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Article

The Impact of Social Media Interaction Frequency on Purchase Intention: Evidence from the Guiyang IT Market Mediated by Consumer Trust

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Abstract: With the development of social media platforms, the importance of social media marketing is gradually realized by major brands. This paper constructs an SEM test model containing a measurement model and a structural model, discusses the influence of social media participation on consumers' purchase intention, proposes the mediating role of brand equity and the moderating role of AI participation, and puts forward the corresponding research hypotheses for the above influencing roles. Questionnaires are designed to screen target users of social media platforms, research data are collected, data reliability and validity are examined, and relationships between variables are measured through SEM paths. The AVE values of the indicators of social media participation, such as liking and commenting, content creation, attention and interaction, and emotional investment, are all greater than 0.75, which has the fit validity. The standardized path coefficients of different dimensional variables on brand equity are 0.192, 0.162, 0.159, and 0.206, respectively, and social media engagement significantly and positively influences consumer purchase intention through the mediating bridge pair of brand equity. The findings are instructive for brand equity to enhance the marketing effectiveness of social media platforms.

Keywords: SEM test; social media engagement; brand equity; purchase intention; standardized path coefficient

1. Introduction

The rapid development and popularization of social media has greatly changed people's lifestyle and become one of the important channels for enterprises to carry out promotion [1]. With its wide coverage and precise targeting ability, social media has a great influence on consumers' purchase intention, in which brand equity and artificial intelligence (AI) play an important role of mediation and regulation in this process [2-3].

Brand equity is a network of associations centered on the brand name, i.e., the meaning of the brand in the minds of consumers. The meaning of the brand first comes from the literal meaning of the brand name, and on this basis it is learned and accumulated through both marketing activities and product purchase and use [4-5]. The core value of a brand is the personality or benefit that distinguishes it from other competitors and is the main reason why consumers identify with, like or even favor a brand [6]. In the marketing of social media, when consumers participate in the brand-related content, its brand value will subconsciously influence consumers' positive image of the product, thus increasing consumers' purchase intention. The application of AI in social media is mainly reflected in personalized recommendations. The use of AI can effectively collect consumers' social platform interactions, social networks and other data, quickly and accurately assess market trends and consumer preferences, and accurately recommend products that may be of interest to consumers in order to increase the willingness to buy [7-8]; at the same time, it can also be based on the personalized needs of consumers to better formulate marketing strategies, to achieve the purpose of increasing the willingness to buy [9-10].

Aiming at the mediating role of brand equity on consumers' purchase intention in social media, literature [11] examined the impact of social media communication on brand value and purchase intention through linear regression analysis, pointing out that enterprise and user-generated content are fully mediated to the decision-making link through electronic word-of-mouth, and emphasizing the significant driving effect of brand equity in Bosnian consumption context. Literature [12] analyzes the impact of social media interactions on brand equity in Ghanaian fashion consumption based on structural equation modeling, noting that monitoring and information sharing significantly drive equity appreciation while entertainment socialization does not, and emphasizing the fully mediated effect of brand equity in social media influencing purchase intentions. Literature [13] analyzes the role of social media marketing in driving brand equity and purchase intention through structural equation modeling, noting that it significantly enhances brand value perceptions and transforms consumer attitudes, and emphasizing that precision strategy is a key support for strengthening loyalty and gaining competitive advantage. By analyzing the source and intensity of social media communication, literature [14] found that emotional dimensions of brand equity, such as association and loyalty, still play a significant mediating role in driving purchase intention, while the influence of attributional dimensions, such as quality and trust, tends to weaken, which emphasizes the perturbing effect of epidemic anxiety on the regular consumption path. Literature [15] found that online community, interaction and content sharing in social media marketing significantly drove purchase intention of Starbucks Indonesia through path analysis and Sobel's test, and emphasized that brand value plays a key mediating role between marketing stimulus and consumption decision. Literature [16] analyzed the role of social media marketing in driving brand value of luxury fashion brands in Pakistan based on structural equation modeling, pointed out that brand value plays a significant positive mediating effect between marketing campaigns and purchase intention and customer value, and emphasized the constraining influence of experiential aspects and the absence of online communities on omni-channel strategies. Literature [17] analyzed through structural equation modeling indicates that brand equity partially mediates the effects of social media usage and electronic word-of-mouth on purchase intention in Indian apparel consumption and highlights its critical moderating value as an integrative framework for the construction of customized marketing strategies. Literature [18] analyzes the impact of social media communication on brand equity and purchase intentions using Instagram accounts, pointing out that user- and company-generated content positively drives brand awareness and loyalty, and emphasizing that brand equity plays a fully mediating role in the translation of social communication into consumption decisions. Literature [19] examines the role of influencer characteristics in driving brand equity and purchase intentions of Moroccan and Turkish consumers through path analysis, pointing out that authenticity and communication skills significantly enhance perceived quality and brand loyalty, and emphasizing that brand loyalty plays a key mediating effect in the translation of influencer marketing into consumption decisions. Literature [20] based on the SEM-PLS method analysis pointed out that user-generated content has the most significant driving effect on purchase decision of Indonesian tea drinks, examined the mediating transmission mechanism of brand awareness and association dimensions, and emphasized that perceived quality plays a key pivotal role in the transformation of brand equity. Literature [21] points out through quantitative analysis that social media marketing activities have a significant shaping effect on coffee brand awareness and image, examines the formation path of brand equity in Instagram communication, and emphasizes the transmission mechanism of brand awareness through the accumulation of assets that ultimately drive consumers' purchase intention. It can be seen that academics have generally emphasized the key mediating role of brand equity between social media marketing activities and consumer purchase intention, but this role can be affected by product category, cultural context and other aspects.

