

Algorithm Transparency and Its Impact on Mobile App User Experience: A YouTube Case Study

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Abstract: This study examines the relationship between transparency perception and trust in video content consumption and further discusses the mediating role of trust between perceived transparency and purchase intention. The impact of transparency perception on trust was evaluated using a linear regression model. The regression model revealed that for every 1 unit increase in transparency perception, trust increases by 0.494 units ($p < 0.01$). The model's R-squared value of 0.251 indicates that transparency perception explains 25.1% of the variation in trust. In addition, demographic trends in video platform usage, including frequency of use and content preferences, were analyzed. Finally, reliability and validity tests supported the robustness of the measurement tools, with Cronbach's α coefficients of 0.876, 0.877, and 0.847 for transparency perception, trust, and purchase intention, respectively. A mediating effect of trust on the relationship between transparency perception and purchase intention was also found, which means that improving transparency perception can improve trust and further affect purchase intention through trust.

Keywords: Transparency perception, trust, purchase intention, regression analysis, video content

1. Introduction

With the prevalence of self-media platforms, the role of algorithms in personalized recommendations for mobile apps is highly noteworthy. Adithya Madhusoodanan et al. argue that the platform pushes customized content by analyzing user behavior data such as browsing history, likes, and comments, greatly enhancing the user experience and commercial value. [1]

However, mobile app notifications also have drawbacks. Sumaiya Deen Muhammad et al. suggest that users may face large amounts of uninterested information and advertisements, which can distract them when they are engaged in important tasks. [2]

Moreover, users' awareness of data security and privacy protection is rising, making the transparency of algorithm recommendations a critical issue. Concerns around consumer trust, decision bias, and ethical controversies have emerged, particularly regarding whether users can trust the fairness and authenticity of recommended content. Another intriguing research question is the impact of recommendation algorithms on guiding users toward impulsive and unnecessary purchases. Additionally, scholars are concerned about whether personalized recommendations strengthen information cocoons, limiting consumers' choices.

2. Literature Review

Jognwoo Kim et al. studied a personalized recommendation system for mobile applications. The system aimed to analyze user preferences by examining the common attributes between target members and their social members. [3] They developed a prototype using Ontology Web Language, demonstrating the algorithm's feasibility and analyzing mobile users' preferences.

Algorithm transparency refers to the level of understanding that users have about algorithm logic and data processing, including interpretability and operability. René F. Kizilcec built on information processing and procedural justice theory, dividing the impact of transparency on trust into two stages. This study suggests increased transparency may enhance user trust, but excessive disclosure of complex information can lead to cognitive burden, implying that transparency should be balanced to increase trust.

Consumer trust, influenced by the authenticity of algorithm recommendations, brand image, and user experience, can also affect app users' consumption intentions and attitudes toward brands. Siva Simhadri and Sudip Vhaduri conducted a comprehensive study of trust across various app types and channels through which users discover apps. Their research found that professional recommendations boosted trust, particularly for health and payment apps, suggesting that app developers need to consider specific recommendation groups when marketing their applications. [4]

In recent years, studies on consumer behavior, particularly regarding privacy, security, and data use in smartphone apps, have gained prominence. Soo Ling Lim et al. found significant differences in user behavior across countries, revealing preferences regarding the appearance, functionality, and price sensitivity of applications. [5]

2.1. Research Innovation

This study introduces technological literacy as a moderating factor, providing a foundation for managing different user groups. Consumers will be grouped based on their level of technological literacy to study how this influences their trust and attitude toward using apps. Technological literacy can be quantified using variables such as years of education, educational background, or major.

Another innovation lies in the experimental methods. By simulating real platform scenarios and varying transparency levels, the study will enhance ecological validity. A virtual self-media platform will be designed to display recommended products with different algorithm explanations for various user groups. This flexibility will allow respondents to engage with the platform at their convenience, ensuring more authentic behavior.

Lastly, the study expands beyond previous research's narrow focus on algorithm performance to explore the broader impact of transparency on consumer behavior. The study will use an inter-group comparative experiment with three levels of transparency: completely transparent, partially transparent, and completely black box. Participants will receive varying levels of explanation for algorithm recommendations, allowing the study to assess transparency's impact on consumers' cognition, interest, and purchase intention using the AIDA model.

