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Predicting University Students' Satisfaction and Continuance Intentions to Use AI-Powered Chatbots in Chengdu, China

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Abstract

Purpose: This study aims to investigate the determinants of university students' satisfaction and continuance intentions toward AI-powered chatbots in Chengdu, China. The conceptual framework was adapted from previous studies, which proposed a significant relationship among problem-solving, user interface, perceived usefulness, perceived ease of use, trust, satisfaction, and continuance intention. **Research design, data, and methodology:** The researcher used a quantitative method (n=500) to distribute questionnaires to undergraduate students. The researcher applied probability and non-probability sampling, including purposive, stratified random, and convenience sampling. The research applied the Structural Equation Model (SEM) and Confirmatory Factor Analysis (CFA) for the data analysis, including model fit, reliability, and validity of the constructs. **Results:** The results explained that problem-solving, user interface, perceived usefulness, and perceived ease of use support have a significant influence on satisfaction. Perceived Usefulness support showed the strongest influence on satisfaction, followed by user interface, perceived ease of use, and problem-solving. Satisfaction and trust have a significant influence on continuance intention. Satisfaction has the strongest influence on continuance intention, followed by trust. **Conclusions:** Six hypotheses were proven to fulfill research objectives. By measuring and evaluating user satisfaction, companies providing AI-powered chatbots can understand users' needs and expectations and their feelings about the user experience.

Keywords : AI-powered Chatbot, Satisfaction, Continuance Intention, Student, China

JEL Classification Code: E44, F31, F37, G15

1. Introduction

In the digital era, the expectation is for artificial intelligence (AI) to assume diverse job functions (Ashfaq et al., 2020). AI, performing tasks like decision-making and problem-solving akin to human behavior, finds applications in various industries. AI-powered chatbots, simulating real-time human-like conversations via text and audio, leverage AI algorithms for interactive experiences (Ashfaq et al., 2020). AI-powered chatbots combine cognitive automation, machine learning, reasoning, and natural language processing to produce insights like human intelligence (Le, 2023). They use AI and natural language processing to simulate human conversation, communicating through text or voice for various tasks.

AI-powered chatbots, automated programs enabling natural-language conversations, operate across digital devices. They integrate into various interfaces like websites, software, and social media and are referred to as conversational agents. Their significance lies in 24/7 availability, offering consistent, accurate responses with robust data collection (Chen et al., 2023). Some chatbots, especially in the market, use robotic process automation (RPA), automated frequently asked questions (FAQs) based on pre-built software instances (Przegalinska et al., 2019).

AI-powered chatbot applications span customer service, healthcare, tourism, and more, gaining popularity globally (Ashfaq et al., 2020; Chen et al., 2023; Hsiao & Chen, 2021;

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Le, 2023; Pillai & Sivathanu, 2020). In China, Baidu's "ERNIE Bot" and JD's "Yanxi" showcase AI-powered chatbots' integration with search services (CNNIC, 2023).

AI influencing students means integrating AI-powered chatbots into their learning and daily routines as they have more free time (Ashfaq et al., 2020). Challenges arise from autonomous engagement, late-start research in China, and evolving technology. Given the autonomous nature of AI-powered chatbot use, continuous adaptation is crucial for developers. Late-start research in China reveals a gap in factors influencing student adoption of AI-powered chatbots, necessitating a comprehensive analysis of satisfaction and intention to continue. This understanding is vital for developing strategies to enhance AI-powered chatbots and contribute to the broader discourse on AI-powered chatbot integration in education, aligning with evolving user needs.

2. Literature Review

2.1 Problem-Solving

AI-powered chatbots serve diverse purposes, from customer service to emotional support, information retrieval, and entertainment, suggesting a potential replacement for human support. Notably, their ability to assist individuals in need makes them crucial. Users value AI-powered chatbots' quick responses, saving time and effort (Hsiao & Chen, 2021). Their problem-solving prowess enhances trust and satisfaction, especially for low-complexity tasks (Przegalinska et al., 2019; Xu et al., 2020).