As for the moderating role of AI engagement, literature [22] analyzes the driving path of AI elements in social media on consumer purchase intention based on the technology acceptance model, pointing out that recommender systems and chatbots influence decision-making by enhancing engagement and perceived usefulness, and emphasizing the positive moderating effect of globalism on the relationship between AI recommendation and engagement. Literature [23] analyzed the path of AI anthropomorphic features on consumer purchase intention based on media richness theory, pointed out that perceived intelligence and anthropomorphism drive decision-making through the mediation of trust, and emphasized their key role in moderating consumer incentives and shopping experience in retail scenarios. Literature [24] analyzes the driving role of AI virtual netizens' trustworthiness, information value and human touch on consumers' engagement and purchase intention through questionnaires, pointing out that post attractiveness only affects engagement without touching decision-making, and emphasizing its moderating potential and theoretical gaps as an emerging marketing tool. Based on the stimulus-subject-response model, literature [25] analyzes the driving role of AI recommendation, personalized information flow and quality on consumer engagement and purchase intention in social media, and emphasizes that AI technology features ultimately positively regulate the formation of consumer decisions through the transmission of user behavior. Based on the stimulus-subject-response model, literature [26] analyzes the positive drivers of information, interactivity, accessibility and personalization of AI marketing campaigns on bank customers' brand experience and repurchase intention, and emphasizes that brand experience plays a key mediating role between AI marketing and customer loyalty. Literature [27] analyzes the conversion effect of AI-driven elements of personalized recommendation, behavioral targeting and predictive analytics on purchase intention in digital marketing through a sample survey and highlights the key moderating role of AI in reshaping the online retail experience and optimizing real-time ad delivery. Literature [28] points out that AI and digital marketing significantly affect millennials' purchase intention through structural equation modeling analysis, and emphasizes the moderating role of technological embeddedness on the consumer decision path. Literature [29] analyzed the sentiment analysis of social media data based on generative AI and BERT model, and found that the positive sentiment of vehicle performance accounted for 57.8% while the negative feedback of comfort amounted to 17.2%, and emphasized that the sentiment tendency has a significant moderating effect on the purchase intention of new energy vehicles. Literature [30] points out through quantitative analysis that the synergy between social media marketing and AI can significantly enhance the trust and satisfaction of tourism consumption, and emphasizes the key moderating value of the integration of the two to optimize online purchase decisions and enhance the competitiveness of the industry. The above studies reveal that AI in social media significantly drives consumer purchase intention through mechanisms that enhance user engagement, perceived usefulness, trust, and brand experience, while being constrained by factors such as affective disposition and technology acceptance.

