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Exploring the factors affecting ChatGPT acceptance among university students

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Abstract The integration of artificial intelligence (AI) technology, particularly ChatGPT, into higher education settings is becoming increasingly prevalent. However, there remains a gap in understanding the factors that shape students' acceptance and utilization of ChatGPT. This study seeks to address this gap by investigating these factors and offering insights to enhance the adoption of ChatGPT in higher education. Data for this research was gathered through a questionnaire adapted from the UTAUT model, and analyzed using Structural Equation Modeling (SEM). The findings reveal significant relationships between variables such as Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions with Behavioral Intention and User Behavior concerning ChatGPT. These results underscore the importance of higher education institutions in formulating strategies for AI technology integration, with a focus on psychosocial factors influencing student acceptance and usage. Moving forward, future research could delve deeper into contextual factors that may impact the adoption of AI technologies in higher education, thus providing further insights into this evolving field.

Keywords: Chatgpt, university students, utaut model, sem

1. Introduction

Higher education has become increasingly shaped by technology, playing a pivotal role in expanding access, improving the quality of learning, and preparing students for the changing demands of the workforce. In this context, artificial intelligence (AI) has emerged as a revolutionary force, offering innovative solutions to various educational challenges (Kamalov et al., 2023; Kurdoğlu & Khaki, 2024). One prominent example is ChatGPT, which combines advances in natural language processing with AI to create interactive interfaces capable of understanding and responding to human conversation (Javaid et al., 2023; Ngoc Hai, 2023).

In an era where students are increasingly digitally connected and seeking more dynamic learning experiences, understanding the acceptance of ChatGPT among university students is critical (Strzelecki, 2023). Research that delves into the factors influencing ChatGPT adoption in academic settings is practically relevant and has significant implications for the technology-driven future of higher education.

Although AI technology promises great potential to improve the learning experience in higher education, its adoption has not always been smooth (Celik et al., 2022). Several obstacles arise in implementing AI technology in academia, including technical (Jafari & Keykha, 2023), policy (Misra et al., 2020; Rohde et al., 2021), and data security challenges (Khisamova et al., 2023). Additionally, specific factors influence students' acceptance of ChatGPT, such as uncertainty about the system's reliability and accuracy (Menon & K, 2023), concerns about AI replacing humans in the learning process (Ma, 2023), and limitations in technical proficiency required to use such platforms effectively (Alzu'bi et al., 2023; Hua et al., 2023). Understanding these potential barriers is crucial. Only by identifying and understanding these barriers can we develop effective strategies to facilitate the adoption of AI technologies in higher education environments while ensuring these changes support and enrich the student learning experience.

The main aim of this study was to investigate the factors influencing the acceptance of ChatGPT among university students. By understanding these factors, this research aims to identify behavioral patterns and preferences for using ChatGPT in academic settings. This research is expected to provide valuable insights for higher education practitioners and AI technology developers on how to increase the adoption of ChatGPT in higher education environments. By gaining a deeper understanding of user preferences and needs, this research can better direct the use of ChatGPT to meet student expectations.

Previous research has provided valuable insight into adopting AI technology among college students (Bantugan et al., 2024; Delello et al., 2024; Rodway & Schepman, 2023), but knowledge gaps still need to be addressed. Although much research has focused on the technical and functional aspects of AI technology, understanding the factors influencing the adoption of AI technology still needs improvement. Additionally, the limitations of previous research in exploring the preferences and needs of ChatGPT users in higher education settings indicate the need for more in-depth and holistic research.

The successful development of AI technology requires a deep understanding of user preferences and how the technology can be optimally integrated into the higher education context (Xia & Li, 2022). By identifying these knowledge gaps, this research aims to complement the existing literature and contribute to understanding the acceptance and use of AI technologies, particularly ChatGPT, among university students.

