frequency of Purchases	Q15
	Amount Spent per Purchase	Q16

3.3. Questionnaire design and data collection

This study employs a questionnaire survey to collect data. The questionnaire was designed based on the S-O-R theoretical framework and tailored to the characteristics of the Douyin platform, integrating the measurement content into four main modules: algorithmic content, convenience, interactivity, and promotional incentives. All measurement items were adapted from established domestic and international scales and assessed using a five-point Likert scale. Prior to the formal survey, a pilot study was conducted to refine the initial questionnaire, with key adjustments focusing on expanding the coverage of income options, enhancing the completeness of behavioural response choices, and improving the clarity of scale descriptions. During the data collection phase, the study targeted internet users with shopping experience on Douyin as the research subjects. A stratified random sampling method was adopted, with sample size allocation based on the population proportion of each district and county, and the minimum sample size was determined using Cochran's formula to be 730. Multiple quality control measures were implemented to ensure data validity, including the use of screening questions, restrictions on duplicate submissions, the exclusion of questionnaires completed in less than 100 seconds, and logical consistency checks. The resulting sample is predominantly composed of young adults aged 21–30, with a balanced gender distribution, providing strong representativeness and a solid foundation for analysis.

4. Statistical Analysis of Users' Purchase Intention in Douyin E-Commerce

4.1. Descriptive statistics

Table 2. Descriptive statistical analysis of the research sample

Indicator	Category	Frequency	Percentage (%)
Gender	Male (Code 1)	361	49.45
	Female (Code 2)	369	50.55
Age	20 and Under (Code 1)	92	12.60
	21-30 (Code 2)	468	64.11
	31-40 (Code 3)	89	12.19
	41-50 (Code 4)	53	7.26
	51 and Over (Code 5)	28	3.84
Monthly Disposable Income	Below ¥1,000 (Code 1)	148	20.27
	¥1,001-¥2,000 (Code 2)	203	27.81
	¥2,001-¥5,000 (Code 3)	226	30.96
	¥5,001-¥8,000 (Code 4)	105	14.38
	Above ¥8,000 (Code 5)	48	6.58
Daily Time Spent on Douyin	Less than 1 hour (Code 1)	135	18.49
	1-2 hours (Code 2)	187	25.62
	2-3 hours (Code 3)	201	27.53
	3-4 hours (Code 4)	128	17.53
	4 hours and above (Code 5)	79	10.82
Purchases in the Past 3 Months	0 times (Coded 1)	186	25.48
	1-2 times (Coded 2)	324	44.38
	3-5 times (Coded 3)	157	21.51
	More than 5 times (Coded 4)	63	8.63
Highest Single Purchase Amount	Below ¥100 (Coded 1)	198	27.12
	¥101-¥300 (Coded 2)	265	36.30
	¥301-¥500 (Coded 3)	172	23.56
	Above ¥500 (Coded 4)	95	13.01

