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Research on Influencing Factors of AI Chat Robot on Customer Satisfaction of Online Shopping Platform

-- Take Alibaba as an example

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Abstract: Based on the technology acceptance model, this study deeply investigates the factors influencing customer satisfaction of AI Chatbot, and portrays the relationships between different latent variables from both TAM and external factors to reveal the information quality, usability, self-efficacy, perceived enjoyment, subjective norms, perceived ease of use, perceived usefulness and customer satisfaction. A total of 481 valid questionnaires were obtained through online questionnaire distribution and offline interview research, and the samples were analyzed by SPSS software for reliability and heterogeneity, and then the SEM model path analysis was conducted by Amos software to derive the direct or indirect relationships among the variables. Main research conclusions include:(1) information quality, usability, self-efficacy, perceived enjoyment have a direct impact on customers' perceived ease of use (2) subjective norms can positively affect customers' perceived usefulness; (3) perceived ease of use and perceived usefulness have a direct positive impact on customers' satisfaction. Last, this study further discusses the research results, elaborates the theoretical significance and practical significance of this study, and finally puts forward the limitations and looks forward to future studies.

Keywords: AI chatbot, Customer satisfaction, ALIBABA, SE.

1. Introduction

From bustling cities to the countryside, the daily lives of Chinese consumers were already changing even before the Covid-19 pandemic ended. As the country emerges from the pandemic and focuses on economic recovery, changes are likely to accelerate for some Chinese consumers, mainly because they are facing shifts in consumption patterns and habits, including the widespread use of generative artificial intelligence, the rise of revenge travel, and changing attitudes toward health and sustainability.

As Chinese consumers are eager to return to their pre-pandemic habits, the competition has become more intense. The ability of brands to deliver superior customer experiences online and offline, raise customer satisfaction to new heights, and effectively manage various friction points in the purchasing process has become a core focus of the competition. As consumers continue to change and adapt, retailers must follow suit to maintain their competitiveness and relevance in the market.

In a volatile market, retailers need to ensure not only the immediate viability of their business, but also the long-term priorities that will drive sustainable future growth. The race requires the flexibility to deploy a diverse range of strategic tools to steer a steady path toward sustainable growth in this new era. At the same time, this new era is bringing retailers innovative technologies, such as AI-powered chatbots, to add new impetus to their growth strategies. AI chatbots have emerged as a potential customer service application for providing 24/7 customer service. Statistics show that nearly a quarter of customer service organizations have adopted AI chatbots for customer service (Gartner, 2019), and the related market is expected to grow to more than $142 billion by the end of 2024 (Yuen,2022).

The application of advanced chatbot technology in the consumer market continues to increase. When asked which features of AI chatbots are most appealing to them, Chinese consumers are interested in using various features of chatbots, including searching for product information (46 percent; Global: 44 percent), personalized offers (40 percent; Worldwide: 31%), send alerts and updates about products (39%; Worldwide: 34 percent), and enhancing customer service and support (30 percent; Worldwide: 35 percent). AI chatbots have significant implications for the retail and e-commerce industries. By serving and responding to customers in a timely manner, chatbots help increase sales and conversion rates, enhance the shopping experience, collect customer data, and more.

Although chatbots have special functions, there are still questions about the efficiency of such applications compared to human customer service agents ((Janssenetal, 2021). A recent survey (Chatbots, 2018) found that 53% of users considered customer service chatbots to be "ineffective" or only "somewhat effective." In particular, 59% of respondents were frustrated by repeating the same information multiple times when chatbots were unable to effectively meet their needs and had to transfer related tasks to human agents. Therefore, in order to evaluate the effectiveness of the application of chatbots in e-retail, this paper analyzes the background of the emergence of chatbots and the various factors influencing them, which are key to improving customer satisfaction.

2. Literature Review and Research Model

This research seeks to understand and leverage the determinants of user technology acceptance to influence technology design and implementation processes to minimize user resistance and improve user satisfaction. TAM is a theoretical model that predicts how users will accept and use a given piece of information technology. It prescribes contingent relationships between external variables, belief and attitude structures, and actual usage behavior (Hubona et al.,1996). The model suggests that when introducing users to a particular information technology, a number of factors, in particular perceived usefulness and perceived ease of use, influence their decisions.

Since its introduction by Davis (1989), the TAM model has been commonly used to predict the acceptance, adoption, and use of information systems. However, in this study, the TAM model is used for a different purpose. Instead of predicting the acceptance and use of information systems, this study analyze how TAM factors may primarily contribute to improving customer satisfaction. At present, there is no comprehensive literature on customer perception of TAM factor, and the influence of external variables such as information quality, availability, self-efficacy, perceived enjoyment and subjective normative factors on customer e-satisfaction.

E-satisfaction is an important content in the literature related to online services, because it affects the user's decision whether to continue using the distribution channel (Lin and San, 2009). Szymanski and Hise (2000) view e-satisfaction as a user's judgment of their overall online experience over a period of time. In this paper, e-satisfaction measures the degree to which users are satisfied and dissatisfied with the use of AI chatbots. Bansal (2004) reviewed many studies on the factors that influence e-satisfaction. They found that most of the variables that contribute to e-satisfaction are either related to the website or the perceived value of the website and this classification of variables that produce e-satisfaction is clearly related to the quality-of-service factor rather than the TAM factor. Some scholars have conducted in-depth studies on the relationship between different factors such as e-service quality, reliability, responsiveness, personalization, security, trust, interactivity, accessibility and e-satisfaction, and most of these studies have found a positive correlation between e-quality factors and e-satisfaction. However, few articles attempt to link TAM factor with e-satisfaction and e-loyalty in the environment of online shopping. Lin and Sun (2009) conducted a study and found that TAM factor had a significant positive correlation with e-satisfaction and e-loyalty. However, the influence of different TAM factors on e-satisfaction and e-loyalty was not clearly defined in their research. Instead, all the factors were aggregated into a structure called the "technology acceptance factor". As a result, there is no precise definition as to which or how each TAM factor may affect e-satisfaction. In this study, two factors of TAM are proposed perceived ease of use (PEOU) and perceived usefulness (PU), as well as five other external factors: information quality (INF), usability (US), self-efficacy (SLEF), perceived enjoyment (ENJ), and subjective norms (SN) as independent variables affecting satisfaction.

