ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Research on the Role Mechanism of AIGC-Generated Content on E-commerce Live Streaming Platform to Enhance the Effect of Product Promotion

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SUMMARY: *This paper takes the e-commerce live broadcasting platform of Company M as the research object, and explores the path and mechanism of the influence of AIGC-generated content on e-commerce live broadcasting consumer willingness. Based on the theory of consumer behavior, a structural equation model containing 6 variables of product involvement, preferential discount, entertainment, trust, perceived value and purchase intention is constructed. The 405 valid data collected were analyzed by questionnaire survey method and statistical analysis method. The validity of the structural equation model was tested by relying on SPSS, SmartPLS and AMOS software to validate the proposed hypotheses and suggest relevant countermeasures to promote the purchase intention of e-commerce live streaming consumers in Company M. Hypotheses H1, H4, H6, H7, and H8 passed the empirical test, and the product involvement increased the consumers' trust by increasing the consumers' trust, and the entertaining and discounting efforts increased the consumers' 's perceived value, which in turn increases consumers' purchase intention.*

KEYWORDS: *e-commerce live streaming platform; AIGC generated content; structural equation modeling; product promotion*

1 Introduction

With the rapid development of the Internet, live e-commerce has become a new favorite in the e-commerce industry. Live e-commerce combines product display, sales and user interaction through a live broadcast platform, providing consumers with a new shopping experience [1-3]. However, with the increasingly fierce competition in the live e-commerce market and the wide application of artificial intelligence (AI), how to utilize AI technology, especially AIGC-generated content, for intelligent product promotion has become an important issue that live e-commerce companies need to face.

Artificial Intelligence Generated Content (AIGC) is one of the application types of AI, which relies on powerful algorithms and massive data to quickly generate a large amount of high-quality content, such as text, images, audio, video, etc., which is conducive to improving the production efficiency and quality [4-6]. The mechanism of the role of the e-commerce live platform AIGC generated content on product promotion effect improvement is mainly reflected in the product recommendation system, online customer service and chatbot and intelligent recommendation. Commodity recommendation system is one of the core functions on the e-commerce live platform. AIGC technology automatically generates personalized commodity

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https://doi.org/10.65102/is2026848 Published: 30 April, 2026

recommendations by analyzing the user's purchasing records, browsing habits, and personal preferences, and by mining the massive amount of commodity data [7-9]. In this way, users are able to quickly find goods that meet their needs, improving the efficiency and satisfaction of shopping [10]. Secondly, online customer service and chatbots are important services provided to users by live e-commerce platforms [11]. AIGC technology can enable chatbots to have higher intelligence and natural language comprehension, which can accurately answer users' questions and provide timely help and support [12, 13]. In this way, it can provide users with a better shopping experience and improve customer satisfaction [14]. In addition, e-commerce live platforms need a large amount of high-quality content to attract users' attention and enhance brand image, and AIGC can automatically generate all kinds of marketing content, such as product descriptions, advertisement copy, and promotional activities, based on market trends and user data [15-18]. This not only reduces the marketing burden of enterprises, but also can enhance the promotion effect of products.

This paper adopts structural equation as the research method, taking product involvement, discount, and entertainment as the antecedent variables, trust and perceived value as the mediating variables, and purchase intention as the dependent variable. The basic principles of structural equation modeling were systematically sorted out, and a structural equation model of the influence of AIGC-generated content on e-commerce live streaming consumption intention was constructed. The initial questionnaire was designed and pre-surveyed to optimize the scale structure and item formulation. Distribute the questionnaire to active users relying on the official channels of M Company to obtain the research data. Analyze and process the data through statistical software to verify the hypotheses of this paper. Analyze the influence mechanism of product involvement, preferential discounts and entertainment on consumers' purchase intention, and verify the mediating role of trust and perceived value. Combining the research results, discuss the mechanism of the role of AIGC-generated content on the enhancement of product promotion effect.

2 Research design on the impact of AIGC-generated content on e-commerce live streaming consumption intention

With the wide application of Artificial Intelligence Generated Content (AICG) technology in the field of e-commerce live broadcasting, platforms are able to automatically generate product display copy, interactive dialogues and scenario-based visual materials through algorithms, thus improving the efficiency of content production and dissemination effects. This trend not only changes the traditional e-commerce marketing model, but also brings new possibilities and challenges for product promotion. Taking e-commerce live broadcast platform as the research background, this paper constructs and tests a structural equation model containing product involvement, discount, entertainment, trust, perceived value and purchase intention, aiming at revealing how AICG-generated content plays a role in consumer's purchasing decision process through multi-dimensional factors.

