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Using an extended technology acceptance model to determine university students' behavioral intentions of ChatGPT

Veronica Aguilos*, Kevin Fuchs*

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Abstract

New technologies have contributed to propel transformations in higher education over the last decade and the emergence of ChatGPT has ignited considerable interest within academia. The study aims to analyze how different factors—perceived usefulness, perceived ease of use, attitude, and subjective norm— shape the behavioral intentions of university students when using ChatGPT in an educational setting. Therefore, the purpose of the study is to examine behavioral intentions of university students in utilizing ChatGPT. To achieve this objective, an extended Technology Acceptance Model has been used. Following a focus group discussion, students were recruited for the data collection using random sampling to investigate the model empirically. The findings revealed an enduring significance of perceived usefulness and ease of use in influencing students' attitudes toward ChatGPT. The article presents implications for theory and practice and advances the discussion about natural language processing models in higher education. Moreover, the study contributes to the body of knowledge by closing a theoretical gap in the literature on university students' behavioral intentions of ChatGPT.

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Introduction

In an era marked by rapid technological advancements, the integration of innovative technologies into various aspects of society has become inevitable. Technology has contributed significantly to profound transformations in higher education over the last decade (Benavides et al., 2020). This ongoing evolution is generating considerable interest within the academic community (Chen et al., 2020). Notably, the ascent of the natural language processing model, ChatGPT, has ignited extensive speculation among researchers and educators (Fitria, 2023). ChatGPT stands for Chat Generative Pre-Trained Transformer and is a natural language processing (NLP) model (Fuchs, 2023). It was developed by OpenAI and has the potential capability to revolutionize higher education (Fuchs, 2023). ChatGPT has the capacity to produce responses that resemble human-like interactions when presented with open-ended prompts, including questions, statements, or academic-related inquiries (Kasneci et al., 2023). In an era marked by rapid technological advancements, the integration of innovative technologies into various aspects of society has become inevitable (Machkour & Abriane, 2020). Understanding the factors influencing individuals' acceptance and utilization of these technologies has emerged as a critical concern (Almaiah et al., 2020). One foundational framework that has consistently contributed to unraveling this complex dynamic is the Technology Acceptance Model, or TAM for short (Ali et al., 2020).

ChatGPT's influence on educational systems raises intriguing questions about its potential impact on teaching methodologies, student learning processes, and the broader educational landscape (Tlili et al., 2023). As the landscape of technology evolves, it is imperative to adapt TAM to suit the ever-changing technological milieu (Granić & Marangunic, 2019). Over time, different researchers have extended

the model by introducing new variables and further fine-tuning the relationships among them (Granić & Marangunic, 2019). According to Abdel and Al-Yuzbaki (2023), perceived social norms have a significant influence on technology acceptance and usage. These concerns require a comprehensive empirical investigation into university students' behavioral intentions regarding ChatGPT with an adapted version of the TAM with the addition of subjective norms as an additional variable. Consequently, the study aims to analyze how different factors—perceived usefulness, perceived ease of use, attitude, and subjective norm—intersect to influence the behavioral intentions of university students in utilizing ChatGPT within an educational context.

Literature review and hypotheses development

In today's rapidly evolving technological landscape, the Technology Acceptance Model (TAM) has become a cornerstone for understanding why people embrace or resist new technologies (Montargot & Lahouel, 2018). Particularly, since the global pandemic in 2020, educators and students started to (willingly or unwillingly) adapt to digital learning technologies (Bereiter & Sansone, 2022). ChatGPT has markedly influenced educational systems, leading to inquiries about its potential effects on teachers' work methods and students' learning processes. Having charted the journey from the inception of TAM, its extension, the rise of AI and chatbots, and the advent of ChatGPT, it becomes imperative to delve into the core elements that constitute these models and technologies (Kasneci et al., 2023). The constructs of perceived usefulness (PU) and perceived ease of use (PEOU) form the backbone of the TAM, influencing behavioral intentions toward technology use. Perceived usefulness refers to the extent a user believes that using a specific application will enhance their performance (Liaw & Huang, 2013). Liaw and Huang (2013) argue that this belief can significantly influence an individual's attitude toward using technology. On the other hand, perceived ease of use is related to the effort the user believes they must expend to use the application (Yuan et al., 2016).

Prospective users may feel that a system or technology is advantageous while also believing that the system or technology is difficult to use (Kasneci et al., 2023). Therefore, the perceived usefulness and perceived ease of use are crucial parts of the model and significantly shape the user's attitude toward adopting new technology (Mantello et al., 2023; Montarget & Lahouel, 2018). The user's belief in the technology's ability to improve performance (perceived usefulness) and their perception of its ease of use directly impact their overall receptivity towards adopting the technology (Mantello et al., 2023). When users perceive technology as both beneficial and user-friendly, their inclination to embrace it becomes more favorable (Cho & Sagynov, 2015).