2.2. Expected Results

This research was conducted through an online questionnaire from January 1st, 2025 to January 5th, 2025, with a period of 5 days. Research targeted users of short-video platforms. A total of 120 questionnaires were distributed both online and offline, with 107 valid responses, resulting in an effective response rate of 89.17%. This research conformed to the ratio requirement that the number of test items and the number of questionnaires in the reliability and validity analysis should not be lower than 1:5, thus the sample size was adequate.

After obtaining the data, the following steps will be taken:

Data Preprocessing: Results from the questionnaire will be entered into Excel for preliminary checks and cleaning. Missing values will be handled using the mean imputation method.

Statistical Analysis: Data will be analyzed using SPSS, with basic statistics such as mean, standard deviation, and frequency distributions of transparency perception, consumer trust, and purchase intention. Pie charts and bar charts will be used to visualize the sample characteristics, such as gender and age distribution.

Correlation and Regression Analysis: Correlation analysis, variance analysis, and simple regression analysis will be conducted. The expected results include a significant positive impact of algorithm transparency on consumer trust and purchasing intentions.

3. Empirical analysis results

3.1. Demographic information distribution

In the demographic frequency analysis results. First, in terms of gender distribution, male and female users are almost evenly divided, with female users slightly more dominant, accounting for 51.40%.

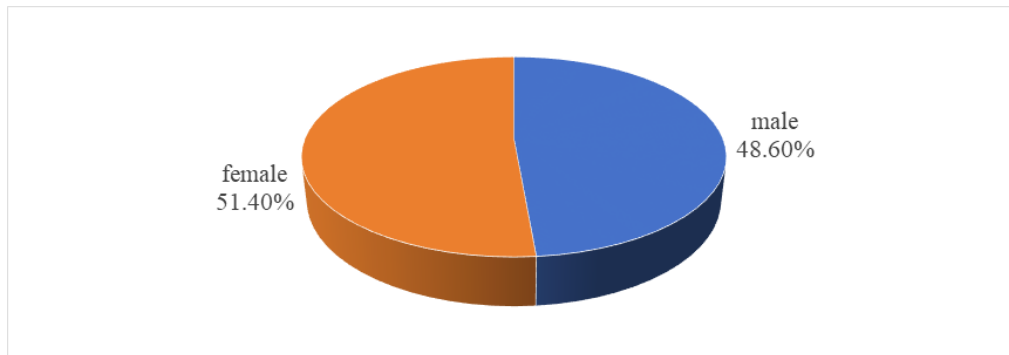


Figure 1: Gender distribution of the sample

In terms of age distribution, the user group aged 18-25 is the largest, accounting for 31.78%, which reflects the strong demand of young people for video content. At the same time, users aged 26-35 also account for a certain proportion, reaching 29.91%, indicating that the middle-aged group also has a high degree of attention to video content. The user groups under 18 and 36 and above are relatively small.

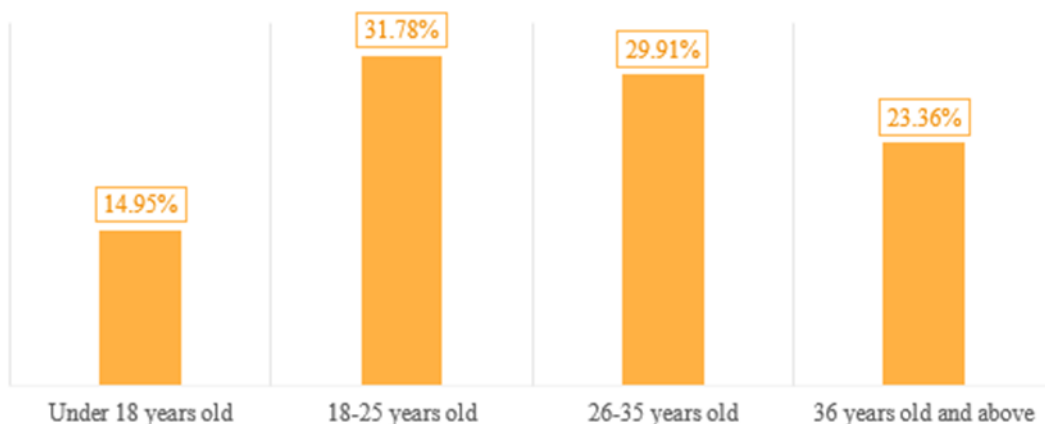


Figure 2: Age distribution of the sample

In terms of occupational distribution, corporate employees and freelancers account for a considerable proportion, which is 47.66% and 23.36% respectively. There are also a certain number of students and users from other professions.

