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Artificial Intelligence Technology in Live Streaming E-commerce: Analysis of Driving Factors of Consumer Purchase Decisions

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Abstract

With the rapid rise of live streaming e-commerce, artificial intelligence (AI) technology has become pivotal in shaping consumer behaviors and purchase decisions. This study explores the application of AI in live streaming e-commerce and analyzes its impact on driving factors behind consumer purchase decisions. Employing a comprehensive methodology including literature review, data analysis, and empirical research, this study identifies key AI-driven factors such as personalized recommendation systems, real-time interaction features, intelligent customer service, and social influence, trust. Conduct a questionnaire survey analysis on 1084 consumers who have participated in live streaming platforms using artificial intelligence technology. The findings reveal that AI significantly enhances consumer engagement and purchase intention, offering valuable insights for both academic research and practical applications in e-commerce platforms.

Keywords: Live streaming e-commerce, artificial intelligence, consumer behavior, purchase decision

1 Introduction

The rapid rise of live streaming e-commerce has completely changed the retail landscape, providing consumers with an interactive and immersive shopping experience. As consumers increasingly seek authenticity and engagement in their purchasing journeys, platforms are citing artificial intelligence (AI) technology to enhance these experiences. Artificial intelligence has become a key element in shaping consumer behavior and influencing purchasing decisions, so a deeper understanding of its application in this dynamic environment is necessary. Through a review of the literature, it was found that there are currently not many articles that analyze the factors that influence artificial intelligence on consumers' purchase intention on live broadcast e-commerce platforms. They mainly studied the following directions: examined electronic service quality on live streaming platforms from the perspective of fast relationships, emphasizing the importance of customer participation in driving purchase intention [1];Focusing on the impact of reducing uncertainty in live broadcast commerce on consumer purchase intention, emphasizing the role of reducing uncertainty in enhancing purchase behavior [2]; conducted an in-depth study of customer engagement and purchase intention in live broadcast digital marketing platforms, revealing emphasized the importance of attracting consumers through live broadcasts[3]; explored the impact of e-commerce live broadcast background fit on consumers' purchase intention from a cognitive and emotional perspective, revealing its inherent psychological mechanism[4]; proposed a live broadcast e-commerce The theoretical framework of the impact of social presence on consumer purchasing decisions emphasizes the role of social interaction in shaping purchase intention. Live e-commerce allows consumers to communicate directly with anchors about product features in real time[5]. This format has gained huge traction, especially among younger demographics who prefer a personalized and engaging shopping experience. explored the factors influencing consumers' adoption and use of online purchase recommendation systems[6]. Research shows that AI-driven features, such as personalized recommendation systems, can significantly improve consumer satisfaction by tailoring content to meet individual preferences degree and loyalty. In addition, intelligent customer service solutions and real-time interaction capabilities create a supportive environment and increase consumer confidence during the purchase process.

Although there is a growing body of literature on e-commerce and artificial intelligence, there is a lack of research on the impact of artificial intelligence on consumer purchase intentions on live streaming e-commerce platforms. The purpose of this paper is to study how artificial intelligence technology affects the purchase intention of consumers on live broadcast e-commerce platforms, such as intelligent recommendation systems, intelligent customer service, intelligent product selection on the help platform, intelligent assistance to anchors, etc. This study uses a comprehensive approach including literature review, data analysis and empirical research to explore the impact of artificial intelligence technology on consumers' purchase intention on live streaming e-commerce platforms.

In order to collect relevant data, we conducted a questionnaire survey among 1,084 consumers who participated in the artificial intelligence technology live broadcast platform. Research results show that artificial intelligence significantly increases consumer participation and purchase intention, contributing to academic research and practical applications within e-commerce platforms. By analyzing the mechanism by which artificial intelligence affects consumer behavior, this study helps to more effectively understand the trans-formative potential of artificial intelligence in live e-commerce.