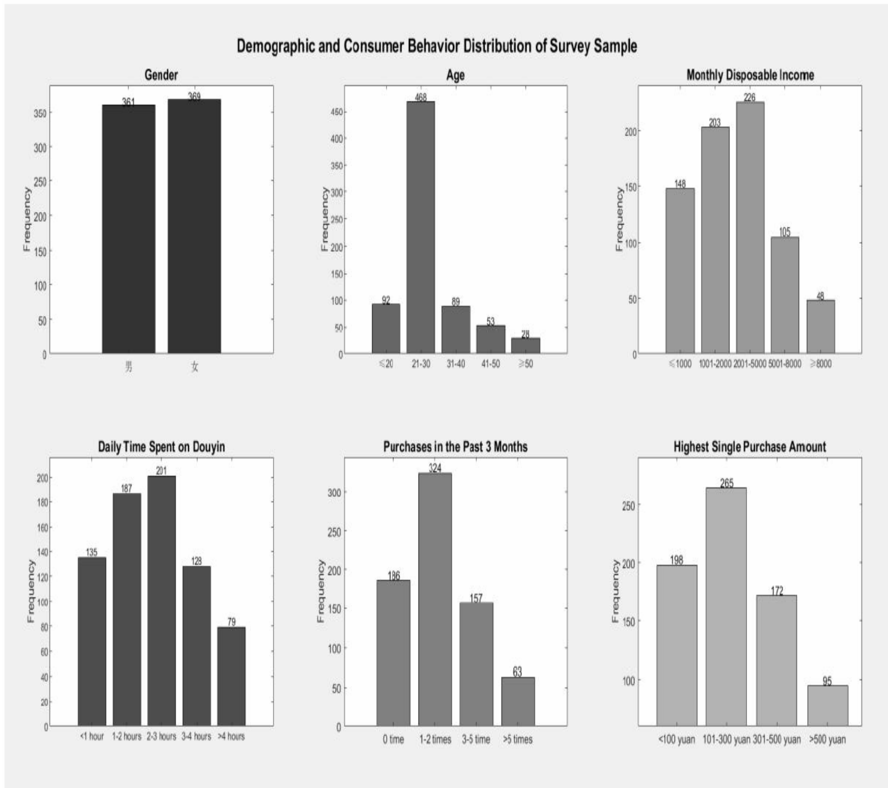

Figure 2. Demographic and consumer behaviour distribution of survey sample.

Table 3. Descriptive statistical analysis of research variables

Variable Group	Item	Mean	Std Deviation Statistic	Skewness Statistic	Skewness Std. Error	Kurtosis Statistic	Kurtosis Std. Error
Algorithm Content	SC1	3.95	0.872	-0.583	0.122	0.291	0.245
	SC2	3.82	0.936	-0.417	0.122	-0.153	0.245
	SC3	3.78	0.905	-0.392	0.122	0.108	0.245
Convenience	OE1	3.65	1.021	-0.286	0.122	-0.327	0.245
	OE2	3.59	0.984	-0.214	0.122	-0.285	0.245
Interactivity	SI1	3.81	0.957	-0.453	0.122	-0.096	0.245
	SI2	3.74	0.923	-0.378	0.122	-0.174	0.245
Incentives	PI1	3.90	0.864	-0.526	0.122	0.254	0.245
	PI2	3.83	0.912	-0.471	0.122	0.186	0.245
Algorithm Content	PW1	3.76	0.948	-0.342	0.122	-0.413	0.245
	PW2	3.68	1.005	-0.279	0.122	-0.356	0.245

4.2. Reliability analysis

Regarding the satisfaction survey questions in the questionnaire, we divided the nine scale items into four groups based on their content, corresponding to the four dimensions of algorithmic content, convenience, interactivity, and promotional incentives. The Cronbach's α coefficient was used to assess the authenticity and reliability of the sample.

Table 4. Reliability test

Construct	Cronbach's α	Number of Items	Interpretation
Algorithm Content	0.914	3	Excellent Scale Reliability
Convenience	0.881	2	Good Scale Reliability
Interactivity	0.863	2	Good Scale Reliability
Incentives	0.851	2	Good Scale Reliability

The Cronbach's α coefficient indicates excellent internal consistency of the scale.

4.3. Validity analysis

4.3.1. Structural validity test

To demonstrate the rationality of the classification, we need to employ factor analysis. For this purpose, prior to conducting the factor analysis, it is necessary to perform the Kaiser-Meyer-Olkin (KMO) Test and Bartlett's Test of Sphericity to determine whether the data are suitable for factor analysis. Subsequently, factor analysis is applied to extract common factors, which are then compared with the four pre-established components to evaluate the appropriateness of the initial grouping.

Table 5. KMO and Bartlett's test of sphericity

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**0.973**
Bartlett's Test of Sphericity	Approx. Chi-Square	7126.090
	df (Degrees of Freedom)	36
	Sig. (Significance)	0.000

The commonly used KMO measure indicates that values above 0.9 denote excellent suitability, 0.8 denotes suitability, 0.7 denotes moderate suitability, 0.6 denotes marginal suitability, and below 0.5 denotes extreme unsuitability. The test results show a KMO value of 0.973, and Bartlett's test of sphericity yields a *p*-value less than 0.05, which is statistically significant. This demonstrates that the collected data are suitable for factor analysis.

Furthermore, the calculated χ^2 value for Bartlett's test of sphericity is 7126.090. At a significance level of 0.05, this allows us to reject the null hypothesis that "the partial correlation matrix among the variables corresponding to each item is not an identity matrix". This indicates the presence of common factors within the overall correlation matrix underlying the surveyed sample population, confirming the suitability of the data for factor analysis.