In this paper, we first propose the relationship between social media engagement on brand equity and brand equity on consumer purchase intention, and put forward the corresponding research hypotheses, while introducing AI engagement to discuss the moderating effect of high autonomy and low autonomy on consumers' purchase intention, and set up the research hypotheses. Then, research modeling methods are established, structural equation modeling is selected to explore the causal relationship between variables, and the SEM analysis process is studied with path diagram, path coefficients and effect analysis. Finally, the analyzed data are tested by reliability and validity analysis, CFA factor test, path test, and moderating effect test to discuss the relationship between the variables and verify the research hypotheses proposed in the previous section.

2. Research hypothesis

2.1. Social Media Engagement and Brand Equity

Participation refers to the extent to which users are involved mentally and physically in the process of a specific activity. Participation is recognized by scholars as an important characteristic of social media. Participation in social media empowers consumers to participate on their own, and the more involved consumers are, the more likely they are to be exposed to social cues in social media, thus creating a sense of social presence. In addition, engagement gives consumers more control, and engagement behaviors are often accompanied by clear goals (to obtain information, offers, etc.), which makes it easier to focus on and build brand equity when consumers are more involved. Based on this, the following hypotheses are proposed:

H1: Social media engagement has a positive impact on brand equity building.

2.2. Brand Equity and Consumer Purchase Intention

Brand equity image through the brand consumption identity brought to consumers and advocate the brand to get a sense of superiority, so that consumers in the consumption process to realize the self-effacement, and thus enhance the willingness to buy. Social boosting theory is widely used to explain the mechanism of brand equity image on consumer purchasing behavior, that is, when people feel the brand effect will have an impact on individual behavior. Based on this, the following hypotheses are proposed:

H2: Brand equity image has a positive effect on consumer purchase intention.

2.3. The moderating role of artificial intelligence

The emergence of artificial intelligence as a new technology is accompanied by the immaturity of its technology in the process of its development, which leads to a high perceived risk for consumers. In the process of social media engagement marketing, the level of autonomy of AI directly affects the level of its agency. Low autonomy AI compared to high autonomy AI, people in the process of human-computer interaction with a higher degree of interaction and greater decision-making power, which also reflects that consumers can have more freedom and space for choice, and this freedom and space for choice to reduce people's perceived risk of artificial intelligence. At the same time, perceived risk also directly affects purchase intention, i.e., consumers' purchase intention is lower for high-autonomy AI that perceives higher risk, while it is higher for low autonomy AI that perceives lower risk. This paper suggests that AI (high autonomy vs. low autonomy) has a moderating effect on consumers' purchase intention, as evidenced by consumers' higher purchase intention for low autonomy AI compared to high autonomy AI. Based on this, the following hypotheses are proposed:

H3: Artificial intelligence (high autonomy vs. low autonomy) has a positive effect on consumers. Specifically, consumers are more willing to purchase low autonomy AI than high autonomy AI.

3. Research methodology

3.1. Structural equation modeling

Structural equation modeling (SEM) is a multivariate statistical technique, which is called “the second generation of multivariate statistical analysis” [31]. In the fields of sociology, economics, psychology and education, many common phenomena, such as people's happiness, satisfaction, subjective norms, anxiety, motivation to learn, etc., these indicators usually can not be measured directly, but people can use some observable variables to show these indicators, for example, when we judge a person's personality, we can not know a person's personality directly, we can only know their personality through some external behavior. For example, when we judge a person's personality, we can't know a person's personality directly, we can only know his/her personality through some external behaviors, so personality is the latent variable, and external behaviors are its observable variables. When dealing with these observational variables, traditional statistical methods are using linear regression processing, this method can not avoid the problem of indicator covariance in the measurement process, as well as can only deal with an independent variable to a dependent variable, and does not take into account the existence of measurement error, these limitations will make linear regression analysis of the results of the bias.

The structural equation model, shown in Figure 1, contains two main parts, where the solid part represents the measurement model and the dashed part represents the structural model, the rectangles in the model diagram represent the observed variables in the measurement model (Y1, Y2, Y3...), and the ellipses in the model diagram represent the latent variables (X1, X2, X3...) that These variables cannot be directly observed or measured and are reflected by the indicator variables, but due to measurement error, each observed variable cannot fully represent the latent variables, so e1-e2 represents the residuals of each observed variable.

