



Research on the Impact of Emotional Interaction on Consumer Purchase Intention in Social Commerce

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Abstract

Background and Aim: The significance of internet celebrity influencers in social commerce is rapidly increasing due to their ability to engage large audiences and shape consumer behavior. This study aims to explore how emotional interactions, characterized by intimacy and familiarity, influence consumer purchase intentions.

Materials and Methods: This study employs quantitative analysis to investigate the impact of intimacy and familiarity between internet celebrity influencers and consumers on purchase intention within the context of social commerce. A sample size of 507 users was chosen. Data was collected using accidental and convenient sampling techniques, with an online questionnaire as the most suitable instrument. The questionnaire was designed with six key variables and tested for internal consistency using Cronbach's alpha coefficient.

Results: The results indicate that affective trust and cognitive trust serve as mediators between intimacy, familiarity, and purchase intention. Social overload acts as a moderator between intimacy, familiarity, and purchase intention.

Conclusion: In social commerce, intimacy and familiarity also enhance purchase intention through affective trust and cognitive trust. However, social overload impedes the impact of intimacy and familiarity on purchase intention. These insights offer practical implications for influencers and marketers, emphasizing the importance of fostering emotional connections while managing social overload to optimize consumer engagement and purchase intentions.

Keywords: Social commerce; Emotional interaction; Cognitive trust; Affective trust; Purchase intention; Social overload

Introduction

The China Consumers Association released the "Annual Report on the Status of Consumer Rights Protection in China (2023)," highlighting a significant trend for 2024: the increasing importance of emotional release in influencing the purchasing decisions of the younger generation. This trend is expected to become a new consumer hotspot, indicating a shift beyond merely seeking cost-effectiveness (China Consumers Association, 2023).

Social commerce, defined as the integration of social media and e-commerce, creates interactive platforms where users share experiences, reviews, and recommendations, ultimately influencing others' buying behaviors (Busalim, Hussin, & Iahad, 2019). This unique environment underscores the importance of emotional interactions between consumers and influencers, as these interactions can significantly impact purchase intentions.

Recent studies have explored these dynamics within various contexts, such as live streaming and green innovation, revealing that both emotional and rational factors significantly impact online purchase intentions (Akram et al., 2021; Chen et al., 2021). For example, Hu, Zhang, and Wang (2019) found that live streaming enhances consumer purchasing behavior through interactive communication, highlighting the importance of real-time engagement in building emotional connections.

While previous studies have provided valuable insights, there remains a gap in understanding the specific role of emotional interactions between internet celebrity influencers and consumers in social commerce. This study aims to address this gap by focusing on how emotional interactions, characterized by intimacy and familiarity, influence consumer purchase intentions.

This research contributes uniquely to the field by investigating the mediating role of affective and cognitive trust and the moderating effect of social overload on the relationship between emotional interactions and purchase intentions. By doing so, it extends existing knowledge and offers practical implications for influencers and marketers seeking to optimize consumer engagement and drive purchase intentions in social commerce.





Therefore, this study aims to explore the following research question: How do emotional interactions, characterized by intimacy and familiarity, influence consumer purchase intentions in the context of social commerce?

Objectives

To explore the direct impact of intimacy and familiarity on purchase intention, the mediating role of affective and cognitive trust, and the moderating role of social overload between internet celebrity influencers and consumers in social commerce.

Literature Review

1. The Concepts of Familiarity and Intimacy

Familiarity and intimacy are pivotal in emotional interaction due to their strong connection with emotional bonds and communication quality. Intimacy, defined as feelings of closeness and emotional ties—including strong liking, moral support, and tolerance for flaws (Tolstedt & Stokes, 1983)—is crucial in interactions and adaptation (Lowenthal & Haven, 1968). It plays an indispensable role in strengthening interpersonal relationships (Schaefer & Olson, 1981). In social commerce, intimacy refers to the emotional bond between consumers and internet celebrity influencers, encompassing interaction and psychological support (Lee, 2011). Familiarity, defined as "an individual's understanding of an entity based on prior interactions, experiences, and learning" (Gefen, 2000; Komiak & Benbasat, 2006), complements intimacy by providing a foundation for trust through repeated engagements.

2. The Concepts of Affective Trust and Cognitive Trust

Affective trust, which stems from interactions and attraction, deepens through frequent communication and concern for the trusted person's well-being (Mian & Hattab, 2013). Cognitive trust, on the other hand, is based on rational evaluation of information, focusing on others' abilities, reliability, and integrity (Mayer et al., 1995). Both forms of trust are critical in social commerce: affective trust builds from emotional interactions, such as familiarity and intimacy, while cognitive trust arises from consistent, reliable information shared by influencers. Together, they significantly impact purchase intentions by fostering a sense of reliability and emotional connection.

