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Investigating the Drivers of Attitudes and Behavioral Intentions Toward AI Chatbot Use Among Undergraduate Students in Guangdong, China

Qian Wan*

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Abstract

Purpose: This study examines the key factors influencing undergraduate students' attitudes and behavioral intentions toward AI chatbot use in Guangdong, China, using ChatGPT as a representative case. **Research design, data and methodology:** A quantitative approach was adopted by surveying 500 undergraduate students from the College of Mechanical and Electrical Engineering at Guangdong University of Petrochemical Technology. A non-probability sampling strategy was applied, including judgment sampling, quota sampling, and convenience sampling. A pilot test with 30 respondents ensured content validity and reliability. Data were analyzed using confirmatory factor analysis and structural equation modeling to assess reliability, validity, and model fit. **Results:** The findings indicate that effort expectancy, social influence, facilitating conditions, hedonic motivation, and performance expectancy significantly influence attitude. Among these factors, social influence shows the strongest effect ($\beta = 0.375$, $p < 0.05$). Attitude has the strongest direct effect on behavioral intention ($\beta = 0.450$, $p < 0.05$) and plays a central role linking user perceptions to behavioral intention. **Conclusions:** The results suggest that universities should integrate interactive AI-based learning activities, strengthen institutional support, and develop AI literacy programs. This study extends TAM and UTAUT by incorporating hedonic motivation and providing empirical evidence on the mediating role of attitude in AI chatbot adoption within a Chinese higher education context.

Keywords: Attitude, Behavioral Intention, AI Chatbots, Technology Acceptance, Undergraduate Students

JEL Classification Code: A22, C12, I23, M15, O33

1. Introduction

Artificial intelligence (AI) is developing rapidly. AI chatbots powered by large language models (LLMs) have become an important technology in natural language processing. They have strong potential to transform education and learning experiences. ChatGPT is a leading example. It has strong conversational ability and wide user adoption. These features make it suitable for studying technology acceptance among users, especially undergraduate students (Ray, 2023). In China, direct access is restricted. However, interest in ChatGPT continues to grow in academic and business fields. It is widely discussed in education, customer service, and content generation (Kumar et al., 2024).

Existing studies on technology adoption show that perceived usefulness and ease of use are key predictors of behavioral intention. However, most evidence is based on traditional systems and Western contexts. AI chatbots introduce new forms of interaction that differ from earlier technologies. As a result, current knowledge does not fully explain how users respond to these systems in learning environments. Empirical evidence on these emerging contexts remains limited (Dwivedi et al., 2023; Ray, 2023).

This limitation is more evident in the Chinese context. Cultural norms, regulatory conditions, and educational practices influence how technologies are used. Chinese users may emphasize compliance, institutional support, and local adaptation of AI tools (Kumar et al., 2024). In addition, the exam-oriented education system may shape students' motivations. These factors suggest that established technology acceptance relationships may not fully apply in

[1] *Qian Wan, Guangdong University of Petrochemical Technology, China. Email: w7_rich@163.com

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this setting. However, empirical evidence in Chinese higher education is still limited.

To address this gap, this study applies constructs from the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003). It examines the drivers of attitudes and behavioral intentions toward AI chatbots among undergraduate students in Guangdong, China. The study focuses on hedonic motivation and performance expectancy. These factors reflect enjoyment and perceived usefulness. The study also includes effort expectancy, social influence, and facilitating conditions.

This study adapts these models to the context of AI chatbot use. It incorporates hedonic motivation to capture user experience and examines the mediating role of attitude. Unlike traditional systems, ChatGPT provides interactive responses that may influence how users evaluate usefulness and ease of use. This approach reflects both cognitive and experiential aspects of technology acceptance.

The objective of this study is to examine how these factors influence undergraduate students' attitudes and behavioral intentions toward AI chatbot use. By focusing on a Chinese higher education context, the study provides empirical evidence on how cultural and institutional factors shape technology acceptance. It also refines the application of TAM and UTAUT in an AI-based learning environment. In addition, the findings offer practical implications. Universities in Guangdong can use the results to improve AI integration and enhance teaching strategies.

