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Determinants of Undergraduate Students' Attitude and Intention to Use AI Chatbots in a Private University at Chengdu, China

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Abstract

This research investigates the key determinants affecting undergraduates' willingness to adopt and continue engaging with artificial intelligence (AI) chatbots used for academic advising, course information, and campus service guidance in China's private universities. Against the backdrop of accelerated higher education digitalization and national policies such as the Education Informatization 2.0 Plan and the Digital China Strategy, chatbots have gained prominence as tools for academic assistance and campus services. However, despite their growing presence, their diffusion and acceptance within private institutions remain underexplored. A survey was conducted with 500 undergraduate students enrolled at Geely University of China in Chengdu. Structural equation modeling (SEM) was applied to test six proposed paths, and factor analysis verified the stability, reliability, and validity of the measurement model. Findings reveal that perceived usefulness and perceived ease of use strongly influence students' attitudes, while social influence and trust provide supplementary effects. Moreover, perceived usefulness was identified as the key driver of attitude, which subsequently served as the most influential predictor of students' behavioral intention to continue adopting chatbots. In addition, attitudes functioned as a mediating mechanism, converting initial perceptions into long-term usage intentions. The findings underscore the necessity of tailoring chatbot functionalities to academic requirements, strengthening trust mechanisms and data governance, and fostering teacher and peer support to enhance engagement. Overall, the study offers practical insights into promoting equitable access to intelligent learning technologies and optimizing the allocation of higher education resources in the digital era.

Keywords: Perceived Usefulness, Perceived Ease Of Use, Attitude, Performance Expectancy, Social Influence, Behavioral Intention, Ai Chatbots

Introduction

In recent years, China has advanced the digital transformation of education, encouraging the application and governance of intelligent technologies in higher education; chatbot practices have gradually emerged in campus advising, instructional support, and service contexts (Okonkwo & Ade-Ibijola, 2021), forming an institutionalized backdrop for on-campus promotion. As intelligent tools that assist teachers and students in academic consultation and administrative services, AI chatbots have become representative applications of digital learning environments.

However, existing research has primarily focused on public universities, large-scale online learning platforms, or generalized educational technologies, leaving the private higher-education context underexplored. In particular, little is known about how centralized service processes and stronger peer/teacher modeling in Chinese private universities shape the mechanisms of social influence (SI) and trust (TR). This research gap limits understanding of how students in private institutions form attitudes and behavioral intentions toward AI chatbot adoption.

Therefore, this study aims to explore the key determinants affecting undergraduates' adoption and continuance of AI chatbots in private universities, focusing on their academic-support functions such as advising, learning assistance, and service navigation. The study takes undergraduates at Geely University of China in Chengdu as the research subjects and examines how perceived usefulness (PU), perceived ease of use (PEOU), performance expectancy (PE), social influence (SI), and trust (TR) affect attitude (ATT) and behavioral intention (BI).

Practically, understanding students' acceptance of AI chatbots provides valuable guidance for universities to promote digital transformation and optimize intelligent service systems. Beyond institutional management, the findings also offer social value by informing equitable access to intelligent resources and improving educational resource allocation in the digital era.

Literature Review

Theoretical Background and Model Development

To explain the mechanisms shaping students' attitudes and behavioral intentions toward AI chatbot adoption, this section outlines the theoretical foundations and model development underlying the study. In higher-education settings, students often calibrate their technological beliefs and behavioral tendencies by observing how instructors and peers—especially those in leading or opinion-shaping roles—use and evaluate AI chatbots; when their affective experience aligns with the "digital learner" role, they are more likely to form a stable attitude and enact context-congruent use behaviors(Adamopoulou & Moussiades, 2020; Ajzen, 1991; Venkatesh et al., 2003). Previous studies have identified perceived usefulness (PU) and perceived ease of use (PEOU) as fundamental precursors to attitude (ATT): when students expect chatbots to improve learning efficiency and assignment quality while imposing low effort, their overall evaluations and acceptance increase markedly (Davis, 1989; Holmes et al., 2019; King & He, 2006; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000; Winkler & Söllner, 2018). High-quality social identification, accompanied by positive affect, further bolsters confidence and agency under learning pressure, thereby consolidating attitudes(Allen & Meyer, 1990; Fishbein & Ajzen, 1977).

Performance expectancy (PE) and social influence have significant and robust effects on usage outcomes; in campus micro-contexts, modeling by peers and instructors promotes continuance tendencies through subjective norms and conformity motives(Venkatesh et al., 2003). Meanwhile, trust (TR) functions as a risk-mitigation mechanism: stronger beliefs in system ability, reliability, and ethical compliance lower concerns about erroneous outputs and data security, facilitating the positive conversion from attitude to behavioral intention (BI)(Gefen et al., 2003; McKnight et al., 2002; Venkatesh et al., 2012). When PEOU further drives PU, the transmission chain "PEOU → PU → ATT → BI" becomes more explicit(Davis, 1989; Wixom & Todd, 2005).