2.1 Definition of model variables

2.1.1 Product Involvement

Involvement theory is used to predict a person's attitude towards the persuasion of others due to their position or role. It was later introduced to the field of marketing to study the decision-making process of consumers. Product involvement is an important moderating and explanatory variable in consumer theory, and is an important factor in helping to understand consumer purchase intention. In the context of e-commerce live streaming, product involvement not only enhances consumers' attention to AIGC-generated content, but also prompts them to form a more positive evaluation of the authenticity of the content and the objectivity of the recommendations, which significantly and positively affects consumers' trust. At the same time, a high degree of involvement means that consumers have more in-depth knowledge of product attributes and selling points, which provides an information basis for the formation of perceived value.

Based on the above analysis of product involvement, this paper proposes the following hypotheses:

H1: The product involvement degree of AIGC-generated content positively affects consumer trust.

H2: The product involvement degree of AIGC-generated content positively affects consumer perceived value.

2.1.2 Preferential discounts

Offers of products in the live broadcast, limited-time seconds, full-reduced activities, buying and giving activities, shopping lottery, etc. are all preferential discounts. Preferential discounts, as a common promotional stimulus, directly affect consumers' economic perception and sense of urgency to buy, and are presented in live broadcasts through real-time price discounts, limited-time rush, etc., which can quickly stimulate purchase motivation and reduce decision-making risks.The various preferential discounts presented in AIGC-generated content not only enhance consumers' perception of the functional value of products, thus significantly and positively affecting perceived value, but also may enhance consumer trust in platforms and recommended content through The discounts and scarcity signals enhance consumers' trust in the platform and the recommended content.

Based on the above analysis of discounts, this paper proposes the following hypotheses:

H3: Preferential discounts on AIGC-generated content positively affect consumer trust.

H4: Preferential discounts on AIGC-generated content positively affect consumers' perceived value.

2.1.3 Entertainment

Entertainment reflects the fun and interactivity of live content. According to incomplete statistics, more and more consumers watch live broadcasts not only to buy cost-effective products and discover products of interest, but also to watch live broadcasts as a way of leisure and relaxation has become a major reason. aicg can enhance the audience's viewing experience by generating humorous scripts, contextualized interpretation, etc., so that the shopping process is both leisure and social attributes, thus prolonging the user's residence time and enhancing the brand's goodwill. Favorable impression of the brand.

Based on the above analysis of entertainment, this paper proposes the following hypotheses:

H5: The entertainment of AIGC-generated content positively affects consumer trust.

H6: The entertainment of AIGC-generated content positively affects consumers' perceived value.

2.1.4 Trust

In marketing, trust refers to the degree to which people believe in an economic organization and the products or services it provides based on their reliability and trustworthiness. Consumers' positive beliefs about the authenticity of the content, the objectivity of the recommendations, and the reliability of the platform during their exposure to AIGC-generated content can enhance their determination to accept the recommendations and make purchase decisions.

Based on the above analysis against trust, this paper proposes the following hypotheses:

H7: Consumers' trust in AIGC-generated content positively affects consumers' purchase intention

2.1.5 Perceived value

As we all know, the perceived value is determined by the subjective will of consumers, which refers to the result that consumers get after weighing the benefits and payments of the product. Since each person's cognitive level is affected by education, age, environment and other factors, the perceived value of a product varies from person to person. Under the guidance of AICG content, the perceived value may be significantly increased by the relevance and attractiveness of the information presented.

Based on the above analysis for perceived value, this paper proposes the following hypotheses:

H8: Consumers' perceived value of AIGC-generated content positively affects consumers' purchase intention.

2.1.6 Willingness to buy

The research in this paper is conducted in a live streaming scenario, so all the aforementioned factors in a live streaming scenario will affect consumers' purchase intention. In this paper, trust and perceived value are set as mediating variables to capture the indirect influence path of product involvement, discount and entertainment on purchase intention.

2.2 Principles of structural equation modeling

Structural equation modeling is a multivariate data analysis method, which can simultaneously study the relationship between the influence of multiple measurement variables and latent variables, influence the results, allow the existence of errors in the variables and accurately calculate the fitting indexes of the measurement variables and latent variables, and is equipped with technical means to adjust the fitting indexes. Considering the complexity of the relationship between logistics cost and service quality, structural equation modeling is selected for the study.

Structural equation modeling matrix equation:

$$x = \Lambda_x \xi + \delta \tag{1}$$

$$y = \Lambda_y \eta + \varepsilon \tag{2}$$

$$\eta = B\eta + \Gamma \xi + \zeta \tag{3}$$

where Eqs. (1) and (2) are measurement model equations and Eq. (3) is the structural model equation.

Where x is the exogenous measurement vector, Λ_x is the factor loading matrix of the exogenous variable on the exogenous latent variable, and δ is the vector of residual terms of the exogenously observed variable;

y is the vector of endogenous measures, Λ_y is the factor loading matrix of the endogenous variable on the endogenous latent variable, and ε is the vector of residual terms for the endogenous observed variable;

B and Γ are path coefficients, B denotes the relationship between endogenous latent variables, Γ denotes the relationship between exogenous latent variables, and ζ is the error term in the structural equation.