2. Literature Review

2.1 Factors Affecting Student Attitude and Behavioral Intention

The adoption of AI tools in education, particularly ChatGPT, is influenced by psychological, social, and contextual factors. Based on the Unified Theory of Acceptance and Use of Technology and related frameworks, this section reviews key determinants of students' attitudes and behavioral intentions.

Hedonic motivation refers to the enjoyment or pleasure derived from using technology (Venkatesh et al., 2012). In AI and educational contexts, it reflects the extent to which users find ChatGPT engaging and enjoyable. Prior studies show that hedonic motivation plays an important role in technology use and user engagement (Foroughi et al., 2023; Strzelecki, 2023a). It has also been linked to trust and continued usage in digital environments (Baabdullah, 2018; Sharif & Raza, 2017).

Performance expectancy is defined as the degree to which technology helps users improve task performance (Venkatesh et al., 2012). In education, it reflects the perceived usefulness of ChatGPT for learning and task completion. Previous studies highlight its importance in shaping technology adoption in academic settings (Gunasinghe et al., 2019; Lee et al., 2023).

Effort expectancy refers to the perceived ease of using a system (Davis, 1989). In the context of ChatGPT, it reflects how simple and intuitive the system is for learning purposes. Research indicates that users are more likely to adopt technologies that require less effort and are easy to use (Bin-Nashwan et al., 2020; Strzelecki, 2023a).

Social influence describes the extent to which individuals are affected by the opinions of others when using technology (Venkatesh et al., 2003). In educational settings, it includes the impact of peers, instructors, and social networks. Prior studies show that social influence affects users' attitudes and technology acceptance (Dwivedi et al., 2017; Gulati et al., 2024).

Facilitating conditions refer to the availability of resources and support for using technology (Venkatesh et al., 2012). These include technical infrastructure, user skills, and external assistance. Existing research emphasizes their role in supporting technology adoption in learning environments (Samsudeen & Mohamed, 2019; Tewari et al., 2023).

Attitude is defined as an individual's evaluation of a behavior (Ajzen, 2005). It reflects a positive or negative perception toward using ChatGPT. Behavioral intention refers to a user's willingness to use a technology (Davis, 1989). It is widely recognized as a strong predictor of actual usage (Teo, 2019; Venkatesh et al., 2003).

2.2 Research Hypothesis and Relationship between Variables

2.2.1 Relationship between Hedonic Motivation and Attitude toward ChatGPT

Hedonic motivation reflects the enjoyment users experience when interacting with ChatGPT. In educational settings, enjoyable experiences increase engagement and shape positive perceptions of the system. From an intrinsic motivation perspective, positive emotional responses reinforce favorable evaluations, which contribute to the formation of positive attitudes toward technology use. Prior research shows that hedonic motivation influences students' attitudes toward using ChatGPT for learning purposes (Tiwari et al., 2023), and enjoyable systems tend to promote trust and positive evaluations (Baabdullah, 2018).

In addition, the novelty of AI tools can further enhance user interest and engagement (De Kervenoael et al., 2020; Mishra et al., 2023). ChatGPT provides interactive and dynamic responses that make learning more engaging. Students in higher education are more likely to adopt technologies that are engaging and interactive (Strzelecki,

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2023b). However, empirical evidence focusing specifically on AI chatbot learning contexts remains limited.

H1: Hedonic motivation has a significant effect on attitude toward ChatGPT.

2.2.2 Relationship between Performance Expectancy and Attitude toward ChatGPT

Performance expectancy reflects the extent to which using ChatGPT improves users' academic performance (Alshebami, 2022; Venkatesh et al., 2012). In educational settings, students tend to value technologies that enhance learning efficiency and support task completion. From a utility evaluation perspective, users form favorable attitudes when they perceive that a system provides clear and meaningful performance benefits. Prior studies indicate that individuals are more likely to adopt AI technologies when improvements in performance and interaction are evident (Alhwaiti, 2023).

ChatGPT supports tasks such as information retrieval, content generation, and problem solving, which can improve learning outcomes and productivity. Empirical evidence shows that students are more likely to use ChatGPT when it is perceived as useful for academic purposes (Foroughi et al., 2023). Perceived usefulness strengthens positive evaluations and contributes to attitude formation.