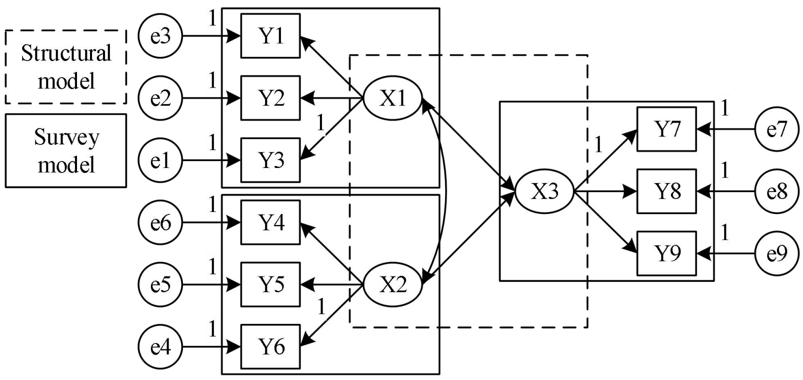

Figure 1. The basic procedure of structural equation model analysis

3.2. Specific structure of SEM

3.2.1. Measurement models

Measurement modeling is an important part of SEM that measures the relationship between observed variables and latent variables. Researchers also call the measurement model a factor model because the latent variable is counted as a factor in the model and the measurement model measures the relationship between the factor and its item indicators. The principle equations of the model are shown in equations (1) and (2):

$$\begin{gathered} X = \Lambda_x \xi + \delta \\ (q \times 1)\ (q \times n)(n \times 1)\ (q \times 1) \end{gathered} \tag{1}$$

$$\begin{gathered} Y = \Lambda_y \eta + \varepsilon \\ (p \times 1)\ (P \times m)(m \times 1)\ (p \times 1) \end{gathered} \tag{2}$$

where X is the observed variable of ξ, δ is the residual term of X, and Λ_x is the $(q \times n)$ coefficient matrix of the factor loadings of X on ξ; Y is the observed indicator of η, ε is the residual term of Y, and Λ_y is the $(p \times m)$ coefficient matrix of the factor loadings of Y on η. q is the number of X and p is the number of Y. The conditions under which this holds are $E(\xi)=0$, $E(\eta)=0$, $E(\varepsilon)=0$, $E(\delta)=0$; where ε is independent of η, ξ, and δ; δ is independent of η, ξ, and ε independently.

The measurement model in SEM is essentially a validated factor analytic model, which refers to an indirect measure of the fit between the latent variable and its derived observational variables, that is, the reliability and validity of each of the observational variables that make up the latent variable (the items in the questionnaire) with respect to its latent variable. Reliability refers to the fact that after factor analysis, the resulting clone bach number of the latent variable and its observed variables meets the fit index, which means that the reliability is at an acceptable level. While validity includes content validity and structural validity, content validity refers to the representativeness of the items in the questionnaire, and structural validity refers to the extent of the test of the traits under study, which can be carried out by conducting a suitability test such as KMO, and then utilizing the factor extraction and the cumulative variance explained ratio conducted by factor analysis to indicate that the established variables have structural consistency with the extracted factors.

3.2.2. Structural models

Structural modeling is another important part of SEM that measures the latent variable to latent variable relationship. Researchers also call it the causal model because it measures the latent variable to latent variable causality. The principle equation of its model is shown in equation (3):

$$\begin{gathered} \eta = B\eta + \Gamma\xi + \zeta \\ (m \times 1)\ (m \times m)(m \times 1)\ (m \times n)(n \times 1)\ (m \times 1) \end{gathered} \tag{3}$$

where η is the endogenous latent variable; ξ is the exogenous latent variable; ζ is the error term, i.e., the portion of η that is unexplained by ξ; B is the matrix of $(m \times m)$ coefficients of the relationship between multiple η; Γ is the matrix of $(m \times n)$ coefficients of the relationship between multiple ξ; m is the number of η. matrix; m is the number of η and n is the number of ξ. The conditions under which this holds are $E(\zeta)=0$, $E(\eta)=0$, and $E(\zeta)=0$.

And structural equation modeling is a composite of causal model and factor relationship model, thus the principle equation of SEM is as in equation (4):

$$\begin{cases} \eta = B\eta + \Gamma\xi + \zeta \\ X = \Lambda_x \xi + \delta \\ Y = \Lambda_y \eta + \varepsilon \end{cases} \tag{4}$$

Among the conditions to be satisfied are:

(1) Measurement error: $E(\varepsilon)=0$, $E(\delta)=0$; residual term: $E(\zeta)=0$;

(2) ε is independent of η, ξ, δ, and ζ, δ is independent of η, ξ, ε, and ζ; ζ is independent of ξ.