3. The Concept of Social Overload

Social overload refers to the stress users feel from excessive demands for attention and interaction on social media platforms as their network grows (Maier et al., 2015). In social commerce, social overload manifests as excessive pressure from information and social interactions, potentially leading to decreased user engagement and trust. Understanding social overload's implications is crucial for marketers and influencers, who must balance interaction quality and quantity to maintain consumer trust and engagement.

4. The Concept of Purchase Intention

Purchase intention is generally defined as the likelihood or determination of a consumer to buy a product or service (Fishbein & Ajzen, 1975). In the context of social commerce, purchase intention is influenced by emotional interactions, trust levels, and the consumer's overall experience with the influencer and platform.

5. Parasocial Interaction Theory

First proposed by Horton and Wohl (1956), parasocial interaction theory describes an illusionary interpersonal relationship between media figures and users, where consumers feel as though they are interacting with media figures in real-life social exchanges (Labrecque, 2014). In social commerce, parasocial interactions enhance intimacy and familiarity between influencers and consumers, thereby influencing purchase intentions through perceived personal connections.

6. Bounded Rationality Theory

Simon's bounded rationality theory (1955) suggests that decision-making is limited by information costs, cognitive limitations, and time pressures. In social commerce, consumers often use heuristics and simplified strategies due to the overwhelming amount of information and choices available. This theory



underscores the importance of influencers presenting clear, trustworthy information to aid consumer decision-making within their cognitive limits.

By integrating these concepts, this study aims to explore how emotional interactions, characterized by intimacy and familiarity, influence consumer purchase intentions in social commerce. It also examines the mediating role of affective and cognitive trust and the moderating effect of social overload, contributing to a deeper understanding of consumer behavior in the digital age.

While foundational texts provide essential definitions, recent studies offer contemporary insights into these concepts' applications in social commerce. The increasing role of digital platforms in fostering emotional connections and trust highlights a shift from traditional commerce models. However, critiques of parasocial interaction theory and bounded rationality theory suggest that these interactions and decision-making processes might be more complex in modern, digital contexts. For instance, while parasocial interactions can build trust, they can also create unrealistic expectations and dependencies. Similarly, bounded rationality might not fully account for the sophisticated decision-making tools available today.

To address these gaps, this study will focus on the nuanced roles of emotional interactions and trust in social commerce, particularly how these factors influence purchase intentions amidst potential social overload. By examining these dynamics within the context of China, and considering broader global implications, this research will provide a comprehensive view of current consumer behavior trends. The methodological choices, informed by key studies, will ensure robust measurement of constructs like intimacy and trust, ultimately enhancing the study's validity and relevance.

Research Framework and Hypothesis

1. The relationship between intimacy, familiarity, and purchase intention

Grayson and Ambler (1999) found that intimacy enhances customer repurchase intention, while Lee and Kwon (2011) noted its impact on continued use intention. Verhoef et al. (2002) showed that intimacy increases service purchase frequency. Intimacy also strengthens emotional bonds with brands, making consumers more willing to purchase and use their products (Thomson et al., 2005).

H1a: Intimacy positively affects consumers' purchase intention.

Research indicates a positive link between emotional familiarity and repeat use behavior (Söderlund, 2002). Familiarity creates positive feelings, such as liking and satisfaction, leading to higher repurchase intention. In social commerce, emotional interactions help users understand each other's needs and habits better, fostering deeper connections.

H1b: Familiarity positively affects consumers' purchase intention.

2. The relationship between intimacy, affective trust, and cognitive trust

Affective trust is built on emotional connections, deepening with frequent communication and concern for the other's well-being (McAllister, 1995). As intimacy increases, emotional bonds strengthen, fostering affective trust.

H2a: Intimacy positively affects affective trust.

Intimacy, representing close ties and deep understanding, encourages sharing personal information and experiences, enhancing mutual understanding and trust (Granovetter, 1973). Cognitive trust, based on evaluations of ability, reliability, and integrity, grows with increased interaction and assessment opportunities (Mayer et al., 1995).

H2b: Intimacy positively affects cognitive trust.

3. The relationship between familiarity, affective trust, and cognitive trust

Higher familiarity enhances affective trust through increased mutual dependence and predictability of behavior, reducing uncertainty (Blau, 1964).

Social capital theory emphasizes the value of resources and support obtained through social networks (Putnam, 2000). In a social commerce environment, as familiarity increases, connections within the social network are strengthened, promoting the accumulation of social capital. Affective trust is one important form of social capital. As interactions on social commerce platforms become more frequent and in-depth,

people establish emotional connections and trust through these interactions, contributing to the formation of strong social capital (Putnam, 2000).

H3a: Familiarity positively affects affective trust.

In social commerce, frequent information exchange builds familiarity, which fosters cognitive trust (Walther, 1992).

H3b: Familiarity positively affects cognitive trust.

4. The relationship between affective trust, cognitive trust, and purchase intention

According to social exchange theory, affective trust enhances social interaction and cooperation, increasing purchase intention.

H4a: affective trust positively affects consumers' purchase intention.