2 Literature Review

2.1 Evolution of Live Streaming E-commerce

With the development and application of artificial intelligence, more and more industries are using artificial intelligence technology to research and solve problems in their profession. For example, the financial industry is also using artificial intelligence technology. Our findings indicate that many major financial institutions AI-driven solutions are being adopted to potentially enhance real-time risk assessment, trading Efficiency and predictive analytics.In the era of intelligent information interconnection and knowledge-driven economy, there is a growing interest in how to manage high-volume data, unlock its potential value, and provide intelligent analysis and decision-making support for enterprise's technological innovation[7].The e-commerce industry also involves some research related to artificial intelligence technology.The current situation and future trends of web celebrity e-commerce live streaming, highlighting the industry's historical evolution and benefit distribution mechanisms[8]. The author predicts the future development of the industry and identifies possible risk factors for consideration. The public opinion evolution on normative policies for the live streaming e-commerce industry under the COVID-19 epidemic in China, using online comments to extract topics and sentiment analysis models to study policy implementation effects[9]. The concept of live streaming e-commerce first emerged in China in 2016 with Taobao, a social retail giant. This innovation revolutionized the online shopping landscape and quickly evolved into an innovative sales channel .With the rapid advancement of technology and the widespread adoption of mobile devices, live streaming platforms have emerged as powerful tools for businesses to engage with consumers[10]. China's digital consumer market, with nearly one billion tech-enabled consumers, has been at the forefront of live streaming e-commerce evolution. Overall, the evolution of live streaming e-commerce has transformed the retail industry, offering new opportunities for businesses to engage with consumers in innovative ways. From the above literature, we can see that the development of live streaming e-commerce is in the ascendant, and it can be said to be an important stage in promoting the economic development of e-commerce.The industry's growth and development continue to be shaped by technological advancements, consumer preferences, and policy implementations, making it a dynamic and evolving sector in the e-commerce landscape.Live streaming e-commerce has seen explosive growth, particularly in China, where platforms like Taobao Live and JD Live dominate the market. This model combines entertainment and shopping, offering a dynamic and engaging shopping experience that enhances user interaction and immediacy of purchase.

2.2 AI in E-commerce

The integration of Artificial Intelligence (AI) in E-commerce has been a topic of increasing interest in recent years. A model for AI customer service in E-commerce, highlighting the collaboration between human agents and AI to enhance customer service and productivity. The benefits of AI in E-commerce design, such as improving efficiency and reducing costs, leading to the growth of the E-commerce sector [11]. AI technologies, such as chatbots and generative AI, are being used to understand customer preferences, guide them through purchases, and enhance the shopping experience. Key applications of artificial intelligence in e-commerce are identified, highlighting its impact on improving efficiency and driving business growth[12]. Cross-border e-commerce services can be automated using AI models for data-intensive inventory forecasting, demonstrating the need for optimization processes tailored to specific companies[13]. A technology acceptance model of artificial intelligence in e-commerce was assessed through an online survey, highlighting the positive impact of valuing norms, trust, and cognitive tendencies on perceived usefulness and usage attitudes [14]. Overall, these studies collectively demonstrate the diverse applications, implications, and challenges of AI in E-commerce, paving the way for further research and development in this field[15]. The above-mentioned literature mainly studies how artificial intelligence can improve customer service quality and e-commerce efficiency, and also talks about the issue of human trust in artificial intelligence. AI-powered e-commerce live streaming can improve customer service quality and efficiency, which also provides a theoretical basis for research.AI technologies in e-commerce include personalized recommendation systems, intelligent customer service, user behavior prediction, trust ,and social data analytics. These applications aim to optimize user experiences and operational efficiencies, significantly influencing consumer purchasing behavior.