This research highlights its unique contribution to understanding the acceptance of ChatGPT in higher education by using the UTAUT analysis model proposed by Venkatesh (Venkatesh et al., 2003). According to Venkatesh (Venkatesh et al., 2003), behavioral intention and user behavior in adopting technology are influenced by factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions. In an evolving context where AI technology is increasingly changing how we learn and teach, a deep understanding of how students receive and use this technology is critical. Additionally, this research has significant potential implications for improving learning and teaching effectiveness in the digital era. By understanding the factors that influence the acceptance of ChatGPT among students, educational developers, and administrators can direct their efforts to optimize the use of this technology to support a more interactive, personalized, and effective learning process.

This research is crucial in informing relevant educational policies and practices. By understanding student preferences and needs regarding the use of ChatGPT, higher education institutions can develop more focused policies and strategies to facilitate the adoption of this technology. Thus, this research will improve students' learning experiences and support the development of more adaptive and innovative education in line with current demands.

Based on this background, the hypothesis of this research can be formulated as follows:

H1: Performance Expectancy significantly affects students' behavioral intention to use ChatGPT.

H2: Effort Expectancy significantly affects students' behavioral intention to use ChatGPT.

H3: Social Influence significantly affects students' behavioral intention to use ChatGPT.

H4: Facilitating Conditions significantly affect students' behavior when using ChatGPT.

H5: Behavioral Intention significantly affects students' behavior when using ChatGPT.

2. Materials and Methods

This research employs a quantitative research design with a cross-sectional survey approach. This approach allows researchers to collect data from respondents at a specific time, which suits the study's focus on the acceptance of ChatGPT among college students. The population of this study consisted of students enrolled in universities in Indonesia. The research sample included 293 bachelor's and master's level students, randomly selected from six universities across Java, Sumatra, and Maluku Island. Stratified random sampling was used to represent the Indonesian student population better. To protect respondents' anonymity, all collected data were encrypted and stored anonymously, with no personal identifying information linked to their responses. After fully explaining the research objectives and their rights as participants, written consent was obtained from each respondent.

Data were collected using a questionnaire adapted from the UTAUT model developed by Venkatesh (Venkatesh et al., 2003), Duman (Duman & Oğuz, 2024), and Rani (Rani et al., 2023). The questionnaire was designed to measure factors influencing the acceptance of ChatGPT among college students. The research instrument is detailed in Table 1. Questionnaires were distributed to respondents via an online platform using Google Forms. Validity and reliability testing were conducted before distributing the questionnaire to ensure the quality and reliability of the measurement instrument.

This study analyzes structural equation models (SEM) using SmartPLS 3 software. SEM examines the claim that the suggested theoretical model accounts for the gathered data (Fan et al., 2016). SEM is also used because of its flexibility in handling sample sizes and data that are not normally distributed (Kline, 2016). Item validity refers to the loading factor value, where the higher the loading factor, the greater the item's contribution to the construct measured by the latent factor. Hair (2010) states that the minimum loading factor value is 0.5, while the minimum acceptable reliability value is 0.7. The model fit index values refer to Kline (2016), Hair (2010), and Hu (1999). Hypothesis testing is based on the p-value, where, according to Hair (Hair J. et al., 2010), if the p-value is less than 0.0001, then the hypothesis is accepted.

Table 1 Questionnaire Items.

Construct	Code	Question
Performance Expectancy (PE)	PE1	– Using ChatGPT helps increase efficiency in my learning.
	PE2	– Using ChatGPT helps improve my understanding of the learning material.
	PE3	– I believe ChatGPT can provide positive benefits in my learning process.
Effort Expectancy (EE)	EE1	– I feel that using ChatGPT is relatively easy.
	EE2	– I do not need too much effort to be able to use ChatGPT.
	EE3	– I believe that understanding how to use ChatGPT does not require significant time or effort.
	EE4	– I feel that using ChatGPT does not require complex technical skills.
Social Influence (SI)	SI1	– Lecturers provide support in using ChatGPT.
	SI2	– Friends gave me recommendations to use ChatGPT.
	SI3	– My college does not prohibit the use of ChatGPT.
Facilitating Conditions (FC)	FC1	– Resources and technical support for using ChatGPT are well available.
	FC2	– Facilities and infrastructure at universities support the use of ChatGPT.
	FC3	– Colleges provide adequate training to use ChatGPT.
	FC4	– The college offers easy and smooth access to ChatGPT.
Behavioral Intention (BI)	BI1	– I intend to continue using ChatGPT in my learning and work.
	BI2	– I plan to use ChatGPT in my learning activities regularly.
	BI3	– I plan to continue using ChatGPT in the future.
User Behavioral (UB)	UB1	– I believe using ChatGPT has positively impacted my learning outcomes.
	UB2	– I recommend that my friends use ChatGPT.