H2: Performance expectancy has a significant effect on attitude toward ChatGPT.

2.2.3 Relationship between Effort Expectancy and Attitude toward ChatGPT

Effort expectancy reflects the extent to which users perceive ChatGPT as easy to use and requiring minimal effort (Strzelecki, 2023a; Venkatesh et al., 2012). In educational settings, systems that are simple and user-friendly are more likely to be accepted by students. From a cognitive effort perspective, lower perceived complexity reduces user burden and allows individuals to focus on task completion, which supports more positive evaluations of the system.

Prior studies indicate that individuals are more likely to adopt technologies that require less time and effort (Bin-Nashwan et al., 2020), while systems that are complex or produce uncertain outcomes are more likely to be rejected (Alshebami, 2022). ChatGPT uses natural language interaction, which reduces operational effort. This ease of interaction can enhance user confidence and strengthen favorable attitudes toward the system.

H3: Effort expectancy has a significant effect on attitude toward ChatGPT.

2.2.4 Relationship between Social Influence and Attitude toward ChatGPT

Social influence reflects the extent to which individuals are affected by the opinions of people important to them, such as peers, friends, and family (Chaouali et al., 2016). From a social conformity perspective, individuals tend to align their attitudes with perceived expectations in order to gain social approval and reduce uncertainty when adopting new technologies. Cultural norms also play a role in shaping trust and technology-related attitudes (Chen et al., 2024).

Prior research indicates that individuals' behavior is influenced by their social environment (Lee et al., 2023). Observing others using a technology can signal its usefulness and appropriateness. In educational settings, students often rely on peers and instructors when forming perceptions about new tools. Such social validation can reinforce positive evaluations and influence attitude formation. Empirical studies confirm that social influence is associated with users' attitudes toward technology (Ashraf et al., 2023; Dwivedi et al., 2017).

H4: Social influence has a significant effect on attitude toward ChatGPT.

2.2.5 Relationship between Facilitating Conditions and Attitude toward ChatGPT

Facilitating conditions refer to the availability of resources, knowledge, and support that enable users to effectively use ChatGPT. From a resource-based perspective, adequate support reduces uncertainty and increases perceived control, which encourages positive evaluations of the system. When students perceive that they have sufficient infrastructure and assistance, they are more likely to develop positive perceptions (Balakrishnan et al., 2022).

In educational settings, access to technical support and guidance can enhance students' confidence and engagement (Cokins et al., 2020; Menon & Shilpa, 2023). Facilitating conditions also influence trust, as reliable systems and institutional support signal stability and effectiveness (Cheng et al., 2022). Prior studies show that access to resources contributes to technology adoption (Tewari et al., 2023). These conditions enable effective system use and strengthen favorable attitudes.

H5: Facilitating conditions have a significant effect on attitude toward ChatGPT.

2.2.6 Relationship between Attitude toward ChatGPT and Behavioral Intention

Attitude reflects individuals' overall evaluation of using ChatGPT, whether positive or negative (Chatterjee et al., 2021). In technology adoption, attitude plays an important role in shaping users' intentions. From a behavioral decision perspective, individuals are more likely to form intentions that align with their evaluations, where positive attitudes increase the likelihood of continued use. Prior studies indicate that cognitive evaluations influence attitude, which then predicts behavioral intention (Al Breiki & Al-Abri, 2022).

Empirical evidence shows that attitude has a strong impact on intention to use technology (Acikgoz et al., 2023). Positive attitudes are reinforced when users perceive usefulness and effectiveness (Rahman & Watanobe, 2023).

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Attitude also influences actual usage behavior (Chatterjee et al., 2021), while behavioral intention predicts use in UTAUT (Venkatesh et al., 2012). Evidence in educational contexts further supports this relationship (Ahadzadeh et al., 2024).

H6: Attitude toward ChatGPT has a significant effect on behavioral intention.