Theoretically, a full model of a structural equation should contain several measurement models and a structural model.

3.2.3. Basic ideas

The use of SEM to solve the problem to be studied is to use the data collected to verify the conjecture. In this process SEM is utilized to present the degree of closeness between the hypothesized model developed and the actual data model, defining the difference as a fit function, and the desired outcome is to minimize the maximum value of the fit function.SEM differs from traditional analytical methods in that it can effectively and scientifically account for a number of psychologically and managerially unmeasurable variables in a direct way, and it is largely tolerant of error (error). The resulting use of SEM to explain phenomena is to explore the covariance matrix between hypothesis and actuality, expressed as:

$$\sum=\sum(\theta) \tag{5}$$

where $\sum$ is the covariance matrix that can be calculated using the data of the observed variables; θ is the parameter to be estimated in the model; and $\sum(\theta)$ the fitting function of the covariance matrix. According to Eq. (4), the parameter θ is derived by making the elements of the two matrices at the corresponding positions equal and performing constant iterations so that $\sum(\theta)$ is infinitely close to S. A complete SEM contains 8 parameter matrices: Λ_x, Λ_y, B, Γ, Φ, Ψ, Θ_ε and Θ_δ.

3.2.4. Path analysis

Path analysis is a method of exploring the causal relationship between variables and even analyzing the indirect effect influence between variables. Therefore path analysis is an important part of problem solving using structural equation modeling. Path analysis consists of three steps: first, label the path diagram according to the model diagram of structural equation modeling; second, use the software to fit the path coefficients; and finally, analyze the effect share for each path of the model. Path analysis can be used to explain the results of exploring a certain problem by knowing the causal relationship between variables and the magnitude of their effects. It includes three parts: path diagram, path coefficients and effect analysis. Path analysis is also an important part of structural equation modeling. In this case, path diagrams are used to graphically represent the subordination of variables to each other in a visual form. For any two variables x and y in the model, there are four possible relationships:

(1) If x affects y and y does not affect x, then there is a single arrow line between them pointing from x to y;

(2) If y affects x and x does not affect y, then there is a single arrow line between them pointing from y to x;

(3) If x affects y and y also affects x, then there is a double arrow line between x and y;

(4) If there is only a correlation between x and y, then x and y are connected by an arc with an arrow.

4. Empirical testing

4.1. Research design and data collection

(1) Questionnaire Measurement

This study adopts the questionnaire method to collect research data. The research object of this study is the users of social media platform use, designed according to the existing mature scale, the questionnaire mainly includes three parts: questionnaire screening, measurement of potential variables, and user statistical information. First of all, the questionnaire first explains the purpose of the questionnaire and the use of data collection to the respondents to ensure the confidentiality of the questionnaire content. The three parts of the questionnaire are as follows: the first part is target user screening, asking the respondents whether they use the microblogging social media platform and follow the microblogging account of a certain brand, in order to screen the target user survey group, and allow the respondents to fill in a microblogging brand they often pay attention to on a daily basis, and according to this brand for the next question to be answered.

The second part is to measure the latent variables, for the survey theme part of the scale question items, based on the research theory and assumptions, reference to the existing mature scale and related theories, collect data to verify the hypothesis. There are a total of 9 variables in this study, which are 4 dimensions under social media participation: liking and commenting (SMP1), content creation (SMP2), following and interacting (SMP3), and emotional investment (SMP4), 3 dimensions under brand equity image: brand awareness (BE1), perceived quality (BE2), and brand loyalty (BE3), and consumers' willingness to purchase (CPI), as well as the degree of AI intervention (high autonomy vs. low autonomy, INV-H vs. INV-L). The scales of this study refer to the existing mature scales of previous scholars and existing literature to ensure the reliability and validity of the scales. Finally, the basic information of the respondents was investigated, including gender, age, education, occupation, etc., and the length of time the users used the social media platforms daily was investigated.