H4b: affective trust mediates the relationship between intimacy and purchase intention.

H4c: affective trust mediates the relationship between familiarity and purchase intention.

Cognitive trust reduces perceived risk and enhances information credibility, promoting online purchase intention (Pavlou, 2003; Cheung & Lee, 2006; Gefen et al., 2003).

H5a: Cognitive trust positively affects consumers' purchase intention.

H5b: Cognitive trust mediates the relationship between intimacy and purchase intention.

H5c: Cognitive trust mediates the relationship between familiarity and purchase intention.

The development of trust undergoes a gradual process, evolving from the initial cognitive trust, which depends on evaluations of others' abilities and reliability, to a deeper trust based on shared values and emotional connections. In the early stages of trust building, individuals primarily rely on assessments of others' competence and dependability. Over time and with increased interaction, this cognitive-based trust can develop into trust grounded in shared values and emotional bonds (Lewicki & Bunker, 1996).

Cognitive trust, based on evaluations of reliability and capability, provides a foundation for affective trust (McAllister, 1995).

H6: Cognitive trust positively affects affective trust.

H7a: Intimacy positively affects purchase intention through the chain mediation of cognitive and affective trust.

H7b: Familiarity positively affects purchase intention through the chain mediation of cognitive and affective trust.

5. The moderating effect of social overload

In social overload environments, trust may not effectively mitigate the impact of excessive information, leading to decision fatigue and reduced purchase intention (Lee et al., 2014).

H8a: Social overload negatively moderates the effect of intimacy on purchase intention.

H8b: Social overload negatively moderates the effect of familiarity on purchase intention.

In this study, the intimacy scale was derived from Tomasi (2007) and Chelune & Waring (1984). The familiarity scale was sourced from Gefen (2000) and Gefen et al. (2003). The scales for cognitive trust and affective trust were derived from Becerra & Korgaonkar (2011) and Johnson & Grayson (2005). The purchase intention scale was sourced from Heijden (2003).

Methodology

This part introduces the fundamental ideas of study design, population and sample size determination, data collection methods, research instrument preference, and data analysis techniques. The provided information is outlined as follows:

1. Research Design

This study adopted a quantitative method, which was selected for several compelling reasons. Firstly, the quantitative approach is particularly well-suited for testing the relationships among constructs through empirical investigations and statistical analyses. This method allows for the collection of numerical data that can be analyzed to identify patterns, correlations, and causal relationships, providing a robust framework for validating the hypotheses.



Secondly, quantitative research is advantageous for this study's aims as it enables a large sample size, ensuring the findings are generalizable and representative of the target population. This is crucial for understanding the broad impacts of emotional interactions, trust, and social overload on purchase intentions in social commerce.

Moreover, the use of statistical tools such as Partial Least Squares Structural Equation Modeling (PLS-SEM) facilitates a detailed examination of the intricate relationships between the variables, including mediation and moderation effects. This level of analysis is essential to comprehensively address the research questions and to provide actionable insights for practitioners in the field.

In summary, the quantitative method was chosen for its ability to rigorously test theoretical relationships, its suitability for handling large datasets, and its capacity to provide precise, generalizable results, which align perfectly with the study's objectives.

2. Population and Sample Size

The study targeted respondents with experience in watching and making purchases on social commerce live-streaming platforms. A total of 542 respondents participated in the survey, and 520 (95.9%) passed the screening question, confirming their relevant experience. Ultimately, 507 valid questionnaires were obtained.

The sample was selected using accidental and convenient sampling methods, which, while practical for reaching respondents quickly, come with potential limitations. These non-probability sampling techniques may impact the generalizability of the results, as the sample may not perfectly represent the broader population. To mitigate these limitations, efforts were made to ensure a diverse sample by targeting a wide range of social commerce platforms and varied demographics within the user base.

The sample size of 507 was considered sufficient based on several considerations. Firstly, statistical power analysis was conducted to determine the appropriate sample size needed to detect significant effects, ensuring that the study had adequate power to identify relationships among the constructs. A sample size of over 500 is generally deemed robust for structural equation modeling, providing reliable and valid results (Kline, 2015). Additionally, similar studies in the field have utilized comparable sample sizes, supporting the adequacy of 507 respondents for the planned statistical analyses.

By carefully considering sample size and using statistical power analysis, the study aimed to achieve reliable and generalizable findings despite the inherent limitations of the sampling methods used.

3. Data Collection

Accidental sampling and convenient sampling techniques were employed in this research. These non-probability sampling techniques enabled data gathering from participants who were readily available and willing to partake.

This study collected data through an online survey method. The preliminary Chinese questionnaire was developed using the "translation-back translation" method proposed by Brislin.