3. Research Methods and Materials

3.1 Research Framework

This study is primarily grounded in the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), which provide a well-established basis for explaining user acceptance of new technologies. TAM explains how perceived usefulness and ease of use shape user attitudes, while UTAUT extends this perspective by incorporating social influence and facilitating conditions as key determinants of behavioral intention.

To reflect the characteristics of AI chatbot use, this study incorporates Hedonic Motivation Theory, which captures the role of enjoyment in shaping user experience and attitudes. In addition, the Stimulus-Organism-Response (SOR) framework (Mehrabian & Russell, 1974) is used to explain how external factors influence internal evaluations, which in turn lead to behavioral responses.

These perspectives are combined to provide a focused framework that captures both cognitive evaluations and experiential aspects of AI chatbot use.

Based on these foundations, a conceptual framework is developed, as illustrated in Figure 1.

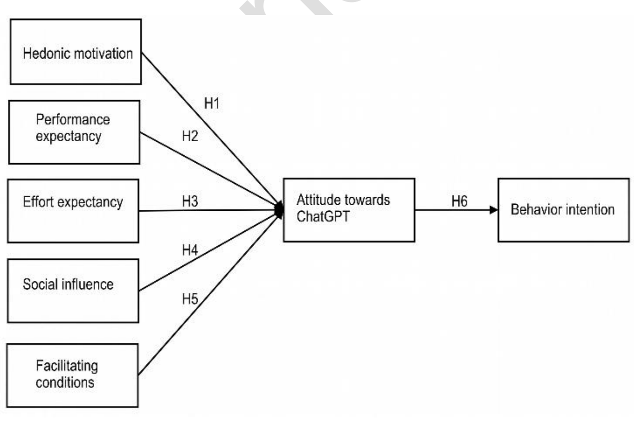

Figure 1: Conceptual Framework

3.2 Research Methodology

This study employed a quantitative research design using a non-probability sampling approach. Data were collected through an online questionnaire distributed to undergraduate students at the College of Mechanical and Electrical Engineering, Guangdong University of Petrochemical Technology. Prior to data collection, the study received approval from the relevant academic authority, and ethical procedures were followed throughout the research process. Participation was voluntary, and respondents were provided with an informed consent statement outlining the study purpose, confidentiality, and their right to withdraw at any time before completing the questionnaire. All responses were collected anonymously, and no personally identifiable information was recorded to ensure data protection and confidentiality.

The questionnaire consisted of three parts. The first part included screening questions to confirm eligibility, including whether respondents were at least 18 years old and had at least one year of experience using artificial intelligence chatbots, such as ChatGPT. The second part measured the study variables using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The items were designed to assess the constructs related to the proposed hypotheses. The third part collected demographic information, including gender, and academic year.

A pilot test was conducted with 30 respondents to assess content validity. Three experts in the field evaluated the questionnaire using the item-objective congruence (IOC) method, and all items exceeded the acceptable threshold of 0.67 (Turner & Carlson, 2003), indicating that the instrument was appropriate for measuring the intended constructs. Reliability was assessed using Cronbach's alpha (Cronbach, 1951), and the results indicated satisfactory internal consistency.

A total of 500 valid responses were obtained for data analysis. The data were analyzed using SPSS and AMOS. Confirmatory factor analysis (CFA) was conducted to assess construct validity, including convergent validity. Structural equation modeling (SEM) was then applied to examine the causal relationships among the variables and to test the proposed hypotheses.

3.3 Population and Sample Size

This study employed a non-probability sampling approach that combined judgment sampling, quota sampling, and convenience sampling. Judgment sampling was used to identify appropriate respondents, specifically undergraduate students from four academic years at the College of Mechanical and Electrical Engineering, Guangdong University of Petrochemical Technology. Quota sampling was then applied to determine the number of participants from each academic year to ensure proportional representation, as shown in Table 1.

Table 1: Population and Sample Size by Academic Year

Academic Year	Population Size	Sample Size
First-year students	504	140
Second-year students	429	119
Third-year students	383	107
Fourth-year students	480	134
Total	**1,796**	**500**

Source: Guangdong Provincial Education Department

This sampling approach ensures that respondents have relevant experience with AI chatbot use while maintaining balanced representation across academic years. However, the focus on a single institution may limit the generalizability of the findings.