3. Result

3.1. Respondent Demographics

Table 2 presents demographic data from respondents involved in research on factors influencing ChatGPT acceptance among university students. These data provide an overview of the demographic characteristics of the study sample.

Table 2 Respondent Demographics.

Category	Forms	Number of Observations	Frequency (%)
Gender	Male	56	19,11
	Female	237	80,89
Age	18-22	255	87,03
	23-27	10	3,41
	28-32	2	0,68
	33-37	8	2,73
	38-42	11	3,75
	43-48	7	2,39
Semester	1-2	52	17,75
	3-4	112	38,23
	5-6	120	40,96
	7-8	4	1,37
	9-10	3	1,02
	11-12	-	0,00
	13-14	2	0,68
Degree	Bachelor	267	91,13
	Master	26	8,87

Based on gender, the majority of respondents were women, comprising 80.89%, while male respondents accounted for only 19.11%. In terms of age, most respondents were in the 18-22 year age range, representing 87.03%. Other age ranges had smaller proportions, with the 23-27 year age range accounting for only 3.41%, and the different age ranges (28-42 years) contributing around 0.68-3.75% each. Regarding study semesters, most respondents were in semesters 3-6, with a significant number in semesters 3-4 (38.23%) and 5-6 (40.96%). As for education level, most respondents were bachelor's degree students (91.13%), while only a small portion were master's degree students (8.87%).

3.2. Descriptive Statistics of Variables

The data in Table 3 presents the results of a descriptive analysis of the variables observed in this research, which describe student perceptions and behavior related to the use of ChatGPT in higher education environments. The main variables observed include Performance Expectation, Effort Expectation, Social Intervention, Facilitating Condition, Behavioral Intention, and User Behavior.

Table 3 Descriptive Statistics of Variables.

Latent Variables	Items	Mean	SD
Performance Expectation	PE1	3.70	0.757
	PE2	3.59	0.765
	PE3	3.70	0.731
Effort Expectation	EE1	3.53	0.729
	EE2	3.23	0.741
	EE3	2.86	0.969
	EE4	3.04	0.780
Social Intervention	SI1	2.50	0.942
	SI2	2.58	0.917
	SI3	2.46	0.877
Facilitate Condition	FC1	2.28	0.981
	FC2	2.90	0.854
	FC3	2.72	0.980
	FC4	3.41	0.792
Behavioral Intention	BI1	2.71	0.893
	BI2	2.74	0.861
	BI3	2.88	0.846
User Behavioral	UB1	3.35	0.764
	UB2	3.15	0.882

The average value provided indicates the level of student expectations, intentions, and behavior related to ChatGPT. For instance, the average performance expectation value ranges from 3.59 to 3.70, indicating relatively high expectations for ChatGPT's performance assisting the learning process. Meanwhile, skewness and kurtosis offer an overview of asymmetry and the presence of heavy tails in the data distribution. These results offer an initial understanding of student perceptions and behavior regarding ChatGPT, which will aid in further analysis using SEM techniques.

3.3. Measurement Model

The data in Table 4 presents the results of the factor loading analysis and the validity and reliability of the latent variables in this study. Factor loading measures how well each observed variable represents the related latent variable. A high factor loading value (minimum 0.5) (Hair et al., 2010) indicates a strong relationship between observed and latent variables.