From a social-exchange perspective, trust (TR) serves as the core mechanism sustaining the relationship between students and the platform. Higher levels of trust mean that students believe the system is competent, reliable, and ethically compliant, thereby reducing perceived risks and uncertainties(Gefen et al., 2003). Such trust-based exchange relationships strengthen students' willingness to rely on AI chatbots, allowing positive learning experiences to be more stably converted into continuance behavioral intention(McKnight et al., 2002; Venkatesh et al., 2012). Accordingly, within the overall framework, TR not only directly promotes the formation of BI but also functions as a risk-mitigation mechanism that supports and complements the main chain of "PU/PEOU → ATT → BI." This logic is also consistent with the findings of recent digital trust research (Dwivedi et al., 2021).

As diverse actors within a learning community, students glean information about technology use through observation and listening and respond to course and academic norms accordingly (Dwivedi et al., 2021; Raman & Don, 2013). A digital campus climate and facilitating conditions—operationalized through institutional policies, resources, and processes—provide external support for technology acceptance and motivate positive responses toward learning performance goals (Venkatesh et al., 2003, 2012). In this process, digital literacy and prior knowledge (KN) shape the depth of feature utilization and strategy transfer; higher professionalism is more likely to trigger new ideas and improve learning performance (Bass, 1985; Davenport & Prusak, 1998; Hargittai, 2005).

Enhancing learning performance depends not only on training and practice provided by the organization but, more importantly, on reconfiguring existing knowledge and strategies after learning to create more efficient human-AI collaboration paths and foster stable positive experiences (Argote & Miron-Spektor, 2011). Accordingly, this study treats PU, PEOU, PE, social influence (SI), and TR as key antecedents of ATT and BI, with ATT as a proximal determinant and potential mediator; we subsequently propose and test the relevant hypotheses and model.

In the context of the rapid penetration of digital teaching and intelligent academic-support services in higher education, students' adoption and continuance of AI chatbots are jointly shaped by technological attributes and the interplay of social context and individual beliefs. To examine these mechanisms in a more structured manner, , this study builds upon these theoretical insights by integrating the TAM, UTAUT, and TPB.

The integration of the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Theory of Planned Behavior (TPB) provides a more comprehensive analytical lens for understanding AI chatbot adoption. Each framework contributes a distinct explanatory strength: TAM offers the core belief-attitude-intention mechanism (Davis, 1989), emphasizing how perceived usefulness (PU) and perceived ease of use (PEOU) shape positive attitudes. UTAUT extends this by introducing social and performance-related constructs—performance expectancy (PE) and social influence (SI)—that capture contextual and normative pressures(Venkatesh et al., 2003). TPB further complements the model by linking attitude to behavioral intention (BI) through volitional control and trust-based decision mechanisms(Ajzen, 1991; Pavlou & Fygenson, 2006). Integrating these three perspectives allows the present research to capture both cognitive and social-psychological antecedents of adoption, explaining not only how students form favorable evaluations but also how institutional trust and social endorsement translate into sustained use intentions.

Under this integrated framework, perceived usefulness (PU), perceived ease of use (PEOU), performance expectancy (PE), social influence (SI), trust (TR), and attitude (ATT) are identified as the main antecedent constructs, whereas behavioral intention (BI) is designated as the core outcome variable. The model highlights the fundamental chain of "beliefs → attitude → intention," while also recognizing that performance expectancy, social influence, and trust exert direct influences on behavioral intention. The empirical setting is undergraduates at a private university in Chengdu, China, where campus service processes are highly centralized and instructor/peer modeling is particularly salient, thereby offering an ideal context to validate the direct SI/TR channels and the mediating role of ATT.

Perceived Usefulness (PU)

PU refers to the extent to which an individual believes that using a given system will enhance learning/work performance(Davis, 1989). A large body of cross-context evidence confirms that PU is a core predictor of attitude and adoption/continued use intention(Adamopoulou & Moussiades, 2020; King & He, 2006); it strengthens positive attitudes by improving overall evaluations of instrumental value and, in some settings, also exerts a direct effect on intention (Ho Cheong & Park, 2005). In higher-education tasks, PU typically manifests as "improving assignment quality/completion efficiency, saving time, and obtaining more accurate feedback." PU and PEOU are stably linked—systems that are easier to use are more likely to be perceived as useful(Venkatesh & Davis, 2000). Accordingly, reinforcing students' belief that AI chatbots significantly improve learning outcomes is a key precondition for activating downstream attitudes and intentions. Hence: H1: Perceived usefulness positively influences attitude.