2.3 Factors Influencing Consumer Purchase Decisions

Consumer purchase decisions are influenced by a variety of factors across different product categories. The decision to purchase travel products online is analyzed along with factors such as customer attitude, website design quality, customer satisfaction and trust as key decision factors for purchase intention[16]. The impact of consumers' environmental awareness and consumption values on bamboo product purchase intention highlights the importance of consumer values in promoting green consumption[17]. The impact of packaging elements on consumer purchasing decisions highlights the role of visual and verbal cues in influencing consumer choice. The visual impact of the live broadcast room is the strength of artificial intelligence technology[18]. Electronic word-of-mouth (including consumer reviews and website features) has a great impact on consumer purchase intentions[19]. These studies underscore the significance of external factors in shaping consumer decisions. On the other hand, By examining specific product categories, such as organ meats and organically grown products, it was found that factors such as freshness, price and availability significantly influence organ meat consumption. The study identified factors that influence purchase intentions for organically grown products such as fruits and vegetables[20]. Moreover, Utilize the S-O-R model to understand consumers' organic food purchasing decisions. They found that attitudes toward organic food labels and perceptions of environmental impact were key drivers of purchase intention[21]. These studies collectively highlight the diverse range of factors that influence consumer purchase decisions, from product-specific attributes to broader environmental and social considerations [22].Consumer purchase decisions are affected by product quality, price, brand trust, social influence, and shopping experience. In the context of live streaming e-commerce, additional factors such as influencer credibility and real-time engagement also play crucial roles.From the above literature, we can see that the current research focus is on the impact of online store decoration, product decoration, price, visual scenes, consumer emotions, consumer brand recognition, etc. on consumer desires. However, artificial intelligence technology can improve the visual scene of products and their online stores, which will further attract consumers. This provides a theoretical basis for studying the factors that AI technology affects consumer purchasing decisions.

3 Research Hypotheses and Theoretical Model

3.1 Research Hypotheses

Hypothesis 1 (H1): AI improving product quality and word of mouth will have a direct impact on purchase intentions.

Hypothesis 2 (H2): The price and discount strategies provided by AI through market data analysis will directly affect purchase intentions.

Hypothesis 3 (H3): The AI-enhanced interactive ability and professionalism of anchors will directly affect the purchase intention.

Hypothesis 4 (H4): The authenticity of live content and personalized recommendations provided by artificial intelligence will directly affect the purchase intention.

Hypothesis 5 (H5): The shopping environment and atmosphere created by artificial intelligence will directly affect the purchase intention.

Hypothesis 6 (H6): AI improves product quality and word of mouth influences purchase intentions by enhancing user trust.

Hypothesis 7 (H7): Price and discount strategies provided by AI through market data analysis influence purchase intentions by enhancing user trust.

Hypothesis 8 (H8): AI-enhanced anchor interaction and professionalism influence purchase intention by enhancing user trust.

Hypothesis 9 (H9): The authenticity of live content and personalized recommendations provided by artificial intelligence influence purchase intention by enhancing user trust.

Hypothesis 10 (H10): The shopping environment and atmosphere created by artificial intelligence can influence purchase intention by enhancing user trust.

3.2 Theoretical basis for hypothesis

Based on the existing research on the impact of artificial intelligence on consumers' purchase intention on live broadcast e-commerce platforms, we tried to make a hypothetical model.Consumer factors influencing the adoption and use of online purchasing recommendation systems are explored. A key analysis is conducted on the influencing factors of consumers' purchase intention in the context of e-commerce live shopping from three aspects: people, goods and market [23]. The Global Consumer

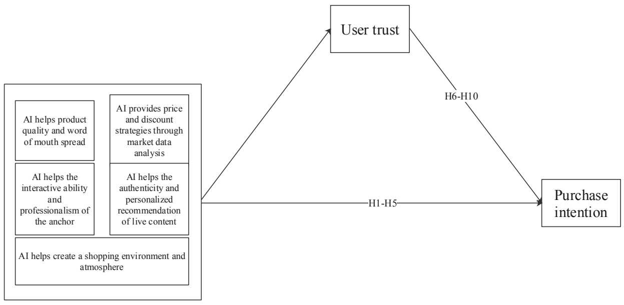

Figure 1: Resaerch Model

Insights Pulse Survey highlighted the potential of generative AI in revolutionizing how consumers explore, evaluate, and make purchase decisions in e-commerce[24].On the basis of these studies, we propose a hypothesis on how artificial intelligence technology affects consumer purchasing decisions on live streaming e-commerce platforms.