The analysis results indicate that all reported loading factors have significant values with high t-statistics, confirming the validity of the loading factors. Visually, the loading factor value for each item can be observed in Figure 1. Construct validity, measured by Average Variance Extracted (AVE), assesses how well the observed variables reflect the related latent variables. An AVE value above 0.5 indicates good validity of the measured construct. Additionally, construct reliability is evaluated using composite reliability and Cronbach's Alpha. A high composite reliability value (above 0.7) indicates good internal consistency of the construct. Similarly, a high Cronbach's Alpha value indicates reliability in measuring the variables' internal consistency. The results of this analysis demonstrate that the measurement instrument used in this research exhibits good validity and reliability for measuring the observed variables.

Table 5 displays the correlation matrix between the variables in this study. Correlation is a statistical measure that describes the strength and direction of the relationship between two variables. In the context of this research, the observed variables include Behavioral Intention (BI), Effort Expectation (EE), Facilitating Condition (FC), Performance Expectation (PE), Social Intervention (SI), and User Behavior (UB). Correlation values are measured on a scale between -1 to 1, where positive values indicate a positive relationship between the variables, while negative values indicate a negative relationship.

The results from the table indicate a significant correlation between the observed variables. For instance, there is a strong positive correlation between Behavioral Intention (BI) and other variables such as Effort Expectation (EE), Facilitating Condition (FC), Performance Expectation (PE), Social Intervention (SI), and User Behavior (UB), with correlation values ranging from 0.542 to 0.901. This suggests that the higher the user's behavioral intention (BI), the higher the expectations, efforts, facilitating conditions, performance, social interventions, and actual user behavior related to ChatGPT.

Table 4 Loading Factor, Validity, and Reliability.

Latent	Obs	Loading Factor	t-value	AVE	CR	Alpha
PE	PE1	0.876	50.861	0.750	0.900	0.833
	PE2	0.857	40.343			
	PE3	0.865	39.978			
EE	EE1	0.596	9.135	0.583	0.846	0.761
	EE2	0.816	28.330			
	EE3	0.794	27.348			
	EE4	0.825	32.526			
SI	SI1	0.893	52.551	0.819	0.931	0.889
	SI2	0.927	77.819			
	SI3	0.894	55.145			
FC	FC1	0.528	5.416	0.527	0.813	0.729
	FC2	0.810	23.845			
	FC3	0.750	18.923			
	FC4	0.781	25.200			
BI	BI1	0.909	71.619	0.811	0.928	0.884
	BI2	0.914	72.074			
	BI3	0.879	53.748			
UB	UB2	0.887	57.472	0.773	0.872	0.707
	UB1	0.871	45.902			

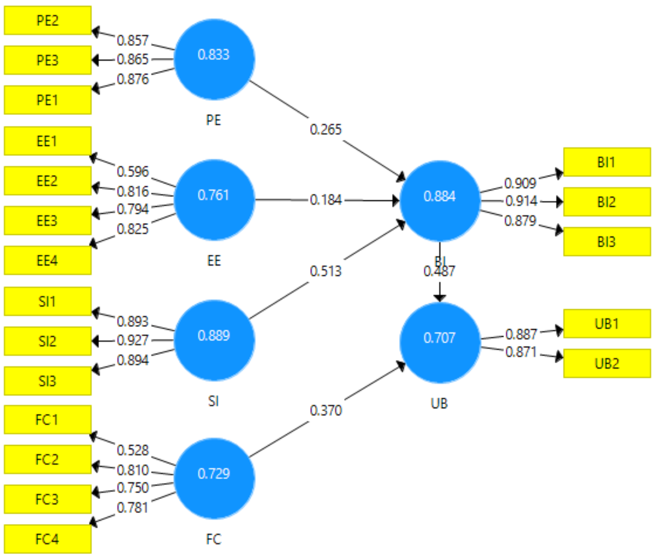

Figure 1 Loading Factors of Observation Variable.

Furthermore, there are also significant correlations between other variables. For example, there is a positive correlation between Performance Expectation (PE) and other variables such as Effort Expectation (EE), Facilitating Conditions (FC), and Social Intervention (SI). This implies that the higher the user's performance expectations of ChatGPT, the higher the expectations of effort, facilitating conditions, and social interventions involved.