Consumers perceive AI-powered chatbots as adept problem solvers, creating positive attitudes through quick information retrieval and a seamless experience (Yoon & Yu, 2022). Problem-solving, considered a key consumption value, ensures AI-powered chatbots deliver sufficient value (Chung et al., 2020). It positively influences satisfaction and stands out among the five quality dimensions (Chung et al., 2020). Problem-solving emerges as the most critical service quality influencer for AI-powered chatbot services, underscoring its paramount role in user satisfaction (Hsiao & Chen, 2021; Jansom et al., 2022). Positive problem-solving experiences contribute significantly to overall user satisfaction. Based on this, we propose the following hypothesis that:

H1: Problem-solving has a significant influence on satisfaction.

2.2 User Interface

An AI-powered chatbot's user interface (UI) encompasses overall usability, menu usability, aesthetics, and general design, crucial for providing an enjoyable conversation experience (Hsiao & Chen, 2021). Users tend to be attracted to platforms with an attractive UI, associating it with ease of use and fostering a positive relationship with the product (Wang et al., 2019). Well-designed UIs are pivotal in reducing perceived system complexity, enhancing navigation, and instilling user confidence (Alagarsamy & Mehrolia, 2023; Zhao et al., 2012).

While UI may not be the primary driver for engaging with AI-powered chatbots, it remains essential for user satisfaction (Hsiao & Chen, 2021). Literature suggests that UI positively influences the use of information systems (Hong et al., 2017). Although users may not prioritize the UI over other aspects, its thoughtful design is critical (Alagarsamy & Mehrolia, 2023). The study recognizes the nuanced relationship between UI and user satisfaction, anticipating a meaningful influence on Satisfaction (SA) (Song et al., 2023). Insights from this study are expected to shed light on the intricate dynamics of UI design and its impact on overall user satisfaction in the realm of AI-powered chatbots. Based on this, we propose the following hypothesis that:

H2: User Interface has a significant influence on satisfaction.

2.3 Perceived Usefulness

Perceived Usefulness (PU), a pivotal construct in the Technology Acceptance Model (TAM), encompasses the user's perception of the anticipated benefits of using AI-powered chatbots (Bhattacherjee, 2001). This concept refers to the perceived benefits derived from utilizing chatbots and the degree to which individuals believe that using such systems will enhance their task performance (Gümüş & Çark, 2021). Functioning as an extrinsic motivator, perceived usefulness plays a crucial role in the dichotomy of hedonic and utilitarian motivations, influencing user satisfaction and continuance intentions (Rese et al., 2020).

Efforts in designing AI-powered chatbots should prioritize enhancing perceived usefulness and employing user-centric implementation strategies (Rodríguez Cardona et al., 2021). Recognized as a well-established predictor in information technology research, perceived usefulness significantly influences users' attitudes, intentions, and behavior toward technology adoption (Ambalov, 2021; Yang & Brown, 2015). This construct, central to the use of technology, also holds significance in users' attitudes toward the continuance intention to reuse AI-powered chatbots (Brachten et al., 2021).

Perceived usefulness is a core construct in the Expectancy Confirmation Model and Technology Acceptance Model literature, exerting a substantial influence on user satisfaction in information technology (Dhiman & Jamwal, 2023). Users who find intrinsic enjoyment and entertainment value in a system beyond performance improvement tend to derive higher satisfaction from perceived usefulness (Ashfaq et al., 2020). Higher levels of perceived usefulness are expected to correlate with elevated satisfaction levels and increased continuance intentions (Ashfaq et al., 2020).

In AI-powered chatbots, perceived usefulness emerges as the primary driver of technology adoption, influencing users' satisfaction (Ashfaq et al., 2020; Le, 2023). The current study anticipates a significant and positive influence of Perceived Usefulness (PU) on Satisfaction (SA), aligning with the well-established role of perceived usefulness in shaping user attitudes and satisfaction within the evolving landscape of technology adoption. Based on this, the study proposes the following hypothesis:

H3: Perceived usefulness has a significant influence on satisfaction.