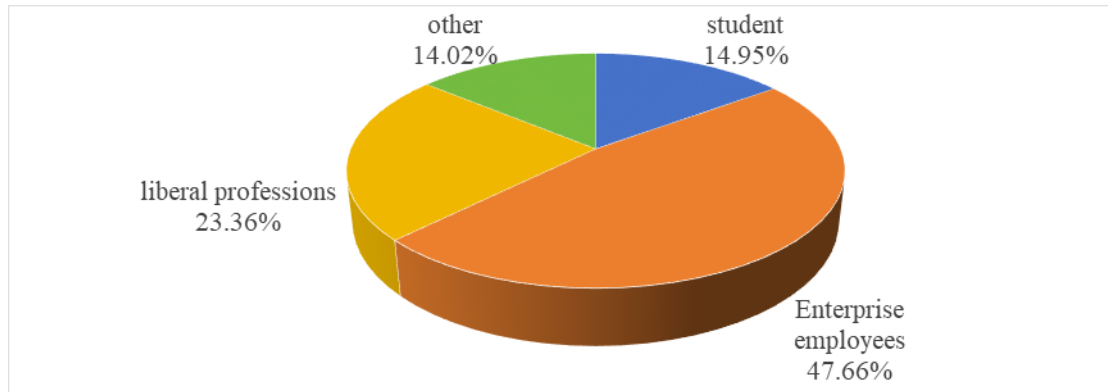


Figure 3: Occupational distribution of the sample

In terms of platform usage frequency, daily users account for the highest proportion, reaching 43.93%. This shows that users are highly dependent on and sticky to YouTube. More than 20% of users use it several times a week or several times a month and are users who regularly browse video content, while the number of users who use it occasionally is relatively small.

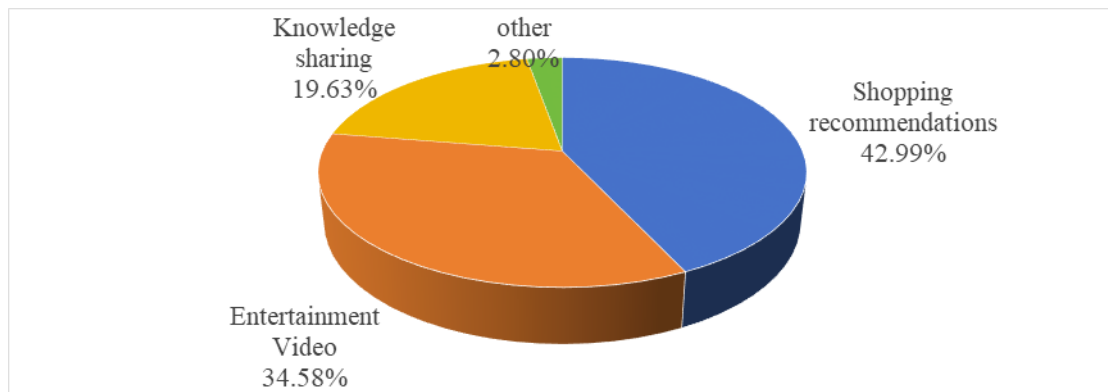


Figure 4: the content focus of the sample

In terms of the most frequently viewed content types, shopping recommendations, and entertainment videos took the top two spots, accounting for 42.99% and 34.58% respectively, reflecting users' strong interest in these two types of content. Knowledge sharing and other types of content accounted for a smaller proportion.

3.2. Reliability Analysis

In the range of Cronbach's α coefficient, the α coefficient ranges from 0 to 1. Reliability above 0.70 is generally considered to be an ideal reliability, indicating that the scale has high reliability. Between 0.60 and 0.65, the reliability is low and it is recommended to avoid using it unless it has to be used in specific circumstances. 0.65 to 0.70 is the lowest acceptable reliability, but it may affect the explanatory power of the results. It is best to further optimize the scale. 0.70 to 0.80 is a higher reliability level, which is generally considered to have good stability and consistency. 0.80 to 0.90 is a very reliable reliability level, indicating that the scale is very consistent and suitable for more rigorous research. In the dimensions of transparency perception, trust, and purchase intention, the

reliability levels of 0.876, 0.877, and 0.847 were obtained respectively, which shows that the scales of these dimensions have good internal consistency when measuring and can be used as reliable indicators for subsequent analysis.