Measurement model: responding to the relationship between latent variables and measured variables, the equation is:

$$x_1 = \lambda_{x11}\xi_1 + \sigma_1 \tag{4}$$

$$y_1 = \lambda_{y11}\eta_1 + \varepsilon_1 \tag{5}$$

Among them:

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}, \quad \Lambda_x = \begin{bmatrix} \lambda_{x11} \\ \lambda_{x21} \\ \lambda_{x31} \end{bmatrix}, \quad \xi = [\xi_1], \quad \sigma = \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \end{bmatrix} \tag{6}$$

$$y = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}, \quad \Lambda_y = \begin{bmatrix} \lambda_{y11} & 0 & 0 \\ \lambda_{y21} & 0 & 0 \\ \lambda_{y31} & \lambda_{42} & 0 \\ 0 & \lambda_{52} & 0 \\ 0 & \lambda_{62} & 0 \end{bmatrix}, \quad \eta = \begin{bmatrix} \eta_1 \\ \eta_2 \end{bmatrix}, \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \end{bmatrix} \tag{7}$$

Structural model: responds to the causal relationship between underlying variables with the equation:

$$\eta_1 = \gamma_{11}\xi_1 + \zeta_1 \tag{8}$$

$$\eta_2 = \beta_{21}\eta_1 + \gamma_{21}\xi_1 + \zeta_2 \tag{9}$$

$$B = \begin{bmatrix} 0 & 0 \\ \beta_{21} & 0 \end{bmatrix}, \quad \Gamma = \begin{bmatrix} \gamma_{y11} \\ \gamma_{y21} \end{bmatrix}, \quad \zeta = [\zeta_1] \tag{10}$$

Structural equation modeling has high requirements for data quality, including sample size, measurement relationship and influence relationship, and substandard data quality will lead to poor fitting effect, and the final result is substandard fitting index. In terms of sample size, a sample size of 10 times the number of measured variables is generally required, and 15-25 times or at least 300 samples are required if the fitting quality is poor; in terms of the quality of the measurement relationship and the influence relationship, exploratory factor analysis and validation factor analysis, and path analysis are generally carried out prior to analyzing the study in order to ensure the quality of the subsequent structural equation model fitting. Structural equation model fitting effects and related indicators are obtained by comparing the covariance matrix of predicted and fitted relationships. There are many indicators of structural equation model fitting relationship, and academics have their own views on the requirements of the indicators, and the commonly used indicators are generally the chi-square degrees of freedom ratio χ^2 / df , GFI, RMSEA, RMR, CFI, NFI, NNFI and so on, and all the fitting indicators are up to the standard is very difficult, and according to the requirements of the research will be adjusted to the fitting indicators to within the acceptable range can be.

3 Analysis of the mechanism of the role of AIGC-generated content on the willingness to consume e-commerce live streaming

3.1 Design of the questionnaire

This paper takes the e-commerce live streaming platform of Company M as the case background, and the data comes from the research of the users using the platform. In the questionnaire design stage, reference is made to relevant mature scales at home and abroad on product involvement, preferential discounts, entertainment, perceived value, and purchase intention, and localized revisions are made in light of the characteristics of the live broadcasting business of Company M to ensure that the measurement questions can accurately reflect the consumption psychology and behavioral characteristics of the platform's users.

In addition to basic personal information, the survey section of this article chose the Likert scale to measure consumers' perceptions. This is the most commonly used attitude scale, as it clearly describes the content of the questionnaire, making it easy for consumers to understand and respond. Participants made their choices from the options of "strongly agree", "agree", "uncertain", "disagree", and "strongly disagree" in the Likert scale.

The questionnaire of this survey contains the following contents:

(1) The first part of the questionnaire investigates the basic information of the respondents, including gender, age, education, each disposable income, occupation, the type of live broadcasts usually watched, and what platforms are used for live broadcasts, as well as whether or not they have purchased any goods from Netflix's live broadcasting room.

(2) The second part of the survey investigates consumers' perceptions when watching live streams. Both use Likert scales, which contain instructions for a series of explanations to respondents.

3.2 Pre-survey

In order to verify the validity and reliability of the scale, a small-scale pre-survey was first carried out in the user group of Company M's e-commerce live broadcasting platform, and a total of 120 consumers who had recently watched the company's live broadcasting and participated in the interaction were selected for the trial test, and the wording, order, and option settings of some of the questions were optimized according to the results of the pre-survey, and the items that were insufficient or ambiguous were deleted, so as to improve the reliability and structural validity of the scale. The scale was then optimized to improve the reliability and structural validity of the scale.