(2) Data collection

In this study, 977 questionnaires were collected according to the respondents' screening questions and invalid answer data set in the questionnaire, and 963 valid questionnaires were obtained by removing the infrequent social media population as well as invalid questionnaires. The demographic analysis of the respondents was conducted using SPSS 22.0, and the demographic characteristics are shown in Table 1.

(1) In terms of gender, the sample consisted of 403 males (41.85%) and 560 females (58.15%).

(2) In terms of age, there are 241 surveyed users aged 18 to 24 in the sample, accounting for 25.03, 306 aged 25 to 31, accounting for 31.78%, 368 aged 32 to 38, accounting for 38.21%, and a total of 48 aged 39 and above, accounting for 4.99%; there are no surveyed users under the age of 18. From the overall data, the age of the surveyed users is concentrated in 18~38 years old, accounting for 95.01%, which is in line with the main user group portrait of the Internet social media users, so that this study can better reflect the impact of social media marketing in the core user groups in the study.

(3) In terms of education, there are a total of 159 people in the sample with specialties and below, accounting for 16.51%, and 804 people with bachelor's degree or above, accounting for 83.49%.

(4) In terms of occupation, the highest percentage of the sample is private enterprise personnel, amounting to 44.13%, totaling 425 people.

(5) In terms of the length of daily use of social media, 78 surveyed users in the sample used social media for less than 30 minutes per day, accounting for 8.10%, 522 people used social media for 30 to 60 minutes, accounting for 54.21%, 315 people used social media for 60 to 120 minutes, accounting for 32.71%, and 48 people used social media for more than 120 minutes, accounting for 4.98%. Sample surveyed users daily use of social media time is concentrated in 30 ~ 120 minutes, the total share of 86.92%, the surveyed users use social media frequently, this study for the group of users for research more in line with the purpose of research on social media marketing.

Table 1. Demographic characteristics

Item	Classification	Count	Percentage (%)
Gender	Male	403	41.85
	Female	560	58.15
Age	18~24	241	25.03
	25~31	306	31.78
	32~38	368	38.21
	39~45	28	2.91
	>45	20	2.08
Educational background	High school and below	48	4.98
	Associate	111	11.53
	Undergraduate	705	73.21
	Master	88	9.14
	Doctor	11	1.14
Occupation	Student	199	20.66
	State-owned enterprises	184	19.11
	Civil Servant	34	3.53
	Private enterprises	425	44.13
	Public Institution	121	12.56
Daily duration of social media usage	<30 min	78	8.10
	30~60 min	522	54.21
	60~120 min	315	32.71
	>120 min	48	4.98

4.2. Reliability and validity analysis

In this study, the consistency, stability and reliability of the measurement results were verified using the reliability test, and the Cronbach's α after deletion of each measurement item and the Cronbach's α of each variable were calculated using SPSS 22.0.The results of the reliability test are shown in Table 2, and the reliability of the variables measured by the questionnaire is good when the Cronbach's α value is greater than 0.7. According to the results of Cronbach's α value of the data in the table, the Cronbach's α value of each variable in this study is greater than 0.85, which proves that the questionnaire has good reliability.

Table 2. Reliability test results

Variable	Indicators	The Cronbach's α after deletion	Cronbach's α
Social media participation	SMP1	0.872	0.914
	SMP2	0.855	
	SMP3	0.948	
	SMP4	0.879	
Brand equity	BE1	0.862	0.926
	BE1	0.902	
	BE1	0.915	
Consumer purchase intention	CPI	0.902	0.922
The involvement of artificial intelligence	INV	0.938	0.945

Validity analysis is to test whether the measurements are valid or not and is mostly used to test the quality of the scale. Most scholars use factor analysis to measure the validity of a scale. The validity of the questionnaire is determined in the factor analysis method by the KOM value. The statistical caliber of this method is: the larger the KMO value, the smaller the correlation coefficient, which indicates the greater variability of the measurement results. In this paper KMO and Bartlett sphericity were used to test the quality of the research variables set in the questionnaire and the results of the validity test are shown in Table 3. The KMO values of the measured variables are all between 0.8 and 0.9, among which the KMO value of brand equity is the largest at 0.884. While the Bartlett's spherical test values are all significant, based on the above results, it can be seen that the data of the questionnaire passes the validity check. In this study, all the question items in the questionnaire were attributed to 6 types of factors. According to the results of factor loading coefficients, it can be seen that the coefficients of each question item are greater than 0.8 and the results are significant. It indicates that each question item can be aggregated together according to the theoretical distribution. The questionnaire scale in this paper has good content validity and meets the requirements of the study.