Perceived Ease of Use (PEOU)

PEOU denotes the subjective feeling that a system is "effort-saving and simple to use" (Davis, 1989). Prior evidence shows that higher PEOU not only directly improves overall evaluations and adoption propensity, but also indirectly enhances attitudes and subsequent responses by boosting PU(Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). In educational technology contexts, PEOU operates mainly by lowering cognitive load, shortening learning curves, and reducing operational uncertainty—effects that are especially pronounced in early adoption/high-voluntariness classroom settings. As usage experience accumulates, PEOU's direct effect may attenuate, yet its "spillover" to PU remains salient(Venkatesh et al., 2003). Moreover, students' digital literacy and prior tool experience may moderate the magnitude of PEOU's effect, yielding heterogeneity across majors, cohorts, or course types. Therefore, we treat PEOU as a key antecedent of ATT and propose: H2: Perceived ease of use positively influences attitude.

Attitude (ATT)

Attitude is an individual's overall evaluation and affective judgment toward performing the target behavior(Ajzen, 1991). In technology-acceptance research, ATT is widely evidenced as the proximal determinant in the "belief → intention" chain, formed jointly by cognitive evaluations (useful/easy) and affective experience (pleasant/annoying)(Davis, 1989; Dwivedi et al., 2021; Venkatesh et al., 2003). On the one hand, the positive predictive link ATT → BI is robust across most educational technology and online-service settings; on the other, ATT often partially mediates "PEOU/PU → BI," translating instrumental beliefs into concrete usage choices. For AI chatbots, favorable attitudes typically stem from a composite experience of "efficiency gains, smooth interaction, and reliable feedback," and are reinforced through repeated use in courses/assignments. Hence: H3: Attitude positively influences behavioral intention.

Performance Expectancy (PE)

PE is the degree to which an individual expects performance gains from using a technology, a core UTAUT construct closely tied to extrinsic motivation/instrumental returns(Venkatesh et al., 2003, 2012). Closely related to PU conceptually but with a slightly different measurement emphasis, PE focuses more on anticipated goal-attainment returns (e.g., higher grades, faster completion, lower error rates). Consequently, it often shows a significant and stable direct effect on BI—especially in courses and assignments with clear goals and quantifiable outputs. Prior studies across online learning and public services repeatedly validate this path and note that PE's explanatory power increases when course requirements and assessment standards are explicit. We therefore include PE in the direct channel to BI and propose: H4: Performance expectancy positively influences behavioral intention.

Social Influence (SI)

SI denotes the extent to which important others (e.g., instructors, peers, teaching teams) are perceived to believe that one should use the technology(Venkatesh et al., 2003). Its mechanisms can be parsed into normative pressure (compliance) and internalization/identification: the former promotes use via subjective norms and conformity motives, while the latter enhances internal endorsement of technology value through role-modeling and group identification. UTAUT research shows that voluntariness and experience are key boundary conditions: SI → BI effects are stronger in classrooms with more mandatory elements, higher collaboration requirements, or salient instructor modeling(Raman & Don, 2013; Venkatesh et al., 2012). In private-university settings, centralized processes and clear promotion pathways make SI cues—classroom word-of-mouth, peer help, instructor guidance—more likely to produce “social reinforcement.” Hence: H5: Social influence positively influences behavioral intention.

Trust (TR)

TR is an individual’s belief and willingness to rely on a system’s competence, reliability, and integrity, commonly operationalized as competence-integrity-benevolence (McKnight et al., 2002; Morgan & Hunt, 1994). In educational uses of AI chatbots, sources of TR include the accuracy/consistency of model outputs, security and controllability of data and privacy, and transparency around processes and boundaries (e.g., citations, explainability, academic-integrity prompts). Prior studies indicate that TR can not only directly raise BI, but also indirectly strengthen attitudes and intentions by reducing perceived risk and alleviating concerns about error/privacy/ compliance (Gefen et al., 2003; Pavlou & Fygenson, 2006). Given higher-education’s stringent requirements for academic integrity and data compliance, TR exhibits a notable threshold effect in students’ continued-use decisions. Accordingly, we treat TR as a key social-institutional cue and propose: H6: Trust positively influences behavioral intention.