The target population consisted of undergraduate students aged 18 years or above who had prior experience using artificial intelligence chatbots, such as ChatGPT. These criteria were applied during the data screening process to ensure the relevance and suitability of the respondents.

Data were collected from June to December 2025. Convenience sampling was used during this stage, as questionnaires were distributed through an online platform based on participants' accessibility and willingness to respond. A total of 500 valid responses were obtained and used for subsequent analysis. The sample size is considered adequate for structural equation modeling, as it exceeds commonly recommended thresholds for model estimation and reliability (Hair et al., 2019).

4. Results and Discussion

4.1 Demographic Information

Demographic data were collected from 500 undergraduate students at the College of Mechanical and Electrical Engineering, Guangdong University of Petrochemical Technology. The variables included gender and academic year.

The sample consisted of 279 male students (57.8%) and 211 female students (42.2%). The distribution across academic years was relatively balanced. First-year students accounted for 28.0%, followed by second-year students at 23.8%, third-year students at 21.4%, and fourth-year students at 26.8%.

All participants had more than one year of experience using artificial intelligence chatbots, such as ChatGPT. This ensured that respondents were familiar with the technology and could provide meaningful responses. Table 2 presents the detailed demographic profile.

Table 2: Demographic Profile of Respondents

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	279	57.8%
	Female	211	42.2%
Academic Year	First-year students	140	28.0%
	Second-year students	119	23.8%
	Third-year students	107	21.4%
	Fourth-year students	134	26.8%

Source: Created by the author

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was conducted to evaluate the measurement model. All measurement items were statistically significant, with p-values below 0.05. The standardized factor loadings ranged from 0.695 to 0.802, exceeding the recommended threshold of 0.50 (Hair et al., 2019). These results indicate that the items adequately represent their respective constructs.

All constructs also demonstrate strong internal consistency. Cronbach's alpha and composite reliability (CR) values exceed 0.70 for all variables. In addition, the average variance extracted (AVE) values are above 0.50, indicating that the constructs capture sufficient variance from their indicators (Fornell & Larcker, 1981). The detailed results are presented in Table 3.

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

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
Hedonic Motivation (HM)	Sehabuddin and Oktarina (2022)	4	0.831	0.726-0.769	0.832	0.553
Performance Expectancy (PE)	Davis (1989)	4	0.841	0.712-0.802	0.841	0.569
Effort Expectancy (EE)	Moore and Benbasat (1991)	4	0.861	0.776-0.783	0.861	0.608
Social Influence (SI)	Venkatesh and Davis (2000)	4	0.834	0.695-0.779	0.834	0.557
Facilitating Conditions (FC)	Venkatesh et al. (2012)	4	0.827	0.721-0.760	0.827	0.545
Attitude (ATT)	Ajzen (1988)	4	0.845	0.719-0.788	0.844	0.576
Behavioral Intention (BI)	Kim and Wang (2021)	4	0.857	0.739-0.801	0.858	0.601

Note: CR = Composite Reliability, AVE = Average Variance Extracted

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Discriminant validity is supported by the results shown in Table 4. The square root of AVE for each construct is greater than its correlations with other constructs. This indicates that each construct is distinct and measures a unique concept.

Table 4: Discriminant Validity

Variable	Factor Correlations						
	HM	PE	EE	SI	FC	ATT	BI
HM	**0.744**						
PE	0.336	**0.755**					
EE	0.305	0.405	**0.780**				
SI	0.328	0.326	0.361	**0.738**			
FC	0.281	0.345	0.293	0.307	**0.738**		
ATT	0.465	0.499	0.517	0.517	0.481	**0.759**	
BI	0.268	0.304	0.289	0.331	0.314	0.439	**0.775**

Note: The diagonally listed value is the AVE square roots of the variables

The overall model fit is also satisfactory. As shown in Table 5, the CMIN/df value is 1.540, which is below the acceptable threshold of 5.00. The GFI, AGFI, NFI, CFI, and TLI values all exceed their recommended levels. The RMSEA value is 0.033, which is below 0.08. These indices indicate that the model fits the data well (Hu & Bentler, 1999).