Although some previous TAM studies acknowledged that the existence of external variables had an impact on perceived usefulness and perceived ease of use, most TAM studies ignored the evaluation of these variables. As a result, most TAM studies and extensions do not adequately account for users' external difficulties and psychological interactions with a given technology. The role of external variables that influence TAM usage behavior has not been well studied (Hubona,1997), Venkatesh (2000) argues that the initial drivers of perceived ease of use depend heavily on individual difference variables and situational characteristics. The TAM study conducted by Hubona provides perhaps the most extensive assessment of the effect of external variables on actual system use (i.e., usage behavior) (Burton-Jones and Hubon, 2005, Hubon and Burton-Jones, 2022, Hubon and Geitz, 1997, and Hubon and Kennick, 1996).

Although TAM factors have been used as quality factors in different studies, there is a lack of focused discussion in the literature on the importance of TAM factors as strong predictors of customer satisfaction in an AI chatbot environment.

Information quality refers to "the quality of the information provided by the portal and its usefulness to users to the extent that users can achieve the stated goals of the system". When studying the overall information system success of any given system, information quality is considered to be one of the most important success factors (McKinney et al., 2002). Information quality is the customer's perception of the quality of information about products or services offered by a website (Pudjihardjo, 2015). Kim et al. (2016) shows that when customers receive a good piece of information, they tend to influence others' purchasing decisions. Chen et al. (2014) also pointed out that the higher the quality of information, the more users will feel it. In summary, hypothesis 1 was proposed:

H1: The perceived ease-of-use of AI chatbots is positively affected by information quality.

Less emphasis has been placed on the assessment of customer characteristics, that contribute significantly to the user's perception and satisfaction with the technology. In essence, there is a reasonable assumption that usability is a prerequisite for acceptance. Thus, if a technology is perceived to be highly available and useful, it is likely to be highly accepted by its intended users. This is often not the case, as many technologies are considered highly available and useful but are never accepted by their target users (Dillon, 2001), and these technologies are developed without full knowledge of the target user group.

Regarding the usability of chatbots, this refers to how easy it is to use a chatbot, but if customers do not understand how to use a chatbot, they will not use certain features and the chatbot will not reach its potential. This can have a limiting effect on the effectiveness of the chatbot and can lead to customer dissatisfaction. To sum up, hypothesis 2 is proposed:

H2: The perceived ease of use of AI chatbots is positively affected by usability.

Self-efficacy refers to a person's confidence in their ability to perform a particular task or behavior (Bandura, 1986). More specifically, self-efficacy measures a person's confidence in mastering a new technology (Compeau and Higgings, 1995). If a person has a high sense of self-efficacy, then that person will believe that others can successfully use the technology. If one shows low self-efficacy, then one will believe that others will have trouble using the technology (Lai, 2008). Venkatesh and Davis (1996) found that self-efficacy is a determinant of perceived ease of use, both before and after actually using a system (Venkatesh and Davis, 1996). Other TAM researchers have found that self-efficacy has implications for TAM (Chen et al., 2002). In summary, hypothesis 3 is proposed:

H3: The perceived ease of use of AI chatbots is positively affected by self-efficacy.

Perceived enjoyment refers to the degree to which the activity itself is perceived as enjoyable in addition to any performance consequences arising from using the system. Venkatesh and Davis (2000). A person's perceived enjoyment of using technology can influence the intention and intensity of using the technology (Muslimah and Aisyah, 2016). A person's convenience and enjoyment while using the technology will make the user comfortable with the perception of the app because they have achieved the initial comfort. The TAM model discusses the perception of comfort, whereby a person's attitude toward using a technology depends on how comfortable he feels about the person believing in using the technology (Venkatesh and Bala, 2008). Amelia (2019) shows that perceived enjoyment has a positive and significant effect on the ease of use of an application. The higher comfort level of using AI chatbots will affect the ease of use of AI chatbots. Based on the explanations already described, the following hypothesis can be formulated as follows:

H4: The perceived ease of use of AI chatbots is positively influenced by perceived enjoyment.

Subjective norms in economics refer to an individual's perceptions or beliefs about the expectations of society or others (Davis,1989). Subjective norms are determinants of intent that arise from social pressures and influence a person's perception of others' beliefs as a consideration of doing or not doing certain behaviors (Ajzen, 1991). In the digital age, social communities formed as a result of social media technology have a powerful influence in providing information and establishing an opinion about something in a group. The use of AI chatbots has been widely spread to customers. Venkatesh and Davis (2000) point out that subjective norms can indirectly influence the behavioral intent of perceived usefulness using technology. Research conducted by Muslimah and Aisyah (2016) has shown that subjective norms significantly affect customers' perceived usefulness. Based on this the hypothesis can be formulated as follows:

H5: The perceived usefulness of AI chatbots is positively influenced by subjective norms.

Perceived ease of use explains the extent to which a person trusts an information technology system that will not require physical and mental effort (Davis,1989). Like chatbots, it is a form of digital assistant widely used today, which means that the application is easy to use and useful to its customers. Many previous studies have shown a relationship between perceived ease of use and perceived usefulness when using technology (Bogea and Brito,2018; Hasan, 2007; Kang et al., 2014; Padilla-Melendez et al., 2013; Winarno and Putra, 2020). As in Muslimah's (2016) study, an easy-to-operate system makes it easier and provides benefits to customers. If the user perception of the ease of use of the app system is high, then the perceived usefulness will also increase. Based on the above explanation and previous studies that have been interpreted, the following hypotheses can be proposed:

H6: Perceived ease of use positively affects perceived usefulness of perceived AI chatbots.

E-satisfaction is defined as follows: "e-satisfaction is defined as the customer's satisfaction with their previous purchase experience at a given e-commerce company" (Doll and Torkzadeh, 1988). Customer satisfaction is important because dissatisfied customers are more likely to seek out alternative information and turn to a competitor. In this paper, the relationship between chatbots and customer satisfaction was examined using surveys. When customers have a good online shopping experience, it creates positive attitudes, improves self-efficacy, and influences future intentions, while if they have a bad experience, it may have the exact opposite effect. In addition, customers are more likely to trust and rely on sellers if they have a positive experience with online shopping (Pappas et al., 2014). In the paper by Chen et al., customer satisfaction in 2021 is defined as "reactions and feelings related to customer experience in e-commerce." Users expect systems to be fast, efficient and reliable, and their perception of the time spent is also important. Considering the importance of the fundamental value in chatbot customer support services in achieving higher customer satisfaction, the following hypothesis was formed:

H7: Perceived ease of use has a positive impact on customer satisfaction.