2.4 Perceived Ease of Use

Perceived Ease of Use (PEOU), a central construct in the Technology Acceptance Model (TAM), is defined as the degree to which a person believes that using a particular system, such as an AI-powered chatbot, would be free of effort or cost (Ashfaq et al., 2020; Gümüş & Çark, 2021; Silva et al., 2023). It signifies a user's ease and effortlessness in utilizing a specific system (Pillai & Sivathanu, 2020). In the context of AI-powered chatbots, PEOU is considered a precursor to users' behavioral intentions, as individuals are more likely to use chatbots if they find them easy and helpful (Huang & Chueh, 2021; Pillai & Sivathanu, 2020).

Perceived ease of use is pivotal in influencing user experience and intention to reuse AI-powered chatbots. Users who find these chatbots easy to use are more likely to share positive experiences, positively influencing the adoption decisions of others (Gümüş & Çark, 2021). Emphasizing the perceived ease of use can effectively remove barriers to internet-based services, including AI-powered chatbots (Alagarsamy & Mehrolia, 2023).

In the proposed chatbot usage intention model, empirical analysis results highlight that perceived ease of use increases user satisfaction with AI-powered chatbots (Huang & Chueh, 2021). Service providers can enhance user satisfaction and continuance intentions by ensuring that AI-powered chatbots are user-friendly, reducing the perceived cost associated with their utilization (Ashfaq et al., 2020).

The current study expects a significant influence of Perceived Ease of Use (PEOU) on Satisfaction (Zhu et al., 2022). The proposed hypothesis posits that higher perceived ease of use positively impacts user satisfaction with AI-powered chatbots (Kelly et al., 2023). This hypothesis aligns with the collective findings of existing literature, reinforcing the critical role of perceived ease of use in shaping user perceptions and overall satisfaction within the dynamic landscape of technology adoption. Based on this, the study proposes the following hypothesis:

H4: Perceived ease of use has a significant influence on satisfaction.

2.5 Trust

Trust is the belief in the AI-powered chatbot service's reliability, authenticity, or competence (Hsiao & Chen, 2021). It encompasses competence, honesty, and friendliness (Benamati et al., 2010). Users may trust computer programs more than humans, perceiving them as more objective and rational (Przegalinska et al., 2019). Trust, a precursor to user experience, evolves based on interactions, focusing on privacy, security, and information quality (Pillai & Sivathanu, 2020). In the context of AI-powered chatbots, trust is dynamic, growing over time as users overcome ambiguity (Alagarsamy & Mehrolia, 2023). Socially engaging AI-powered chatbots with problem-solving skills and friendly interfaces are more likely to be trusted (Pantano & Pizzi, 2020).

Trust plays a crucial role in technology adoption, assuring individuals that vulnerabilities will not be exploited in online situations (Silva et al., 2023). In AI-powered chatbots, trust is pivotal; users hesitate to provide personal information to untrustworthy chatbots (Przegalinska et al., 2019). Trust resolves the risk puzzle in uncertain situations (Kasilingam, 2020). Customer satisfaction with a bank's chatbot is strongly influenced by perceived trustworthiness (Eren, 2021). Trust influences users' trust in text-based chatbots in e-commerce (Cheng et al., 2022). Trust significantly and positively influences the intention to use AI-powered chatbots (Rodríguez Cardona et al., 2021) and continuance intention in banking services (Nguyen et al., 2021). Lack of trust may deter users from returning, highlighting trust's essential role in users' continued engagement with chatbots (Brachten et al., 2021).

The current study posits a significant positive influence of Trust (TR) on Continuance Intention (CI) in AI-powered chatbots, aligning with the broader literature emphasizing trust's central role in shaping user intentions and experiences within the evolving realm of AI-powered technologies. Based on this, we propose the following hypothesis that:

H5: Trust has a significant influencing on continuance intention.

2.6 Satisfaction

Satisfaction, defined as a user's affective response to the previous application, is a psychological state reflecting pleasure or disappointment after comparing actual performance with expectations (Bhattacherjee, 2001; Chen et al., 2023). It combines feelings associated with unfulfilled expectations and prior use experiences (Dhiman & Jamwal, 2023). Another perspective defines satisfaction as the extent to which users are satisfied with an AI-powered chatbot for their needs (Huang & Chueh, 2021). Positive feelings arise when expectations are met (Ashfaq et al., 2020), and user satisfaction with AI-powered chatbots is a primary predictor of continued use (Dhiman & Jamwal, 2023). Ease of use contributes significantly to user satisfaction, as a user-friendly interface reduces perceived costs and enhances attitudes, leading to increased satisfaction, especially when basic needs are met (Ashfaq et al., 2020; Kwangsawad & Jattamart, 2022). Access to accurate, up-to-date, and reliable information, coupled with a good user interface and problem-solving ability, is vital for AI-powered chatbot success, with problem-solving as a key antecedent to satisfaction (Ashfaq et al., 2020; Hsiao & Chen, 2021).