4.3.2. Factor Analysis Test

Table 6. Total variance explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	Variance %	Cumulative %	Total	Variance %	Cumulative %	Total	Variance %	Cumulative %
1	7.153	79.479	79.479	7.15 3	79.479	79.479	2.60 3	28.920	28.920
2	.287	3.187	82.666	.287	3.187	82.666	1.95 1	21.674	50.594
3	.267	2.961	85.628	.267	2.961	85.628	1.78 3	19.806	70.400
4	.241	2.682	88.309	.241	2.682	88.309	1.61 2	17.909	88.309
5	.225	2.499	90.808						
6	.220	2.449	93.257						
7	.209	2.327	95.584						
8	.208	2.310	97.894						
9	.189	2.106	100.000						

After interpreting the total variance, the cumulative contribution rate of the first four factors reached 88.309%, indicating that they contain sufficient information.

After solving the initial factor model, the factors are generally not easily interpretable. Therefore, rotation is performed. We used the Varimax method to rotate the factor axes, obtaining linear combinations of common factors to express the standardized indicators. This process polarizes the elements in the matrix toward smaller (0) and larger (1) extremes.

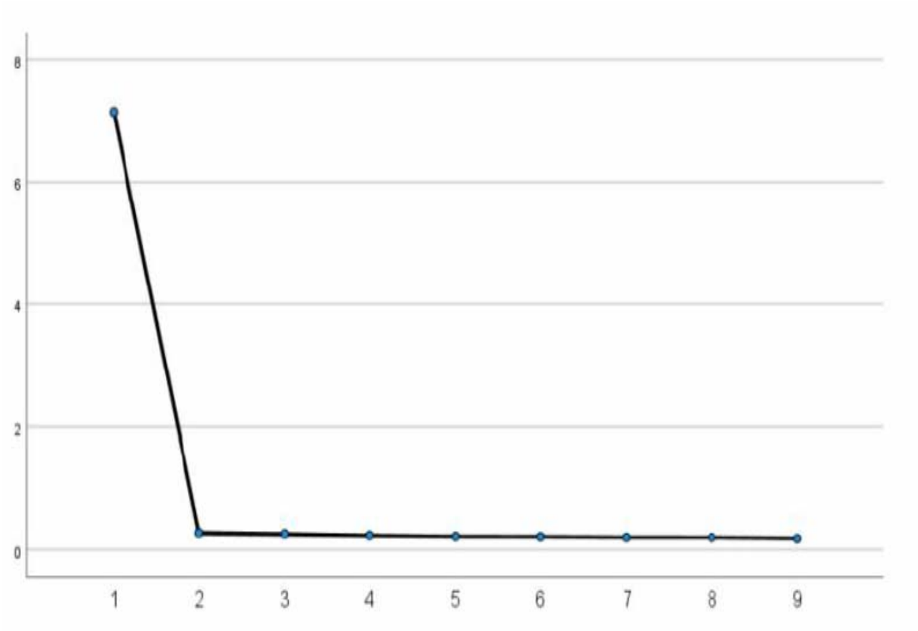

Figure 3. Scree plot

Table 7. Rotated Component Matrix

	Component			
	1	**2**	**3**	**4**
Accuracy of Product Recommendation	0.626			
Live Streaming Interactivity	0.743			
Short Video Attractiveness	0.677			
Product Link Visibility		0.604		
Payment Process Simplicity		0.587		
Sharing with Friends			0.740	
Comment Section Atmosphere			0.612	
Time-limited Discounts				0.766
Exclusive Benefits for Fans				0.675

The above table presents the rotated principal component matrix obtained through orthogonal rotation using the Varimax method. A total of four principal components were extracted, with accumulative contribution rate of 88.309%. Initially, the questionnaire was designed to measure four dimensions of the Douyin platform, including content related to algorithmic content, convenience, interactivity, and promotional incentives, totaling nine items. As can be observed from the calculated rotated component matrix, the extracted four principal components align perfectly with the conceptual framework of the questionnaire scale design. Therefore, it can be concluded that the scale demonstrates good structural validity.

4.4. Run Test

During the actual survey process, it is essential to consider whether the occurrence of sample data is related to sequence in order to determine the independence between data points, thereby ensuring the accuracy and reliability of the analysis results. Here, we use gender to conduct a randomness test on the sample data. For the 730 valid questionnaires, the gender sequence is a binary sequence of 730 observations, consisting of males and females, with 1 representing males and 2 representing females. According to the survey results, there are 358 males and 372 females, with a total of 359 runs. The test statistic for the Runs Test is R, which represents the number of runs.

