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The Impact of Artificial Intelligence Technology on Customer Purchase Intention in Social Commerce within Electrical Systems Applications

Abstract: With the rapid development of artificial intelligence technology, its application fields are becoming increasingly widespread. Artificial intelligence technology is also ubiquitous in today's most popular social commerce. The perfect combination of the two deeply affects the shopping experience and purchase intention of consumers. This article first elaborates on the current development of artificial intelligence technology and social commerce, and outlines the relationship between the two. Then, through literature review, we will sort out and study artificial intelligence technology, customer experience, customer expectations, customer purchase intention, perceived usefulness, perceived value, and relationships in social commerce, and propose hypotheses. Construct a model using PLS-SEM and analyze a questionnaire survey of 320 people using SPSS and SMART-PLS software. It has been found that artificial intelligence technology has an impact on customer purchase intention through customer experience and expectations in social commerce. Artificial intelligence technology influences customer purchase intention through their experience, perceived usefulness, and perceived value in social commerce. Artificial intelligence technology has an impact on customer purchase intention through customer experience and perceived usefulness in social commerce. Customer experience in social commerce influences customer purchase intention through customer expectations. The customer experience in social commerce has an impact on customer purchase intention through perceived usefulness and perceived value. The customer experience in social commerce has an impact on customer purchase intention through perceived usefulness.

Keywords: artificial intelligence technology, social commerce, customer experience, customer expectations, perceived usefulness, perceived value, purchase intention

1. INTRODUCTION

In recent years, China's social and commercial development has been rapid. In 2021, the scale of China's social commerce market has expanded to 2.5 trillion yuan

(over 374 billion US dollars), with nearly 800 million participants. Like most other countries, social media is also an important component of people's daily lives here. According to Statista's data, the number of social media users in 2021 is close to 1 billion. This makes China the country with the largest population on social media, and it is expected to reach nearly 1.3 billion by 2026. In addition, the average daily online time of Chinese netizens is about 5 hours and 15 minutes, of which nearly half is spent browsing social media. A survey conducted in 2020 showed that over 70% of Chinese consumers tend to shop through social media channels. This proportion is much higher than the global average of 42%(ITC, 2023).

Social commerce, as an emerging e-commerce model, has had a significant impact on consumer behavior and has enormous research potential in China. Today, customer needs are shifting towards experiential methods, with customers no longer focusing on short-term price discounts, but rather on the process of value acquisition(Herrando et al., 2019). The characteristics of social commerce are very compatible with consumer needs. Therefore, only by truly providing customers with high-quality social and business experiences can we gain a core competitive advantage.

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With the arrival of the big data era and the impact of the information technology wave, the rise of knowledge in related fields such as cloud computing and 3D technology, the development of artificial intelligence technology has also ushered in new opportunities. Artificial intelligence related technologies such as big data, cloud computing, voice/image recognition, and deep neural networks are increasingly being applied in the field of social commerce, promoting the intelligent development of social commerce and deeply influencing consumer purchasing habits.

Therefore, researchers have conducted research on the two hot topics of social commerce and artificial intelligence technology today, especially the impact of artificial intelligence technology on customer purchase intention in social commerce.

2. LITERATURE REVIEW

2.1 *Customer purchase intention*

Fishbein and Ajzen found that consumer purchase intention determines their purchasing behavior, and purchase intention is an important predictor of behavior. The most important thing in understanding purchasing behavior is to clarify their purchasing intentions(Fishbein & Ajzen, 1977). Mullet and Karson extended their explanation of purchase intention, pointing out that purchase intention is a subjective attitude of consumers towards specific brand products and an important indicator for predicting

and measuring consumer behavior(Mullet & Karson, 1985). Dodds et al. believe that purchase intention is the likelihood or probability that consumers are willing to consume a certain brand of product(Dodds et al., 1991). Some scholars have also conducted research on the online purchase intention of customers. For example, purchase intention plays a mediating role between online purchasing attitude and online purchasing behavior(Zarei et al., 2019). In the context of social commerce, consumer purchase intention is defined as a probability that describes the likelihood of users purchasing products or services in this environment(S. Huang et al., 2020).