Behavioral Intention (BI)

Behavioral intention (BI) refers to an individual’s perceived inclination and degree of willingness to engage with a specific technology within a foreseeable timeframe(Ajzen, 1991). Within technology-acceptance research, BI has consistently been recognized as the most reliable predictor of actual or continued system use, functioning as the bridge that converts prior beliefs and social influences into tangible adoption behaviors(Venkatesh et al., 2003, 2012). Conceptually, two major pathways explain its formation: (1) an evaluative route driven by Attitude, in which perceptions of usefulness and ease of use cultivate favorable attitudes that subsequently lead to stronger intentions; and (2) a direct-influence route, where PE, SI, and TR independently enhance BI by signaling expected benefits, normative endorsement, and assurance of reliability or reduced risk. Existing studies also highlight moderating factors such as voluntariness, prior usage experience, and contextual enablers (e.g., course requirements, system accessibility), which can alter the strength of these relationships (Bhattacherjee, 2001; Venkatesh et al., 2003, 2012). Accordingly, in this study BI is positioned as the ultimate dependent construct, predicted jointly by ATT, PE, SI, and TR, with hypotheses H3-H6 assessing the magnitude and significance of these paths. BI was operationalized using established items such as "I intend to use," "I would prioritize using," and "I am willing to continue using this chatbot."

Summary and Model Positioning

In sum, PEOU and PU are linked to BI via the belief → attitude backbone; PE, SI, and TR directly predict BI through performance, social, and trust channels; and ATT serves as a pivotal mediator between antecedents and intention. Based on the above theories and evidence, this study tests H1-H7 on a sample of undergraduates from a private university in Chengdu and, accordingly, develops the research model (see Figure 1) and operationalizes the measures to provide empirical evidence and actionable insights for the design and promotion of intelligent academic-support tools in higher education.

Research Methodology

Research Framework

Building on the theoretical integration discussed above, this framework synthesizes TAM's cognitive evaluation process, UTAUT's contextual performance and social dimensions, and TPB's behavioral control and trust-based intention mechanisms to provide a holistic account of technology adoption.

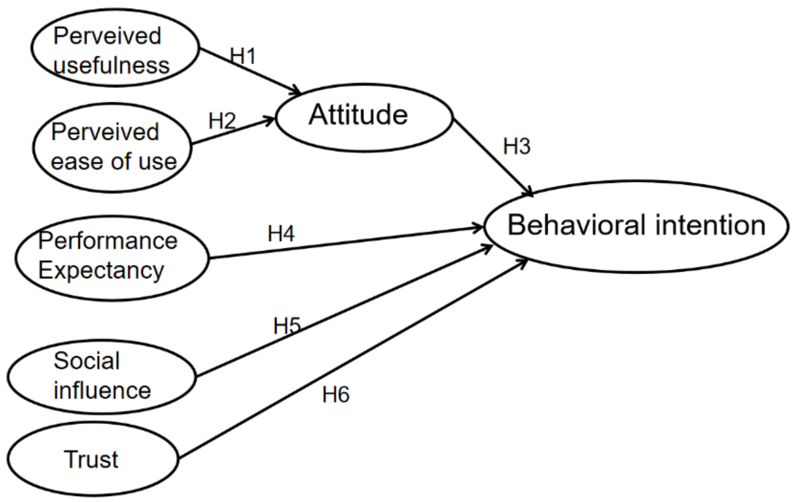
Anchored in the TAM, the UTAUT/UTAUT2, and the TPB (Davis, 1989; Venkatesh et al., 2003, 2012), this study formulates a central pathway where belief factors—specifically PEOU and PU—shape ATT, which in turn drives BI. Additionally, PE, TR, and SI are treated as direct antecedents of BI. Guided by these theoretical integrations, a conceptual framework was constructed for the present research, as illustrated in Figure 1.

Before presenting the visual model, it is essential to clarify the dual-path logic underlying the proposed framework. The model includes both a mediating chain and several direct-effect routes. The mediating chain (PEOU → PU → ATT → BI) represents the internal cognitive pathway derived from TAM, in which perceived ease of use enhance perceived usefulness, which in turn strengthen attitudes and subsequently behavioral intention. In parallel, the direct-effect paths (PE, SI, TR → BI) capture contextual and social influences drawn from UTAUT and TPB, reflecting how performance expectancy, social influence, and trust exert immediate effects on behavioral intention. Together, these two mechanisms explain how students' internal cognition and external social context jointly determine their adoption and continuance of AI chatbots in private universities.

Specifically, the framework corresponds directly to the six hypotheses proposed in this study. H1 and H2 describe the cognitive evaluation process derived from TAM, where perceived ease of use (PEOU) enhances perceived usefulness (PU), and both jointly strengthen attitude (ATT). H3 captures the belief-attitude-intention linkage, reflecting that favorable attitudes lead to stronger behavioral intentions (BI). H4-H6 represent the extended influences introduced from UTAUT and TPB: performance expectancy (PE) reflects instrumental motivation, social influence (SI) represents normative pressure and modeling effects, and trust (TR) captures risk mitigation and volitional control. Together, these paths explain how students' cognitive evaluations, contextual factors, and trust beliefs interact to shape their willingness to adopt and continue using AI chatbots. Hence, the framework as a whole address the central research question—what determinants and mechanisms drive undergraduates' adoption and continuance intention toward AI chatbots in private universities.