H8: Perceived usefulness has a positive impact on customer satisfaction.

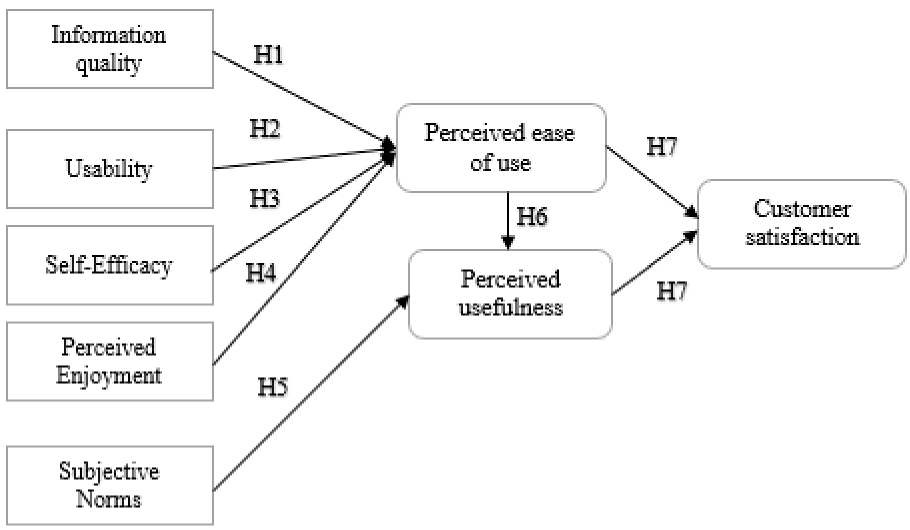

Figure 2-1. Research model

3. Research Methods

Questionnaire is chosen as the tool of empirical research in this study because it is a data collection method that can quantify individual attitudes, facilitate research data processing, and is an important method to obtain first-hand empirical research data. In order to ensure the validity and accuracy of the measurement items, the questionnaire was compiled using scales in domestic and foreign research literature. It also integrated specific features related to customer satisfaction, and improved the initial questionnaire according to the feedback of consultants and peers to form the final questionnaire used in this study. Prior to the formal survey, a preliminary survey was conducted in this study with 36 valid and truthful responses. According to the feedback of the preliminary sample and the content of the questionnaire, some items in the preliminary questionnaire were refined. This was done to ensure clarity and eliminate uncertainty in the final questionnaire used by the research. In this study, both online and offline survey methods were used to distribute questionnaires and collect data. For the online survey, Credamo was used to distribute digital questionnaires and share questionnaire links for the study. The offline survey was mainly conducted through random distribution at Chongqing University of Posts and Telecommunications.

The questionnaire in this study was divided into two parts. The first part covers the respondents' basic personal information, including gender, age, educational background, occupation, and the use of AI chatbots. The second part is the measurement of the study variables and develops the measurement items for the eight study variables.

(1) Personal basic information survey

The respondents' basic personal information consists of six questions, including details such as gender, age, educational background and occupation. In addition, this part also includes a survey on the use of AI chatbots by the surveyed customers, including whether they actively use chatbots and how often they use AI chatbots each month.

(2) Customer satisfaction survey of AI chatbot

This section forms the core of the questionnaire and mainly deals with the measurement items discussed in the next section. This part is divided into 8 measurement scales to measure the 8 variables involved in this study, namely information quality, usability, self-efficacy, perceived enjoyment, subjective norms, perceived ease of use, perceived usefulness, and satisfaction.

All measurement items were measured by Likert 7-level scale, with 1-7 representing "strongly disagree" to "strongly agree" respectively. Respondents were required to answer all questions according to their real experience of using "AI chatbot on Alibaba Taobao shopping platform". Through a combination of paper questionnaire and online questionnaire, a sample survey is conducted on various types of consumers. This paper can provide a more accurate sample source for the heterogeneity analysis of AI chatbot customer satisfaction among potential customers at different levels, so as to ensure the integrity and representativeness of the samples.

In the follow-up data analysis of this study, SPSS and Amos software are mainly used for processing. SPSS is mainly used for descriptive statistical analysis, including statistics of demographic characteristics, statistics of questionnaire measurement items, questionnaire reliability analysis and analysis of individual heterogeneity of consumers. Amos software is used for validity testing, construction of structural equation models, and testing of model path assumptions. The combination of these two software is conducive to the comprehensive and in-depth analysis of research data.

4. Study the Results

A total of 600 questionnaires were filled out. Invalid surveys were excluded based on gender, age and response time. There were 481 valid questionnaires, and the response rate was 80.2%. See Table 4-1 for sample questions on demographic characteristics. Respondents include individuals with different socioeconomic attributes, and the sample is well representative on the whole. The demographic characteristics of the residents concerned in this study mainly include gender, age, education, occupation, whether they use chatbots actively or passively, and the monthly frequency of using chatbots.

Table 4-1. Descriptive statistical analysis of the sample

Variable names	Species	N = 481	Percentage (%)
Gender	male	279	58.0
	female	202	42.0
Age	< 18	24	4.99
	18-25	180	37.42
	26 -- 34	143	29.73
	35-45	115	23.91
	> 45	19	3.95
Education	Hight school or below	81	16.84
	Undergrad	212	44.07
	Masters	112	23.28
	PHD	76	15.80
Occupations	Students	84	17.46
	Educational workers	111	23.08
	Corporate personnel	161	33.47
	Government personnel	77	16.01
	Other	48	9.98
Whether to use chatbots actively or passively	Active	337	70.89
	Passive	144	29.11
How often chatbots are used per month	Hardly ever	60	12.47
	Seldom use	85	17.67
	Occasionally	214	44.49
	Used often	122	25.36

In this section, SPSS software is used for statistical analysis of the minimum, maximum, average and standard deviation of each measurement item in different dimensions. The specific results are shown in Table 4-2.