2.2 *Artificial Intelligence Technology*

Artificial intelligence technology is achieved by analyzing and interpreting data, learning from data, and utilizing learning to achieve specific goals and tasks. More broadly, artificial intelligence enhances the intelligence of products, services, or solutions. Artificial intelligence is used to perform many cognitive functions related to humans, such as learning, problem-solving, and decision-making. The algorithms used in artificial intelligence can enable machines to understand and generate natural language, learn and describe emotions from experience. Today, artificial intelligence has changed and redefined marketing in many fields, including the retail industry(Shankar, 2018).

Nowadays, social commerce platforms use artificial intelligence technology to help customers quickly filter massive amounts of data. When consumers enter keywords, speech, or images in the search bar, artificial intelligence can use text, speech, and image analysis techniques to identify problems and conduct searches to find potential target products and prioritize them(Y. Zhang et al., 2019)

In 2019, iFlytek's speech recognition rate reached 98%, and at this stage, AI speech recognition will reach the same level as humans. The increase in data volume leads to the complexity of individual decision-making, making the customer decision-making process very difficult. Intelligent search engines can help users extract noise and accurately locate target products. The accuracy and effectiveness of "intelligent" advertising through artificial intelligence technology are more significant than traditional retail(Song & Feng, 2019). The above fully reflects the precise experience that AI technology can bring to consumers.

Machine learning can customize the content of social commerce platforms to achieve consistency with user preferences and payment intentions, and seamlessly and personalized connect customers across all channels and devices. The software system that applies big data and artificial intelligence technology is an interactive consulting and decision-making system, with its most obvious characteristics being automatic knowledge discovery and intelligent decision-making(Yang et al., 2020). From a user perspective, the main application of AI in the marketing field is precise marketing for thousands of people on demand(M.-H. Huang & Rust, 2021).The most common application is personalized recommendation systems(Chung et al., 2016), The "recommendation" function of intelligent push on social e-commerce shopping platforms. Artificial intelligence technology fully utilizes the large amount of data retained by social e-commerce platforms to achieve information insights into consumer behavior(Song & Feng, 2019). It utilizes recommendation engines to recommend potential future purchasing behaviors based on user's past purchasing behavior, reducing consumer cognitive load, and is committed to providing optimal services to consumers through prediction. The above reflects the personalized experience that AI technology brings to customers.

Natural language interaction and machine learning technology lead artificial intelligence customer service to replace human customer service. Artificial intelligence customer service can understand consumer language and respond, providing users with a human like communication mode (Fan et al., 2018), Assist enterprises in conducting consumer marketing and sales services, recording customer behavior and preferences. The virtual assistant of social commerce platforms has begun to play the role of intelligent customer service and has been deeply applied in communication between consumers and businesses, especially in consulting common issues such as products, inventory, invoices, logistics, etc. Many social commerce platforms use AI virtual assistants as a starting point, which can help customers make complex purchasing decisions, complete consumption cycles, and bring intelligent interactive experiences to customers through voice interaction.

This article will study artificial intelligence technology from three aspects: accuracy, personalization, and interactive quality.

2.3 *Customer Experience in Social commerce*

Customer experience is the specific and profound feeling that consumers experience by actively participating in activities and performances in specific contexts provided by relevant enterprises(Xu, 2020). This article believes that customer experience refers to the perception and emotional response of consumers when interacting with situational factors such as enterprise products, services, and brands, emphasizing their psychological feelings.

Compared with traditional e-commerce, social commerce has significant characteristics. Firstly, social commerce is an e-commerce based on social media, which is the integration of social media and e-commerce. Social media enables social commerce users to communicate and interact on the platform. Secondly, social commerce relies on interpersonal interaction, which forms a network of interpersonal relationships and rapidly generates social resources. Once again, social commerce will definitely integrate business objectives, and the integration of business objectives is a necessary condition and core driving force of social commerce. Finally, information flow is an inherent characteristic and external manifestation of social commerce. These characteristics also constitute the difference between social commerce and traditional e-commerce, therefore there are significant differences in customer experience between social commerce and traditional e-commerce environments(Wang & Xie, 2020).

Firstly, traditional e-commerce is the interactive business model of "customer e- commerce websites". In social commerce scenarios, customers mainly interact with other customers and extend to social and consumer activities(Han et al., 2018). Therefore, customer experience in social interaction should be valued.