Figure 1

Conceptual Framework



In the model, ATT is specified as a proximal mediator, and PEOU→PU captures the "spillover" from ease-of-use perceptions to usefulness evaluations(Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Drawing on the three-dimensional structure of information-systems trust—ability, integrity, benevolence(Gefen et al., 2003; McKnight et al., 2002)—the framework explains undergraduates' attitudes toward and intentions to use AI chatbots at a private university in Chengdu.

Research Method

We adopted a quantitative, cross-sectional questionnaire design and administered all data collection online through the university platform. The target population consisted of undergraduates from four colleges at a private university in Chengdu (Geely University of

China). To ensure representativeness, a stratified quota-sampling approach was implemented, aligning sample proportions with each college's population size and balancing majors and cohorts (Lohr, 2021; Palinkas et al., 2015).

The questionnaire consisted of three sections: (1) eligibility screening items used to confirm participant qualification and filter out ineligible cases; (2) a five-point Likert scale (1 = strongly disagree, 5 = strongly agree) assessing PEOU, PU, PE, SI, TR, ATT, and BI, with items mapped to the six hypotheses (H1-H6) (Davis, 1989; Venkatesh et al., 2012); and (3) demographic details such as gender, age, academic year, and college. A pilot test (n = 50) was first conducted, followed by expert review of content validity (IOC/CVI), ensuring item clarity and cultural/linguistic equivalence (DeVellis & Thorpe, 2021; Polit & Beck, 2006).

Data preparation adopted a "clean-then-model" procedure, involving removal of invalid or duplicate responses, treatment of missing values, and checks for outliers and multicollinearity(Black & Babin, 2019; Tabachnick et al., 2007). Descriptive statistics, such as means, standard deviations, and correlation matrices, were presented. To minimize common method bias (CMB), both procedural controls (e.g., anonymity, random item sequencing, and separating antecedents from outcomes) and statistical checks were applied. Results from Harman's single-factor test indicated that the first factor explained 28.5% of the variance, well below the 40% threshold, suggesting that CMB did not pose a significant concern (Fuller et al., 2016; Podsakoff et al., 2003).

For statistical analyses, SPSS was used for descriptive summaries and reliability testing, while AMOS supported CFA (Confirmatory Factor Analysis) and SEM. Through CFA, this study examined convergent and discriminant validity along with overall model fit, using criteria such as standardized loadings, composite reliability (CR), average variance extracted (AVE), the Fornell-Larcker criterion, heterotrait-monotrait ratio (HTMT), and goodness-of-fit indices including CFI, TLI, RMSEA, and SRMR.SEM tested the significance of H1-H6 path coefficients and reported endogenous R^2. Indirect effects along the PEOU, PU → ATT → BI chain were estimated via bootstrapping. Where appropriate, group measurement invariance and path-difference tests were conducted to examine contextual heterogeneity across colleges and years (Cheung & Rensvold, 2002; Kline, 2023).

Population and Sample Size

The population consisted of undergraduates from four colleges at a private university in Chengdu. We employed a judgmental and stratified quota sampling approach and administered the survey through the university's online platform. To ensure structural alignment between sample and population, we set quotas by college size and organized recruitment with administrative support (teaching offices and counselors circulated invitations via course announcements and study groups, emphasizing voluntariness and anonymity). The research team distributed the questionnaires to the target sample and obtained 500 acceptable, valid responses. College populations and the 500-case proportional quotas are shown in Table 1 (quotas were based on internal administrative statistics for proportional control; if minor deviations occurred between quotas and valid cases, post-stratification weights were planned for correction in modeling). Table 1.demonstrated the specific sampling for this study.

Table 1

Sample size distributed four main Colleges

Four Main Colleges	The population in each college	Proportional Sample Size
college of Information Engineering	2176	174
college of Foreign Languages	1823	146
college of Art and Design	1176	94
college of Marxism	1068	86
Total	6243	500

Source: constructed by author （The data comes from the enrollment of students and the number of graduates statistics of Geely University of China）

Results and Discussion

Demographic Information

This study obtained a valid sample of N = 500, consisting of undergraduates from four colleges at a private university in Chengdu. Gender: female 271 (54.2%), male 229 (45.8%). Age: 19-21 years 241 (48.2%), 22-24 years 173 (34.6%), ≥25 years 86 (17.2%). Grade: freshman 181 (36.2%), sophomore 137 (27.4%), junior 113 (22.6%), senior 69 (13.8%). College: Information Engineering 174 (34.8%), Foreign Languages 146 (29.2%), Art and Design 94 (18.8%), Marxism 86 (17.2%). Monthly living expenses (RMB): ≤1,000 yuan 97 (19.4%), 1,001-2,000 yuan 211 (42.2%), 2,001-3,000 yuan 133 (26.6%), >3,000 yuan 59 (11.8%). Usage frequency: at least once per day 297 (59.4%), several times per week 177 (35.4%), several times per month 26 (5.2%).Table 2.presented demographic information for this study.