4. Research instrument

The research instrument was a structured online questionnaire, comprising 21 items distributed among six key variables. Each variable, namely intimacy, familiarity, affective trust, cognitive trust, purchase intention, and social overload, was represented by six items. The items in the questionnaire were crafted with insights from prior empirical studies to ensure validity. Participants responded to each statement using a seven-point Likert scale, where '1' indicated 'Strongly Disagree' and '7' meant 'Strongly Agree'. The internal consistency of the questionnaire, which is crucial for ensuring the validity of the responses, was tested using Cronbach's alpha coefficient.

5. Data Analysis

To investigate the relationships among the variables and validate the hypotheses, Partial Least Squares Structural Equation Modeling (PLS-SEM) was performed. This analytical technique was chosen due to its suitability for complex models and its ability to handle both reflective and formative measurement models. PLS-SEM is particularly advantageous in our research context as it can efficiently manage mediation effects and provide robust results even with smaller sample sizes and non-normal data distributions.

PLS-SEM is well-suited for exploratory research where the primary goal is to predict and explain the variance in key target constructs, such as purchase intention in this study. It is particularly useful in handling complex models with multiple constructs and indicators, which is essential in our analysis of intimacy, familiarity, affective trust, cognitive trust, and their combined effects on purchase intention. PLS-SEM



allows for the assessment of direct, indirect, and total effects, making it ideal for evaluating the mediating roles of affective and cognitive trust.

Results

The primary objective of this study is to explore how emotional interaction affects consumers' purchase intention in a social commerce environment. To achieve this, the research employed a comprehensive set of analytical tools. Notably, descriptive statistics were used to evaluate the normal distribution of variables.

1. Descriptive statistics

To determine whether the questionnaire has value for in-depth analysis, a descriptive statistical analysis of the survey data was conducted. This analysis focuses on the mean and standard deviation of the items. The mean reflects the central tendency of the items, and ideally, all items should have means close to the midpoint to avoid bias. The standard deviation assesses the dispersion and variability relative to the mean. Typically, in survey research, the standard deviation should not be less than 0.5. A smaller standard deviation indicates lower discrimination among responses, while a larger standard deviation indicates higher discrimination and better differentiation in responses.

The results of the descriptive statistics for the items are shown in Table 1. The means range from 4.40 to 5.17, and all standard deviations are greater than 1. This indicates that there are no extreme mean values and that the responses have a high degree of differentiation, providing sufficient variability for further analysis. Overall, the quality of the questionnaire design and the survey data is high, supporting further measurement and structural model analysis.

Table 1 Descriptive statistics of the variables

Variables	Item	Mean	S.D
INT	INT1	5.08	1.798
	INT2	5.09	1.780
	INT3	5.07	1.770
	INT4	5.13	1.787
FAM	FAM1	5.09	1.847
	FAM2	5.12	1.859
	FAM3	5.14	1.800
AT	AT1	5.12	1.731
	AT2	5.09	1.791
	AT3	5.17	1.726
CT	CT1	5.03	1.877
	CT2	5.10	1.779
	CT3	5.14	1.774
PI	PI1	4.93	1.822
	PI2	5.00	1.878
	PI3	5.04	1.942
	PI4	5.10	1.832
SO	SO1	4.40	1.875
	SO2	4.58	1.901
	SO3	4.54	1.868
	SO4	4.65	1.879

Note: Intimacy (INT), Familiarity (FAM), Affective Trust (AT), Cognitive Trust (CT), Purchase Intention (PI), and Social Overload (SO).

2. Exploratory Factor Analysis

This study first used SPSS 27.0 to conduct an Exploratory Factor Analysis (EFA) to determine the questionnaire items. The Kaiser-Meyer-Olkin (KMO) test statistic was used to assess the suitability of the original variables for factor analysis. The KMO value ranges from 0 to 1, with values closer to 1 indicating stronger correlations among variables, making them more suitable for factor analysis. Generally, a KMO value above 0.9 indicates excellent suitability, 0.8 indicates good suitability, 0.7 is acceptable, and below 0.6 is unsuitable.



The KMO statistic is 0.903, and Bartlett's test of sphericity is significant ($p = 0.000$), indicating that the data is very suitable for factor analysis.

Principal Component Analysis (PCA) was used to extract common factors, with the criterion for retaining factors being an initial eigenvalue greater than 1. The results indicate that six common factors have initial eigenvalues greater than 1, explaining a total variance of 78.527%. Each factor explains 15.660%, 15.090%, 14.493%, 11.305%, 11.062%, and 10.916% of the variance, respectively. Table 2 shows the factor loadings after rotation using the Varimax method.

Table 2 Results of Exploratory Factor Analysis

Items	1	2	3	4	5	6
INT1			0.795			
INT2			0.765			
INT3			0.829			
INT4			0.829			
FAM1						0.805
FAM2						0.808
FAM3						0.800
AT1					0.796	
AT2					0.834	
AT3					0.793	
CT1				0.792		
CT2				0.825		
CT3				0.848		
PI1		0.846				
PI2		0.826				
PI3		0.833				
PI4		0.814				
SO1	0.873					
SO2	0.904					
SO3	0.897					
SO4	0.916					

Factor loadings greater than 0.5 are considered very important. The EFA results show that Intimacy (INT), Familiarity (FAM), Affective Trust (AT), Cognitive Trust (CT), Purchase Intention (PI), and Social Overload (SO) each load onto their respective factors, indicating that the factor structure in the study is meaningful.