Perceived usefulness substantially influences user satisfaction with AI-powered chatbots (Dhiman & Jamwal, 2023). The strong, direct positive influence of satisfaction on continuance intention is consistently observed, underlining the pivotal role of user contentment in shaping future interaction intentions (Ashfaq et al., 2020; Wang et al., 2019). The current study anticipates a significant positive influence of Satisfaction (SA) on Continuance Intention (CI) (Jiang et al., 2022). Based on this, we propose the following hypothesis that:

H6: Satisfaction has a significant influence on continuance intention.

2.7 Continuance Intention

Continuance intention, as operationally defined, reflects a user's intention to persist in using an application, such as an AI-powered chatbot (Bhattacherjee, 2001). It goes beyond initial adoption, measuring users' inclination to continue usage after the initial acceptance phase (Wang et al., 2023). This intention involves considering whether to stop using, explore alternatives, or continue using the application in the future (Huang & Lee, 2022). For AI-powered chatbots, retaining existing users is crucial due to the higher cost associated with acquiring new users (Wang et al., 2019). Continuance intention reflects users' overall assessment of the AI-powered chatbot based on accumulated usage experiences (Wang et al., 2019).

Satisfaction emerges as a pivotal motivator for users' intentions to continue using AI-powered chatbots, being the critical variable triggering this intention (Dhiman & Jamwal, 2023). Positive attitudes and increased continuance intentions are associated with easy-to-use chatbots that meet users' basic needs, reducing perceived costs (Ashfaq et al., 2020; Kwangsawad & Jattamart, 2022). Satisfied users are more likely to express intentions to continue using AI-powered chatbots, with outcome satisfaction exerting a strong direct positive influence on continuance intention (Ashfaq et al., 2020). Earlier studies corroborate the positive impact of satisfaction on continuance usage of information technology (Dhiman & Jamwal, 2023). Satisfaction is the most significant direct factor influencing users' continuance intention (Hsiao & Chen, 2021).

Trust is identified as one of the critical variables influencing the intention to use an AI-powered chatbot, with its significant effect on continuance intention (Jo, 2022; Rodríguez Cardona et al., 2021). This underscores the importance of user trust in shaping their decisions to persist in using AI-powered chatbots.

3. Research Methods and Materials

3.1 Research Framework

This study's conceptual framework is constructed by integrating insights from three distinct theoretical models. The initial theoretical framework, established by Hsiao and Chen (2021), incorporates five specific beliefs: Problem-solving (PS), User Interface (UI), Trust (TR), Satisfaction (SA), and Continuance Intention (CI). The second theoretical framework, formulated by Dhiman and Jamwal (2023), introduces three specific beliefs: Perceived Usefulness (PU), Satisfaction (SA), and Continuance Intention (CI). The third theoretical framework, developed by (Ashfaq et al., 2020), consists of three specific beliefs in this framework: Perceived Ease of Use (PEOU), Satisfaction (SA), and Continuance Intention (CI). The research framework of this study is shown in Figure 1.