H₁. Perceived usefulness significantly impacts the attitude toward using ChatGPT

H₂. Perceived ease of use significantly impacts the attitude toward using ChatGPT

In essence, TAM is a reliable framework for understanding technology adoption (Mantello et al., 2023). However, the extent to which it explains adoption and the significance of different predictor variables can fluctuate depending on the specific samples studied (Scherer & Teo, 2019). Moreover, how easy or difficult a technology is to use significantly affects how users perceive its usefulness (Blut & Wang, 2020). When technology is user-friendly and straightforward, people tend to see it as more practical and beneficial (Ghazali et al., 2018). On the other hand, if a technology is complicated and hard to navigate, users may view it as less useful, leading to reluctance to adopt it (Arif et al., 2020). Therefore, understanding this connection between ease of use and perceived usefulness is crucial for researchers and developers aiming to create user-friendly technologies that are more likely to be embraced by users in different contexts.

H₃. Perceived ease of use significantly impacts the perceived usefulness of ChatGPT

H₄. Perceived usefulness significantly impacts the behavioral intentions of ChatGPT

Over time, different researchers have extended the model by introducing new variables and further fine-tuning the relationships among them (Granić & Marangunic, 2019). A study conducted by Abramson et al. (2015) investigated the usage of e-learning throughout an extended TAM and discovered that perceived ease of use affected attitudes toward usage substantially. In another study, the factor subjective norm was incorporated into the core model to acknowledge societal factors and perceived social norms significantly influencing individual technology acceptance and usage, aiming to present a more comprehensive view of determinants impacting technology adoption (Abdel & Al-Yuzbaki, 2023). Subjective norm is defined as an individual's opinion that the majority of key individuals in his or her life believe he or she should or should not conduct the action in issue (Reynolds et al., 2015). Venkatesh and Davis (2000) mention that subjective norm has a positive effect on an image, which in turn has a positive effect on perceived usefulness and the direct effect of subjective norm on intentions may subside over time with increased system experience.

H₅. Subjective norm significantly impacts the behavioral intentions toward ChatGPT

The role of attitude in the context of technology acceptance is pivotal and therefore said to significantly impact users' behavioral intentions (Chi et al., 2022). Defined within the Technology Acceptance Model (TAM), an attitude reflects a user's positive or negative feelings about performing the target behavior, primarily influenced by the system's perceived usefulness and ease of use (Song, 2019). Empirical studies have substantiated the correlation between a user's attitude toward technology and their intention to use it, indicating that a more favorable attitude often leads to a higher intention to utilize the technology (Abdel-Maksoud, 2018). Furthermore, attitude is influenced by other TAM components, including PU and PEOU, which subsequently affect behavioral intentions (Abdel-Maksoud, 2018). In the context of AI technologies, some studies have demonstrated that us-

ers' attitudes toward these systems can greatly dictate their inclination to utilize them (Song, 2019).

H₆. Attitude significantly impacts the behavioral intentions toward ChatGPT

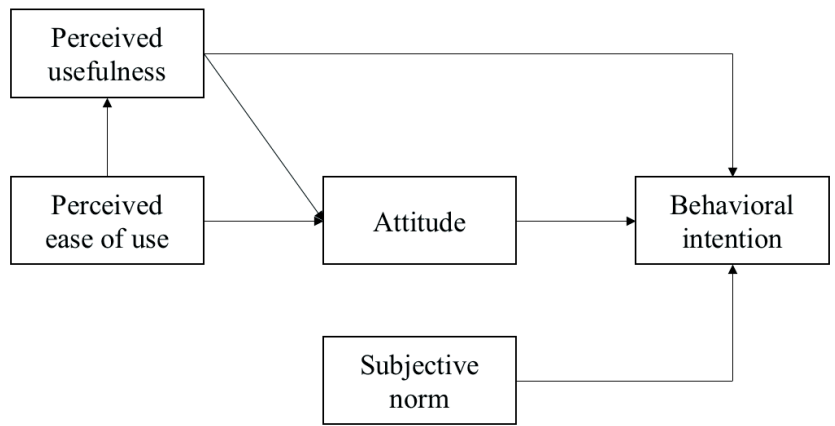
Additionally, as alluded to earlier, ChatGPT has ignited considerable attention in the academic world for its transformative potential in education (Fuchs, 2023). However, it has also raised concerns about its ethical application, academic integrity, and the maintenance of moral values (Fuchs, 2023; Kasneci et al., 2023). It is important to note a limitation in the validity of this claim as the information used does not directly come from educators or students who have used the system. Acknowledging the limitation that the previous claims lacked direct input from educators and students who have experienced the system, there is a potential for the understanding of the system's genuine impact and practical implications to be distorted.