Table 1: Reliability Analysis

Dimensions	Questionnaire content	Correction Total Correlation	α coefficient with term deleted	Cronbach's α
Perception of transparency Trust Dimensions	I understand how the platform recommends content	0.759	0.830	0.876
	The platform discloses the basic principles of the recommendation algorithm to users	0.756	0.831	
	I can choose to adjust the preferences of recommended content (such as tags, areas of interest)	0.720	0.846	
	The platform's recommended content meets my expectations	0.697	0.854	
Perception of transparency Trust Dimensions	I trust the content recommended by the platform	0.787	0.823	0.877
	I believe that the content recommended by the platform meets my real needs	0.668	0.869	
	I believe that the platform will not abuse my personal data	0.789	0.821	
	The platform can objectively recommend high-quality goods or services	0.712	0.852	
Perception of transparency	I am willing to buy products recommended by the platform	0.614	0.835	0.847
	The content recommended by the platform makes me want to buy	0.672	0.811	
	If my friends need it, I will recommend the goods or services on the platform	0.718	0.790	
	I have actually purchased under the recommendation of the platform	0.733	0.784	

3.3. Validity analysis

In the variable validity analysis, the KMO value range is [0,1]. The larger the value, the more suitable the selected sample is for factor analysis (>0.6 is the minimum threshold). In this sample, the KMO values of transparency perception, trust, and purchase intention are 0.828, 0.828, and 0.809, respectively. All three values are greater than 0.6, indicating that the sample has good internal consistency and is suitable for the numerical standard of factor analysis.

Table 2: Validity Analysis

Dimensions	Questionnaire content	Factor loading	CR	KMO coefficient
Perception of transparency Trust Dimensions	I understand how the platform recommends content	0.871	0.759	0.828
	The platform discloses the basic principles of the recommendation algorithm to users	0.869	0.756	
	I can choose to adjust the preferences of recommended content (such as tags, areas of interest)	0.844	0.713	
	The platform's recommended content meets my expectations	0.830	0.688	
Perception of transparency Trust Dimensions	I trust the content recommended by the platform	0.888	0.789	0.828
	I believe that the content recommended by the platform meets my real needs	0.806	0.649	
	I believe that the platform will not abuse my personal data	0.889	0.790	
	The platform can objectively recommend high-quality goods or services	0.837	0.701	
Perception of transparency	I am willing to buy products recommended by the platform	0.775	0.600	0.809
	The content recommended by the platform makes me want to buy	0.820	0.673	
	If my friends need it, I will recommend the goods or services on the platform	0.852	0.726	
	I have actually purchased under the recommendation of the platform	0.863	0.744	

3.4. Difference analysis

From the difference analysis in Table 2, it can be observed that there are individual differences in the impact scores of the fully transparent, partially transparent, and completely black box groups on respondents' transparency perception, trust, and purchase intention. The grouping is significant at the 0.01 level of transparency perception ($F=10.639$, $p<0.01$). Therefore, the score comparison results are: fully transparent group>completely black box group; partially transparent group>completely black box group.

The result of the trust group significance test is $F=8.439$, $p<0.01$, and the comparison results are: fully transparent group>partially transparent group; fully transparent group>completely black box group.

The result of the purchase intention group significance test is $F=5.032$, $p=0.008<0.01$, and the comparison results are: fully transparent group>completely black box group.

Table 3: ANOVA of different groups on transparency perception, trust level, and purchase intention

	Category (M±SD)			<i>F</i>	<i>p</i>
	Completely transparent group(<i>n</i> =48)	Partially transparent group(<i>n</i> =30)	Completely black box group(<i>n</i> =29)		
Transparency perception	4.03±0.88	3.96±0.75	3.04±1.24	10.639	0.000
Trust level	4.24±0.72	3.67±1.11	3.34±1.14	8.439	0.000
Purchase intention	4.07±0.87	3.77±0.90	3.37±1.06	5.032	0.008