Table 5: Goodness of Fit for Measurement Model

Index	Criterion	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1.540
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.932
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.916
NFI	≥ 0.80 (Wu & Wang, 2006)	0.926
CFI	≥ 0.80 (Bentler, 1990)	0.973
TLI	≥ 0.90 (Hair et al., 2006)	0.968
RMSEA	< 0.08 (Hu & Bentler, 1999)	0.033

Note: 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

Overall, the results confirm that the measurement model demonstrates acceptable reliability, convergent validity, discriminant validity, and model fit. Therefore, the model is suitable for subsequent structural model analysis.

4.3 Structural Equation Model (SEM)

The structural model was evaluated to assess the overall model fit. Several fit indices were considered, including CMIN/df, GFI, AGFI, NFI, CFI, TLI, and RMSEA. The analysis was conducted using SPSS AMOS version 26. These indices were selected to provide a comprehensive assessment of model fit, as they capture different aspects of model adequacy, including absolute fit, incremental fit, and parsimonious fit.

The results indicate that the structural model demonstrates an acceptable fit to the data. As presented in Table 6, all reported indices meet the recommended criteria. These results suggest that the model adequately represents the observed data and provides a reliable basis for testing the hypothesized relationships.

Table 6: Goodness of Fit for Structural Model

Index	Criterion	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	2.620
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.865
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.841
NFI	≥ 0.80 (Wu & Wang, 2006)	0.869
CFI	≥ 0.80 (Bentler, 1990)	0.914
TLI	≥ 0.90 (Hair et al., 2006)	0.906
RMSEA	< 0.08 (Hu & Bentler, 1999)	0.057

Note: 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 the regression weights and significance levels, the structural model was evaluated to test the proposed hypotheses. The results are presented in Table 7. All hypotheses in this study are supported.

Table 7: Hypothesis Testing Result

Hypothesis	Standardized path coefficients (β)	S.E.	t-value	Test Result
H1: HM → ATT	0.280	0.041	5.865*	Supported
H2: PE → ATT	0.284	0.041	5.931*	Supported
H3: EE → ATT	0.341	0.038	7.097*	Supported
H4: SI → ATT	0.375	0.046	7.356*	Supported
H5: FC → ATT	0.335	0.043	6.774*	Supported
H6: ATT → BI	0.450	0.068	7.850*	Supported

Note: * $p < 0.05$

The results show that Hedonic Motivation has a significant effect on students' Attitude toward using ChatGPT (β = 0.280). Similarly, Performance Expectancy also exerts a significant influence on Attitude (β = 0.284). These findings indicate that both intrinsic enjoyment and perceived usefulness contribute to shaping students' evaluations, reflecting the combined role of experiential and cognitive factors in technology acceptance.

Effort Expectancy demonstrates a stronger effect on Attitude (β = 0.341), indicating that ease of use plays an important role in forming favorable evaluations. Social Influence shows the strongest impact on Attitude (β = 0.375), highlighting the importance of peer and social context in influencing students' perceptions. The comparatively higher coefficient of Social Influence suggests that external social factors may play a more prominent role than individual perceptions in this setting.

Facilitating Conditions also contribute significantly to Attitude ($\beta = 0.335$). This result suggests that the availability of resources and institutional support enhances users' confidence, which in turn strengthens their evaluations of the system. In addition, Attitude has a significant effect on Behavioral Intention ($\beta = 0.450$), indicating that more positive attitudes lead to a higher likelihood of continued usage. This finding highlights the central role of attitude in translating user perceptions into behavioral intention within the context of AI chatbot adoption.

5. Conclusions and Recommendation

5.1 Conclusions

This study examines the factors influencing undergraduate students' attitudes and behavioral intentions toward using AI chatbots in Guangdong, China. With the rapid development of artificial intelligence, chatbots based on large language models have become important tools in education. Understanding how students evaluate and adopt these technologies is essential for effective integration. To address this, six hypotheses were proposed to explain the relationships among key variables.