In the pre-survey stage, the number of questionnaires recovered was 120, and the number of valid questionnaires was 103. In terms of gender, males accounted for 39.81% of the total number of people, and females accounted for 60.19% of the total number of people; the age group of 21-30 years old accounted for the largest proportion.

Reliability analysis is an analytical tool that uses measurement tools to examine whether the data are stable or consistent. Usually, after the researcher collects the questionnaire, the authenticity and reliability of the questionnaire is tested, and this is when most of the researchers will use the reliability test. Whether it is the researcher who designed the questionnaire or the respondents who answered the questionnaire, there is a certain difference in thinking between them and they have different ideas, which requires the researcher to analyze the reliability to test the design of this questionnaire.

In this paper, the next reliability analysis was carried out by SPSS software, taking the item has been deleted α coefficient and Cronbach's Alpha value, corrected item total correlation (CITC) index. It is generally accepted that when the Cronbach's Alpha value is within the range of values and higher than 0.8, it represents high reliability of the scale; when $0.7 < \alpha < 0.8$, it represents good reliability of the scale; when $0.6 < \alpha < 0.7$, it represents acceptable reliability of the scale; when the Cronbach 's Alpha value is lower than 0.6, it represents poor reliability of the scale.

The reliability test results of the antecedent variable, the mediating variable and the outcome variable are shown in Tables 1, 2 and 3 respectively. As can be seen from Table 1, the Cronbach's Alpha values of "product involvement", "discount offer" and "entertainment" are within the range and higher than 0.9, indicating that the reliability of the scales of these three variables is high. Moreover, the "total correlation of correction items" of the three variables are within the qualified range. Therefore, the reliability test is qualified and all the questions can be used. From Table 2, the Cronbach's Alpha values of "trust" and "perceived value" are within the range and reach 0.904 and 0.894 respectively, indicating that the reliability of the scales of these two variables is high. Moreover, the "total correlation of correction items" values are within the qualified range. The Cronbach's Alpha values after deleting items are all smaller than the Cronbach's Alpha values of each variable. Therefore, the reliability test is qualified and all the questions can be used. From Table 3, it can be seen that the Cronbach's Alpha value of "purchase intention" reaches 0.906, indicating that the reliability of the scale of this variable is high. Moreover, the "total correlation of correction items" value is within the qualified range. The Cronbach's Alpha values after deleting items are all smaller than the Cronbach's Alpha values of each variable. Therefore, the reliability test is qualified and all the questions can be used. In conclusion, from the above results, it can be known that the reliability of this questionnaire is qualified. Next, a formal survey will be conducted.

Table 1: Reliability test results of antecedent variables

Variable name	Subject number	CITC	Item deleted α coefficient	Cronbach's Alpha
Product involvement	A1:I am interested in the products introduced by AICG's generated content	0.905	0.907	0.957
	A2:I believe that AICG's products that generate content recommendations are helpful to me	0.911	0.909	
	A3:I would like to buy products recommended by AICG generated content	0.908	0.916	
Discount	A4:I buy because the item is limited or limited.	0.876	0.824	0.932
	A5:I buy things because they are on sale in the broadcast room.	0.782	0.913	
	A6:I will buy goods because of the coupons and lottery activities distributed during the live broadcast.	0.811	0.865	
Entertainment	A7:I really enjoy the content generated by AICG.	0.804	0.701	0.909
	A8:I am always happy and relaxed in the broadcast room.	0.793	0.746	
	A9:I think live broadcast can make me as happy as variety show.	0.632	0.906	

Table 2: Results of reliability test for mediating variables

Variable name	Subject number	CITC	Item deleted α coefficient	Cronbach's Alpha
Trust	A10:I think the products introduced by AICG have good quality.	0.872	0.899	0.904
	A11:I think the products that AICG generates content recommendations are trustworthy.	0.824	0.908	
	A12:I think the quality of products recommended by AICG is extremely reliable.	0.855	0.884	
Perceived value	A13:I think AICG produces content presentations that are good value for money.	0.794	0.845	0.894
	A14:AICG generated content that convinced me that the product would meet my needs.	0.801	0.826	
	A15:I can feel that AICG generated content and showed the product in all aspects.	0.792	0.861	

Table 3: Results of reliability test of outcome variables

Variable name	Subject number	CITC	Item deleted α coefficient	Cronbach's Alpha
Purchase intention	A16:If there is a purchase demand, I am willing to buy goods through the live streaming platform.	0.786	0.901	0.906
	A17:I will buy products while watching the live broadcast.	0.891	0.855	
	A18:Live streaming platform will significantly affect my purchase intention.	0.885	0.874	

3.3 Descriptive statistical analysis

During the formal survey stage, questionnaires were distributed through channels such as push within M's official app, announcements in the live broadcast room and members' emails, inviting users who have engaged in live shopping behaviors in the past three months to participate in filling out the questionnaires, and a total of 405 valid questionnaires were eventually recovered. The samples covered users of different age groups, genders, consumption levels and live broadcast viewing frequencies to ensure that the data is fully representative and the analysis results are robust.