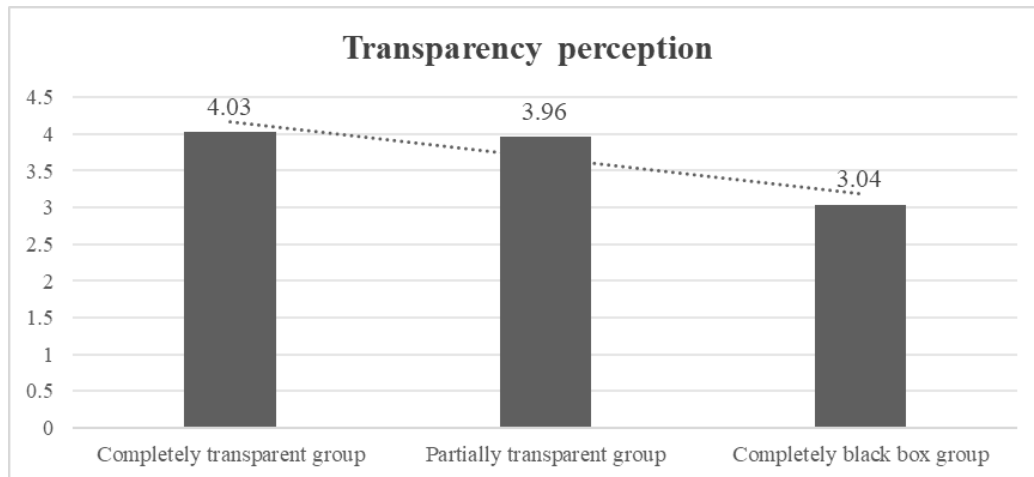


Figure 5: Transparency perception of respondents

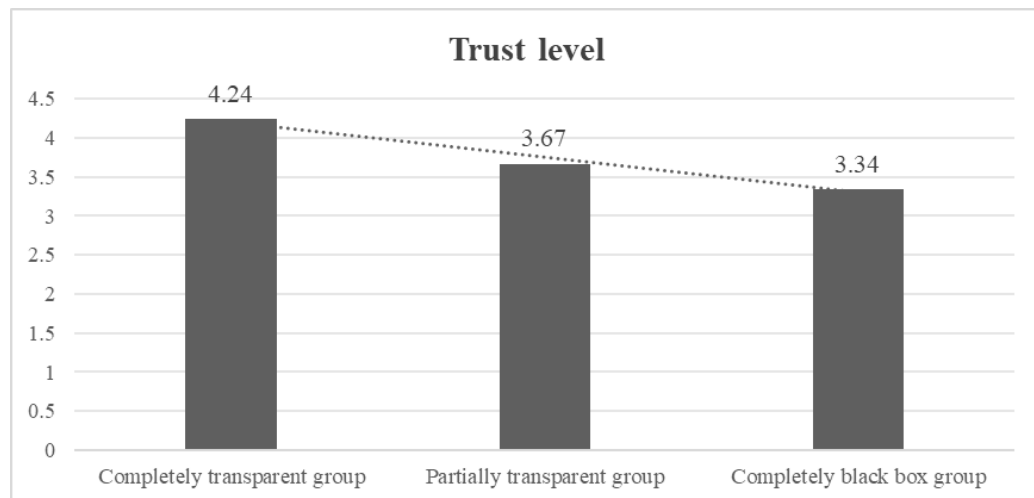


Figure 6: Trust level of respondents

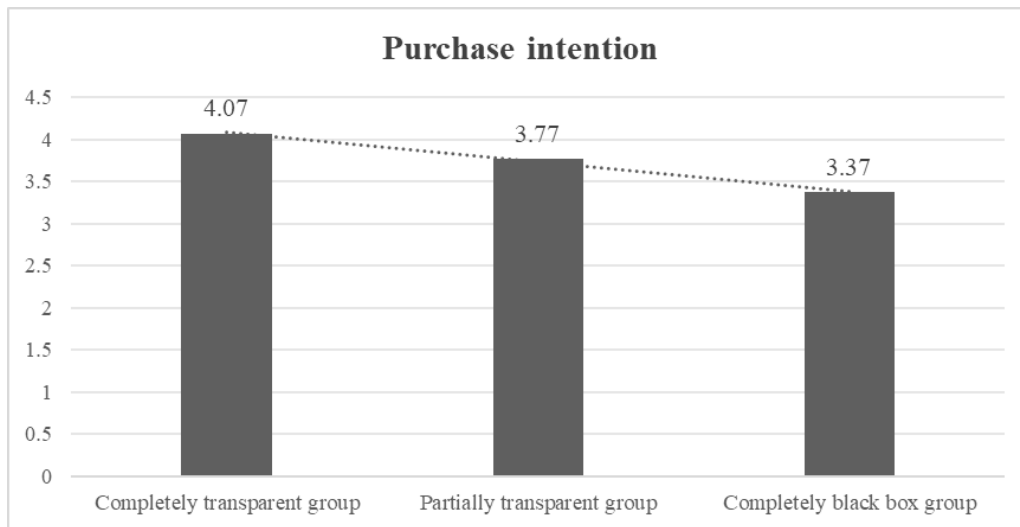


Figure 7: Purchase intention of respondents

3.5. Correlation analysis

Table 4 shows the correlation between transparency perception, trust, and purchase intention. From the results in the fourth column, it is found that the correlation coefficient between transparency perception and trust is 0.501 ($p < 0.01$), indicating that the two variables have a strong positive correlation, while the correlation coefficient between transparency perception and purchase intention is 0.605 ($p < 0.01$), which also has a strong positive correlation.