Table 2

Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	female	271	54.2%
	male	229	45.8%
Age	19-21 years old	241	48.2%
	22-24 years old	173	34.6%
	age 25 and older	86	17.2%
grade	freshman	181	36.2%
	Sophomore	137	27.4%
	junior	113	22.6%
	senior	69	13.8%
college	Information Engineering	174	34.8%
	Foreign Languages	146	29.2%

Demographic and General Data (N=500)		Frequency	Percentage
	Art and design	94	18.8%
	Marxism	86	17.2%
living expenses	1000 yuan and below	97	19.4%
	1001-2000 yuan	211	42.2%
	2001-3000 yuan	133	26.6%
	more than 3000	59	11.8%
usage frequency	One or more times a day	297	39.4%
	Several times a week	177	55.4%
	Several times a month	26	5.2%

Source: Created by the author

Confirmatory Factor Analysis (CFA)

At the scale level, all items exhibit statistically significant standardized factor loadings in the medium-to-high range; each construct shows adequate internal consistency and CR above the conventional threshold (≥ 0.70), and the AVE exceeds the 0.50 convergence benchmark—together indicating solid convergent validity and reliability (see Table 3). Cross-loadings and residuals do not display systematic anomalies, and items align cleanly with their intended constructs.

For discriminant validity, following the Fornell-Larcker criterion, the √AVE values on the diagonal of the correlation matrix are higher than the corresponding inter-construct correlations, indicating clear separation and controlled overlap among latent variables (see Table 4). As a complement, the HTMT indices remain below conservative cutoffs, further supporting discriminant validity; even for theoretically proximate constructs (e.g., PU and PE), observed correlations are moderate and do not threaten construct distinctiveness (see Table 4).

At the model level, global CFA fit indices (e.g., χ^2/df, CFI, TLI, RMSEA, SRMR, GFI/AGFI) meet or exceed recommended thresholds, with no large modification indices necessitating cross-construct error covariances; any within-construct error correlations are theory-justified and kept minimal (see Table 5). Overall, the measurement model exhibits strong reliability, along with satisfactory convergent and discriminant validity and acceptable fit indices, thereby justifying subsequent structural path analysis and hypothesis verification (see Tables 3, 4, and 5).

Confirmatory factor analysis (CFA) was conducted to evaluate the measurement adequacy of the constructs in the proposed framework. Findings revealed that all items loaded significantly on their intended factors, with loadings falling within acceptable thresholds, indicating that the model provided a good representation of the data. Specifically, every standardized loading exceeded 0.30 with p-values under 0.05; CR values were above 0.70, and AVE scores surpassed 0.50, confirming both reliability and validity of the measures. A summary of these results is presented in Table 3.

Table 4 shows that the square roots of AVE were greater than the corresponding inter-construct correlations, thereby confirming discriminant validity. Model fit was further examined using indices such as GFI, AGFI, NFI, CFI, TLI, and RMSEA, all of which fell within acceptable benchmarks. Table 5 and 6 consolidate the results for convergent and discriminant validity, both of which satisfied recommended standards. Taken together, these outcomes demonstrate that the measurement and structural model applied in this research are robust and statistically sound.

Table 3

Confirmatory Factor Analysis Result, CR and AVE

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Usefulness (PU)	(Bhattacherjee, 2001)	4	0.866	0.758- 0.822	0.867	0.621
Perceived Ease of Use (PEOU)	(Gefen et al., 2003)	4	0.846	0.713- 0.813	0.847	0.582
Attitude (ATT)	(Taylor & Todd, 1995)	3	0.835	0.754- 0.846	0.836	0.630
Performance Expectancy (PE)	(Compeau & Higgins, 1995)	4	0.875	0.762- 0.823	0.875	0.638
Social Influence (SI)	(Thompson et al., 1991)	3	0.832	0.755- 0.805	0.831	0.622
Trust (TRU)	(McKnight et al., 2002)	5	0.864	0.698- 0.798	0.865	0.562
Behavioral Intention (BI)	(Ajzen, 1991)	3	0.833	0.749- 0.844	0.835	0.628

Note: CR = Composite Reliability, AVE = Average Variance Extracted
Source: Created by the author