Secondly, customers can generate content on social media platforms, which can promote the free flow of product information and user experience between customers(Nisar et al., 2019), More and more customers are accessing product information through social commerce platforms, and obtaining product information is also one of the main motivations for customers to join social commerce (Lee et al., 2018). In the context of traditional e-commerce, customer product information mainly comes from e-commerce websites. Compared to social e-commerce platforms, their product information mainly comes from e-commerce websites. Trust and richness both have certain drawbacks, therefore, information experience is an important component of customer experience in the context of social commerce.

Finally, entertainment content is increasingly becoming one of the main ways for social commerce to attract and retain customers (Felix et al., 2017). The biggest difference between social commerce and traditional e-commerce is that it can achieve communication and interaction between customers on social commerce platforms (K. Zhang & Benyoucef, 2016). Customers form social relationships through interaction with other customers (Hassan et al., 2018).

Based on previous research on customer experience and social commerce characteristics, this article divides social commerce customer experience into cognitive (information experience), emotional (entertainment experience), social (social

existence), and sensory (sensory experience) for research.

2.4 *Customer Expectations*

Before the transaction, customers will have certain expectations for social commerce shopping, including comparisons with traditional shopping methods and the quality of service experienced during the transaction process. The particularity of social commerce prevents customers from accessing real products, and most customers hope to purchase high-quality and affordable products on social e-commerce platforms. According to the satisfaction level of customer expectations for the purchased product or service, it is divided into ideal expectations, tolerance zone, and acceptable expectations. When the quality of a product or service is higher and closer to their expectations, customers will achieve their ideal expectations, thereby improving their satisfaction. When the customer's expectations are lower than the actual acceptable level, they will generate customer complaints. Customer expectations within tolerance are referred to as acceptable expectations. The tolerance zone is defined as the part between the two, in which neither customer satisfaction nor customer complaints are generated (Alshibly, 2014) (Leung et al., 2022) (Wijaya et al., 2019).

Based on the above literature, propose hypotheses:

H1: Artificial intelligence technology affects customer purchase intention through customer experience in social commerce and customer expectation.

H2: Customer experience in social commerce affects customer purchase intention through customer expectation.

2.5 *Perceived usefulness*

Perceived usefulness has a significant impact on the acceptance of artificial intelligence technology applications by customers in social commerce. Perceived usefulness directly affects people's attitudes towards using new technologies (Hwang et al., 2016). Perceived usefulness has a positive impact on the satisfaction of college students who continue to use Tiktok (Jia & Liu, 2022). Perceived usefulness has a positive impact on brand attitude (Li & Zhao, 2019). In the study of virtual fitting systems, it is proposed that perceived usefulness has a significant positive impact on user attitudes(Ye & Guo, 2021). Customers using artificial intelligence technology to purchase products in social commerce will be faster and more efficient. Customers believe that using e-commerce in cyberspace does not require physical and mental effort. Therefore, if social commerce customers feel that shopping websites and social mediaplatforms require less physical and mental energy and can be easily used, their perception of the usefulness of this technology will be greater, and their willingness to use social commerce will also be higher.

2.6 *Perceived Value*

Scholars have discussed the theory of customer perceived value from different perspectives, but their understanding of customer perceived value is essentially similar. They all believe that customers' perceived value determines their purchase intention and ultimately leads to purchasing behavior. For example, the impact of consumer perceived value on purchase intention was studied from the perspective of consumer value perception, and peripheral products were classified by brand. The final research results showed a significant positive impact relationship (Zheng & Zhang, 2021).

When studying the relationship between consumer perception, brand cognition, and product purchase motivation, it was found that consumer perceived value can significantly promote the generation of purchase motivation and directly affect the relationship, providing multi-dimensional marketing strategies and product control suggestions for brand enterprises from a micro perspective (Xie & Hou, 2022). In the combination of social media and e-commerce platforms, perceived value has a positive impact on customer purchase intention (Liu et al., 2021). Based on social business scenarios, this article divides perceived value into three aspects: functional value, emotional value, and social value.

Based on the above literature, propose hypotheses:

H3: Artificial intelligence technology affects customer purchase intention through customer experience in social commerce, perceived usefulness, and perceived value.

H4: Artificial intelligence technology affects customer purchase intention through customer experience in social commerce, and perceived usefulness.

H5: Customer experience in social commerce affects customer purchase intention through perceived usefulness and perceived value.