Table 4: Pearson correlation

	Mean	Standard Deviation	Transparency perception	Trust level	Purchase intention
Transparency perception	3.743	1.043	1		
Trust level	3.836	1.029	0.501**	1	
Purchase intention	3.797	0.970	0.605**	0.462**	1

* $p < 0.05$ ** $p < 0.01$

3.6. Regression analysis

In the linear regression, transparency perception is the independent variable and trust is the dependent variable. The regression model formula is:

$$Trust = 1.986 + 0.494 \times Transparency\ Perception$$

The intercept term (1.986) indicates that when the transparency perception is 0, the expected value of trust is 1.986. The regression coefficient (0.494) indicates that for every 1 unit increase in the transparency perception, the expected value of trust increases by 0.494 units. The R-squared value = 0.251 indicates that the transparency perception of the respondents in the sample explains more than a quarter of the variation in trust. $F = 35.189$, $p < 0.01$, the entire regression model is highly significant. Since the value is less than 0.01, it shows that in this model, the transparency perception of the respondents has a statistically significant predictive effect on trust.

Table 5: Linear regression analysis results of transparency perception on trust n=10

	Unstandardized coefficients		Standardized coefficients	t	p
	B	Standard error	Beta		
constant	1.986	0.324	-	6.136	0.000
Transparency perception	0.494	0.083	0.501	5.932	0.000
R ²			0.251		
Adjusted R ²			0.244		
F			F (1,105)=35.189,p=0.000		
D-W value			1.707		

Note: Dependent variable: Trust level

* p<0.05 ** p<0.01

3.7. Mediating effect analysis

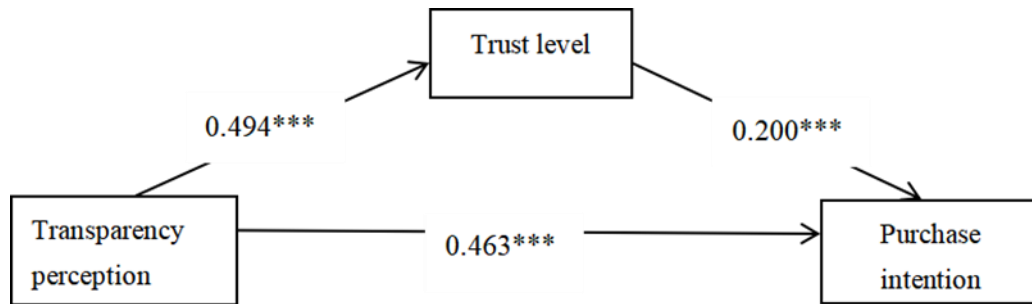


Figure 8: The mediating effect model of trust in transparency perception on purchase intention

In studying the mediating effect of trust on transparency perception and purchase intention, we first regressed transparency perception and purchase intention, and found that transparency perception has a significant positive impact on purchase intention; then we regressed transparency perception and trust and found that transparency perception can positively affect trust. Finally, we regressed transparency perception and trust with purchase intention at the same time and found that both transparency perception and trust have a significant positive impact on purchase intention.

Table 6: A model test of the mediating effect of trust on transparency perception and purchase intention

	Purchase intention	Trust level	Purchase intention
constant	1.692** (6.023)	1.986** (6.136)	1.294** (4.044)
Transparency perception	0.562** (7.778)	0.494** (5.932)	0.463** (5.674)
Trust level			0.200* (2.417)
N	107	107	107
R ²	0.366	0.251	0.399
AdjustedR ²	0.360	0.244	0.388
F value	F (1,105)=60.498,p=0.000	F (1,105)=35.189,p=0.000	F (2,104)=34.564,p=0.000
* p<0.05 ** p<0.01, () is the t value			

The indirect effect and confidence interval of the path "transparency perception → trust → purchase intention" were tested using the PROCESS plug-in of SPSS. The results showed that the indirect effect value of the path above is 0.099, with a confidence interval [0.013-0.244] ("0" is not included). Therefore, it can be inferred that in the collected samples, the trust of the respondents played a partial mediating role in the process of their transparency perception affecting purchase intention.