3.3.1 Demographic characterization

The first part of the questionnaire is the basic information of the respondents, which reflects the basic demographic characteristics of the consumers of Company M's e-commerce live streaming platform, mainly including gender, age, education, average monthly income and weekly viewing hours. Through the data collection of the returned valid questionnaires, the statistical results of the basic information of the surveyed sample of e-commerce live streaming viewers of Company M are shown in Table 4. From the gender distribution of the respondents, among the valid samples of this research, there are 143 males and 262 females, with the two groups accounting for 64.69% and 35.31% respectively. At present, the female group is still the main audience of M's e-commerce live shopping, the questionnaire distribution takes the form of randomization, and the recovery results are in line with the actual situation of the gender of M's e-commerce live audience. The user groups are all dominated by the group of 21-30 years old, followed by 31-40 years old and over 40 years old, and the research samples are basically in line with the current audience characteristics of M Company's e-commerce live business. The two groups of undergraduate and master's degree in this research have the highest proportion, and the proportion of groups with different average monthly incomes does not differ much. From the weekly viewing hours of the respondents, the largest proportion of the audience who watched M Company's e-commerce live streaming for less than 4 hours per week reached 91.85%, which to a certain extent indicates that consumers of M Company's e-commerce live streaming platform retain a certain degree of rationality in viewing, and also indicates that the transaction conclusion efficiency of e-commerce live streaming is high, which can reduce the time cost of consumers' choice of goods.

Table 4: Statistics of basic information of the sample

Basic information	Type	Number	Proportion
Gender	Male	262	64.69%
	Female	143	35.31%
Age	Under 20 years old	17	4.20%
	21 to 30 years old	178	43.95%
	31 to 40 years old	152	37.53%
	Over 40 years old	58	14.32%
Education background	High school includes the following	16	3.95%
	Junior college degree	38	9.38%
	Undergraduate college	185	45.68%
	Master's degree or above	166	40.99%
Average monthly income	2000 yuan or less	90	22.22%
	2001-6000 yuan	101	24.94%
	6001-10000 yuan	108	26.67%
	10000 yuan or more	106	26.17%
Weekly viewing time	0~4 hours	372	91.85%
	5~8 hours	29	7.16%
	More than 9 hours	4	0.99%

3.3.2 Consumer perception status

In order to have an overall grasp of the results of the survey data, the minimum, maximum, mean and standard deviation of each variable were calculated. The results of the descriptive statistics of the consumer perception scale are shown in Table 5. As can be seen from the table, the consumer perception ratings of the six dimensions of product involvement, preferential discounts, entertainment, trust, perceived value and willingness to buy all exceed the mean value of the question score setting (the mean value is 2.5), and the maximum and minimum values of all the question scores are 5 and 1, which indicates that there is a large difference in the respondents' evaluations of the consumer perceptions. The largest mean value was perceived value at 3.840, while the smallest mean value was trust at 3.738.

Table 5: Descriptive statistical results of the Consumer perception Scale

Variable name	Subject number	Minimum	Maximum	Mean value	Standard deviation
Product involvement	A1	1.00	5.00	3.773	1.048
	A2	1.00	5.00	3.694	1.022
	A3	1.00	5.00	3.872	1.093
Discount	A4	1.00	5.00	3.822	1.147
	A5	1.00	5.00	3.798	1.208
	A6	1.00	5.00	3.874	1.099
Entertainment	A7	1.00	5.00	3.802	1.187
	A8	1.00	5.00	3.951	1.104
	A9	1.00	5.00	3.704	1.126
Trust	A10	1.00	5.00	3.719	1.094
	A11	1.00	5.00	3.684	1.118
	A12	1.00	5.00	3.812	1.227
Perceived value	A13	1.00	5.00	3.864	1.172
	A14.	1.00	5.00	3.879	1.037
	A15	1.00	5.00	3.778	1.111
Purchase intention	A16	1.00	5.00	3.812	1.248
	A17	1.00	5.00	3.798	1.209
	A18	1.00	5.00	3.701	1.213

3.4 Questionnaire Reliability Test

3.4.1 Reliability test

Reliability analysis can be used to test the reliability of the measurement results of the questionnaire and the reasonableness and validity of the setting of the questions, which reflects the relationship between the questions under the same index in the questionnaire and whether the questions are able to measure the same content well, highlighting the stability of the design, which is also known as the reliability analysis of the questionnaire. Currently, the more commonly used measure of questionnaire reliability is the Cronbach coefficient. If this coefficient is lower than 0.35, it indicates that the questionnaire question items are not reasonably set, the scale is not desirable, the measurement results are invalid, and the questionnaire needs to be redesigned. Combined reliability (CR) represents the degree of internal consistency of the variables in the questionnaire, and the internal correlation of the variables is better as the value of combined reliability (CR) increases. It is generally recognized that a combined reliability (CR) value greater than 0.7 represents a good composite reliability of the data.