While TAM and eTAM have been extensively applied to a variety of contexts to predict and explain technology acceptance and usage behaviors, their specific application to natural language processing (NLP) technologies within educational settings is an underexplored area (Granić & Marangunić, 2019). This represents a notable gap, given the increasingly pivotal role that NLP technologies, such as chatbots and AI-driven learning tools, play in modern educational contexts (Escotet, 2023). Essentially, the study adopts a conceptual framework by extending the TAM adapted from Lee et al. (2003) as well as Marangunić and Granić (2015) with the factor subjective norm from the Theory of Reasoned Action (TRA) adapted from Madden, Ellen, and Ajzen (1992) as well as LaCaille (2020) with as seen in Figure 1 in order to empirically determine university students' behavioral intentions of ChatGPT.

The application of the eTAM, particularly with the addition of the subjective norm variable, to the study of ChatGPT is compelling and essential (Taherdoost, 2018). Within an educational context, the acceptance and usage of such tools cannot exclusively be predicted by their capabilities in aiding tasks and facilitating learning environment factors (Oke & Fernandes, 2020). This is where the eTAM becomes

Figure 1.

A conceptual framework based on an extended technology acceptance model (eTAM)



especially relevant. Subjective norm, as an additional factor, acknowledges the influence of peers, teachers, or even broader societal perceptions on using AI-based tools like ChatGPT. The complex interplay of these factors — perceived usefulness, perceived ease of use, attitude, and subjective norm — in determining students’ behavioral intentions toward ChatGPT makes this a necessary area of research.

Methodology

The objective of this study was to analyze how different factors—perceived usefulness, perceived ease of use, attitude, and subjective norm—intersect to influence the behavioral intentions of university students in utilizing ChatGPT within an educational context. To achieve this goal, we employed an extended Technology Acceptance Model (eTAM) as the methodological framework for empirical investigation. The establishment of a robust and reliable methodological framework involved a series of steps, which have been meticulously undertaken and documented as outlined below.

Focus group discussion

The focus group discussion was organized as a preliminary step in the research process, involving seven undergraduate university students (including three Thai nationals and four Chinese students). Participants were selected by the researcher based on their availability and voluntary acceptance to participate in the discussion. Before proceeding, all participants provided written consent, which included ethical considerations such as confidentiality agreements, voluntary participation, and compensation for their time. The discussion, conducted in a casual environment outside the university, lasted for three hours. Initially, participants were provided with the initial list of survey statements and a Google Form sample and were encouraged to provide individual comments and suggestions. Following this, they engaged in a discussion guided by semi-structured questions about their general experiences with ChatGPT in an educational context. These questions aimed to gain more insights into their usage and the influence of using ChatGPT, potentially uncovering additional questions that might have been missed. The discussion was recorded with their consent.

The intended survey structure consisted of a 5-point Likert scale for evaluating the various factors of the Technology Acceptance Model (TAM) accompanied by sociodemographic questions (available through <https://dx.doi.org/10.6084/m9.figshare.25656315>). Feedback from the focus group, including individual comments and recorded discussions, was thoroughly analyzed using content and narrative analysis. The content analysis enabled the researchers to systematically examine the themes and patterns within the participants' feedback on the survey structure, including the length, complexity, and relevance of the questions. Narrative analysis, on the other hand, facilitated an in-depth understanding of the personal stories and experiences shared by participants regarding ChatGPT. These informative areas may have been overlooked in the initial survey design. The combined use of these analysis methods provided a comprehensive perspective on students' attitudes towards ChatGPT in the educational context. The analysis revealed that the questions

might have been too long and complicated due to limited English skills. Subsequent revisions were made to simplify the survey statements and remove redundancies. Thereafter, the survey statements were translated into Chinese and Thai to facilitate a trilingual survey. These changes were essential for the study, ensuring that the questions and length would be appropriately tailored for the target participants. By aligning the survey with the linguistic needs and comprehension levels of the participants, the refined survey is anticipated to more accurately reflect the behavioral intentions and attitudes toward ChatGPT within the university student population.