Table 6 displays the results of the various model fit indices evaluated for the model used in this study. Referring to the model fit index criteria proposed by Hair (Hair et al., 2010), Kline (Kline, 2016), and Hu (Hu & Bentler, 1999), the evaluation results indicate that the proposed model achieves a reasonable degree of fit to the observed data. The p-value from the Chi-Square test indicates no significant differences between the model and the observed data, suggesting good agreement between the proposed model and the existing data. Additionally, the RMSEA and SRMR values are below the critical threshold, indicating that the model fits the data well, with values close to zero suggesting a low error level in modeling the data. Other indices, such as the Goodness of Fit Index (GFI), Comparative Fit Index (CFI), and others, also show high values, confirming the suitability of the model and the data. This suggests that the proposed model accurately represents the relationship between the variables in the research, providing confidence that the model can be used to explain the phenomenon of acceptance and use of ChatGPT among students.

Table 5 Correlation matrix of variables.

	BI	EE	FC	PE	SI	UB
BI	0.901					
EE	0.555	0.764				
FC	0.587	0.597	0.726			
PE	0.542	0.506	0.536	0.866		
SI	0.693	0.461	0.554	0.359	0.905	
UB	0.704	0.611	0.656	0.723	0.541	0.879

Table 6 Model Fit Indices.

Model Fit Indices	Values	Acceptable Values	Fitness
Chi-Square p-value	88,59	>0,05	Yes
RMSEA	0,074	<0,08	Yes
SRMR	0.058	<0,06	Yes
GFI	0.985	>0,90	Yes
CFI	0.985	>0,90	Yes
AGFI	0.973	>0,90	Yes
TLI	0.982	>0,90	Yes
NFI	0.980	>0,90	Yes
NNFI	0.982	>0,90	Yes
RNI	0.985	>0,90	Yes
RFI	0.976	>0,90	Yes
IFI	0.985	>0,90	Yes
PNFI	0.808	>0,05	Yes
PGFI	0.562	>0,05	Yes

The excellent fit between the model and the observed data provides additional confidence in the results of this study. These findings suggest that the proposed model can serve as a robust framework for understanding the factors that influence the acceptance and use of ChatGPT among college students. With a better understanding of the relationships between observed variables, stakeholders in the education sector can develop more effective strategies to increase the adoption of AI technologies in higher education environments. Additionally, the suitability of the model confirms that the measurement instruments used in the research have sufficient validity and reliability to be applied in this context. Therefore, these results not only offer valuable insights for researchers in this field but also contribute significantly to the development of educational policies and practices that are more adaptive and responsive to technological advancements.

3.4. Structural Model

Table 7 presents the correlation results between exogenous and endogenous variables in the research model. Exogenous variables are independent variables that influence endogenous variables, which are dependent on the research context. Referring to Hair (2010), the analysis results show significant correlations between exogenous and endogenous variables, as indicated by the reported t-values and p-values. Visually, the t-values between exogenous and endogenous variables can be observed in Figure 2.

Table 7 Correlation Between Exogenous and Endogenous.

Exogenous	Endogenous	t-values	p-values
Performance Expectancy	Behavioral Intention	5.893	0.000
Effort Expectancy	Behavioral Intention	3.111	0.002
Social Influence	Behavioral Intention	10.451	0.000
Facilitating Conditions	User Behavioral	8.334	0.000
Behavioral Intention	User Behavioral	11.397	0.000

First, a significant positive correlation exists between Performance Expectancy and Behavioral Intention, with a t-value of 5.893 and a p-value of 0.000. This indicates that the performance expectations associated with using ChatGPT positively influence users' behavioral intentions. Second, the correlation between Effort Expectancy and Behavioral Intention is also significant, with a t-value of 3.111 and a p-value of 0.002. This suggests that expectations of the effort required to use ChatGPT also influence user behavioral intentions. Furthermore, the correlation between Social Influence and Behavioral Intention is significant, with a high t-value of 10.451 and a p-value of 0.000. This demonstrates that social influences from the surrounding environment, such as peers or lecturers, play an essential role in shaping users' behavioral intentions toward ChatGPT.