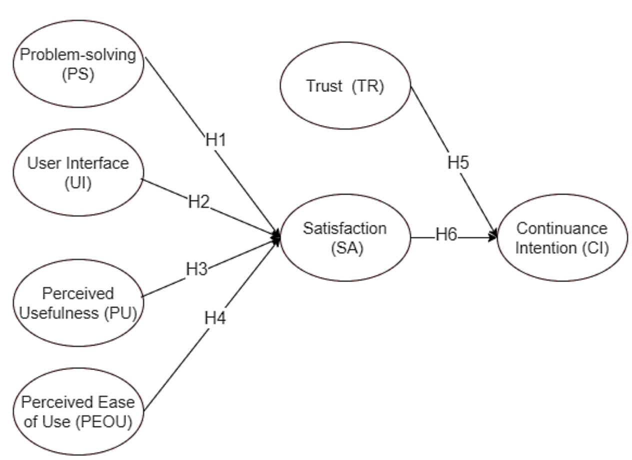

Figure 1: Conceptual Framework

H1: Problem-solving has a significant influence on satisfaction.
H2: User interface has a significant influence on satisfaction.
H3: Perceived usefulness has a significant influence on satisfaction.
H4: Perceived ease of use has a significant influence on satisfaction.
H5: Trust has a significant influencing on continuance intention.
H6: Satisfaction has a significant influence on continuance intention.

3.2 Research Methodology

A quantitative approach was employed in this study. The target population consisted of students from three majors at a university in Chengdu, China. A sample size of 500 participants was determined for the research to ensure statistical robustness. Data collection utilized a questionnaire instrument, which underwent testing for reliability and validity before analysis.

Validity was assessed using Item Objective Congruence (IOC) to ensure content validity. The questionnaire was administered to 41 respondents in a pilot test as a preliminary step. The Cronbach's Alpha score exceeded 0.7, affirming the dependable measurement of the targeted construct and enhancing the overall credibility of the test outcomes (Nunnally & Bernstein, 1994).

To confirm the instrument's reliability, data were collected from 500 respondents representing three university majors, selected through multi-stage sampling. Confirmatory Factor Analysis (CFA) was employed to assess the measurement model's reliability. Subsequently, Structural Equation Modeling (SEM) was adopted to scrutinize the structural model, shedding light on the relationships outlined in the conceptual framework encompassing seven variables and six hypotheses.

3.3 Population and Sample Size

The target population is the population of interest to be studied, and the inclusion criteria adopted for it were to check whether an individual qualified as a participant by reflecting the main characteristics of the population in question (Bolarinwa, 2015; Majid, 2018; Sürücü & Maslakçi, 2020). Therefore, this paper's target population was undergraduate students from three majors at Xihua University in Chengdu City who had experience using AI-powered chatbots.

Sample size, the calculation of the specific number of people in the sample population, is an important part of research (Taherdoost, 2016). Because the sample population is a subset of the target population, an adequate number of participants, known as the sample size, is essential to making appropriate statistical inferences (Vaidyanathan, 2023).

The researcher used the calculator developed by Soper (2015), which suggested a minimum sample size of 425. Based on the results of previous research and to increase the statistical robustness of the study, the researcher chose a sample size of 500. Subsequently, 500 valid samples were collected.

3.4 Sampling Technique

In this study, the target population must meet the following requirements: undergraduate students in Chengdu, China; students in one of the three majors at Xihua University; and students with experience using AI-powered chatbots. Hence, the researcher used purposive or judgmental sampling and convenience sampling to select and reach the target sample. Purposive sampling is the selection of a target population that could satisfy research requirements and objectives (Cooksey & McDonald, 2019). It is first employed to choose undergraduate students from three majors at Xihua University. Then, stratified random sampling is used to collect data proportionately from these three majors based on the number of the students, as shown in Table 1. The number of target students was illustrated and proportioned to the sample size as follows:

Table 1: Sample Units and Sample Size

Major	Population Size	Proportional Sample Size
Intelligent Science and Technology (IST)	541	214
Computer Science and Technology (CST)	390	154
Software Engineering (SE)	334	132
Total	**1265**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The demographic information collected from the respondents was gender and year of study. Five hundred questionnaires were distributed to the students of the five selected higher education institutions. The respondents comprised 316 males and 184 females, representing 63.2 percent and 36.8 percent, respectively. In terms of age, there were 217 students aged 18–19, representing 43.4 percent; 264 students aged 20–21, representing 52.8 percent; and 19 students aged 22–23, representing 3.8 percent.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Female	184	36.8%
	Male	316	63.2%
Age	18-19 years old	217	43.4%
	20-21 years old	264	52.8%
	22-23 years old	19	3.8%

4.2 Confirmatory Factor Analysis (CFA)

Cronbach's Alpha was employed in this study to assess the reliability of the questionnaire in the context of Confirmatory Factor Analysis (CFA), as stated in Vongurai (2022). All groups' alpha coefficient values surpassed 0.7, indicating the reliability of all underlying structures. To establish construct validity, Byrne (2001) highlighted the significance of both convergent and discriminant validity, which are both assessable through CFA.