Table 7: Results of the mediation test

Test	meaning	Effect size	95% CI		z-value/ t-value	p-value	Effect results
			Lower limit	Upper limit			
Transparency perception=>Trust level=>Purchase intention	Indirect effects	0.099	0.013	0.244	1.677	0.094	Partial mediation effect
Transparency perception=>Trust level	X=>M	0.494	0.331	0.658	5.932	0.000	
Trust level=>Purchase intention	M=>Y	0.200	0.038	0.362	2.417	0.017	
Transparency perception=>Purchase intention	Direct Effect	0.463	0.303	0.624	5.674	0.000	
Transparency perception=>Purchase intention	Total Effect	0.562	0.421	0.704	7.778	0.000	

The results of this survey indicate that there are significant differences in the scores of transparency perception, trust level, and purchase intention among the fully transparent, partially transparent, and completely opaque groups. Transparency perception has a significant positive impact on trust levels. Trust level plays a partial mediating role in the influence of algorithm transparency on purchase intention. The level of algorithm transparency has a significant impact on the trust level and purchase intention of respondents. The fully transparent group scored higher than the partially transparent group and the completely opaque group in terms of transparency perception, trust level, and purchase intention, indicating that respondents are more inclined to trust products or services with high algorithm transparency. Meanwhile, the partially transparent group also scored higher than the completely opaque group in all three indicators, further demonstrating the importance of transparency in enhancing trust level and purchase intention. There is a significant positive relationship between transparency perception and trust level, meaning that the higher the transparency, the higher the trust level of respondents. This suggests that increasing the transparency of algorithms can help enhance the trust of respondents in algorithms or products. Trust level plays a partial mediating role in the influence of algorithm transparency on purchase intention, indicating that transparency not only directly affects purchase intention but also indirectly influences it through its impact on the trust level. Therefore, algorithm transparency has a significant effect on enhancing the trust level and purchase intention of respondents. When designing and applying algorithms, enterprises should focus on improving the transparency of algorithms to enhance consumers' trust and purchase intention.

4. Conclusion

This study underscores the critical role that transparency perception plays in fostering trust and driving consumer purchase intentions in digital platforms. The findings, derived from regression and mediation analyses, offer robust evidence that transparency perception has a direct, positive effect on trust. This trust, in turn, significantly influences consumers' intentions to purchase, establishing transparency as a key factor in enhancing consumer engagement and behavior.

The linear regression model demonstrated that transparency perception is a strong predictor of trust, with an R-squared value of 0.251, signifying that more than a quarter of the variation in trust is explained by transparency perception. The significant p-value ($p < 0.01$) further reinforces the statistical validity of the model. This relationship aligns with previous research that highlights transparency as a cornerstone of building consumer trust, particularly in e-commerce and digital content consumption.

Moreover, the mediating effect analysis revealed that trust partially mediates the relationship between transparency perception and purchase intention. This suggests that while transparency perception directly affects purchase intentions, trust plays a crucial intermediary role in shaping consumer decisions. This finding is particularly relevant for marketers and businesses aiming to optimize their digital platforms and enhance consumer loyalty.

Additionally, the study identified demographic patterns that could further inform marketing strategies. For instance, younger consumers (ages 18-35) were found to engage more actively with digital platforms, particularly about content consumption. This insight suggests that businesses targeting this demographic may benefit from increasing transparency in their communications to build trust and drive engagement.

While the current research has provided valuable insights into the relationship between transparency, trust, and purchase intention, several avenues for future research remain. First, it would be beneficial to explore the role of other potential mediators, such as perceived value or perceived quality, in the transparency-trust-purchase intention relationship. Further investigation could also examine how transparency influences consumer behavior across different industries, such as finance, health care, or retail, where the stakes of trust and information sharing may vary significantly. Additionally, cross-cultural studies could provide a broader perspective on how transparency is perceived and valued in different global markets.

In conclusion, this study contributes to the growing body of knowledge on consumer behavior in the digital age. By emphasizing the importance of transparency in building trust and driving purchase intention, the findings provide actionable insights for businesses seeking to strengthen their relationships with consumers. By prioritizing transparency in their communication strategies, businesses can enhance trust, foster loyalty, and ultimately drive greater consumer engagement and sales.