Table 4-2. Table of statistical analysis of samples

Dimensions	Item	Average	Standard Deviation	Minimum	Maximum value
Quality of information	INF1	4,9771	1,61681	1.00	7,00
	INF2	4,7173	1,59918	1.00	7,00
	INF3	4,7796	1,54154	1.00	7,00
	INF4	4,8711	1,57057	1.00	7,00
	INF5	5,2744	1,49428	1.00	7,00
Usability	US1	5,0894	1,48545	1.00	7,00
	US2	5,1954	1,51357	1.00	7,00
	US3	5,1975	1,50847	1.00	7,00
Self-efficacy	SLEF1	5,1913	1,61658	1.00	7,00
	SLEF2	5,0832	1,55769	1.00	7,00
	SLEF3	4,9834	1,62908	1.00	7,00
	SLEF4	4,6798	1,61290	1.00	7,00
Perceived enjoyment	ENJ1	4,7713	1,59481	1.00	7,00
	ENJ 2	4,8857	1,61291	1.00	7,00
	ENJ 5	4,7942	1,59597	1.00	7,00
Subjective norm	SN1	5,1559	1,60553	1.00	7,00
	SN 2	4,9064	1,57902	1.00	7,00
	SN 3	4,9148	1,60955	1.00	7,00
	SN 4	5,1767	1,49581	1.00	7,00
	SN 5	4,8649	1,48900	1.00	7,00
	SN6	4,9418	1,48490	1.00	7,00
Perceived ease of use	PEU1	4,9771	1,45255	1.00	7,00
	PEU2	5,2058	1,58681	1.00	7,00
	PEU3	5,0395	1,55607	1.00	7,00
	PEU4	5,1559	1,53657	1.00	7,00
Perceived usefulness	PU1	5,1227	1,55440	1.00	7,00
	PU2	5,2370	1,51037	1.00	7,00
	PU3	5,0520	1,54090	1.00	7,00
	PU4	4,9813	1,60911	1.00	7,00
	PU5	4,7131	1,60365	1.00	7,00
	PU6	4,7401	1,64603	1.00	7,00
Satisfaction	SAT1	4,9709	1,60182	1.00	7,00
	SAT2	4,7838	1,61343	1.00	7,00
	SAT3	5,2578	1,42305	1.00	7,00
	SAT4	4,9252	1,45867	1.00	7,00
	SAT5	5,0083	1,48462	1.00	7,00

As can be seen from the table, the average value of each item in this study is above 4, which indicates that potential customers have optimistic and positive views on information quality, usability, self-efficacy, perceived enjoyment, subjective norms, perceived ease of use, perceived usefulness and satisfaction.

The question design of this study is based on the previous research, drawing on the existing scale and making necessary modifications. Therefore, the reliability of the scale must be evaluated so that the data collected from the scale is stable and reliable. In the model hypothesis, the scale of influencing factors of customer satisfaction of AI chatbot was divided into 8 variables including information quality, usability, self-efficacy, perceived enjoyment, subjective norms, perceived usefulness, perceived ease of use, and satisfaction, with a total of 36 items (see Table 4-3). In order to ensure the reliability of the questionnaire and its measurement items, Cronbach's α (Cronbach reliability coefficient) was adopted for reliability test. This step was designed to assess the internal consistency of each item in the questionnaire and the overall reliability of the measurement tool. Cronbach's α of each factor in the model is usually above 0.7, while the reliability coefficients of each variable are close to 0.7, and the lowest value is not less than 0.6. These values are within the acceptable range, indicating that the scale has good internal consistency and reliability. Cronbach's α of the questionnaire as a whole is 0.944, indicating that the design of the questionnaire is very reasonable, and the questionnaire and the scale of each variable are accurate and reliable, which is within the reliability test requirements.

In this study, an exploratory factor analysis (EFA) using SPSS 29.0 was performed. The main goal of exploratory factor analysis is to capture the core structure that reflects the research question by reducing the dimensionality of multiple observed variables to compress these variables into fewer potential variables. According to the criterion of eigenvalues greater than 1, we successfully extracted 8 factors (see Table 4-5 for details), which is consistent with our theoretical expectations and provides a basis for further analysis.

Table 4-3. Cronbach's α

Variables	Measurement items	Measurement item	Cronbach's alpha
Quality of Information	INF1	AI chatbots can provide me with ample information.	0.898
	INF2	AI chatbots can provide me with accurate information.	
	INF3	AI chatbots can provide me with very clear information.	
	INF4	AI chatbot Customer service bots can provide me with new information.	
	INF5	AI chatbots provide me with better pre-selection information.	
Usability	US1	Searching with the help of an AI chatbot saved me hours.	0.812
	US2	AI chatbots make the platform easy to use and effortless.	
	US3	The AI chatbot knows the context during the session.	
Self-efficacy	SLEF1	If there's no one around to tell me what to do, I can get things done with an AI chatbot.	0.812
	SLEF2	I can complete tasks using AI chatbots if there is assistance with built-in help facilities.	
	SLEF3	I can use an AI chatbot to complete the task if someone tells me how to do it first.	
	SLEF4	I can use an AI chatbot for this task if I've used a similar AI chatbot for the same task before.	
Perceived enjoyment	ENJ1	I find using AI chatbots enjoyable.	0.845
	ENJ2	The actual process of using an AI chatbot is enjoyable.	
	ENJ3	Using AI chatbots is fun and I love it.	
Subjective norms	SN1	People who influence my behavior think I should use AI chatbots.	0.893
	SN2	People who are important to me think I should use an AI chatbot.	
	SN3	In general, the people around me are supportive of the use of AI chatbots.	
	SN4	Talking about chatbots can improve my relationship with people around me.	
	SN5	I will actively try to reach out and use chatbot recommended by others.	
	SN6	I'm interested in referrals.	
Perceived ease of use	PEU1	I can easily learn to use AI chatbots.	0.866
	PEU2	I have easy access to AI chatbots.	
	PEU3	I find it flexible and convenient to use AI chatbots.	
	PEU4	I can use AI chatbots easily and skillfully.	
Perceived Usefulness	PU1	Using AI chatbots enables me to find and filter targeted product information more efficiently.	0.907
	PU2	Using AI chatbots enables me to learn about target products more efficiently.	
	PU3	The use of AI chatbots can make me more efficient to understand the relevant after-sales service information.	
	PU4	Using AI chatbots can make my shopping process more enjoyable.	
	PU5	Using an AI chatbot makes it easier for me to lose the desire to communicate with human customer service.	
	PU6	Chatbots are great for my other service needs besides shopping.	
Satisfaction	SAT1	AI chatbot provides complete guidance during service.	0.738
	SAT2	The AI chatbot has the features I need to use.	
	SAT3	AI chatbots will get me the help I need.	
	SAT4	I suggest others use AI chatbots.	
	SAT5	Using AI chatbots can make my experience better.	
Overall	-	-	0.944