H6: Customer experience in social commerce affects customer purchase intention through perceived usefulness.

3. METHODOLOGY

This study used PLS-SEM structural equations and validated the hypothesis model

using SPSS and Smart-PLS software. This study was conducted through a questionnaire survey in China, where social commerce development is relatively advanced. In order to improve the representativeness of the sample and the practical application value of the research conclusions, a segmented sampling method was used to survey social and commercial consumers in 9 cities including Beijing, Shanghai, Guangzhou, Shenzhen, Wuhan, Xi'an, Zhengzhou, Luoyang, and Sanmenxia. The questionnaire content was developed through literature review and expert interviews.

This study used PLS-SEM structural equations to analyze the relationships between variables, so it is necessary to start by considering the observed variables and convert the samples to appropriate sizes. The sample size must be less than 20 times the observed variable (Jackson, 2003) (J. Hair & Alamer, 2022). According to this framework, there are a total of 16 measurable variables in this study, so the researchers determined a sample size of 320.

4. RESULTS

4.1 *Descriptive statistical analysis*

The relationship model proposed in this study uses 6 variables and 10 dimensions. All scales use the Likert scale level 5. The descriptive statistical results are shown in Table 4.1.

Table 4.1 Formal Study Descriptive Quantity Statistics and Data Normality Test(N=320)

Variable	***Item***	***Min***	***Max***	***Mean***	***SD***	***Skewness***	***Kurtosis***
Artificial technology	AC1	1	5	4.019	0.948	1.146	-1.031
	AC2	1	5	3.897	1.106	-0.042	-0.838
	AC3	1	5	3.834	1.099	0.516	-0.989
	AC4	1	5	3.878	0.863	0.074	-0.642
	PZ1	1	5	3.956	1.12	0.581	-1.08
	PZ2	1	5	3.769	1.097	-0.174	-0.702
	PZ3	1	5	3.844	1.146	-0.347	-0.768
	IQ1	1	5	3.9	1.062	0.036	-0.806
	IQ2	1	5	3.934	0.948	-0.222	-0.664

	IQ3	1	5	3.859	1.056	0.534	-0.885
Customer Experience in Social Commerce	IE1	1	5	4.209	0.907	1.148	-1.134
	IE2	1	5	3.931	1.061	0.764	-1.028
	IE3	1	5	4.047	0.943	0.961	-1.016
	EE1	1	5	4.013	1.012	1.029	-1.133

Intelligence

Variable	***Item***	***Min***	***Max***	***Mean***	***SD***	***Skewness***	***Kurtosis***
	EE2	1	5	3.797	1.046	-0.565	-0.476
	EE3	1	5	3.906	1.077	0.597	-1.004
	SE1	1	5	3.781	1.085	-1.004	-0.471
	SE2	2	5	3.747	1.099	-1.203	-0.351
	SE3	1	5	3.441	1.144	-0.488	-0.583
	SO1	1	5	4	1.022	-0.062	-0.83
	SO2	1	5	4.078	1.017	0.805	-1.142
	SO3	1	5	3.95	0.917	0.372	-0.731
	CE1	1	5	4.031	0.961	-0.1	-0.72
	CE2	1	5	3.972	1.014	0.103	-0.812
Customer Expectation	CE3	1	5	4.047	0.884	0.738	-0.827
	CE4	1	5	3.794	0.87	-0.282	-0.33
	CE5	1	5	3.962	0.809	0.278	-0.536
	PU1	1	5	4.109	0.875	0.093	-0.748
Perceived usefulness	PU2	2	5	4.172	0.843	0.201	-0.869
	PU3	1	5	4.181	0.921	1.107	-1.139
	PU4	1	5	3.916	0.838	0.415	-0.672
	FV1	1	5	3.541	0.983	-0.572	-0.243
	FV2	1	5	3.547	0.944	0.157	-0.527
	FV3	1	5	3.462	1.027	0.318	-0.794
	EV1	2	5	3.519	0.707	-0.251	0.147
	EV2	1	5	3.397	0.936	-0.171	-0.111
	EV3	1	5	3.388	0.729	1.211	-0.602
	SV1	1	5	3.362	0.68	1.559	-0.421
	SV2	1	5	3.337	0.732	1.069	-0.192
Perceived Value	SV3	1	5	3.472	0.72	1.899	-0.735
Customer Purchase Intention	CI1	1	5	3.459	0.813	-0.291	0.167
	CI2	1	5	3.325	0.729	0.037	-0.153
	CI3	1	5	3.359	0.749	1.686	-0.788