3. Reliability and Validity Test

Table 3 Results of the Measurement Model's Reliability and Validity Test

Variables	Item	factor loading	P-value	AVE	CR (rho c)	Cronbach's α
INT	INT1	0.872	0.000	0.749	0.923	0.888
	INT2	0.844	0.000			
	INT3	0.876	0.000			
	INT4	0.868	0.000			
FAM	FAM1	0.890	0.000	0.765	0.907	0.847
	FAM2	0.862	0.000			
	FAM3	0.872	0.000			
	AT1	0.877	0.000			
AT	AT2	0.882	0.000	0.788	0.918	0.866
	AT3	0.903	0.000			
	CT1	0.870	0.000			
	CT2	0.910	0.000			
CT	CT3	0.901	0.000	0.799	0.923	0.874
	PI1	0.905	0.000			
	PI2	0.864	0.000			
	PI3	0.868	0.000			
PI	PI4	0.892	0.000	0.778	0.934	0.905



Variables	Item	factor loading	P-value	AVE	CR (rho c)	Cronbach's α
SO	SO1	0.893	0.000	0.816	0.947	0.925
	SO2	0.906	0.000			
	SO3	0.892	0.000			
	SO4	0.922	0.000			

Reliability and validity are used to measure whether the results of a scale reflect objective reality and achieve the test's purpose. Before hypothesis testing, the reliability and validity of the scale need to be analyzed. This study uses CFA to evaluate the reliability and validity of the scale. Cronbach's α is used to assess reliability, while factor loadings, AVE, and CR values are used to evaluate convergent validity. Table 3 shows the reliability and validity results of the measurement model.

According to Table 3, the Cronbach's α values range from 0.847 to 0.925, indicating good reliability. All factor loadings range from 0.844 to 0.922, exceeding the recommended threshold of 0.5, demonstrating that all items are significant. The CR (rho_c) values range from 0.907 to 0.947, both above the recommended threshold of 0.7, and the AVE values range from 0.749 to 0.816, above the recommended threshold of 0.5. Therefore, all variables exhibit good convergent validity. In summary, the measurement model in this study has good reliability and validity.

4. Discriminant Validity Test

Discriminant validity was assessed by comparing the square root of the AVE of each latent variable with the correlation coefficients between all latent variables. Table 4 shows that the correlation coefficients between latent variables range from -0.189 to 0.515. The square root of each latent variable's AVE is greater than the correlation coefficients between all latent variables, indicating that the measurement model has satisfactory discriminant validity.

Table 4 Results of the Discriminant Validity Test

	AT	CT	FAM	INT	PI	SO
AT	0.888					
CT	0.451	0.894				
FAM	0.515	0.43	0.875			
INT	0.474	0.477	0.436	0.865		
PI	0.443	0.436	0.442	0.442	0.88	
SO	-0.108	-0.174	-0.108	-0.189	-0.1	0.903

5. Common Method Bias

This study first used Harman's (1967) single-factor test to detect potential common method variance (CMV). An exploratory unrotated factor analysis on 21 items across six factors revealed that the six factors explained 78.527% of the total variance. The largest factor accounted for less than 50% of the total variance (36.358%). According to the single-factor test, the largest factor should not explain more than 50% of the total variance, indicating that CMV is not significant in this study.

Following Podsakoff et al. (1986), a common method factor was used to further check for CMV. A comparison was made between the variance explained by each item's latent variable and the common method factor. If the latent variable explains much more variance than the common method factor, CMV is likely not a concern. The average variance explained by the latent variables is 0.781, while the common method factor's average variance is 0.001, indicating that each item is primarily explained by its latent variable rather than the method factor. Additionally, all items had significant substantive loadings (R1), and most method factor loadings (R2) were not statistically significant. Therefore, CMV is not a serious issue in this study and is unlikely to adversely affect the research conclusions.

6. Variance Inflation Factor (VIF)

Based on the results of the reliability and validity analysis, the model of this study demonstrates good reliability and validity, allowing for the subsequent testing of the structural equation model. Before verifying the hypotheses, it is necessary to conduct a multicollinearity test to ensure there are no potential collinearity issues within the model. The measure for this issue is the Variance Inflation Factor (VIF), which



generally should be less than or equal to 5 to indicate the absence of collinearity problems. SmartPLS 4.0 can directly calculate this indicator. It can be observed that the internal VIF values of this study's model are all less than 5, with external VIF values ranging between 1.052 and 1.652. Therefore, this indicates that there are no potential collinearity issues within the model.