The results of the reliability analysis of each variable are shown in Table 6. The Cronbach's α values of the product involvement, preferential discount, entertainment, trust, perceived value and purchase intention factors are all greater than 0.7, and the reliability of the data collected for each factor is good. The Cronbach's α value of the overall consumer perception scale is 0.915, the scale items are set reasonably, and the data can be progressively used for analysis and application. The combined reliability (CR) of each subdivided factor is greater than 0.8, indicating that the internal consistency of each question item is high and the scale setting is reasonable.

Table 6: Results of reliability analysis of each variable

Variable name	Number of items	The Cronbach's α of each factor was calculated	CR	The Cronbach's α of the scale was calculated
Product involvement	3	0.801	0.882	0.915
Discount	3	0.806	0.879	
Entertainment	3	0.723	0.855	
Trust	3	0.814	0.892	
Perceived value	3	0.711	0.856	
Purchase intention	3	0.805	0.894	

3.4.2 Validity tests

Discriminant validity is mainly to calculate the correlation coefficients of the variables themselves and among the variables, the correlation coefficient of a variable itself is greater than the correlation coefficient with other variables, which indicates that there is a significant difference between the variable and other variables, i.e., the variable has a large discriminant validity, and has a significant role in distinguishing other variables. The correlation coefficient of the variable itself was replaced by the square root of AVE. The correlation coefficients between each variable and other variables of the questionnaire data in this paper were obtained by SmartPLS calculation as shown in Table 7. The diagonal line on the lower right is the square root of AVE of each variable itself. Comparing the data in each column, it is found that the square root of AVE of each variable itself is greater than the correlation coefficient with other variables, i.e., there is a weak correlation and a large difference between the variables of product involvement, preferential discounts, entertainment, trust, perceived value, and willingness to buy, which indicates that the discriminative effect of the data of the scale is ideal.

Table 7: Comparison of the variables and their correlation coefficients

	Product involvement	Discount	Entertainment	Trust	Perceived value	Purchase intention
Product involvement	0.922					
Discount	0.636	0.845				
Entertainment	0.514	0.594	0.937			
Trust	0.478	0.615	0.484	0.895		
Perceived value	0.582	0.577	0.495	0.574	0.961	
Purchase intention	0.601	0.558	0.516	0.582	0.616	0.884

After analyzing the variable factor discriminant validity, it is also necessary to analyze the correlation of each variable of the model with all the loading factors, i.e., to analyze the correlation of the question variable studied in the questionnaire with all the scale items. The correlation coefficients between the question variables and the items reflecting themselves should be greater than the correlation coefficients with all other items, and the correlation coefficients in the discriminant condition are replaced by the cross-factor loading coefficients. The calculated cross-factor loading coefficients for the sample data in this paper are shown in

Table 8. The cross-factor loading coefficients of each variable of the model itself are greater than the cross-factor loading coefficients with other variables. It shows that in this study, each measurement item has strong correlation and interpretation with its corresponding question variable, and can be effectively distinguished from other non-corresponding question variables, which meets the requirement of discriminant validity measurement.

Table 8: Cross-factor loading coefficients

Subject number	Product involvement	Discount	Entertainment	Trust	Perceived value	Purchase intention
A1	0.817	0.472	0.482	0.308	0.552	0.419
A2	0.855	0.501	0.418	0.387	0.429	0.464
A3	0.901	0.436	0.512	0.409	0.442	0.503
A4	0.425	0.846	0.417	0.488	0.382	0.360
A5	0.418	0.905	0.428	0.412	0.419	0.442
A6	0.482	0.873	0.433	0.458	0.484	0.405
A7	0.398	0.425	0.894	0.409	0.483	0.409
A8	0.503	0.418	0.911	0.426	0.391	0.418
A9	0.377	0.422	0.906	0.433	0.418	0.444
A10	0.381	0.409	0.419	0.918	0.505	0.398
A11	0.372	0.393	0.508	0.902	0.463	0.472
A12	0.481	0.387	0.372	0.901	0.452	0.471
A13	0.444	0.418	0.418	0.552	0.877	0.449
A14.	0.409	0.402	0.419	0.429	0.826	0.418
A15	0.418	0.476	0.464	0.501	0.883	0.434
A16	0.398	0.488	0.455	0.398	0.427	0.891
A17	0.437	0.426	0.377	0.377	0.422	0.904
A18	0.446	0.442	0.422	0.383	0.409	0.913

Combined with the reliability and validity analysis of the questionnaire data mentioned above, the questionnaire designed in this study is reasonable, accurate, and valid, and at the same time, the computational indexes further illustrate that, the sample data of the questionnaire are reliable and trustworthy, and have the data basis for the analysis of structural equation modeling.