Research instrument

The default responses on the 5-point Likert-type scale ranged from 1 [lowest] to 5 [highest], i.e. Strongly Disagree [1], Disagree [2], Neither Agree nor Disagree [3], Agree [4], and Strongly Agree [5]. A five-point Likert scale strikes a balance between granularity and simplicity, making it comprehensible and accessible to participants of varying familiarity, thus reducing the cognitive load (Jebb et al., 2021). The trilingual survey statements – corresponding to the five factors – were adopted from a previous study (Fuchs, 2022) and modified to the context of this study through the focus group discussion. In addition, eight questions sought to establish the sociodemographic profile of the participants as reported in Table 1. The factor *perceived usefulness* (PU) included three statements such as “ChatGPT helps me study and prepare for assignments and other tasks faster”. The variable *perceived ease of use* (PEU) was assessed through four statements including “I can learn to use ChatGPT quickly”. The third factor, *attitude* (AT), was measured through three statements such as “I like doing my assignments, projects, or reports with ChatGPT”. The fourth variable, namely *subjective norm* (SN), was calculated with four statements, including “People close to me agree that I should use ChatGPT in my studies”. Finally, the last variable, *behavioral intentions* (BI), was measured with four statements, including “I expect that I have to use ChatGPT after I graduate from university”.

Data collection and sample

The data collection was carried out using simple random sampling, a probability-based method, in which a subset of participants was randomly chosen from the overall population (Etikan & Bala, 2017). The data collection was conducted with university students on Phuket Island in Thailand between August and September 2023 and responses were collected via a self-administered survey form. After screening the collected data and excluding incomplete data from inclusion the final sample included 135 responses to represent the population in data analysis. King and He (2006) note that a recommended sample of 225 is desirable to determine correlations using the Technology Acceptance Model, however, Deng et al. (2005) state that a minimum of 100 is required. Therefore, the achieved sample of 135 for this study was considered adequate. Based on eligible responses, the sociodemographic profile of the participants was summarized in Table 1 (including the respondents’ gender, year of study, age range, nationality, place

Table 1.
Sociodemographic profile of the sampled population

Characteristic		Frequency	Percentage
Gender	Female	79	59%
	Male	56	41%
Nationality	Thai	92	68%
	Foreign	43	32%
Degree Level	Bachelor’s Degree	125	93%
	Master’s Degree	10	7%
Study Major	Tourism & Hospitality	97	72%
	Computer & Technology	18	13%
	Business & Economics	12	9%
	Others	8	6%
Year of Study	Year 1	6	4%
	Year 2	51	38%
	Year 3	20	15%
	Year 4 or above	58	43%

Note. The average age of the participants was 21.65 years with a standard deviation (SD) of 4.208

of study, and study major). To protect the identity of the participants, some specific information in the sociodemographic profile was generalized before disclosure in this paper, namely minority nationalities were grouped as “foreign” instead of displaying the particular nationality as this could potentially allow exposing the identity of the participant.

Results and analysis

SPSS (Statistical Package for the Social Sciences) Version 27 was employed for the execution of an array of statistical analyses. Initially, the computation of mean values (represented as μx) and standard deviations (represented as σ) was performed for each respective statement. Subsequently, an evaluation of internal consistency and reliability was conducted utilizing Cronbach’s alpha, followed by an assessment of construct validity through factor analysis. In pursuit of the research objectives, linear correlation analysis was employed to discern statistically significant correlations using the Pearson correlation coefficient.

Principal factor analysis and reliability test

The initial phase of the statistical analysis involved assessing the reliability and construct validity. The measurement aimed to establish internal consistency across the variables to establish robust internal validity. An alpha of more than 0.7 would indicate that the items are homogeneous and measure the same constant (Barbera et al., 2020). Although Cronbach’s alpha coefficients within the range of 0.6 to 0.7 were considered the lower threshold of acceptability, denoting the requisite homogeneity among items (Barbera et al., 2020). The Cronbach’s alpha scores ranged from 0.736 to 0.786 (as reported in Table 2) and therefore exceeded the recommended threshold, confirming the survey’s internal consistency and hence denoting a high reliability. To evaluate the construct validity, a factor analysis was conducted.

Utilizing a principal factor analysis approach with varimax rotation, the analysis targeted the underlying structure of the 18 items

comprising the survey (namely, perceived usefulness, perceived ease of use, attitude, subjective norms, and behavioral intentions). The outcomes of this analysis indicated that the first factor accounted for 14.7% of the total variance, followed by the second factor for 13.2%, the third factor for 18.5%, the fourth for 11.9%, and lastly, the fifth for 18.4% of the total variance. The tabulated results present the factor loadings after rotation, with those below the 0.60 thresholds omitted for enhanced clarity (Table 2). Notably, all the obtained factor loadings surpassed the 0.6 threshold, attesting to a robust convergent validity (Zinbarg et al., 2005). This analysis affirms the unidimensional nature of each construct, with individual items aligning predominantly with a single factor, further affirming the construct’s distinctiveness.