Based on Smart PLS, it can be seen that the total number of questions in this study is 43, with an average value between 3.325 and 4.209, indicating that the respondents are mainly in the upper middle level; The standard deviation is between 0.651 and 1.146, and the data is relatively scattered; The design that explains these issues has good discernment; In addition, the skewness of the problem is between -1.142 and 0.167, with an absolute value less than 3; The kurtosis between -1.203 and 2.373, which is less than 3, indicates that the data for these 43 problems follows a normal distribution and can be directly used for statistical analysis such as reliability and effectiveness.

The reliability test results are shown in Table 4.2, and the Cronbach's Alpha values for all variables are between 0.8 and 0.915, all higher than the 0.7 standard. The range

f composite reliability (CR) values is 0.882 to 0.947, which is also higher than 0.7, indicating that this study has good reliability (Fornell & Larcker, 1981).

Table 4.2: The Reliability and Validity Test of The First Order Constructs

First Order Constructs	*Items*	*Loading*	*Cronbach's Alpha*	*CR*	*AVE*
AC	AC1	0.839	0.889	0.923	0.751
	AC2	0.874			
	AC3	0.846			
	AC4	0.907			
CE	CE1	0.838	0.871	0.906	0.659
	CE2	0.822			
	CE3	0.754			
	CE4	0.805			
	CE5	0.837			
CI	CI1	0.909	0.885	0.929	0.813
	CI2	0.889			
	CI3	0.907			
EE	EE1	0.897	0.85	0.909	0.77
	EE2	0.875			
	EE3	0.86			
EV	EV1	0.93	0.911	0.944	0.848
	EV2	0.918			
	EV3	0.916			
FV	FV1	0.879	0.856	0.912	0.776
	FV2	0.908			
	FV3	0.855			
IE	IE1	0.875	0.87	0.92	0.794
	IE2	0.886			
	IE3	0.911			
IQ	IQ1	0.869	0.85	0.909	0.769
	IQ2	0.911			
	IQ3	0.851			
PU	PU1	0.834	0.859	0.904	0.702
	PU2	0.812			
	PU3	0.825			
	PU4	0.879			

First Order Constructs	***Items***	***Loading***	***Cronbach's Alpha***	***CR***	***AVE***
	PZ1	0.886			
PZ	PZ2	0.852	0.829	0.898	0.745
	PZ3	0.851			
	SE1	0.887			
SE	SE2	0.901	0.865	0.918	0.788
	SE3	0.874			
	SO1	0.871			
SO	SO2	0.845	0.8	0.882	0.714
	SO3	0.82			
	SV1	0.935			
SV	SV2	0.929	0.915	0.947	0.855
	SV3	0.911			

Note: Accuracy is abbreviated as AC , Customer Expectation is abbreviated as CE , Customer Purchase Intention is abbreviated as CI , Entertainment experience is abbreviated as EE , Emotional value is abbreviated as EV , Functional value is abbreviated as FV , Information experience is abbreviated as IE , Interactive Quality is abbreviated as IQ , Perceived usefulness is abbreviated as PU , Personalization is abbreviated as PZ , Social existence is abbreviated as SE , Sensory experience is abbreviated as SO , Social value is abbreviated as SV

This study obtained the effectiveness indicators of each variable by running the PLS algorithm. Using bootstrap sampling method, determine the significant factor load of each variable, as well as the factor load and significance of the first-order variable corresponding to the second-order reflection variable, as shown in Tables 4.2 and 4.3. The factor loadings of all variables are above 0.6, significant at the 0.001 level. In addition, the AVE values of all variables were above 0.5, indicating that this study has good convergence effectiveness(J. F. Hair et al., 2011).