3.5 Structural Equation Modeling Analysis

3.5.1 Modeling

In this paper, a structural equation model is constructed, and maximum likelihood estimation is carried out using AMOS23.0 to obtain the model fitting effect as shown in Figure 1. A total of six latent variables are set in the model to study the main factors of the influence of AIGC-generated content on the willingness to consume e-commerce live streaming, and to explore the interactions that exist between each of the different latent variables.

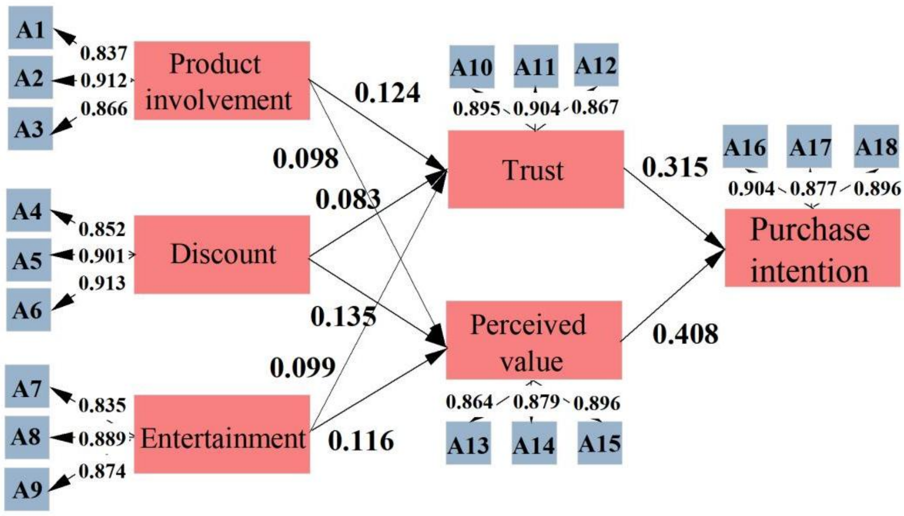

Figure 1: Model fitting effect

The detection of the model fit needs to be measured from the 9 indicators of CMIN/DF, RMR, GFI, AGFI, NFI, IFI, TLI, CFI and RMSEA. The results of the model fit analysis are shown in Table 9, where the value of CMIN/DF is 1.120, and the fit of the other 9 metrics is better.

Table 9: Results of model fitting analysis

Index	Optimal standard value	Acceptable standard value	The statistical value of the study	Fit situation
CMIN	/	/	409.558	/
DF	/	/	375	/
CMIN/DF	<3	<5	1.092	Good
RMR	<0.05	<0.08	0.042	Good
GFI	>0.80	>0.70	0.837	Good
AGFI	>0.80	>0.70	0.892	Good
NFI	>0.90	>0.70	0.905	Good
IFI	>0.90	>0.70	0.973	Good
TLI	>0.90	>0.70	0.989	Good
CFI	>0.90	>0.70	0.976	Good
RMSEA	<0.08	<0.10	0.018	Good

3.5.2 Path analysis

The model can be path analyzed after passing the fit test, and the results of the path analysis in this paper are shown in Table 10. The standard coefficient of the product involvement index to the trust index is 0.211, indicating that the product involvement index will significantly and positively affect consumer trust in consumers' live e-commerce shopping when the P value is less than 0.001, and hypothesis H1 is valid. The standardized coefficient of the product involvement indicator to the perceived value indicator is 0.016, at which time the P-value is 0.476, indicating that the product involvement indicator does not affect consumers' perceived value, and hypothesis H2 is not valid. The standardized coefficient of preferential discount indicator to trust indicator is 0.002, at this time the P-value is 0.318, indicating that the preferential discount indicator did not affect the consumer's trust, hypothesis H3 is not valid. The standard coefficient of the preferential discount indicator to the perceived value indicator is 0.203, which indicates that the preferential discount indicator significantly and positively affects consumers' perceived value in consumers' live e-commerce shopping with a P value of less than 0.01, and hypothesis H4 is valid. The standardized coefficient of the entertainment indicator to the trust indicator is 0.007, at which time the P-value is 0.209, indicating that the entertainment indicator does not affect consumer trust, and hypothesis H5 does not hold. The standard coefficient of the entertainment indicator to the perceived value indicator is 0.308, which indicates that the entertainment indicator will significantly and positively affect consumers' perceived value in consumers' live e-commerce shopping with a P value less than 0.001, and hypothesis H6 is valid. The standardized coefficient of trust indicator to purchase intention indicator is 0.207, indicating that trust indicator will significantly and positively influence consumers' purchase intention in consumers' live e-commerce shopping in the case of P-value less than 0.01, and hypothesis H7 is established. The standardized coefficient of the perceived value indicator to the willingness to buy indicator is 0.214, indicating that the perceived value indicator will significantly and positively influence consumers' willingness to buy in consumers' live e-commerce shopping in the case of P-value less than 0.001, and hypothesis H8 is established.