Table 4

Discriminant Validity

Variable	PU	PEOU	ATT	PE	SI	TRU	BI
PU	0.788						
PEOU	0.424	0.763					
ATT	0.572	0.534	0.794				
PE	0.451	0.416	0.381	0.799			
SI	0.414	0.372	0.353	0.354	0.789		
TRU	0.336	0.332	0.316	0.295	0.375	0.750	
BI	0.513	0.490	0.532	0.522	0.459	0.438	0.792

Note: The diagonal cells in the table contain the square roots of each variable's AVE
Source: Created by the author

Table 5

Goodness of Fit for CFA

Fit Index	Acceptable Criteria	Values
CMIN/df	< 5.00 (Al-Mamary et al., 2015; Awang, 2012)	334.362/278 or 1.203
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.952
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.939
NFI	≥ 0.80 (Wu & Wang, 2006)	0.952
CFI	≥ 0.80 (Bentler, 1990)	0.992
TLI	≥ 0.90 (Hair et al., 2006)	0.990
RMSEA	< 0.08 (Hu & Bentler, 1999)	0.020

Source: Created by the author

Remark: CMIN/DF denotes the chi-square to degrees-of-freedom ratio; GFI assesses the model's overall fit; AGFI adjusts this fit for model complexity; NFI represents the normed fit index; IFI captures the incremental fit index; CFI indicates the comparative fit index; TLI, also known as the Tucker-Lewis index (NNFI), evaluates non-normed fit; and RMSEA measures the root mean square error of approximation

Table 6

Goodness of Fit for SEM

Fit Index	Acceptable Criteria	Values
CMIN/df	< 5.00 (Al-Mamary et al., 2015; Awang, 2012)	851.331/293 or 2.906
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.861
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.834
NFI	≥ 0.80 (Wu & Wang, 2006)	0.878
CFI	≥ 0.80 (Bentler, 1990)	0.916
TLI	≥ 0.90 (Hair et al., 2006)	0.907
RMSEA	< 0.08 (Hu & Bentler, 1999)	0.062

Source: Created by the author

Structural Equation Model (SEM)

When evaluating structural equation modeling (SEM), scholars often rely on established criteria: CMIN/DF is recommended to remain under 5.00 (Al-Mamary et al., 2015; Awang, 2012); a GFI value of 0.85 or above and an AGFI value no less than 0.80 are regarded as acceptable thresholds (Sica & Ghisi, 2007);NFI should exceed 0.80(Wu & Wang, 2006); CFI above 0.80 indicates good incremental fit (Bentler, 1990); TLI greater than 0.90 suggests robust model performance (Hair et al., 2006); and RMSEA values below 0.08 reflect acceptable approximation error(Hu & Bentler, 1999). Collectively, these thresholds capture model adequacy across absolute, incremental, and error-based fit perspectives.

Using SPSS AMOS 26 for estimation and iterative refinement, the model yielded the following fit indices: CMIN/df = 2.906 (851.331/293), GFI = 0.861, AGFI = 0.834, NFI = 0.878, CFI = 0.916, TLI = 0.907, and RMSEA = 0.062 (see Table 6), all of which fall within recommended ranges. Substantively, the CMIN/df falls within the commonly accepted "good" range of 2-3, indicating a favorable balance between parsimony and fit; CFI/TLI > 0.90

indicates strong incremental fit relative to the independence model; GFI/AGFI exceed their recommended lower bounds and NFI approaches 0.90; and RMSEA below the 0.08 benchmark signals a small population-level approximation error. Considering evidence across absolute, relative, and approximation-fit metrics, the structural model demonstrates an overall good fit, satisfying the prerequisites for path estimation and hypothesis testing.

Research Hypothesis Testing Result

According to the latest model estimates (see Table 6), H1-H6 are all significantly supported ($p < .001$). Specifically, the standardized path coefficients are: PU → ATT β = 0.548 (S.E. = 0.047, t = 11.434), PEOU → ATT β = 0.456 (S.E. = 0.045, t = 9.653); on the intention side, ATT → BI β = 0.440 (S.E. = 0.045, t = 8.696), PE → BI β = 0.375 (S.E. = 0.042, t = 7.787), SI → BI β = 0.221 (S.E. = 0.042, t = 4.647), and TR → BI β = 0.270 (S.E. = 0.042, t = 5.730).