Table 3. KMO and Bartlett's sphericity test

Variable	KMO	Bartlett's sphericity test		
		Approximate Chi-square	Df	Sig.
SMP	0.856	3452.66	235	0.003
BE	0.884	2648.27	78	0.004
CPI	0.833	2215.69	78	0.001
INV	0.878	998.47	34	0.001

4.3. CFA factor test

The validation factor analysis (CFA) is a test of hypotheses, the latent variables of the model were tested by AMOS software to see the goodness of fit, if the goodness of fit is good, the analysis of structural equation modeling can be continued. The results of the CFA test for the study variables are shown in Table 4. The standardized factor loadings of the indicators of social media participation, such as liking and commenting, content creation, attention and interaction, and emotional investment, are all greater than 0.65, and the combined reliability of the brand equity characteristics is the highest at 0.754, and the combined reliabilities of the other variables are also greater than 0.70, which meets the requirements of the study, and the aggregated validity of the question items in the scale data is good. It indicates that the fit of the variable model in this paper is high and further research can be conducted.

Table 4. The CFA test results of the research variables

Variable	Indicators	Factor loading	CR	AVE
Social media participation	SMP1	0.815	0.842	0.712
	SMP2	0.747		
	SMP3	0.801		
	SMP4	0.761		
Brand equity	BE1	0.676	0.833	0.754
	BE1	0.83		
	BE1	0.842		
Consumer purchase intention	CPI	0.675	0.874	0.722
The involvement of artificial intelligence	INV	0.745	0.849	0.705

In the study of differential validity, the AVE method is mostly used for assessment, and the differential validity test of the validation factors is shown in Figure 2. According to the test results, it can be seen that the AVE values of variables such as social media participation, brand equity and consumer purchase intention are all greater than 0.75, and they are all greater than the absolute value of the correlation coefficient, which is in line with the requirements, so the research in this paper has the differential validity.

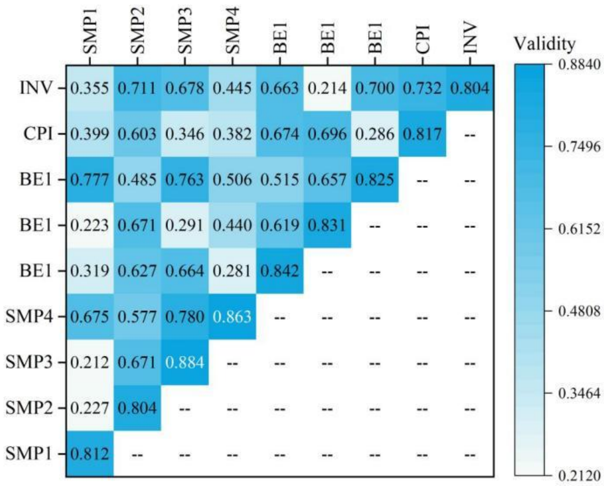

Figure 2. Verification of the discriminant validity of the factors

4.4. Path checking for structural equations

The above analysis can be obtained that the reliability and validity of the variables studied in this paper are good, so the next step of analysis can be carried out. According to the hypotheses presented above, the corresponding structural model is constructed using AMOS as shown in Figure 3. And do the goodness-of-fit measurement of the structural model, it can be seen that $\chi 2/df=2.334<3$, RMSEA= $0.058<0.08$, $GFI=0.862>0.8$, $NFI=0.837>0.8$, $IFI=0.930>0.9$, $CFI=0.921>0.9$, $AGFI=0.855>0.8$, all the indexes are within the critical criterion. It indicates that the hypothesized model has a good degree of fit.