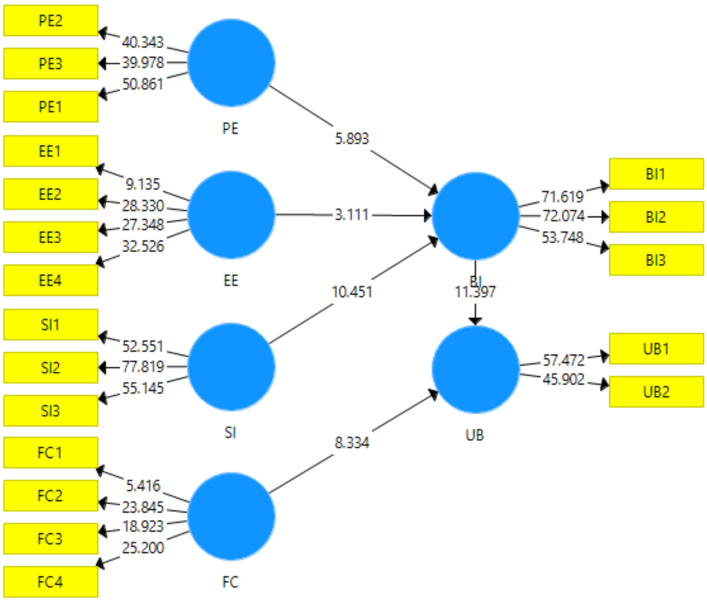

Figure 2 T-values between Exogenous and Endogenous.

Apart from that, there is a significant positive correlation between Facilitating Conditions and User Behavior, with a t-value of 8.334 and a p-value of 0.000. This indicates that conditions facilitating the use of ChatGPT have a positive effect on actual user behavior. Finally, the correlation between Behavioral Intention and User Behavior is also significant, with a t-value of 11.397 and a p-value of 0.000. This confirms that user behavioral intentions have a strong positive relationship with actual user behavior regarding ChatGPT. These results provide a deeper understanding of the factors influencing the acceptance and use of ChatGPT among college students and offer a significant contribution to developing a robust theoretical model in the context of technology adoption in higher education settings.

Table 8 below presents the status of the hypotheses proposed in this research, along with the correlation results and outcomes of the analysis. These hypotheses link different variables in the research model to test the relationships between them.

Table 8 Status of Hypothesis.

Hypothesis	Correlation	Outcome
H1	Performance Expectancy - Behavioral Intention	Accepted
H2	Effort Expectancy - Behavioral Intention	Accepted
H3	Social Influence - Behavioral Intention	Accepted
H4	Facilitating Conditions - User Behavior	Accepted
H5	Behavioral Intention - User Behavior	Accepted

The first hypothesis (H1) linking Performance Expectancy with Behavioral Intention is accepted after correlation analysis, indicating that performance expectations positively and significantly correlated with users' behavioral intentions regarding ChatGPT. Similarly, the second hypothesis (H2), connecting Effort Expectancy with Behavioral Intention, is also accepted after correlation analysis, revealing that the expectation of the effort required in using ChatGPT also positively and significantly correlates with the user's behavioral intention.

Furthermore, the third hypothesis (H3), linking Social Influence with Behavioral Intention, is also accepted, demonstrating that social influence from the surrounding environment is positively and significantly related to users' behavioral intentions regarding ChatGPT. Additionally, the fourth hypothesis (H4), associating Facilitating Conditions with User Behavior, is accepted, indicating that conditions facilitating the use of ChatGPT are positively and significantly correlated with actual user behavior. Finally, the fifth hypothesis (H5), connecting Behavioral Intention with User Behavior, is also accepted after analysis, revealing that user behavioral intention has a positive and significant relationship with actual user behavior regarding ChatGPT.

These results provide robust empirical support for the relationships between the variables proposed in the research model and offer a better understanding of the factors influencing the acceptance and use of ChatGPT among college students.