Data were collected from 500 undergraduate students at the College of Mechanical and Electrical Engineering, Guangdong University of Petrochemical Technology. All respondents had prior experience using AI chatbots. The data were analyzed using SPSS and AMOS. The measurement model demonstrated acceptable reliability and validity, and the structural model supported all proposed hypotheses.

The structural results highlight the combined influence of hedonic motivation, performance expectancy, effort expectancy, social influence, and facilitating conditions on attitude, which in turn drives behavioral intention. Perceived usefulness and ease of use continue to play a central role in shaping user evaluations, while social influence emerges as a comparatively stronger driver in this context, suggesting a shift from purely individual cognition toward socially embedded decision processes (Alhwaiti, 2023; Tiwari et al., 2023; Venkatesh et al., 2003).

Such a pattern reflects the influence of collective norms and structured learning environments within Chinese higher education, where peer behavior and instructor expectations often guide students' technology-related decisions (Kumar et al., 2024). The prominence of social influence indicates that acceptance is reinforced through shared practices and institutional context, rather than being formed solely through individual assessment.

At the same time, the combined effects of hedonic motivation and performance expectancy highlight the dual importance of experiential engagement and functional value in AI-supported learning. The interactive nature of ChatGPT introduces an experience-oriented dimension that extends beyond traditional utility-based explanations, as reflected in recent studies on AI adoption in educational settings (Strzelecki, 2023b).

Overall, this study contributes by offering empirical evidence from a Chinese educational setting and by demonstrating how established acceptance models operate within the evolving context of AI chatbot use. It advances understanding by integrating social, cognitive, and experiential factors into a unified explanation of attitude formation and behavioral intention. These insights provide practical value for universities and policymakers seeking to support effective and responsible AI adoption in education.

5.2 Recommendations

Based on the findings of this study, several practical recommendations are proposed to promote positive attitudes and sustained use of AI chatbots among undergraduate students in Guangdong.

First, universities should design learning activities that enhance hedonic motivation and leverage social influence. For example, instructors can incorporate chatbot-based assignments, group projects, and gamified learning tasks into the curriculum. These activities can increase student engagement and encourage peer interaction, which was found to be the most influential factor shaping attitude.

Second, institutions should strengthen facilitating conditions by improving access to AI tools and support services. Universities can provide campus-wide access to approved chatbot platforms, along with user guides, tutorials, and technical support. Training workshops can also help students develop confidence in using AI tools. These efforts can reduce perceived difficulty and improve ease of use, which are important factors influencing students' attitudes.

Third, universities should promote responsible and effective use of AI through structured AI literacy programs. Courses or seminars can be introduced to guide students on appropriate use, ethical considerations, and critical evaluation of AI-generated content. Faculty training is also important to ensure consistent guidance and integration of AI tools in teaching practices.

In addition, policy-level support can further facilitate the effective use of AI in education. Educational authorities may develop clear guidelines for AI integration, including standards for responsible use, data protection, and academic integrity. Coordinated investment in shared digital infrastructure and cross-institutional collaboration can also

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promote consistent and equitable access to AI technologies.

These recommendations reflect the study's contribution by translating key determinants of attitude and behavioral intention into actionable strategies. They support the effective integration of AI chatbots in higher education and contribute to the development of sustainable AI-supported learning environments.

5.3 Limitation and Further Study

This study has several limitations that should be considered when interpreting the findings. First, all variables were measured at the individual level using self-reported data collected at a single point in time. This cross-sectional design limits the ability to establish causal relationships (Glick, 1985). Procedural measures such as clear questionnaire design, anonymity assurance, and voluntary participation were applied to reduce potential response bias. Nevertheless, the use of a single data source may still introduce some degree of common method bias.

Second, the sample consisted of undergraduate students from a specific college within one university. Although this approach ensured that respondents had relevant experience with AI chatbot use, it may limit the applicability of the findings across different institutions, regions, and educational contexts.

Future research can address these limitations by adopting longitudinal or experimental designs to better examine causal relationships. Collecting data at multiple time points may provide deeper insight into changes in attitudes and behavioral intentions. In addition, expanding the sample to include diverse institutions and academic disciplines would improve external validity. Researchers may also consider incorporating additional variables, such as perceived risk or trust, to further extend and validate the proposed model.

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