$X_1, X_2 \ldots X_n$ is a sequence composed of $1s$ and $2s$. The hypothesis testing question is:

H_0 : The gender sequence sample data appear in random order.

H_1 : The gender sequence sample data do not appear in random order.

When $n = 730,\ n_o = 358,\ n_1 = 372:\ R = 359,$ the value of R can be calculated for large sample scenarios.

The approximate normal distribution mean and variance are:

$$E(R) = \frac{2n_0 n_1}{n_0 + n_1} + 1 = 365.8658, \tag{4.1}$$

$$\mathrm{Var}(R) = \frac{2n_0 n_1 (2n_0 n_1 - n_1 - n_0)}{(n_0 + n_1)^2 (n_0 + n_1 + 1)} = 181.61717. \tag{4.2}$$

Thus, it can be concluded that:

$$Z = \frac{R - E(R)}{\sqrt{\mathrm{Var}(R)}} = -0.5095. \tag{4.3}$$

Taking $\alpha = 0.05$, $-1.96 < Z = 0.5095 < 1.96$, the null−hypothesis H_0 cannot be rejected, indicating that

The occurrence of the gender sequence sample data is completely random.

We utilized SPSS software to conduct randomness tests on various categorical variables in the questionnaire. The results indicate that, for most variable sequences, the order of the sample data does not violate the principle of randomness. Therefore, we can conclude that the survey data from this questionnaire exhibit a high degree of randomization, indicating a successful survey.

5. Model Analysis of Users' Purchase Intention in Douyin E-Commerce

5.1. Regression Analysis

5.1.1. Model establishment

To explore the differences in users' willingness to shop on Douyin based on gender, age, monthly disposable income, and duration of Douyin usage, we adopted a binary logistic regression model with “whether the user is willing to shop on the Douyin platform” as the dependent variable. Compared to ordinary linear regression, this model transforms linear predictions into probability values with in the [0, 1] interval using the logit link function, making it more suitable for handling categorical dependent variables [7].

Our dependent variable is "whether the user is willing to shop on the Douyin platform", which is a binary categorical variable. Based on correlation analysis among variables, we selected gender, age, monthly disposable income, and duration of Douyin usage as independent variables. Among these, gender is a binary categorical variable, while the others are ordered multi-categorical variables, requiring dummy variable processing [8]. The following model is established:

$$\log it(P) = In\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k + \varepsilon, \tag{5.1}$$

where P is the probability that a user has purchase intention (Y), β_0 is the intercept term, β_1 to β_k are the regression coefficients, ε is the random error term, X_1 to X_k the independent variables, Based on our selection of independent variables, $k = 4$, Based on this model, we conducted a regression analysis of the data, with the variables defined as follows:

Table 8. Variable definitions

Variable Name	Variable Symbol	Dummy Variable Coding
Willingness to Purchase on the Douyin Platform	Y	$\begin{cases} 1 = \textit{Willing to purchase} \\ 0 = \textit{Unwilling to purchase} \end{cases}$
Gender	Male	$\begin{cases} 1 = \textit{Female} \\ 0 = \textit{Male} \end{cases}$
Age	age 18_25	$age\_18\_25 = \begin{cases} \&1\ 18 - 25 \text{ years old} \\ \&\ 0 \text{ others} \end{cases}$
	age 26_35	$age\,26\_35 = \begin{cases} \&1\ 26 - 35 \text{ years old} \\ \&\ 0 \text{ others} \end{cases}$
	age 36_45	$age\,36\_45 = \begin{cases} \&1\ 36 - 45 \text{ years old} \\ \&\ 0 \text{ others} \end{cases}$
	age_above 46	$age\_above\,46 = \begin{cases} \&1\ 46 \text{ years old and above} \\ \&\ 0 \text{ others} \end{cases}$
		The base category is "under 18 years old"
Monthly Disposable Income	inc_below 500	$inc\_below\,500 = \begin{cases} \&\ 1 \text{ below ¥500} \\ \&\ 0 \text{ others} \end{cases}$
	inc 500-1000	$inc\,500 - 1000 = \begin{cases} \&1 \text{ ¥500 - ¥1000} \\ \&\ 0 \text{ others} \end{cases}$
	inc 1000-1500	$inc\,1000 - 1500 = \begin{cases} \&1 \text{ ¥1000 - ¥1500} \\ \&\ 0 \text{ others} \end{cases}$
	inc 1500-2000	$inc\,1500 - 2000 = \begin{cases} \&1 \text{ ¥500} \\ \&\ 0 \text{ ¥2000} \end{cases}$
		The base category is "Above ¥2000"
Daily Usage T Daily Usage Time on Douyin	time_below 0.5	$time\_below\,0.5 = \begin{cases} \&1 \text{ below 0.5 hours} \\ \&\ 0 \text{ others} \end{cases}$
	time 0.5_1	$time\,0.5\_1 = \begin{cases} \&\ 1\ \ 0.5 - 1 \text{ hours} \\ \&\ 0 \text{ others} \end{cases}$
	time 1_3	$time\,1\_3 = \begin{cases} \&1\ \ 1 - 3 \text{ below} \\ \&\ 0 \text{ others} \end{cases}$
	time 3_6	$time\,3\_6 = \begin{cases} \&1\ 3 - 6 \text{ hours} \\ \&\ 0 \text{ others} \end{cases}$
		The base category is "6 hours and above"