3.3 Research Model

The theoretical model illustrates the relationship between AI applications and consumer purchase decisions, with mediating variables such as user satisfaction and trust, and moderating variables such as user characteristics and live content type.

4 Research Methodology

4.1 Research Object

According to the the current market environment, Douyin,Taobao,JD.com live broadcast is indeed representative among live broadcast e-commerce platforms, with studies focusing on various aspects of this phenomenon, including consumer behavior, brand building, and the influence of different factors on purchase intentions and follow intentions. So this research chose the Douyin, Taobao, JD.com platform for data collection. Further research in this area can continue to shed light on the evolving landscape of live broadcast e-commerce.The study employs a mixed-method approach, utilizing surveys, experimental design, and platform data analysis. Surveys collect data on consumer shopping experiences, satisfaction, trust, and purchase behavior. Experimental design simulates different live streaming scenarios, while platform data analysis examines user behavior and decision-making processes.

4.2 Data Collection

The first part of table 1 is the basic information of the respondents, including their age, gender, the amount of money spent on the Douyin, Taobao, JD.com platform, and the characteristics of watching the live broadcast. By setting screening questions, respondents who had not watched live streaming on Douyin were excluded, so as to ensure a representative and valid questionnaire sample. Ensuring that the characteristics of the research group are consistent with the mainstream consumer groups of the Douyin platform category will help to obtain more accurate research results. The second part of table 2 is variable information, including independent variables, mediating variables and dependent variables.

Table 1: Issues related to the personal situation of consumers

Order Number	Problem Setting
Q1	Your gender
Q2	Your age group
Q3	The average amount you spend on Douyin,Taobao,JD.com (including clothing and shoes)
Q4	The many hours you watch live streaming on Douyin,Taobao,JD.com per week
Q5	Please have you ever seen the TikTok e-commerce Douyin,Taobao,JD.com platform, live streaming with goods
Q6	Watch the Douyin,Taobao,JD.comlive broadcast of Douyin platform every week
Q7	Have you ever bought Douyin platform in the broadcast studio?

5 Data Analysis Results

5.1 Distribution and Recovery of Questionnaires

1,200 questionnaires were distributed online to survey consumers who had participated in e-commerce live broadcasts on Taobao, JD.com, Douyin and other e-commerce live broadcasts, and a total of 1,084 valid questionnaires were collected.

5.2 Reliability Test

As shown in Table 3, Cronbach's α coefficient is 0.986 (still 0.986 after standardization), which indicates that the scale containing 22 items exhibits very high internal consistency confidence in 1084 samples. The coefficient is close to 1, indicating that the items in the scale have high reliability and stability when measuring the same construct.

5.3 Validity test

Table 4 shows that the data is very suitable for factor analysis, because the variables show a strong correlation (KMO value =0.946), and the Bartlett sphericity test significantly rejects the hypothesis that the variables are independent of each other ($P<0.001$), indicating that there is a significant correlation between the variables, which provides strong validity support for factor analysis.

5.4 Correlation Analysis

Figure 2 shows that there is a significant positive correlation between variables (A1 to G1), and the correlation coefficient is generally high, reaching the level of statistical significance. The darker the color, the higher the correlation. The results show that the different variables are closely related, and the change of one variable is likely to have a corresponding impact on the other variables. Specifically, both within the same group of variables and between different groups of variables show a strong positive correlation, reflecting a close and consistent trend of change among them.