Table 4.3 The Reliability and Validity Test of the Second Order Constructs

construct

Second-order	***Item***	***Loading***	***Cronbach's α***	***CR***	***AVE***
	AC	0.849			
AIT	IQ	0.802	0.896	0.915	0.518
	PZ	0.895			
	IE	0.821			
	EE	0.821			
CESC			0.909	0.923	0.501
SE		0.796			
	SO	0.797			
	FV	0.718			
EV		0.79			
PV			0.884	0.907	0.525

SV	0.869

Note: Artificial Intelligence technology is abbreviated as AIT, Customer Experience in Social Commerce is abbreviated as CESC, perceived value is abbreviated as PV

Firstly, conduct Harman univariate test using SPSS software. The results showed that the explanatory power of the first factor was only 25.035%, lower than the 40% standard (Harman, 1976). Therefore, it can be concluded that there is no issue of common method bias.

After conducting preliminary tests on reliability and validity, the author used two commonly used indicators, Kaiser Meyer Olkin (KMO), to measure and interpret cumulative variance to evaluate the external consistency of the measurement scale. The KMO values for each construct range from 0.712 to 0.844, exceeding the threshold of

0.70. The cumulative explanatory variance range of each construction factor is 64.048% to 91.716%, exceeding the 60% standard. In addition, the significance levels of each dimension were all<0.001. Therefore, the structural validity of the variables involved in this study meets the requirements.

As shown in Table 4.4, the values of SRMR (normalized root mean square residual) are 0.091 and 0.107, indicating good fitting performance of the model and reasonable adaptability(Hu & Bentler, 1998).

Table 4.4 Root mean square residual（SRMR）

	Saturated model	Estimated model
SRMR	0.091	0.107

4.2 *Hypothesis Testing and Mediation effect test*

As shown in Table 4.5 and Figure 4.1. Based on these findings, the following conclusions can be drawn:

Table 4.5: Hypothesis Testing Direct Effects

Path relationship	*β*	*M*	*SD*	*T*	*P*
AIT -> CESC	0.558	0.559	0.058	9.595	< 0.001
CE -> CI	0.218	0.218	0.062	3.527	< 0.001
CESC -> CE	0.417	0.419	0.063	6.665	< 0.001
CESC -> PU	0.266	0.268	0.064	4.136	< 0.001
PU -> CI	0.184	0.185	0.064	2.865	0.004
PU -> PV	0.249	0.251	0.060	4.126	< 0.001

PV -> CI	0.287	0.291	0.065	4.421	< 0.001

The standardization coefficient of AI Technology on Customer Experience in Social Commerce was 0.558 and the p-values were all<0.05, which passed the significance test, indicating that AI Technology has a significant positive impact on Customer Experience in Social Commerce. The standardization coefficient of Customer Expectation on Customer Purchase Intention is 0.218 and the p-values are all<0.05, passing the significance test, indicating that Customer Expectation has a significant positive impact on Customer Purchase Intention. The standardization coefficient of Customer Experience in Social Commerce on Customer Expectation is

0.417 and the p-values are all<0.05, which passes the significance test, indicating that Customer Experience in Social Commerce has a significant positive impact on Customer Expectation. The standardization coefficient of Customer Experience in Social Commerce on Perceived Usefulness is 0.266 and the p-values are all<0.05, passing the significance test, indicating that Customer Experience in Social Commerce has a significant positive impact on Perceived Usefulness. The normalization coefficient of Perceived Usefulness on Customer Purchase Intention was 0.184 and the p-values were all<0.05, which passed the significance test, indicating that Perceived Usefulness has a significant positive impact on Customer Purchase Intention. The standardization coefficient of Perceived Usefulness on Perceived Value is 0.249 and the p-values are all<0.05, passing the significance test, indicating that Perceived Usefulness has a significant positive impact on Perceived Value. The standardization coefficient of Perceived Value on Customer Purchase Intention is 0.287 and the p-values are all<0.05, which passes the significance test, indicating that Perceived Value has a significant positive impact on Customer Purchase Intention.