Table 5 Variance Inflation Factor (VIF)

Collinearity Statistics (VIF-Inner model)	AT	CT	PI
AT			1.592
CT	1.405		1.521
FAM	1.340	1.234	1.591
INT	1.413	1.234	1.652
SO			1.052
SO x INT			1.329
SO x FAM			1.284

7. Coefficient of Determination(R^2)

In addition to VIF values, this study also calculated the coefficient of determination R^2 . Generally, $R^2 < 1$, and the closer R^2 is to 1, the higher the explanatory power of the independent variables on the dependent variable. According to the literature, $R^2 \geq 0.67$ indicates high explanatory power, $0.33 \leq R^2 < 0.67$ indicates moderate explanatory power, and $R^2 \leq 0.19$ indicates low explanatory power. The R^2 value can be directly obtained from SmartPLS 4.0. An acceptable R^2 value indicates that the model has a certain explanatory capability. See Table 6 for details.

Table 6 Coefficient of Determination

	R-square	R-square adjusted
AT	0.37	0.366
CT	0.288	0.286
PI	0.378	0.369

8. Results of Model Hypothesis Testing and Analysis of Direct Effects

This study used the Bootstrapping method in SmartPLS 4.0 to test the hypotheses, setting the resampling number to 5000. The model's path coefficients were obtained and their significance was tested using p-values. Significant path coefficients indicate that the hypotheses are supported.

Specifically, CT, FAM, and INT all have a positive impact on AT, with path coefficients of 0.196 ($p < 0.001$), 0.327 ($p < 0.001$), and 0.238 ($p < 0.001$) respectively, supporting hypotheses H6, H3a, and H2a. FAM and INT both have a positive impact on CT, with path coefficients of 0.275 ($p < 0.001$) and 0.357 ($p < 0.001$) respectively, supporting hypotheses H3b and H2b. AT, CT, FAM, and INT all have a positive impact on PI, with path coefficients of 0.157 ($p < 0.01$), 0.144 ($p < 0.01$), 0.208 ($p < 0.001$), and 0.212 ($p < 0.001$) respectively, supporting hypotheses H4a, H5a, H1b, and H1a.

To test the potential impact of individual differences on purchase intention, gender, age, education level, and income of the respondents were included as control variables. The results show that none of these control variables have a significant impact on purchase intention, indicating that gender, age, education level, and income do not interfere with the results of the structural model. The hypothesis test results are shown in Figure 1, and the direct effects results are shown in Table 7.

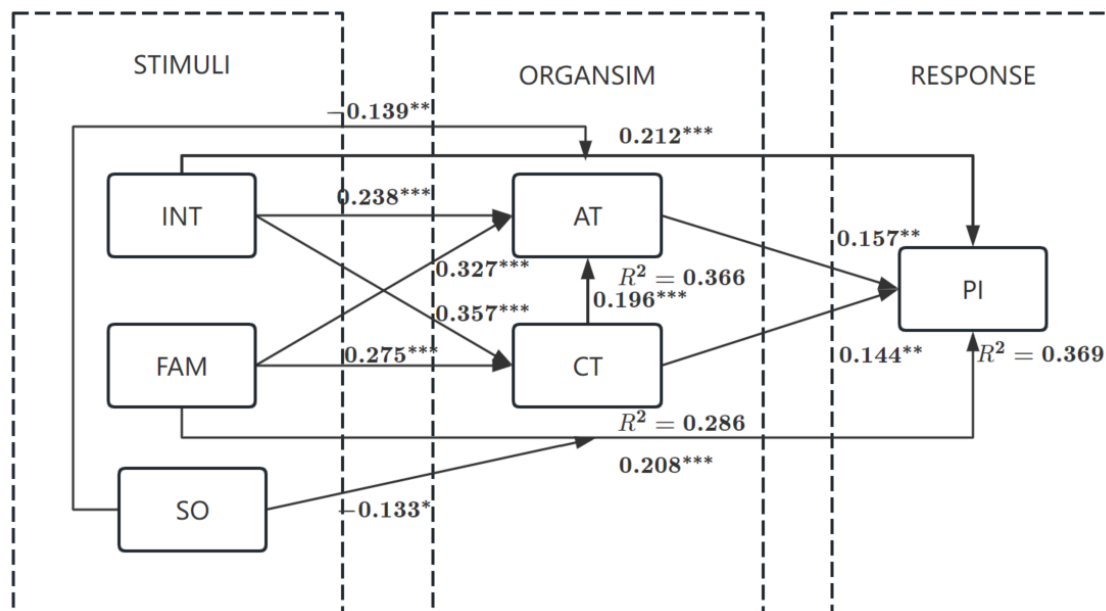


Figure 1 Results of Model Hypothesis Testing
Note: Constructed by the researcher

Table 7 Hypotheses Results

Hyps	Hypotheses Paths	β value	T-values	P-values	Results
H1a	INT -> PI	0.212	3.686	<0.001	Support
H1b	FAM -> PI	0.208	3.493	<0.001	Support
H2a	INT -> AT	0.238	4.415	<0.001	Support
H2b	INT -> CT	0.357	6.965	<0.001	Support
H3a	FAM -> AT	0.327	6.297	<0.001	Support
H3b	FAM -> CT	0.275	5.036	<0.001	Support
H4a	AT -> PI	0.157	2.952	0.003	Support
H5a	CT -> PI	0.144	2.706	0.007	Support
H6	CT -> AT	0.196	3.777	<0.001	Support

9. Mediating Effect Analysis

This study analyzed the mediation effect using the Bootstrap method, which involves repeatedly sampling from the original sample with replacement. In SmartPLS 4.0, the 95% confidence interval values can be directly observed to determine the existence of mediation effects.