5.5 Principal Component Analysis

According to the principal component analysis results in table 5, the high-loading variables in component 1 are D1, D3, D2, C2, C1, E1, and E2. These are variables related to D and E, and the loadings between them are similar, indicating that these variables are There is a strong common influence on the first principal component. These variables represent some kind of comprehensive indicator related to D and E, named AI Market Performance and Product Quality (FACT1). The high-loading variables in component 2 are A4, B1, B2, A2, and A3. These are variables related to A and B, and their loadings on the first principal component are lower, but they have higher loadings on the second principal component. load. The second principal component may represent another different trend or characteristic related to the variables of categories A and B, which represent another

Table 2: Issues related to the personal situation of consumers

Order Number	variable	Problem Setting
A1	Product quality analysis	Do you think the quality of goods analyzed by AI is accurate? (very inaccurate - very accurate)
A2	word-of-mouth communication effect	Do the word-of-mouth products recommended by AI meet your expectations? (Not at all true - Very true)
A3	User feedback processing	How quickly does AI process user feedback? (very slow - very fast)
A4	Negative review management	How effective is AI in dealing with negative comments? (very poor - very good)
B1	Price strategy optimization	Do you think the AI optimized pricing strategy is reasonable? (very unreasonable - very reasonable)
B2	Coupon allocation accuracy	Do the coupons recommended by AI meet your needs? (Not at all true - Very true)
B3	Promotional activity effect	How effective are AI promotions? (very poor - very good)
B4	Market trend forecast	How accurate do you think AI can predict market trends? (very inaccurate - very accurate)
C1	Anchor training effect	What do you think of the interactive capabilities of anchors trained through AI? (very poor - very good)
C2	Anchor interaction skills	With the assistance of AI, have the interactive skills of anchors been improved? (No improvement at all - Significant improvement)
C3	Improvement of anchor's professional knowledge	How effective is AI in helping anchors improve their professional knowledge? (very poor - very good)
C4	Anchor's question answering ability	How accurate is the anchor's answer to questions through AI? (very inaccurate - very accurate)
D1	Product description authenticity	Do you think the product descriptions generated by AI are authentic? (very unreal - very true)
D2	Personalized recommendation accuracy	Do the products recommended by AI match your interests? (Not at all true - Very true)
D3	Richness of live content	Is the AI-assisted live broadcast rich in content? (very dull - very rich)
D4	User engagement	How engaged are you in AI-assisted live broadcasts? (very low - very high)
E1	Visual effects optimization	How satisfied are you with the visual effects of the AI-optimized live broadcast room? (very dissatisfied - very satisfied)
E2	Sound management	What is the effect of live broadcast sound effects under AI management? (very poor - very good)
E3	Improved shopping atmosphere	What do you think of the shopping atmosphere enhanced by AI? (very poor - very good)
E4	User interactive experience	How is your interactive experience in the AI-assisted live broadcast room? (very poor - very good)
F1	Trust	I think live streaming meets my needs and expectations
G1	Purchase intention	I am willing to purchase in the live broadcast room

Table 3: Analysis of the overall questionnaire reliability

Cronbach's α coefficient	Standardization Cronbach's α coefficient	Number of items	Number of samples
0.986	0.986	22	1084