In this investigation, the convergence validity of the conceptual model was evaluated using factor loading, average variance extracted (AVE), and composite reliability (CR), as suggested by Hair et al. (2013). All variables exhibited factor loading values exceeding 0.5, and statistical significance with a p-value below 0.05 was deemed acceptable based on Hair et al.'s criteria. Furthermore, all variables' comprehensive reliability (CR) values were above 0.8, and AVE values surpassed 0.5, indicating satisfactory convergent validity (refer to Table 3).

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Problem solving (PS)	(Hsiao & Chen, 2021)	3	0.865	0.801– 0.848	0.866	0.683
User Interface (UI)	(Hsiao & Chen, 2021)	3	0.846	0.757 – 0.830	0.847	0.649
Perceived Usefulness (PU)	(Ashfaq et al., 2020)	3	0.860	0.797 – 0.836	0.860	0.673
Perceived Ease of Use (PEOU)	(Ashfaq et al., 2020)	4	0.878	0.789 – 0.814	0.877	0.642
Trust (TR)	(Hsiao & Chen, 2021)	4	0.801	0.687 – 0.730	0.801	0.502
Satisfaction (SA)	(Dhiman & Jamwal, 2023)	3	0.819	0.769 – 0.786	0.819	0.602
Continuance Intention (CI)	(Dhiman & Jamwal, 2023)	3	0.867	0.794 –0.848	0.868	0.686

CFA was used to check the degree to which several measurement variables can constitute potential variables (Jöreskog & Sörbom, 1993). As it was shown in Table 4, CMIN/DF = 1.498, GFI = 0.950, AGFI = 0.935, NFI=0.949, CFI = 0.982, TLI = 0.978, and RMSEA = 0.032.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015)	313.141/209 or 1.498
GFI	≥0.90 (Hair et al., 2006)	0.950
AGFI	≥0.85 (Sica & Ghisi, 2007)	0.935
NFI	≥0.90 (Hair et al., 2006)	0.949
CFI	≥0.90 (Hair et al., 2006)	0.982
TLI	≥0.90 (Hair et al., 2006)	0.978
RMSEA	< 0.05 (Hu & Bentler, 1999)	0.032
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

Discriminant validity was confirmed when the AVE's square root was larger than any intercorrelated construct coefficient (Fornell & Larcker, 1981). In this study, the square root of all AVE values was greater than inter-construct correlations. Thus, discriminant validity can be accepted for the measurement model (see Table 5).

Table 5: Discriminant Validity

	PS	UI	PU	PEOU	TR	SA	CI
PS	**0.826**						
UI	0.136	**0.806**					
PU	0.135	0.392	**0.820**				
PEOU	0.094	0.341	0.475	**0.801**			
TR	0.051	0.016	0.030	0.003	**0.709**		
SA	0.351	0.550	0.614	0.563	0.032	**0.776**	
CI	0.193	0.262	0.294	0.242	0.305	0.504	**0.828**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

The Good-of-fit indices for the structural model of SEM are shown in Table 6. The results of statistical values before adjustment are CMIN/DF = 2.512, GFI = 0.909, AGFI = 0.888, NFI = 0.908, CFI = 0.942, TLI =0.934, and RMSEA = 0.055. The results of statistical values after adjustment are CMIN/DF = 2.219, GFI = 0.922, AGFI = 0.898, NFI = 0.923, CFI = 0.956, TLI =0.947, and RMSEA = 0.049. Consequently, from the values above, the fit of structural models is confirmed.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values Before Adjustment	Statistical Values After Adjustment
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015)	562.608/224 or 2.512	470.438/212 or 2.219
GFI	≥0.90 (Hair et al., 2006)	0.909	0.922
AGFI	≥0.85 (Sica & Ghisi, 2007)	0.888	0.898
NFI	≥0.90 (Hair et al., 2006)	0.908	0.923
CFI	≥0.90 (Hair et al., 2006)	0.942	0.956
TLI	≥0.90 (Hair et al., 2006)	0.934	0.947
RMSEA	< 0.05 (Hu & Bentler, 1999)	0.055	0.049
Model Summary		**Unacceptable Model Fit**	**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