5.1.2. Model results

Table 9. Omnibus test of model coefficients

	Chi-square	Degree of freedom	Significance
Steps	65.428	13	0.000
Block	65.428	13	0.000
model	0.000	13	0.000

According to the results in the table, the significance level in the comprehensive test of model coefficients is <0.05, indicating that the model is valid

Table 10. Hosmer−Lemeshaw test

Steps	Chi-square	Degree of freedoms	Significance
1	6.594	8	0.581

After the Hosmer-Lemeshow test, the chi-square value is 6.594, which is relatively small. A smaller value indicates less discrepancy and better model fit. The significance level is >0.05, demonstrating that the model adequately fits the data.

Based on the principles of binary choice models, a logistic regression analysis was conducted. The results of the analysis are as follows [9]:

Table 11. Regression results of binary logistic model

Explanatory variables	coefficient	Standard Deviation S.E.	Wald statistics	*P*-value	Exp(B)
male(1)	-0.048	0.156	0.094	0.759	0.953
age(1)	-2.150	0.458	22.050	0.000**	0.116
age(2)	-2.128	0.478	19.827	0.000**	0.119
age(3)	-2.076	0.487	18.154	0.000**	0.125
age(4)	-2.479	0.465	28.372	0.000**	0.084
inc(1)	-0.742	0.429	2.997	0.083*	0.476
inc(2)	-0.104	0.329	0.100	0.751	0.901
inc(3)	-0.497	0.258	3.710	0.054*	0.608
inc(4)	-0.444	0.187	5.644	0.018**	0.641
time(1)	-0.029	0.390	0.006	0.940	0.971
time(2)	0.060	0.346	0.030	0.863	1.062
time(3)	0.134	0.316	0.179	0.672	1.143
time(4)	-0.029	0.337	0.007	0.932	0.972
constant	2.206	0.562	15.411	0.000**	9.075

Note: *indicates significance at the 0.1 level; **indicates significance at the 0.05 level.

From the above results, it can be concluded that Douyin platform's algorithmic content, convenience, interactivity, and promotional incentives are all significantly positively correlated with both user satisfaction and consumer purchase intention. Additionally, consumer satisfaction and purchase intention also exhibit a significant positive correlation. Therefore, the hypotheses

H_1a, H_1b, H_1c, H_1d, H_2a, H_2b, H_2c, H_2d, H_3, H_4a, H_4b, H_4c, H_4d, are all validated.

5.2. Structural Equation Modelling

5.2.1. Model development

Structural equation modeling is a model used to examine complex causal relationships [10]. When a model involves a set of independent variables and multiple dependent variables, it is common to formulate a relational equation for each dependent variable to represent its linear relationship with the independent variables. SEM describes the relationships between independent and dependent variables through a path paradigm and expresses the quantities of independent and dependent variables using linear equations [11].

This study utilized Amos software to input questionnaire data and construct a structural equation model (SEM). The structural model can be expressed by the following equation:

$$\eta = \Lambda\eta + \Gamma\xi + \zeta. \tag{5.2}$$

In the formula η represents the value of the latent variable; Λ represents the degree of influence of one latent variable on other latent variables; Γ represents the degree of direct influence of an external variable on the latent variable, ξ represents the value of the external variable, ζ represents an unobservable random error term for the latent variables that cannot be explained by other variables.