The Bootstrap analysis revealed the following:

For the path "INT -> AT -> PI," the indirect effect coefficient is 0.037 (T=2.322, p<0.05), with a 95% confidence interval of [0.012, 0.075], not including 0, indicating that AT mediates the relationship between INT and PI, supporting hypothesis H4b.

For the path "FAM -> CT -> PI," the indirect effect coefficient is 0.04 (T=2.266, p<0.05), with a 95% confidence interval of [0.013, 0.085], not including 0, indicating that CT mediates the relationship between FAM and PI, supporting hypothesis H4c.

For the path "INT -> CT -> PI," the indirect effect coefficient is 0.052 (T=2.515, p<0.05), with a 95% confidence interval of [0.017, 0.097], not including 0, indicating that CT mediates the relationship between INT and PI, supporting hypothesis H5b.

For the path "FAM -> AT -> PI," the indirect effect coefficient is 0.052 (T=2.626, p<0.01), with a 95% confidence interval of [0.017, 0.094], not including 0, indicating that AT mediates the relationship between FAM and PI, supporting hypothesis H5c.

For the path "FAM -> CT -> AT -> PI," the indirect effect coefficient is 0.009 ($T=1.966$, $p<0.05$), with a 95% confidence interval of [0.003, 0.021], not including 0, indicating a chain mediation effect of CT and AT between FAM and PI, supporting hypothesis H7b.

For the path "INT -> CT -> AT -> PI," the indirect effect coefficient is 0.011 ($T=2.035$, $p<0.05$), with a 95% confidence interval of [0.003, 0.026], not including 0, indicating a chain mediation effect of CT and AT between INT and PI, supporting hypothesis H7a.

The detailed results are shown in Table 8.

Table 8 Results of the Mediating Effect Test

Hyps	Hypotheses Paths	β value	T-values	P-values	95%CI	Results
H4b	INT -> AT -> PI	0.037	2.322	0.020	[0.012,0.075]	Support
H4c	FAM -> CT -> PI	0.040	2.266	0.023	[0.013,0.085]	Support
H5b	INT -> CT -> PI	0.052	2.515	0.012	[0.017,0.097]	Support
H5c	FAM -> AT -> PI	0.052	2.626	0.009	[0.017,0.094]	Support
H7a	INT -> CT -> AT -> PI	0.011	2.035	0.042	[0.003,0.026]	Support
H7b	FAM -> CT -> AT -> PI	0.009	1.966	0.049	[0.003,0.021]	Support

10. Moderating Effect Analysis

This study analyzed the moderating effects using the Bootstrap method. The results revealed the following:

For the path "SO x INT -> PI," the path coefficient is -0.139 ($T=2.718$, $p<0.01$), with a 95% confidence interval of [-0.242, -0.041], not including 0. This indicates a significant moderating effect of SO between INT and PI, weakening the positive impact of INT on PI, supporting hypothesis H8a.

For the path "SO x FAM -> PI," the path coefficient is -0.133 ($T=2.517$, $p<0.05$), with a 95% confidence interval of [-0.236, -0.031], not including 0. This indicates a significant moderating effect of SO between FAM and PI, weakening the positive impact of FAM on PI, supporting hypothesis H8b.

The detailed results are shown in Table 9.

Table 9 Results of Moderating Effect Test

Hyps	Hypotheses Paths	β value	T-values	P-values	95%CI	Results
H8a	SO x INT -> PI	-0.139	2.718	0.007	[-0.242, -0.041]	Support
H8b	SO x FAM -> PI	-0.133	2.517	0.012	[-0.236, -0.031]	Support

Discussion

1. Direct Impact of Intimacy and Familiarity on Purchase Intention

This study confirms that both intimacy and familiarity significantly influence consumers' purchase intentions, consistent with parasocial interaction theory. This theory posits that virtual interactions can mimic real social interactions, enhancing consumer behavioral intentions. Intimacy reflects the depth of emotional connection between consumers and influencers, while familiarity indicates the level of consumer knowledge about the influencer and the frequency of their interactions. These interactions extend beyond transactions to include social media content, live interactions, and comments. The impact of intimacy and familiarity may vary across social media platforms; for instance, platforms emphasizing visual content, like Instagram, might foster different intimacy levels compared to text-based platforms like Twitter.