Table 4-5. Table of statistical analysis of samples

Latent Variables	KMO	Bartlett	Degrees of Freedom	Sig.
Quality of Information (INF)	0.891	1344.388	10	< 0.001
Usability (US)	0.706	675.139	3	< 0.001
Self-efficacy (SLEF)	0.838	962.075	6	< 0.001
Perceived enjoyment (ENJ)	0.720	608.567	3	< 0.001
Subjective norm (SN)	0.905	1309.979	15	< 0.001
Perceived usefulness (PU)	0.917	1671.104	15	< 0.001
Perceived Ease of Use (PEU)	0.829	885.345	6	< 0.001
Satisfaction (SAT)	0.861	993.894	10	< 0.001
Scale overall	0.933	10341.203	630	< 0.001

To assess the internal consistency and convergent validity of each structure in the proposed model, a confirmatory factor analysis (CFA) was performed for eight variables: information quality, usability, self-efficacy, perceived enjoyment, subjective norms, perceived ease of use, perceived usefulness, and satisfaction. As can be seen from Table 4-6 and Table 4-5, the standard error (S.E.) of the parameters is between 0.051 and 0.072, and there is no large standard error, and the P-values all reach a significant level above 0.001. The standardized factor load values between each item and the potential variable under the 8 variables are within the threshold range of 0.7 to 0.9, and all exceed the standard threshold of 0.5. This indicates that the questionnaire has a high fit, the scale quality is good, and the overall model has a strong explanatory power. The combined reliability (CR) values were within the threshold range of 0.846 to 0.908, all above the recommended standard threshold of 0.6 (Little, 1997). The Average Variance Extracted (AVE) index is within the threshold range of 0.537 to 0.670, which indicates that the explanatory power of the model is basically acceptable. Based on the above analysis, the measurement model shows good convergence validity and internal consistency.

Table 4-6. Results of convergent validity analysis

Paths			Factor load after standardization	S.E.	P	CR	AVE
INF_5	<---	INF	0774				
INF_4	<---	INF	0794	0057	* * *		
INF_2	<---	INF	0813	0057	* * *	0.898	0.638
INF_1	<---	INF	0794	0058	* * *		
INF_3	<---	INF	0818	0056	* * *		
US_3	<---	US	0, 7				
US_2	<---	US	0862	0072	* * *	0.857	0.670
US_1	<---	US	0881	0071	* * *		
SLEF_4	<---	SLEF	0812				
SLEF_3	<---	SLEF	0809	0053	* * *	0.878	0.643
SLEF_1	<---	SLEF	0795	0054	* * *		
SLEF_2	<---	SLEF	0,	0054	* * *		
ENJ_3	<---	ENJ	0835				
ENJ_2	<---	ENJ	0732	0051	* * *	0.846	0.648
ENJ_1	<---	ENJ	0843	0052	* * *		
SN_5	<---	SN	0748				
SN_4	<---	SN	0781	0064	* * *		
SN_2	<---	SN	0751	0064	* * *	0.881	0.553
SN_1	<---	SN	0769	0065	* * *		
SN_3	<---	SN	0665	0064	* * *		
SN_6	<---	SN	0744	0063	* * *		
PEU_4	<---	PEU	0786				
PEU_3	<---	PEU	0777	0055	* * *	0.866	0.612
PEU_1	<---	PEU	0785	0057	* * *		
PEU_2	<---	PEU	0796	0057	* * *		
PU_5	<---	PU	0746				
PU_4	<---	PU	0831	0056	* * *		
PU_2	<---	PU	0771	0056	* * *	0.908	0.621
PU_1	<---	PU	0791	0056	* * *		
PU_3	<---	PU	0762	0057	* * *		
PU_6	<---	PU	0825	0058	* * *		
SAT_5	<---	SAT	0758			0.852	0.537

Discriminative validity is simply discriminant validity, which refers to the low correlation of potential variables with each other. In other words, if there are multiple correlated structures in a conceptual model, and these structures are all related to each other and have some difference in the model, then this indicates that the conceptual model has good discriminative validity. The potential variables in different structures will be distributed at their respective structural levels. Detailed analysis results are shown in Table 4-7. Discriminant validity usually calculates the mean variance extraction value (AVE) of each variable by a formula to determine whether the square root of AVE is greater than the variance between variable and other relevant variables. This method is used to assess the discriminative validity between each structure.

Table 4-7. Results of discriminative validity analysis

Variable	INF	US	SLEF	ENJ	SN	PEU	PU	SAT
INF	0.799							
US	0,329**	0.819						
SLEF	0,414**	0,446**	0.802					
ENJ	0,4**	0,522**	0,404**	0.805				
SN	0,427**	0,44**	0,387**	0,488**	0.744			
PEU	0,564**	0,571**	0,593**	0,538**	0,508**	0.782		
PU	0,454**	0,498**	0,479**	0,47**	0,504**	0,619**	0.788	
SAT	0,415**	0,399**	0,479**	0,464**	0,37**	0,566**	0,455**	0.733
AVE	0.638	0.670	0.643	0.648	0.553	0.612	0.621	0.537

Note: * means <0.05, ** means <0.01 N = 481

The purpose of this study was to measure the interaction between eight variables: information quality, usability, self-efficacy, perceived enjoyment, subjective norms, perceived ease of use, perceived usefulness, and satisfaction. The data in Table 4-6 shows that the square root of AVE value of the relevant factor in the external variable is greater than the correlation coefficient with other variables, which indicates that the model has good discriminative validity. In addition, the eight factors show certain correlation, which makes these data can be used for subsequent research and analysis. Therefore, the scale measurement used in this study has a high degree of reliability, and the final data obtained from the questionnaire survey shows a significant consistency, and the relationship between each potential variable can be analyzed very accurately. Therefore, the data results after testing can be continued for subsequent path analysis.