Based on Table 7, hypotheses testing results revealed that H1, H2, H3, H4, H5, H6 were all supported. The explanation of research hypothesis testing was as follows:

H1: The standardized path coefficient between Problem-solving (PS) and Satisfaction (SA) was 0.333, with a value of 7.442*. It showed that Problem-solving (PS) significantly influences Satisfaction (SA); H1 was supported. This finding was consistent with previous findings. Problem-solving is the most influential service quality factor for AI-powered chatbot services (Hsiao & Chen, 2021). Proactive and effective problem-solving increases user satisfaction (Jansom et al., 2022).

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PS→SA	0.333	7.442*	Supported
H2: UI→SA	0.395	8.564*	Supported
H3: PU→SA	0.481	9.955*	Supported
H4: PEOU→SA	0.370	8.093*	Supported
H5: TR→CI	0.350	6.863*	Supported
H6: SA→CI	0.480	9.177 *	Supported

Note: * $p<0.05$
Source: Created by the author

H2: The standardized path coefficient between User Interface (UI) and Satisfaction (SA) was 0.395, with a value of 8.564*. It showed that User Interface (UI) significantly influences Satisfaction (SA); H2 was supported. This finding was consistent with previous findings. The study found a substantial and meaningful influence of User Interface (UI) on Satisfaction (SA) (Song et al., 2023). Recognizing the multifaceted nature of user satisfaction, the study acknowledges that while users may not explicitly prioritize the user interface, its thoughtful design remains essential for creating a positive user experience (Fan et al., 2022).

H3: The standardized path coefficient between Perceived Usefulness (PU) and Satisfaction (SA) was 0.481, with a value of 9.955*. It showed that Perceived Usefulness (PU) significantly influences Satisfaction (SA); H3 was supported. This finding was consistent with previous findings. Perceived usefulness extends its influence to new technologies like AI-powered chatbots, which are identified as the primary driver of technology adoption (Ashfaq et al., 2020). The study found a substantial and positive influence of Perceived Usefulness (PU) on Satisfaction (SA) (Ambalov, 2021).

H4: The standardized path coefficient between Perceived Ease of Use (PEOU) and Satisfaction (SA) was 0.370, with a value of 8.093*. It showed that Perceived Ease of Use (PEOU) significantly influences Satisfaction (SA); H4 was supported. This finding was consistent with previous findings. The study found a significant influence of Perceived Ease of Use (PEOU) on Satisfaction (Zhu et al., 2022). The study posits that higher perceived ease of use positively influences user satisfaction with AI-powered chatbots (Kelly et al., 2023).

H5: The standardized path coefficient between Trust (TR) and Continuance Intention (CI) was 0.350, with a value of 6.863*. It showed that trust (TR) significantly influences continuance intention (CI); H5 was supported. This finding was consistent with previous findings. The repercussions of trust in the context of AI-powered chatbots extend beyond initial adoption; it directly affects whether users continue to engage with the chatbot over time (Brachten et al., 2021). Trust, therefore, is an indispensable factor in influencing users' intentions to use AI-powered chatbots (Jo, 2022). The collective findings from existing studies underscore the critical nature of trust in shaping user behavior and experiences in the dynamic landscape of AI interactions (Hsiao & Chen, 2021).

H6: The standardized path coefficient between Satisfaction (SA) and Continuance Intention (CI) was 0.480, with a value of 9.177*. It showed that Satisfaction (SA) significantly influences Continuance Intention (CI); H6 was supported. This finding was consistent with previous findings. Research shows the central role of user satisfaction in continuance intention (Dhiman & Jamwal, 2023). Satisfaction is a central and direct factor influencing the intention to continue (W.-T. Wang et al., 2019). Satisfaction's robust and direct positive influence on continuance intention (Ashfaq et al., 2020).