Incorporating the Social Penetration Theory, which suggests that relationships deepen over time through self-disclosure, we see that regular and meaningful interactions deepen consumer relationships. The Technology Acceptance Model (TAM) also supports these findings by explaining that perceived ease of use and perceived usefulness of social media platforms enhance user engagement and interaction frequency, contributing to increased intimacy and familiarity.

2. Mediating Role of Affective and Cognitive Trust

Affective trust and cognitive trust significantly mediate the impact of intimacy and familiarity on purchase intentions, as supported by trust theory. Affective trust arises from consumers' emotional reliance on influencers, while cognitive trust is based on evaluations of the influencer's expertise and reliability.



Both forms of trust are crucial in the consumer decision-making process, significantly increasing the likelihood of product purchases.

3. Moderating Role of Social Overload

The study examines the moderating effect of social overload on the relationship between intimacy, familiarity, and purchase intentions, aligning with the bounded rationality theory. This theory suggests that individuals have limited information-processing capacity and can feel overwhelmed when faced with excessive information, leading to decreased decision quality. In social commerce, excessive information can result in decision fatigue, weakening purchase motivation.

This finding underscores the need for social media platforms to design features that manage information flow effectively. Recommendations include using algorithms to prioritize relevant content, implementing user controls for content frequency, and providing clear content categorization to reduce overload without decreasing engagement.

Marketers and influencers can leverage insights about affective and cognitive trust by focusing on transparent, consistent communication and demonstrating expertise. For instance, providing detailed product information and sharing personal experiences can build cognitive and affective trust, respectively. Managing social interactions' density can be achieved by optimizing content quality and frequency, ensuring value in every interaction to maintain consumer interest without causing overload.

Further research should investigate the role of different types of social media interactions (e.g., video vs. text-based) in enhancing intimacy and familiarity. Additionally, exploring cultural differences or personality traits as moderating factors could provide deeper insights. Addressing limitations, such as the generalizability of findings due to sample size or composition and potential biases from self-reported data, future studies could employ larger, more diverse samples and objective data collection methods.

Conclusion

These findings deepen our understanding of emotional interaction mechanisms in social commerce and guide the operation of social commerce platforms, particularly in leveraging influencer-consumer interactions to enhance purchase intentions. Additionally, the study underscores the importance of balancing information load in complex environments to prevent consumer decision fatigue and offers strategic recommendations to avoid this issue.

Recommendation

The findings of this study provide practical insights for social commerce platforms, influencers, and collaborating brands, guiding them on effectively utilizing social media tools and strategies to enhance consumer purchase intentions. Here are key practical insights based on the research findings:

Enhancing Intimacy and Familiarity: Increasing intimacy and familiarity with consumers through frequent and meaningful interactions is crucial for building lasting consumer relationships. This can be achieved through regular live streaming, interactive social media posts, personalized messages, and effective feedback mechanisms. Personalized messages should be tailored based on consumers' purchase history and interaction behavior, demonstrating an understanding and attention to individual consumer needs. These strategies can increase consumers' purchase intentions and enhance their loyalty and satisfaction.

Building and Maintaining Trust: Establishing affective and cognitive trust among consumers is essential for promoting purchase decisions and maintaining long-term relationships. Affective trust can be nurtured through sincere, transparent, and consistent communication, while cognitive trust can be built by providing accurate, detailed, and timely product information and positive user reviews. Detailed product descriptions, clear usage guides, and positive customer feedback can help consumers form cognitive trust. Regularly publishing industry reports and market analyses can enhance the professional image, thereby strengthening cognitive trust.

Managing the Density of Social Interactions: Social overload is a common issue in the modern social commerce environment, negatively affecting the positive relationship between intimacy, familiarity, and purchase intention. Influencers should control the frequency and volume of their content posts to avoid overwhelming consumers. This involves reducing unnecessary advertisements and promotions, optimizing the quality and relevance of the content, and ensuring each message provides value to consumers. Monitoring consumer engagement and responses can help adjust posting strategies to avoid information overload and maintain consumer interest and engagement.





Enhancing the Chain Mediation Effect of Affective and Cognitive Trust: When implementing strategies to enhance intimacy and familiarity, it is important to recognize how these factors influence purchase intention through the chain mediation effect of affective and cognitive trust. Increasing intimacy may first enhance consumers' cognitive trust in influencers, which can then promote affective trust. The combined effect of these trusts ultimately enhances purchase intention. Therefore, influencers need to ensure synergy between these elements while enhancing each link to maximize purchase conversion rates. This involves considering both emotional appeal and information provision in content creation and interaction strategies.

By adopting these practical insights, participants in social commerce can design and implement their marketing and operational strategies more effectively, increasing consumers' purchase intentions and enhancing overall satisfaction and loyalty. These strategies help improve immediate sales performance and build long-term competitiveness by maintaining and deepening relationships with consumers, promoting sustained growth and success.

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