Table 4: Analysis of the overall questionnaire validity

KMO value	0.946
Approximate chi-square	3385.562
df	231
P	0.000***

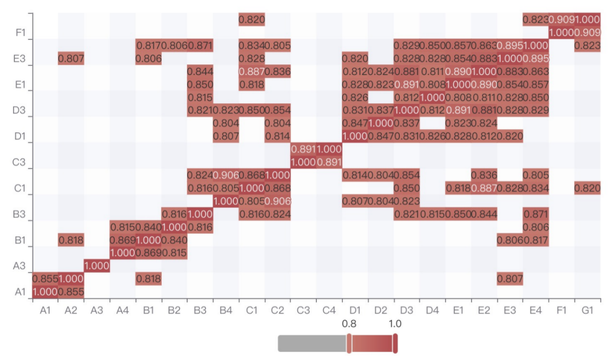

Figure 2: Correlation Coefficient Heat Map

aspect of business performance, named AI Marketing Strategy and User Engagement (FACT2). The high loading variables of component 3 are C4, C3, B4, E3, and A1, among which C4 and C3 have the highest loadings, while B4 and E3 also have significant loadings, and A1 also has a certain loading on the third principal component. The third principal component represents the third aspect that is different from the first two principal components, and is named anchor ability and AI live broadcast experience (FACT3).

5.6 Regression analysis

As shown in table 6, In model 1, the coefficient of FAC1 is 1.3811, and the p value is less than .0000, indicating that FAC1 has a significant positive impact on F1. Confirmed FAC1 to be a significant predictor of F1. Model 2 serves as the baseline for mediation analysis, indicating that FAC1 has a direct effect on G1. Model 3 shows that after adding F1, this direct effect will be weakened, and the coefficient of FAC1 is .5128. Although it is still significant (p value less than .0000), its size is smaller than the FAC1 coefficient in model 1 or the hypothesized model 2. reduced. This indicates that the direct effect of FAC1 on G1 is weakened after the addition of F1. The coefficient of F1 is .7458, and the p value is less than .0000, indicating that F1 has a significant positive impact on G1. This model confirms that F1 plays a mediating role between FAC1 and G1. After calculation, the mediating effect is 66.7%. To sum up, F1 plays a partial intermediary role between FAC1 and G1. That is, FAC1 not only directly affects G1, but also indirectly affects G1 through F1.

As shown in table 7, Model 1 shows that FACT2 has a significant positive impact on the participation variable F1 (coefficient is 1.1373, p value <0.0000), which supports the view that FACT2 is an important predictor of F1. Model 2 shows that FACT2 directly has a significant positive impact on the participation variable G1 (coefficient is 1.1373, p value <0.0000), which supports the view that FACT2 is an important predictor of F1. has a positive impact (coefficient is 0.9211, p value <0.0000), and the model generation degree is very large (R-sq=0.8273). This shows that FACT2 is a weak influence on G1 without considering the flag F1. However, in model 3, when the included variable F1 is added to the model, the effect of FACT2 on G1 is no longer significant (the coefficient is -0.0973, p value = 0.3520), and its confidence interval (-0.3036 to 0.1090)) includes 0. This means that after controlling for the effect of F1, the direct effect of FACT2 on G1 is no longer statistically significant.

Table 5: Principal component analysis

	FACT1	FACT2	FACT3
D1	0.793		
D3	0.773		
D2	0.765		
C2	0.763		0.511
C1	0.763		
E1	0.75		
D4	0.721	0.591	
B3	0.711	0.544	
E4	0.71	0.602	
B4	0.702		0.535
E3	0.676	0.543	
A4		0.801	
B1		0.75	
B2		0.69	
A2		0.681	
A3		0.662	
C4			0.781
C3			0.769
A1		0.539	0.609

Table 6: FACT1 and G1 mediation regression test

	Model 1(F1)				Model 3(G1)			
	R	R-sq	p		R	R-s	p	
	0.5902	0.3484	0.0000		.9272	.8597	.0000	
	coeff	p	LLCI	ULCI		p	LLCI	ULCI
constant	6.7339	0.0000	6.3736	7.0943	1.8218	.0000	1.2201	2.4235
FAC1	1.3811	0.0000	1.0191	1.7430	.5128	.0000	.3115	.7142
F1					.7458	.0000	0.6597	0.8319
	Model 2(G1)							
	R	R-sq	p					
	0.6847	0.4688	0.0000					
	coeff	p	LLCI	ULCI				
constant	6.8440	.0000	6.5308	7.1573				
FAC1	1.5428	0.0000	1.2281	1.8576				
F1								