Table 7

Hypothesis Result of the Structural Model

Hypotheses	Paths	Standardized Path Coefficients (β)	S.E.	T-Value	Tests Result
H1	ATT<---PU	0.548	0.047	11.434.***	Supported
H2	ATT<---PEOU	0.456	0.045	9.653 ***	Supported
H3	BI<---ATT	0.440	0.045	8.696 ***	Supported
H4	BI<---PE	0.375	0.042	7.787 ***	Supported
H5	BI<---SI	0.221	0.042	4.647 ***	Supported
H6	BI<---TR	0.270	0.042	5.730 ***	Supported

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

As shown in Table 7, PU's effect on ATT is slightly stronger than PEOU's, implying that students' perceived instrumental gains (e.g., better outcomes, time savings) are the primary engine of favorable evaluations, even after accounting for ease-of-use. This finding aligns with prior higher-education studies suggesting that students tend to value instrumental and performance-oriented benefits more than reductions in effort when adopting new technologies. Among the direct determinants of BI, ATT has the largest impact, followed by PE, TR, and SI—a hierarchy that signals how internal appraisal (liking/approval of use) and anticipated performance returns jointly propel intention. The comparatively weaker yet significant effects of trust and social influence may reflect the early stage of institutional chatbot adoption, where system credibility and social norms are still developing but remain meaningful facilitators of use. Taken together, the directions, significance, and relative magnitudes of the paths cohere with TAM/UTAUT expectations, reinforcing the proposed belief → attitude → intention backbone and its supplementary performance, trust, and social channels. Practically, this pattern suggests that interventions to strengthen BI should prioritize usefulness cues and experiential quality (to lift ATT), foreground clear, quantifiable performance benefits (to boost PE), and reduce uncertainty via trust-building features (to enhance TR), while leveraging instructor/peer signaling to sustain SI effects.

Conclusions and Recommendations

Conclusion

With China's ongoing higher-education digitalization and the rollout of intelligent-technology policies, campus academic support and teaching services are entering a critical stage of intelligent upgrading. Aligned with national initiatives such as the Education Informatization 2.0 Action Plan and the Digital China Strategy, uncovering the mechanisms that drive undergraduates at private universities to adopt and continue using AI chatbots is both timely and policy-relevant. Drawing on an integrated TAM-UTAUT-TPB framework, this study models a core pathway from beliefs (PEOU, PU) → attitude (ATT) → intention (BI), while incorporating performance expectancy (PE), social influence (SI), and trust (TR) as direct predictors of BI. Based on data from 500 students across four colleges at a private university in Chengdu, CFA confirmed solid reliability and validity, and SEM supported all six hypotheses (H1-H6), indicating strong model-data alignment.

Mechanistically, PU and PEOU both enhance ATT, with PU exerting a slightly stronger influence. This suggests that instrumental performance gains (e.g., efficiency, assignment quality, time savings) are the main driver of favorable evaluations, while ease of use lowers effort and uncertainty, directly improving ATT and indirectly boosting BI through the PEOU → PU spillover. Among the direct determinants of BI, ATT has the strongest effect, followed by PE, TR, and SI. Thus, internal appraisal and anticipated returns jointly drive intention; trust alleviates concerns about errors, privacy, and compliance; and social cues (instructor modeling, peer word-of-mouth) remain significant, though more modest. Attitude further acts as a key mediator, consolidating early beliefs into stable behavioral intentions.

Overall, this study not only validates the robustness of the integrated TAM-UTAUT-TPB framework but also highlights the unique institutional features of private universities in China's digital transformation, offering actionable insights for policy alignment with national digital-education goals and institutional trust governance, thereby extending theoretical insights and contextual applicability.

Recommendations

From a policy and institutional perspective, the findings yield several implications. First, universities should foreground usefulness cues by embedding chatbot functions within course objectives and assessment frameworks, thereby reinforcing perceived academic value. Second, institutional policies should aim to enhance trust by establishing transparent governance of data use, privacy, and academic integrity. Third, social influence can be strengthened through structured initiatives that leverage faculty modeling and peer mentoring, fostering normative endorsement of intelligent support tools. Finally, institutional strategies should incorporate feedback and evaluation mechanisms that integrate usage analytics with student surveys, enabling evidence-based refinement of digital teaching practices. Collectively, these measures provide a strategic basis for improving adoption and continuance, beyond immediate classroom-level interventions.

Limitations and Further Study

This research faces several limitations. First, it employs a cross-sectional, self-report survey, which restricts the ability to establish causality and may affect external validity due to the reliance on a non-probability quota sample from a single private university. To address these concerns, future studies should consider longitudinal tracking or experimental methods, which would capture temporal changes more effectively and strengthen causal interpretations. Furthermore, conducting replication across different universities and regions is essential to strengthen the generalizability and contextual validity of the results. The framework may also be broadened by integrating new constructs—such as facilitating conditions, perceived risk, hedonic motivation, and habit—and by examining moderating factors including digital literacy, voluntariness, and students' academic major or study year, thereby enhancing the model's explanatory power. Finally, adopting mixed-method approaches—such as interviews and classroom observations—would offer richer insights into the development and persistence of trust and social influence in authentic educational environments.

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