In order to verify the hypothesis in the research model, the structural equation model is used in this paper, and the conclusion of hypothesis testing based on the calculation results of the model is summarized. SPSS and Amos software were used to deeply analyze the influence of information quality, availability, self-efficacy, perceived enjoyment, subjective norms, perceived ease of use, perceived usefulness and other factors on customer satisfaction of AI chatbots. Finally, the structural equation model is used to determine the specific impact of independent variables on AI chatbot customer satisfaction, and verify the proposed research hypothesis.

After ensuring the reliability and validity of this research model meet the standards, Amos software is used to carry out a visual analysis of the relationship between observed variables and potential variables, so as to build the structure chart of influencing factors of AI chatbot customer satisfaction in this research. This structure chart provides us with a clear visual framework to deeply understand the interaction and influence path among various variables, as shown in Figure 4-1.

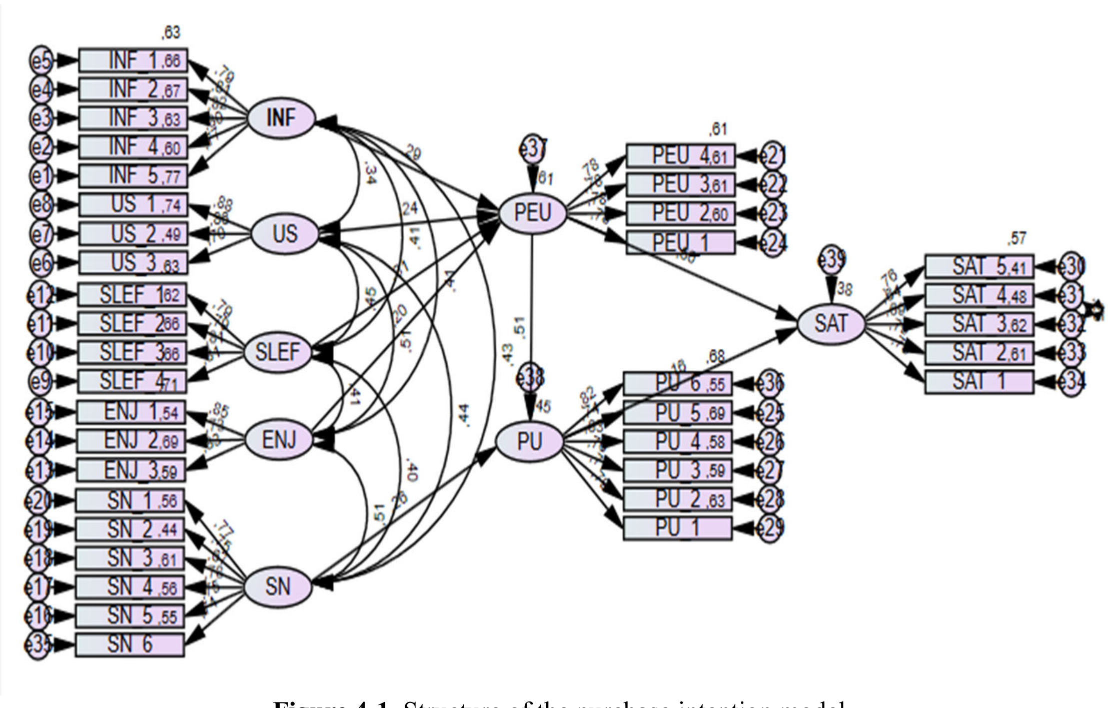

Figure 4-1. Structure of the purchase intention model

This graphical representation allows us to more intuitively understand the relationship between the variables. Determine the measurement model of latent variables and observed variables, construct the appropriate observed variables to reflect each potential variable, and evaluate the fit of the model. Explore the relationships between potential variables in depth, and conduct structural model and internal linkages analysis.

7 indexes CMIN/DF, GFI, AGFI, RMSEA, CFI, RMR and TLI were selected to test the goodness of fit of the model:

Table 4-8. model fitting results

Fitness-test index	Ideal standard	General standard	Model results	Results
CMIN/DF	< 3	< 3.8	1.739	standard
GFI	> 0.9	> 0.7	0.901	standard
AGFI	> 0.9	> 0.7	0.883	standard
RMSEA	< 0.05	< 0.08	0.039	standard
CFI	> 0.9	> 0.7	0.957	standard
RMR	< 0.05	< 0.08	0.0440	standard
TLI	> 0.9	> 0.7	0.953	standard

Table 4-8 shows the overall situation of model fitting in this study, which indicates that the hypothetical theoretical model in this paper has a good fit with the questionnaire sample data, and the model results are persuasive. Through literature reference and field investigation, a survey scale with 36 observed variables was created, including 8 latent variables. 36 observed variables were selected through reliability and validity tests, and the reliability and validity tests of these scales were close to the ideal standard, so subsequent model analysis could be conducted.

The final model was used for structural equation verification, and the operation results of direct effects were shown in Table 4-9:

Table 4-9. Results of structural equation path relationship test

Path relation	Estimate	S.E.	C.R.	P
Perceived ease of use <-- quality of information (PEU<--INF)	0.289	0.045	6.384	* * *
Perceived Ease of use <-- availability (PEU<--US)	0.280	0.058	4.806	* * *
Perceived ease of use <-- Self-efficacy (PEU<--SLEF)	0.320	0.050	6.407	* * *
Perceived ease of use <-- Perceived enjoyment (PEU<--ENJ)	0.184	0.045	4.070	* * *
Perceived usefulness <-- subjective norm (PU<-- SN)	0.278	0.052	5.327	* * *
Perceived usefulness <-- Perceived ease of use (PU<-- PEU)	0.499	0.053	9.361	* * *
Satisfaction <-- Perceived Ease of use (SAT<--PEU)	0.499	0.066	7.528	* * *
Satisfaction <-- Perceived ease of use (SAT<--PU)	0.163	0.062	2.639	0.018