Table 7: FACT2 and G1 mediation regression test

	Model 1(F1)				Model 3(G1)			
	R	R-sq	p		R	R-s	p	
	0.4861	0.2363	0.0012		0.2754	0.0843	0.0028	
	coeff	p	LLCI	ULCI	coeff	p	LLCI	ULCI
constant	6.7339	0.0000	6.3439	7.1240	0.8146	.0106	0.1943	1.4349
FACT3	1.1373	0.0000	0.7455	1.5292	-0.0973	.3520	-.3036	.1090
F1					0.8954	.0000	.8072	0.9836
	Model 2(G1)							
	R	R-sq	p					
	0.9096	0.8273	0.0000					
	coeff	p	LLCI					
constant	6.8440	0.0000	6.4517					
FACT3	.9211	.0000	.5270					
F1								

Table 8: FACT3 and G1 mediation regression test

	Model 1(F1)				Model 3(G1)			
	R	R-sq	p		R	R-s	p	
	0.3072	0.0944	0.0012		0.2834	0.0803	0.0028	
	coeff	p	LLCI	ULCI	coeff	p	LLCI	ULCI
constant	6.7339	0.0000	6.3092	7.1587	0.9599	0.0013	0.3835	1.5362
FACT3	0.7188	0.0012	0.2920	1.1455	0.0104	0.9138	-0.1798	0.2006
F1					0.8738	0.0000	0.7925	0.9551
	Model 2(G1)							
	R	R-sq	p					
	0.9088	0.8259	0.0000					
	coeff	p	LLCI	ULCI				
constant	6.8440	0.0000	6.4318	7.2563				
FACT3	0.6385	0.0028	0.2243	1.0526				
F1								

Even if the direct effect of FACT2 on G1 is not significant in Model 3, as long as the indicators in F1 have a significant impact on G1, it can be said that there is an effect inside. At this time, the effect value inside is 1.0184.

As shown in table 8, FACT3 has a significant positive impact on F1 (coefficient is 0.7188, p value = 0.0012), indicating that FACT3 is an important predictor of F1. FACT3 has a significant positive impact on G1 (coefficient is 0.6385, p-value = 0.0028), indicating that FACT3 can directly predict G1 without considering the intervening variable F1. After adding the mediating variable F1, the direct effect of FACT3 on G1 becomes insignificant (coefficient is 0.0104, p value = 0.9138), and its confidence interval (-0.1798 to 0.2006) includes 0. This indicates that after controlling for the effect of F1, the direct effect of FACT3 on G1 becomes very weak or may no longer exist. At the same time, F1 has a significant positive impact on G1 (coefficient is 0.8738, p value <0.0000), indicating that F1 is an important predictor of G1. FACT3 has an indirect effect on G1 through F1, because FACT3 significantly affects F1, and F1 in turn significantly affects G1. Although the direct effect of FACT3 on G1 is not significant in Model 3, this is because the effect of FACT3 is completely or mostly transmitted through F1. Given G1, the mediation effect is 98.3% at this time.

5.7 Discussion

This study explores the application of artificial intelligence (AI) technology in livestreaming e-commerce, with a specific focus on analyzing the factors driving consumer purchase decisions across