4. Discussion

4.1. Interpretation of Results

The results of this study shed light on the correlation of critical variables within the context of technology acceptance theory, offering valuable insights into the factors influencing the acceptance and utilization of ChatGPT among college students. According to Venkatesh (2003), Duman (2024), and Chao (2019), Performance Expectancy emerges as a pivotal factor influencing users' intention to adopt new technology. The correlation analysis results (Table 3) reveal a positive and significant association between Performance Expectancy and Behavioral Intention (PE-BI), suggesting that students are more inclined to use ChatGPT if they perceive it as enhancing their academic performance. This finding aligns with UTAUT's predictions, underscoring the significance of performance considerations in fostering technology adoption in higher education environments (Mahmud et al., 2024; Polyportis & Pahos; Shaengchart et al., 2023).

Furthermore, an examination of the relationship between exogenous and endogenous variables (from Table 7) bolsters the hypothesis of this study. The positive correlation between exogenous and endogenous variables indicates that specific factors influence users' intentions and behavior concerning ChatGPT. For instance, the positive link between Social Influence and Behavioral Intention (SI-BI) underscores the influential role of social factors from the surrounding environment, such as peers or lecturers, in shaping users' behavioral intentions (Graf-Vlachy et al., 2018; Haverila et al., 2023; Kulviwat et al., 2009; Talukder et al., 2013). Similarly, the correlation between Facilitating Conditions and User Behavior (FC-UB) highlights that conditions enabling the use of ChatGPT, such as easy access or technical support, directly impact actual user behavior (Buraimoh et al., 2022; Kamarozaman & Zaidi, 2021; Mansour et al., 2021).

These findings deepen our understanding of the interplay among critical variables in accepting and adopting ChatGPT in higher education settings. By comprehending the correlation between these critical variables, stakeholders in the education sector can devise more effective strategies to foster the adoption of this technology among students. These insights significantly contribute to refining existing theories of technology acceptance by enhancing our understanding of the factors influencing the acceptance of AI technology in educational environments.

4.2. Implications for Theory, Practice, Social and Ethical

This research significantly advances the existing theories of technology acceptance, particularly within the domain of integrating ChatGPT into higher education environments (Abate et al., 2023). By affirming the relationships between critical variables such as Performance Expectancy, Effort Expectancy, and Social Influence with Behavioral Intention and User Behavior concerning ChatGPT, these findings enrich our understanding of the determinants impacting the adoption of AI technology in academia.

Moreover, the practical implications derived from this research are profound, especially concerning teaching and learning practices within higher education (Montenegro-Rueda et al., 2023; Rejeb et al., 2024). By comprehending the factors influencing student acceptance and utilization of ChatGPT, educational institutions can devise more efficacious strategies for integrating this technology into the learning process. For instance, recognizing the significant impact of Social Influence on Behavioral Intention, educational institutions can design outreach or training programs for both lecturers and students to bolster recognition and acceptance of ChatGPT.

The social ramifications of deploying ChatGPT in higher education prompt crucial considerations across various facets of the educational process (Baldassarre et al., 2023). While ChatGPT technology holds the potential to significantly transform the learning process by facilitating faster access to information and offering more personalized learning assistance, it also poses implications for interactions between students and lecturers. While ChatGPT can serve as a valuable tool to support independent learning, ensuring that its integration does not diminish crucial interpersonal interactions between students and lecturers is imperative. Additionally, the increased utilization of ChatGPT may raise debates regarding its impact on the overall quality of teaching, prompting discussions on whether the technology can supplant or augment traditional teaching practices.

Furthermore, ethical considerations must be paramount when incorporating ChatGPT technology into higher education contexts (Flaih & Jasim, 2023). The issues surrounding data privacy and security are of utmost concern, mainly when students engage with systems leveraging AI technology for learning and assessment. It is imperative to safeguard against the misuse or unauthorized access of student data, ensuring the privacy and security of their personal information.