Acknowledgments

Hongyi Liu contributed to this work and should be considered the first author. I sincerely thank all those who have assisted me in this paper.

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Appendix

Questionnaire content:

Consumer behavior under the transparency level

Dear Sir/Madam:

Hello! This questionnaire is mainly to investigate the differences in consumer behavior under different levels of transparency. Thank you very much for your cooperation in completing the following questionnaire. All questionnaire information is anonymous, please do not worry! Your active cooperation will enable us to obtain valuable first-hand information. I believe that with your great help, we will be able to obtain good research results. We assure you that all the materials we obtain will only be used for academic research, will not involve your privacy, and will not disclose your answers.

Informed Consent

If you agree to participate in this survey, please tick the following options to agree. If you disagree, the answer sheet will be automatically submitted.

☐ Agree ☐ Disagree

Basic Information

1. Your gender:
A. Male B. Female C. Other
2. Your age:
A. Under 18 B. 18-25 C. 26-35 D. 36 and above
3. Your occupation:
A. Student B. Corporate employee C. Freelance D. Other
4. How often do you use the platform:
A. Every day B. Several times a week C. Several times a month D. Occasionally
5. The type of content you most often follow:
A. Shopping recommendations B. Entertainment videos C. Knowledge sharing D. Other
6. Which of the following categories do you belong to?
A. Completely transparent group

In this category, you will be able to fully understand the recommendation logic of the platform for pushing products to you (including details, data basis, algorithm description, etc.)

On the recommendation page, you will be shown the following: Since you have recently frequently browsed products of a certain type, price range, style, color (etc.), we recommend the following to you:

B. Partially transparent group

In this group, you will be able to partially understand the platform's recommendation logic for pushing products to you (may include some related content recommendations)

On the recommendation page, the following is shown to you: Since you have recently frequently browsed products of a certain type (only some algorithms are shown), the following recommendations are made to you.

C. Completely black box group

In this group, you will not be able to know the recommendation logic of the platform to push products to you.

Part II: Formal Questionnaire

- On the following pages, how many times did you click to open the product to browse?
A. 1 time B. 2 times C. 3 times D. 4 times and above
- How long did you stay on the following pages?
A. Within 30 minutes B. 31-60 minutes C. 60-120 minutes D. More than 120 minutes
- What is the percentage of adding products to the shopping cart on the following pages?
A. Within 20% B. Within 50% C. Within 80% D. More than 80%
- How often do you buy on the following pages?
A. Within 20% B. Within 50% C. Within 80% D. More than 80%
- The following questions investigate your perception of transparency and assess consumers' subjective feelings about the transparency of platform algorithms.

Question example (Likert scale, 1=completely disagree, 5=completely agree)

Question		Options				
		Totally disagree	Somewhat disagree	Neither too much	Somewhat agree	Strongly agree
Q1	I understand how the platform recommends content	1	2	3	4	5
Q2	The platform discloses the basic principles of the recommendation algorithm to users	1	2	3	4	5
Q3	I can choose to adjust my preferences for recommended content (e.g. tags, areas of interest)	1	2	3	4	5
Q4	The platform's recommendations meet my expectations	1	2	3	4	5

The following questions investigate your trust and assess consumers' trust in the platform.

Question example (Likert scale, 1=completely disagree, 5=completely agree)

Question		Options				
		Totally disagree	Somewhat disagree	Neither too much	Somewhat agree	Strongly agree
Q1	I trust the content recommended by the platform	1	2	3	4	5
Q2	I think the content recommended by the platform meets my real needs	1	2	3	4	5

Q3	I trust the platform will not abuse my personal data	1	2	3	4	5
Q4	The platform can objectively recommend high-quality goods or services	1	2	3	4	5

The following questions investigate your purchasing intention and evaluate consumers' purchasing intention.

Question example (Likert scale, 1=completely disagree, 5=completely agree)

Question		Options				
		Totally disagree	Somewhat disagree	Neither too much	Somewhat agree	Strongly agree
Q1	I am willing to buy products recommended by the platform	1	2	3	4	5
Q2	The content recommended by the platform makes me want to buy	1	2	3	4	5
Q3	If my friends need it, I will recommend the products or services on the platform	1	2	3	4	5
Q4	I have actually purchased something based on the platform's recommendation	1	2	3	4	5

The questionnaire ends here, thank you for your support!