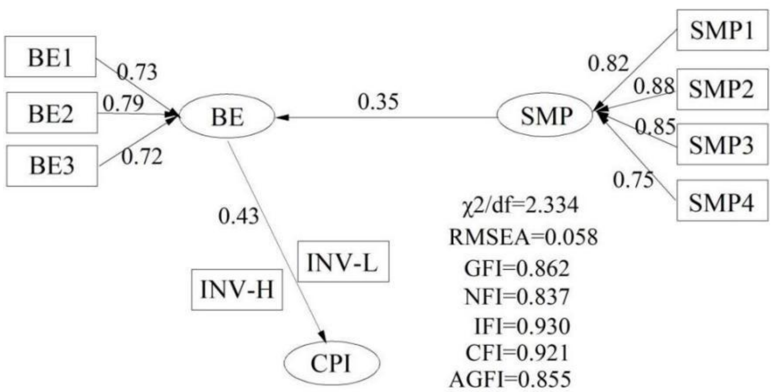

Figure 3. Structural Equation Model

After passing the goodness-of-fit test, the next step of path analysis and hypothesis testing can be carried out according to the structural equation modeling, and the test results of path analysis are shown in Table 5. The standardized path coefficient of liked comments on brand equity is 0.192, with a P-value of less than 0.01, indicating that liked comments will have a significant positive impact on brand equity. The standardized path coefficients of content creation, attention interaction, and emotional investment on brand equity are also 0.162, 0.159, and 0.206, respectively, with P-values of less than 0.01, indicating that social media participation will all have a significant positive impact on brand equity, proving that Hypothesis H1 is valid. The standardized path coefficients of the three dimensions of brand equity (brand awareness, perceived quality, and brand loyalty) affecting consumers' purchase intention are all greater than 0.1, with a significant positive effect, proving that hypothesis H2 is valid.

Table 5. The test results of the path analysis

Path relationship	Path coefficient	S.E	C.R	P
BE←SMP1	0.192	0.038	5.842	***
BE←SMP2	0.162	0.009	5.501	***
BE←SMP3	0.159	0.034	2.057	***
BE←SMP4	0.206	0.036	2.471	***
CPI←BE1	0.391	0.036	4.337	***
CPI←BE2	0.487	0.023	3.284	***
CPI←BE3	0.104	0.083	6.487	***

4.5. Moderating effects test

In this study, AI involvement characteristics were used as moderating variables for two aspects of AI involvement, high autonomy and low autonomy, respectively. SPSS PROCESS software was used to test the moderating role of AI involvement in the relationship between social media participation and consumer purchase intention. Firstly, the AI involvement was put into the model as a moderating variable to be tested and the moderating test of AI involvement is shown in Table 6. It is seen that the P-values of the interaction terms are 0.0002 and 0.0005, which are greater than 0.05, and the confidence intervals do not include 0, which means that the significance test has been passed, indicating that AI involvement plays a moderating role in the relationship between social media and consumers' purchase intention, which proves that the hypothesis H3 is valid.

Table 6. The regulation and verification involving artificial intelligence

	coeff	se	t	P	LLCI	ULCI
Costant	2.314	0.363	12.854	0.0003	2.698	3.047
INV-H* SMP	0.348	0.457	6.351	0.0002	0.061	0.763
INV-L* SMP	0.588	0.512	8.695	0.0005	0.045	0.695

5. Conclusion

This study proposes research hypotheses related to social media engagement, brand equity, and consumer purchase intention, as well as discusses the moderating role of AI engagement among variable associations, collects research data, and examines the path of influence relationships based on structural equation modeling. The research conclusions are as follows:

(1) The standardized factor loadings of social media participation variable dimensions such as liking and commenting, content creation, attention and interaction, and emotional investment are all greater than 0.65, and the fit of the variable model is relatively high; meanwhile, the AVE values of the different variables are greater than the absolute value of the correlation coefficients, and the research variables have distinguishing validity.

(2) The social media participation variables in the structural equation model all significantly and positively affect brand equity, the standardized path coefficients of the four dimensional variables are 0.192, 0.162, 0.159, 0.206, respectively, and the p-value is less than 0.01. All the dimensional variables of brand equity also positively affect the consumer's willingness to purchase, and there is a positive standardized path. In addition, the moderating effect significance of AI engagement in the SEM path P-values are all greater than 0.05. The research hypotheses proposed in this paper are all valid.

Social media participation is an important brand interaction activity for consumers on media platforms, which does not directly affect consumers' purchase intention, but it will build brand equity image in consumers' mind, thus causing consumers' purchase impulse. Meanwhile, artificial intelligence also plays a potential moderating role in social media branding activities, and the high autonomy and low autonomy of intelligent engagement have different impacts on consumers' purchase intention through perceived risk.

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