Note: (1) ***p < 0.01; N = 481

According to the analysis results in Table 4-9, it can be seen that in the path hypothesis relationship test of this study, information quality significantly positively predicts perceived ease of use (β=0.289, p <0.001), so hypothesis H1 is valid. The positive prediction of perceived ease of use with significant usability (β=0.280, p<0.001) is therefore valid for hypothesis H2. Positive prediction of perceived ease of use with significant self-efficacy (β=0.320, p <0.001), therefore hypothesis H3 holds. Perceived enjoyment was a significant positive predictor of perceived ease of use (β=0.184, p <0.001), thus H4 is valid. Subjective norms significant positive predictive perceived usefulness (β=0.278, p <0.001), thus assuming that H5 holds. Perceived ease of use significantly positive predicts perceived usefulness (β=0.499, p <0.001), thus assuming H6 holds. Perceived ease of use significantly predicts positivly satisfaction (β=0.499, p <0.001), thus assuming H7 holds. Satisfaction is positive predicted by perceived usefulness (β=0.163,p=0.018), so hypothesis H8 holds.

Hypothesis testing results based on the model calculation results (Table 4-10):

Table 4-10. Summary of hypothesis testing results

Hypothesis	path	Direction	Result
H1	Perceived ease of use <-- quality of information (PEU<--INF)	positive	established
H2	Perceived ease of use <-- availability (PEU<--US)	positive	established
H3	Perceived ease of use <-- self-efficacy (PEU<--SLEF)	positive	established
H4	Perceived ease of use <-- Perceived enjoyment (PEU<--ENJ)	positive	established
H5	Perceived usefulness <-- subjective specification (PU<-- SN)	positive	established
H6	Perceived usefulness <-- perceived ease of use (PU<--PEU)	positive	established
H7	Satisfaction <-- Perceived ease of use (SAT<-PEU)	positive	established
H8	Satisfaction <-- Perceived Ease of use (SAT<--PU)	positive	established

5. Result discussion

5.1. Information quality and perceived ease of use

Testing the first hypothesis (H1) suggests that information quality does affect perceived ease of use. The structural equation model (SEM) calculation has a good path coefficient of 0.289, a CR of 6.384, and a significance level of $p<0.001$. Based on these results, the data show that information quality plays a role in influencing the perceived ease-of-use of customers, and it can be concluded that if users are satisfied with the quality of information generated from AI chatbots, then according to the perceived ease-of-use, users tend to feel comfortable and safe during work by using AI chatbots. Thus the user feels helpful in completing the job. So, from the user's point of view, the higher the level of information quality, the higher the perception of usage and ease of use. The results of this study support Ali and Younes (2013) 's study that information quality positively affects perceived ease-of-use.

5.2. Usability and perceived ease of use

Usability is one of the most important factors in helping and improving the user experience of AI chatbots. According to the results, the second hypothesis shows positive effect of the usability of AI chatbots on ease of use, therefore is accepted. The calculation of the structural equation model (SEM) has a good path coefficient of 0.280, a CR of 4.806, and a significance level of $p<0.001$. This means that consumers using AI chatbots need to know how to use AI chatbots and be familiar with all the features that AI chatbots offer them. Now that this study proves that the usability of AI chatbots has a positive impact on ease of use, companies should focus on making AI chatbots with high usability.

5.3. Self-efficacy and perceived ease of use

The results of testing the third hypothesis (H3) suggest that self-efficacy does affect perceived ease of use. The structural equation model (SEM) calculation has a good path coefficient of 0.320, a CR of 6.407, and a significance level of $p<0.001$. Based on these results, the data suggest that self-efficacy plays a role in influencing customers' perceived ease of use. The path coefficient of the self-efficacy variable ranked first among the predictors of ease of use of AI chatbots. This hypothesis states that self-efficacy supports the perceived ease of use of AI chatbot applications. According to Kurniawati et al. (2017), a sufficient level of knowledge and experience would undoubtedly lead to self-efficacy correlating with perceived ease of use. In the field of e-commerce, respondents still prioritize ease of use when shopping.

5.4. Perceived enjoyment and perceived ease of use

The results of testing the fourth hypothesis (H4) show that perceived enjoyment affects the perceived ease of use of AI chatbots. The structural equation model (SEM) results have a favorable path coefficient of 0.184, a CR of 4.070, and a significance level of $p<0.001$. The regression coefficient shows a positive effect, meaning that the higher the perceived enjoyment of the customer, the greater the perceived ease of use of the AI chatbot. Based on the results of this test, H4 was accepted. TAM model is about enjoyment, which means that one's attitude toward technology depends on one's own comfort and enjoyment of technology. The results of this study are consistent with previous research conducted by Amelia (2019), which showed that perceived satisfaction affects perceived ease of use and provides evidence for this relationship (Maranguniac & Granic, 2015). The customer's perception of an app is critical to the app's ease of use (Venkatesh & Bala, 2008). When using an AI chatbot application, customers should feel enjoyment.

5.5. Subjective norms and perceived usefulness

The results of testing the fifth hypothesis (H5) suggest that subjective norms have a positive impact on the perceived usefulness of AI chatbots. The structural equation model (SEM) results have a favorable path coefficient of 0.278 and a CR of 5.327, $p<0.001$. The regression coefficient shows a positive effect, meaning that the higher the subjective norm, the perceived usefulness of the AI chatbot increases. The results of this study are consistent with previous research conducted by Muslimah and Aisyah (2016), as well as Amelia (2019), that subjective norms can significantly affect users' perceptions of perceived usefulness. From this, it can be seen that subjective norms have a significant impact on customers' perceived usefulness. The findings suggest that acceptable subjective norms influence customers' perceived usefulness because subjective norms are perceived to be able to provide advice to others.

5.6. Perceived Ease of use and perceived ease of use

The results of testing the sixth hypothesis (H6) show that perceived ease of use affects the perceived usefulness of AI chatbots. The structural equation model (SEM) results have a favorable path coefficient of 0.499, a CR of 9.361, and a significance level of $p<0.001$. The regression coefficient shows a positive effect, meaning that the higher the perceived ease of use, the higher the perceived usefulness of the AI chatbot. Based on these results, H6 was accepted. Perceived ease of use explains the extent to which a person trusts an information technology system that does not require physical and mental effort (Davis, 1989; Davis et al., 1989). A system, application, or technology that has been developed and is easy to operate will provide convenience and benefits to users (Padilla-MeleNdez et al., 2013); Winarno&Putra, 2020). In other words, if the perceived ease of use of the system or application user is high, then the user will also gain the high perceived usefulness of the application (Kurniawati et al., 2017; Muslimah&Aisyah, 2016). The results of this study are consistent with previous research that perceived ease of use affects users' perceived usefulness (Muslimah&Aisyah, 2016). AI chatbots are easy to use in transactions to improve efficiency and productivity for customers. In this case, the customer does not need to know all the information about a particular product or service, but simply uses the AI chatbot to answer all questions and benefit the customer.