Table 10: Results of path analysis

Path	Standard coefficient	S.E.	C.R.	P value	Hypothesis
Trust <= Product involvement	0.211	0.087	1.897	***	Yes
Perceived value <= Product involvement	0.016	0.063	0.009	0.476	No
Trust <= Discount	0.002	0.071	0.007	0.318	No
Perceived value <= Discount	0.203	0.088	1.835	**	Yes
Trust <= Entertainment	0.007	0.079	0.005	0.209	No
Perceived value <= Entertainment	0.308	0.084	1.996	***	Yes
Purchase intention <= Trust	0.207	0.076	1.743	**	Yes
Purchase intention <= Perceived value	0.214	0.088	1.924	***	Yes

4 Mechanism of AIGC-generated content to enhance the effect of product promotion

At the level of consumer trust, product involvement has a significant positive impact on trust. When AIGC-generated content can accurately fit consumers' focus of interest and demonstrate a high degree of relevance to their personal needs, consumers are more inclined to establish positive psychological beliefs about the information source and recommended products. Through the algorithm's in-depth analysis of user profiles and interest labels, it automatically generates product introductions that fit the needs of target users, thus increasing users' attention and trust in the content.

At the level of consumer value perception, discounts and entertainment have significant positive effects on perceived value, respectively. Under the immediacy and interactivity of the live broadcast environment, consumers are more likely to be directly affected by external explicit stimuli in their judgment of product value, and AIGC technology, with its efficient content generation capability, can quickly produce attractive promotional information and creative interactive episodes, which can strengthen the consumers' perception of economic concessions and emotional pleasure in a short period of time, and thus effectively enhance their evaluation of the comprehensive utility of the product. Evaluation of the comprehensive utility of the product.

Consumer trust and perceived value act as parallel intermediary variables in the formation of purchase intention, and AIGC-generated content not only needs to build trust through real and objective recommendations, but also needs to enhance the value perception by satisfying functional and emotional needs, in order to form a complete reason for purchase in the minds of consumers. Specifically, AIGC technology, on the one hand, utilizes the precise matching advantage of algorithms to reduce the cost of user information screening and processing, thus enhancing the recognition of content credibility. On the other hand, through diversified forms of content expression, such as contextualized interpretation, interactive scripts, etc., it enhances the entertainment and emotional connection, and ultimately forms a strong purchase motivation at the psychological level.

From a comprehensive point of view, the effect of AIGC-generated content on product promotion is essentially realized through the two parallel paths of enhancing consumer trust and perceived value, and AIGC technology can efficiently produce content that meets the needs of users, reduce information uncertainty and build trust at the cognitive level, and create a positive experience at the emotional and value levels, which optimizes the consumer's decision-making process and promotes the purchase behavior. Purchase behavior.

5 Conclusion

In this paper, the research model of the influencing factors of AIGC-generated content on consumers' purchase intention is constructed with the consumers of M Company's e-commerce live broadcasting platform as the research object. After modeling and analyzing 405 valid questionnaires, the following research conclusions were drawn.

(1) The Cronbach's α values of the questionnaire scale variables are all above 0.7, the overall reliability is 0.915, and the scale validity also reaches the ideal standard. The structural equation modeling indicators all reached the optimal standard value, and the model fit was good.

(2) In the study of the influence of AIGC generated content on consumers' purchase intention, the entertainment and the strength of the offer significantly affect the perceived value of consumers, of which the entertainment is the most significant, with a standardized coefficient of 0.308, which shows that consumers' standard of living is improving, but also more and more attention is paid to the spiritual demands, and it is only by bringing pleasure to consumers when recommending products that consumers can be further stimulated in their purchase intention. Willingness to buy.

(3) In the study of the influence of AIGC-generated content on consumers' purchasing intention, the degree of product involvement significantly influences consumers' trust in AIGC-generated content. This shows that the all-round presentation of the recommended products in AIGC-generated content significantly affects consumers' trust in it, and correspondingly, the more comprehensive the presentation is, the more consumers trust the products recommended by AIGC-generated content, and vice versa.

(4) In the study of factors influencing consumers' purchase intention of AIGC-generated content, trust and perceived value as mediating variables affect consumers' purchase intention. Among them, perceived value is more significant, with a standardized coefficient of 0.214. When AIGC-generated content affects consumers' perceived value of the recommended products, it is more likely to increase consumers' purchase intention.

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