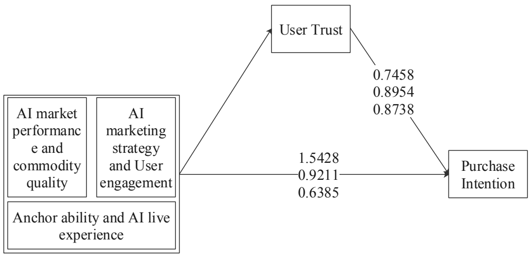

Figure 3: Research Result

major platforms such as Douyin, Taobao, and JD.com. The results provide valuable insights into how various AI-enabled features influence consumer behavior and offer strategic recommendations for e-commerce platforms and marketers aiming to optimize their livestreaming approaches. The findings in figure 3 demonstrate that AI plays a significant role in enhancing the consumer experience in several key areas, including personalization, real-time interaction, and content optimization, each contributing to a more engaging and effective shopping environment. The analysis reveals that AI-powered personalization significantly influences purchase decisions, with a strong positive correlation between AI-driven recommendations and consumer purchase intent. When product suggestions are tailored to individual preferences, consumers are more likely to make a purchase, highlighting the importance of leveraging AI for creating customized shopping experiences. The application of artificial intelligence plays an important role in improving real-time interactive functions, such as quickly responding to consumers' questions and concerns through chatbots and instant messaging tools, which helps improve the shopping experience and enhance consumers' trust in products. AI can also expand the social influence and reputation of products through data analysis, and enhance consumers' trust in promoted products, because consumers are more willing to buy products that appear to be popular and have high ratings. In addition, optimizing live broadcast content and enhancing interaction through AI can create a more attractive and convincing live broadcast experience for consumers, thereby driving sales growth. This research has certain practical value to e-commerce practitioners and marketers.E-commerce practitioners or e-commerce platforms can use advanced AI technology to enhance personalized services, instant interaction and content optimization, which can significantly improve consumer experience and increase sales. Effective training on the use of AI tools for live broadcast e-commerce practitioners can also enhance the influence on consumer purchasing decisions during live broadcasts. At the same time, leveraging the real-time interaction capabilities of AI intelligence and continuously adjusting live broadcast strategies through data analysis can help the platform capture consumer preferences. In general, the strategic application of artificial intelligence in live broadcast e-commerce can not only improve efficiency and reduce costs, but also significantly affect consumer purchasing behavior and gain competitive advantages in a fiercely competitive market.

6 Conclusion

The integration of artificial intelligence (AI) technology and live e-commerce has fundamentally changed the way consumers perceive products and affects purchasing behavior. This study conducts an in-depth analysis of the main influencing factors of consumer purchasing decisions behind live streaming e-commerce, paying special attention to major live streaming platforms such as Douyin, Douyin, and JD.com. The findings highlight the important role that AI capabilities play in enhancing consumer experience and increasing sales performance. According to the research model shown in Figure 3, the following conclusions are drawn: First, artificial intelligence-driven personalized recAI's ability to analyze user behavior and dynamically tailor product recommendations can have a significant and positive impact on purchase intentions. This personalized recommendation can more effectively match potential buyers, creating a more personalized shopping experience that meets specific consumer needs. Second, AI-enhanced real-time interactions, including chatbots and instant customer support, help increase consumer confidence and satisfaction. AI can respond instantly to consumer inquiries, creating a more seamless and integrated shopping journey that enhances consumers' decision-making intentions. Third, AI's ability to analyze and amplify social influence, coupled with word-of-mouth effects, is a key driver building consumer trust and influencing purchasing decisions.ommendations are very effective in meeting consumer needs and conforming to personal preferences.By effectively highlighting positive reviews and recommendations, AI increases consumer confidence in the products being promoted, thereby increasing the product's credibility and appeal.Fourth, leveraging AI to improve content delivery and audience engagement will be more successful in persuading audiences and converting sales. Data analytics generated by AI enable e-commerce livestreamers to better match their presentations and interactions with consumer preferences, resulting in a more targeted approach that increases conversion rates. To sum up, artificial intelligence-driven personalization plays a crucial role in the transformation of live broadcast e-commerce through artificial intelligence technology, significantly affecting consumer experience and purchasing behavior. By studying the role of artificial intelligence in live streaming commerce, focusing on personalization and other key drivers identified in this study, live streaming commerce platforms and e-commerce practitioners can optimize their approaches to more effectively meet consumer needs and Achieve greater success in the dynamic online live streaming e-commerce market.

Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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