4.3. Research Limitations

Methodological limitations play a crucial role in contextualizing this research. Using questionnaires daily in technology acceptance studies has inherent drawbacks. Questionnaires may restrict the depth of responses and fail to capture contextual nuances that influence user perceptions and behavior. Moreover, the limited sample size, drawn from a few universities in specific areas, may impact the generalizability of the findings. Variability across higher education institutions and differences in academic culture could further limit the relevance of the results for the broader student population.

Understanding the implications of these limitations on the generalizability of the research findings is paramount. While the insights gained provide a valuable understanding of the factors influencing ChatGPT acceptance among college students, their applicability may be constrained to the studied population. It is crucial to acknowledge potential biases stemming from sample and methodological limitations, such as response bias induced by questionnaires, which could affect the data's validity and reliability.

Therefore, future research endeavors should address these limitations to enhance the generalizability of the findings. This could involve employing more representative and diverse samples from higher education institutions and contexts. Additionally, employing a mixed-methods approach, integrating in-depth interviews or field observations alongside questionnaires can enrich the research by capturing nuanced insights and contextual details that may be overlooked through surveys alone. By embracing these strategies, future research can offer a more comprehensive understanding of ChatGPT acceptance and utilization across diverse higher education contexts.

4.4. Suggestions for future research

Suggestions for future research are crucial for advancing our understanding of ChatGPT acceptance and usage in higher education contexts. Firstly, it is recommended that future studies adopt more intricate research designs. This could entail employing a mixed-methods approach, integrating questionnaires with in-depth interviews or field observations. Such a comprehensive approach would offer a holistic perspective on ChatGPT usage, enabling researchers to delve deeper into the relationships between variables and explore potential interactions that influence technology adoption.

Secondly, enhancing the sample's representativeness is paramount to ensure the generalizability of research findings. Future studies should aim to recruit participants from diverse higher education institutions across various regions, encompassing a wide range of demographic and academic backgrounds. This broader scope would facilitate a more nuanced understanding of how institutional factors, educational contexts, and individual characteristics impact ChatGPT acceptance and utilization.

Additionally, investigating contextual factors influencing ChatGPT acceptance and usage is essential for informing effective strategies in higher education settings. Future research endeavors could focus on exploring institutional support mechanisms, examining existing technology use policies, and evaluating the readiness of technological infrastructure in educational institutions. By comprehensively understanding these contextual factors, educational institutions can develop tailored strategies to foster ChatGPT adoption and ensure its integration delivers maximum benefits for both students and teaching staff.

5. Conclusion

This research has delved into the factors shaping the acceptance and utilization of ChatGPT among higher-education students. Through data analysis, significant relationships have been identified between variables such as Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions with Behavioral Intention and User Behavior concerning ChatGPT. These findings advance our comprehension of user behavior when adopting AI technologies like ChatGPT within academic environments.

Drawing from these research outcomes, several crucial implications emerge. Firstly, educational institutions need to consider the factors influencing student acceptance and usage of ChatGPT to craft effective strategies for its integration into the learning process. Secondly, further research is needed to employ more representative samples and sophisticated research methodologies to enhance the generalizability of results and deepen our insights into this phenomenon. Thirdly, attention must also be paid to the social and ethical dimensions of utilizing ChatGPT in higher education, encompassing its impact on the learning environment, student-lecturer interactions, and concerns surrounding privacy, data security, and equitable access to technology.

As recommendations for future research, it is encouraged that researchers employ more intricate research designs, broaden sample coverage, and meticulously examine the social and ethical implications of ChatGPT technology. Moreover, further exploration of contextual factors influencing the acceptance and usage of ChatGPT is warranted to enrich our understanding of this phenomenon. By adhering to these suggestions, future research endeavors in this domain can significantly contribute to advancing higher education and AI technology.

Ethical Considerations

To protect the anonymity of respondents, all collected data were encrypted and stored anonymously, with no personal identifying information linked to their responses. We also obtained written consent from each respondent after fully explaining the research objectives and their rights as participants.

Conflict of interest

The authors declare that no conflicts of interest are associated with this research. All analyses and conclusions were conducted independently without any external influence.

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