5.7. Perceived ease of use and satisfaction

Testing the seventh hypothesis (H7) shows that perceived ease of use affects customer satisfaction. The results of the structural equation model (SEM) have a good path coefficient of 0.499, a CR of 7.528, and a significance level of $p<0.001$.

The regression coefficient shows a positive effect, meaning that the higher the perceived ease of use, the higher the customer satisfaction. Based on these results, it is indicated that H7 is accepted. Perceived ease of use is an individual's attitude towards the use of technology, depending on how the technology helps the individual or makes it easier for the individual to use the technology (Davis et al., 1989), such as making online requests about products when using AI chatbots.

5.8. Perceived usefulness versus satisfaction

The results of testing the eighth hypothesis (H8) show that perceived usefulness affects customer satisfaction. The favorable path coefficient of structural equation model (SEM) results is 0.163, CR is 2.639, and significance level is p=0.018. The positive correlation coefficient shows that the higher the perceived usefulness, the higher the customer satisfaction. Based on these results, H8 is accepted. It showed that customers exercising felt minimal or made no effort in learning how to use AI chatbots did contribute to their satisfaction. The interpretation of these results is that most customers are able to learn any new system easily, leading to a feeling of special appreciation when learning the features and functions of the AI chatbot. For perceived ease of use, the square multiple correlation coefficient is R2=0.61. This means that 61% of the difference in perceived ease of use is due to quality information, availability, self-efficacy, and perceived enjoyment. For perceived usefulness, the square-multiple correlation is R2=0.45, meaning that 45% of the variance in perceived usefulness is explained by perceived ease of use and subjective norms. Finally, for customer satisfaction, the squared multiple correlation coefficient is R2=0.38. This means that 38% of the difference in customer satisfaction using chatbots is significantly explained by perceived ease of use and perceived usefulness, as well as subjective norms.

The results of the structural model are summarized in the conceptual schema below:

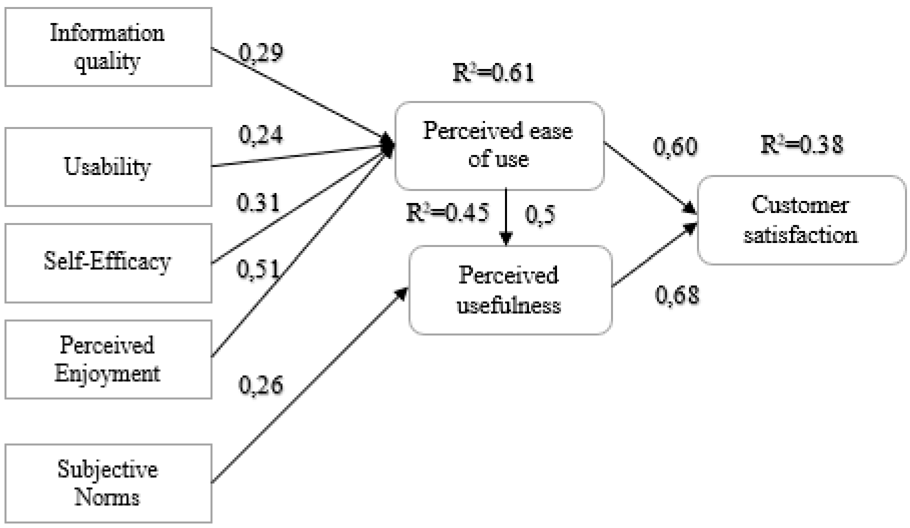

Figure 5-2. Summary of results of the structural model

Based on TAM model, this paper includes AI chatbot satisfaction factors and constructs an evaluation hypothesis model. The research hypothesis is tested through the survey data, and the relationship between eight variables is analyzed in depth. Based on these analyses, conclusions and inferences beneficial to enterprises are drawn, and corresponding suggestions are put forward.

Table 5-1. shows the validity of research hypothesis

Research hypothesis	Support or not
H1: The perceived ease of use of AI chatbots is positively affected by the quality of information.	support
H2: The perceived ease of use of AI chatbots is positively affected by usability.	support
H3: The perceived ease of use of AI chatbots is positively affected by self-efficacy.	support
H4: The perceived ease of use of AI chatbots is positively influenced by perceived enjoyment.	support
H5: The perceived usefulness of AI chatbots is positively influenced by subjective norms.	support
H6: Perceived ease of use positively affects perceived usefulness of perceived AI chatbots.	support
H7: Perceived ease of use has a positive impact on customer satisfaction.	support
H8: Perceived usefulness has a positive impact on customer satisfaction.	support

Based on a complex theoretical model of technology acceptance, this paper explores key factors such as perceived ease of use, perceived usefulness and customer satisfaction of chatbots. By constructing a structural model for hypothesis testing, this paper analyzes several variables that affect the ease-of-use of chatbots in detail. The results show that the ease-of-use of chatbots is improved when they are easy to operate and users feel they can interact easily. This finding fits with a significant amount of previous research on technology acceptance. At the same time, the paper also closely links the ease of use of chatbots to factors such as information quality, usability, self-efficacy and perceived enjoyment.

Further, this study finds that the usefulness of chatbots is influenced by both their ease of use and subjective norms. Customers are more likely to view chatbots as useful when they are easy to use and recognized by those around them. This conclusion is consistent with previous findings by Venkatesh and Davis (2000) and Venkatesh and Bala et al. (2008). Finally, this paper verifies the predictive effects of perceived ease of use and perceived usefulness on customer satisfaction through data analysis. This conclusion is consistent with the research results of Daud (2018) et al., which further emphasizes the importance of improving the usability and usefulness of chatbots to enhance customer satisfaction.

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