We identified four latent variables for consumption behaviour: algorithmic content, convenience, interactivity, and promotional incentives. The mediating variable is consumer satisfaction.

Table 12. Indicator system

Latent variables	Observed variables
Algorithmic content	Product recommendation accuracy
	Live streaming interactivity
	Short video appeal
Convenience	Product link visibility
	Payment process layer simplification
Interactivity	Share with friends
	Comment area atmosphere
Preferential	Limited time discount offer
	Exclusive benefits for fans

5.2.2. Model results

(1) Confirmatory factor analysis

In Structural equation Modelling, it is first necessary to verify the fit of the measurement model, i.e., whether the observed variables effectively reflect the latent variables. The results based on the provided factor analysis are as follows [12]:

The standardized factor loadings for all observed variables are >0.6, indicating that the items have strong explanatory power for the latent variables.

Table 13. CR and AVE

Latent variables	Combined Reliability (CR)	Mean Variance Extraction (AVE)
Algorithmic content	0.92	0.68
Convenience	0.88	0.57
Interactivity	0.85	0.53
Preferential	0.89	0.63

The CR of the latent variables is > 0.7, indicating excellent reliability. The AVE is > 0.5, demonstrating that convergent validity meets the required standards. The measurement model has passed the test, confirming that the observed variables effectively reflect the latent variables. The model exhibits good convergent validity and reliability.

(2) Structural model path analysis

The model was fitted using Amos software. The standardized path coefficients and their significance levels are as follows [13]:

Table 14. Standardized path coefficient table

Path analysis	Normalization coefficient（β）.	*P*-value
Algorithmic content→satifaction	0.72	0.001**
Convenience satisfaction→	0.65	0.001**
Interactive→satisfaction	0.58	0.003**
Preferential→satisfaction	0.61	0.001**
Satisfaction with purchase→intention	0.81	0.001**
Algorithmic content→ purchase intention	0.67	0.001**
Convenience and→willingness to buy	0.74	0.001*
Interactive→purchase intent	0.81	0.001*
Preferential→purchase intention	0.79	0.001*

The value range of β typically falls between−1 and 1, where the sign indicates the direction of influence: a positive sign (+) denotes a facilitating effect, while a negative sign (−) indicates an inhibitory effect. The absolute value of β indicates the strength of the effect—the larger the absolute value, the more significant the influence. A p-value < 0.05 denotes significance at the 95% confidence level (often marked with *). A p-value < 0.01 denotes high significance at the 99% confidence level (often marked with **). A p-value < 0.001 denotes extreme significance at the 99.9% confidence level (often marked with ***).

As shown in the table, the standardized coefficients of algorithmic content, convenience, interactivity, and promotional incentives on satisfaction are 0.72, 0.65, 0.58, and 0.61, respectively. Meanwhile, the standardized path coefficients of algorithmic content, convenience, interactivity, and promotional incentives on purchase intention are 0.67, 0.74, 0.81, and 0.79, respectively, with all p-values less than 0.01. This indicates that algorithmic content, convenience, interactivity, and promotional incentives have significant positive correlations with both satisfaction and consumer purchase intention at the 99% confidence level. The standardized coefficient of satisfaction on purchase intention is 0.81,with a p-value less than 0.01, indicating a significant positive correlation between satisfaction and consumer purchase intention at the 99% confidence level. Therefore, the hypotheses. H_1a, H_1b, H_1c, H_1d, H_2, H_3a, H_3b, H_3c, H_3d, have all been verified.

(3) Model fit evaluation

Table 15. Model fit evaluation table

Chi-square/degrees of freedom ($\frac{\chi^2}{df}$).	**2.35**	**Acceptable**
RMSEA	<0.08	Good
CFI	>0.9	Excellent
TLI	>0.9	Excellent

The overall model fit is excellent, effectively explaining the relationships among the variables.

5.3. Mediation effect analysis

To verify whether the influence of "algorithmic content, convenience, interactivity, and promotional incentives" on "purchase intention" is mediated through "satisfaction", this study employed the Bootstrap resampling method. The results are shown in Tables 5−9.