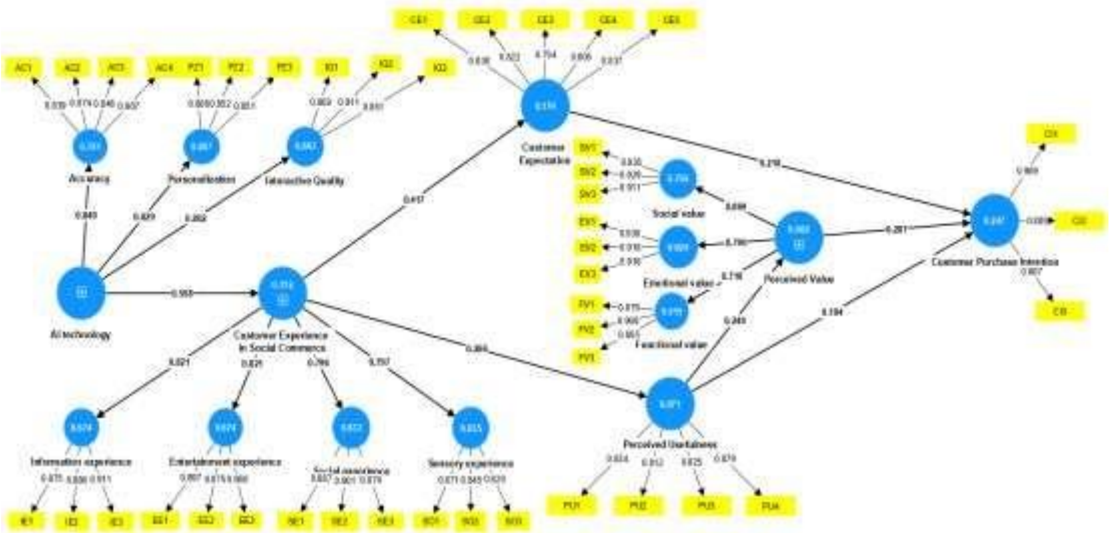

Figure 4.1: Results of the theoretical model using Smart-PLS Regarding the mediation effect test, as shown in Table 4.6

Table 4.6 Hypothesis Testing Indirect Effects

Path relationship	***β***	***M***	***SD***	***T***	***P***	**95%CI**	
AIT -> CESC -> CE -> CI	0.051	0.051	0.019	2.647	0.008	0.016	0.089
AIT -> CESC -> PU -> PV -> CI	0.011	0.011	0.005	2.263	0.024	0.004	0.023

AIT -> CESC -> PU -> CI	0.027	0.028	0.013	2.044	0.041	0.006	0.057
CESC -> CE -> CI	0.091	0.092	0.031	2.91	0.004	0.032	0.151
CESC -> PU -> PV -> CI	0.019	0.020	0.008	2.354	0.019	0.007	0.038
CESC -> PU -> CI	0.049	0.050	0.023	2.137	0.033	0.01	0.099

The mediating effect value of artificial intelligence technology on customer purchase intention through customer experience and customer expectations in social commerce is 0.051, and the confidence interval does not include zero, indicating that hypothesis H1 is valid. The mediating effect value of artificial intelligence technology on customers' purchase intention through their experience, perceived usefulness, and perceived value in social commerce is 0.011, and the confidence interval does not include zero, indicating that hypothesis H2 is valid. The mediating effect value of artificial intelligence technology on customers' purchase intention through customer experience and perceived usefulness in social commerce is 0.027, and the confidence interval does not include zero, indicating that hypothesis H3 is valid. The mediating effect value of customer experience in social commerce is 0.091, and the confidence interval does not include zero, indicating that hypothesis H4 is valid. The mediating effect value of customer experience in social commerce that affects customer purchase intention through perceived usefulness and perceived value is 0.019, and the confidence interval does not include zero, indicating that hypothesis H5 is valid. The mediating effect of perceived usefulness on customer experience in social commerce is 0.049, and the confidence interval does not include zero, indicating that hypothesis H6 is valid.

5. Conclusion

This study used SPSS and Smart-PLS statistical analysis software for descriptive statistics, reliability analysis, validity analysis, factor analysis, and model fit analysis, and tested the direct and mediating effects in the model. The following assumptions were validated through data testing: 1. Artificial intelligence technology affects customer purchase intention through customer experience in social commerce and customer expectation. 2. Artificial intelligence technology affects customer purchase intention through customer experience in social commerce, perceived usefulness, and perceived value. 3. Artificial intelligence technology affects customer purchase intention through customer experience in social commerce, and perceived usefulness.

4. Customer experience in social commerce affects customer purchase intention through customer expectation. 5. Customer experience in social commerce affects

customer purchase intention through perceived usefulness and perceived value. 6. Customer experience in social commerce affects customer purchase intention through perceived usefulness. All six assumptions above are valid, and the model construction is effective.

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