5. Conclusion and Recommendation

5.1 Conclusion

The researcher aimed to investigate the determinants of university students' satisfaction and continuance intentions toward AI-powered chatbots in Chengdu, China. The sampling units in the study were undergraduate students from three majors at Xihua University in Chengdu, China. The selected three majors were Intelligent Science and Technology (IST), Computer Science and Technology (CST), and Software Engineering (SE). Seven variables and six hypotheses were utilized to demonstrate how problem-solving, user interface, perceived usefulness, perceived ease of use, trust, and satisfaction influence continuance intentions toward using AI-powered chatbots. This research was quantitative, and a questionnaire was used to collect data. IOC, pilot test, CFA, and SEM were used to examine the content validity and reliability of the proposed conceptual framework.

The findings from the statistical results could be summarized as follows:

Firstly, the results of the present study showed that users' trust significantly influenced continuance intention. This finding was consistent with previous literature, which showed that trust was essential in influencing users' intentions to continue using AI-powered chatbots (Jo, 2022). Therefore, users' trust was a factor in predicting their continued intention. Second, the results of the present study showed that user satisfaction significantly influenced continued intention. This finding was consistent with previous literature showing user satisfaction's central role in continued intention (Dhiman & Jamwal, 2023). Therefore, user satisfaction was a key factor in predicting continued intention. Third, perceived usefulness had the strongest influence on user satisfaction. It implied that users' basic and core needs were that AI-powered chatbots were useful, which was the most important dimension of user satisfaction. Fourth, perceived ease of use was the second most influential score on user satisfaction. Similar results were found in the study by Kelly et al. (2023), who showed that perceived ease of use and user satisfaction were significantly related.

Fifthly, the user interface was the third most influential factor in user satisfaction. Recognizing the multifaceted nature of user satisfaction, the study acknowledges that while users may not explicitly prioritize the user interface, its thoughtful design interface remains essential to creating a positive user experience for satisfaction (Fan et al., 2022).

Furthermore, the results showed that problem-solving significantly influences user satisfaction. This is consistent with the study, which found that proactive and effective problem-solving increases user satisfaction (Jansom et al., 2022).

Finally, the main purpose of using AI-powered chatbots is to improve productivity, and usefulness, efficiency, and ease of use are the main factors. In addition, AI-powered chatbots with well-designed user interfaces and problem-solving capabilities will create a positive user experience, as satisfaction will continue to be highly valued.

In summary, the determinants of user satisfaction were perceived usefulness, ease of use, user interface, and problem-solving. In addition, user satisfaction and trust were key factors in predicting the intention to continue.

5.2 Recommendation

The researcher identified key factors influencing user satisfaction and continued intention and provided several practical recommendations that AI-powered chatbot developers should consider.

The researcher provides practical recommendations for AI-powered chatbot developers to consider and identify the key factors influencing user satisfaction and continuance intention. According to the results of this study, AI-powered chatbot developers can improve service and user satisfaction and attract more users to improve the market competitiveness of AI-powered chatbots. In order for the research conclusion to play a full role in the implementation of strategy for AI companies, it is suggested that AI companies should pay attention to the following recommendations:

First, the researcher found that user satisfaction and trust significantly influence continuance intention. Therefore, the promotion of user satisfaction and trust must be emphasized.

User satisfaction is an important indicator of continuance intention. It is also an evaluation of usage outcomes and usage services and an important measure for understanding the problem-solving ability, well-designed user interface, perceived usefulness, perceived ease of use, and other projects of AI-powered chatbots.

In addition, many factors affect user satisfaction, including companies providing AI-powered chatbots, AI-powered chatbot technology, users themselves, and other aspects. By measuring and evaluating user satisfaction, companies providing AI-powered chatbots can understand users' needs, expectations, and feelings about the user experience.

Finally, it is important to find the gap between the AI-powered chatbot service quality provided by the AI-powered chatbot platform and the service quality expected by users in order to find the focus of AI-powered chatbot service capabilities, propose targeted improvement measures, increase user satisfaction, expand the user base, and improve competitiveness.

5.3 Limitation and Further Study

The population that the researcher chose to carry out the research was a limitation of the study. In this study, the target population consisted of three undergraduate majors. The results and conclusions differed if the target population was other major or university students.

In addition, to expand the scope of the study and make the results more accurate and representative, the researcher could choose other undergraduate majors or universities as the target population, which might provide new insights into AI-powered chatbots.

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