Table 16. Mediation effect test table

Intermediary path	**Effect type**	**Effect value**	**BootCI lower limit**	**BootCI limit**	***p*-value**
Algorithmic content→satisfaction→purchase intent	Indirect effects	0.58	0.42	0.75	0.004**
Convenience→satisfaction→purchase intent	Indirect effects	0.53	0.37	0.68	0.002**
Interactivity→satisfaction→purchase intent	Indirect effects	0.47	0.31	0.63	0.001**
Preferential→satisfaction→willingnes s tobuy	Indirect effects	0.47	0.35	0.65	0.001**

The significance of the mediation effect is determined based on whether the 95% Bootstrap confidence interval (Boot CI) excludes zero (i.e., both the lower and upper limits do not include zero). As shown in Table 5-9, the indirect effect values of the four mediation pathways range between 0.47 and 0.58, with the corresponding 95% BootCI lower and upper limits both greater than zero, and all p-values less than 0.01. This indicates that the mediating role of satisfaction between algorithmic content, convenience, interactivity, promotional incentives, and purchase intention is statistically significant.

Further comparing the effect strengths reveals that the indirect effect of “algorithmic content→satisfaction→purchase intention” is relatively the highest, meaning that algorithmic content exerts the strongest indirect driving force on purchase intention. The indirect effects of “interactivity→satisfaction→purchase intention” and “promotional incentives→satisfaction→purchase intention” are identical, suggesting that their impact on purchase intention through satisfaction is similar in magnitude.

These results demonstrate that satisfaction is a key mediating variable linking platform experience dimensions to user purchase intention. Optimizing platform experiences such as algorithmic content and convenience can effectively enhance user purchase intention by improving user satisfaction as an intermediate mechanism. This provides empirical evidence for refining future platform operational strategies.

6. Research Conclusions and Recommendations

6.1. Research conclusions

Based on users’ purchasing behaviours on the Douyin platform, this study constructed a research model examining the impact of four dimensions: algorithmic content, convenience, interactivity, and promotional incentives-on consumer purchase intention. A questionnaire survey was conducted, and empirical analysis was performed on the collected data, leading to the following conclusions.

First, all four dimensions of the Douyin platform-algorithmic content, convenience, interactivity, and promotional incentives-significantly and positively influence user satisfaction and consumer purchase intention, with algorithmic content having the most pronounced impact. This is because algorithms directly determine the precision and element of surprise in “goods finding people”, serving as the primary touch point to stimulate user interest and immersive experiences. Second, user satisfaction plays a critical mediating role in the influence of algorithmic content, convenience, interactivity, and promotional incentives on consumer purchase intention. As a holistic evaluation of users' functional, emotional, and cognitive experiences with the platform, satisfaction successfully integrates multidimensional stimuli and translates them into behavioural intentions. Its mediating role is more fundamental than the direct influence of any single dimension. Third, satisfaction itself also significantly and positively affects consumer purchase intention, acting as a direct and powerful emotional engine driving behaviour.

6.2. Research recommendations

Based on the research conclusions, this paper proposes the following core recommendations for the Douyin platform across three dimensions: operations, user experience, and marketing.

6.2.1. Establish a “satisfaction-oriented” experience optimization loop

Establish “Overall User Satisfaction” as the core North Star metric. In the data backend, create a real-time analytics dashboard that correlates experience indicators such as algorithm accuracy and interaction fluency with satisfaction data. Use this dashboard as the key evaluation criterion for A/B testing of new features, ensuring that all optimizations ultimately serve to enhance users' emotional experience.

6.2.2. Promote the deep integration of algorithms and interactivity

Elevate algorithms from precise recommendations to contextualized storytelling, integrating products naturally into recommendations based on users' real-time scenarios and video content. Simultaneously, leverage AIGC technology to enhance the personalization and emotional depth of AI customer service and virtual hosts, transforming their role from functional responders to personalized companions, thereby deepening interactive immersion.

6.2.3. Implement dynamic marketing strategies based on user segmentation

Implement refined operations based on the significant age differences revealed by the research. For young, high-intent core users, leverage AIGC to rapidly generate trend-aligned content to reinforce their sense of identity. For mature users with low purchase intent, focus on delivering authoritative content with high trustworthiness to facilitate cautious conversion. Simultaneously, develop an AIGC system capable of automatically generating marketing content tailored to users' real-time behaviours and emotional states, achieving instant, personalized engagement at scale.

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