Table 2.
Results of principal factor analysis and reliability test for internal consistency

Scale Item	Mean	SD	Cronbach's alpha	F1	F2	F3	F4	F5	
PEU1	3.963	0.950	0.752	0.819					
PEU2	3.844	0.897		0.812					
PEU4	3.674	1.014		0.752					
PEU5	4.015	0.922		0.651					
PU1	3.741	0.828	0.776		0.822				
PU2	4.081	0.947			0.854				
PU4	3.830	1.103			0.828				
AT1	3.296	0.978				0.794			
AT2	3.541	1.056	0.736			0.863			
AT3	3.593	1.053				0.770			
SN1	3.363	0.927		0.738				0.755	
SN2	3.911	0.934						0.618	
SN3	2.956	1.152					0.832		
SN4	3.163	1.073					0.777		
BI1	3.889	0.895	0.786					0.806	
BI2	3.770	0.992						0.797	
BI4	4.207	0.955						0.696	
BI5	3.830	1.048						0.822	
% of variance explained				14.7	13.2	18.5	11.9	18.4	
Cumulative percentages				14.7	27.9	46.4	58.3	76.7	

Note. Principal axis factoring was used with varimax rotation, rotation converged in four iterations.

^a Factors: EU = Perceived Ease of Use; PU = Perceived Usefulness; AT = Attitude, SN = Subjective Norms, BI = Behavioral Intentions

Linear correlation analysis

In the next phase, the Pearson correlation coefficient was calculated, and the results are reported in Table 3 and Figure 2. The Pearson correlation coefficient requirements were all consistent and based on best practices by Benesty et al (2009). Altogether, all six pair-wise combinations have a statistically significant relationship ($< .001$). According to Benesty et al. (2009) and Schober et al. (2018), an r -value between 0.1 and 0.39 indicates a minor positive correlation, whereas an r -value between 0.40 and 0.69 indicates a moderate positive connection. Finally, a strong positive correlation has an r -value of 0.7 or above. Based on the six pair-wise combinations, a moderate correlation exists between all six relationships ranging from 0.484 to 0.630 in strength. Namely, the different strengths resulted in the following measures: *Perceived usefulness* and *attitude* (.630, $p < .001$), *perceived ease of use* and *attitude* (.484, $p < .001$), *perceived ease of use* and *perceived usefulness* (.516, $p < .001$), *perceived usefulness* and *behavioral intentions* (.546, $p < .001$), *subjective norm* and *behavioral intentions* (.570, $p < .001$), and finally, *attitude* and *behavioral intentions* (.517, $p < .001$). Table 3 also includes the results of the Shapiro-Wilk test for bivariate normality and indicates that the result does not significantly deviate from a normal distribution.

Table 3.
Pearson's correlation (r) analysis

Pair-wise correlation	<i>r</i>	<i>p</i>	Lower 95% CI	Upper 95% CI	Shapiro- Wilk
PU → AT	0.630 *	< .001	0.516	0.722	0.969
PEU → AT	0.484 *	< .001	0.343	0.603	0.966
PEU → PU	0.516 *	< .001	0.380	0.630	0.967
PU → BI	0.546 *	< .001	0.461	0.655	0.958
SN → BI	0.570 *	< .001	0.444	0.674	0.956
AT → BI	0.517 *	< .001	0.382	0.631	0.962

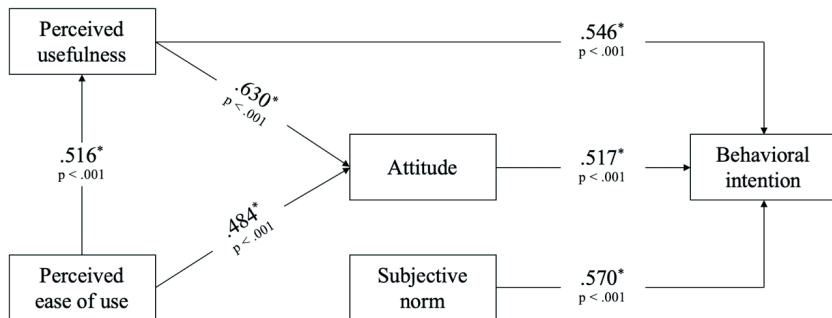
Note. The analysis is based on the conceptual model influencing students' behavioral intentions of using ChatGPT for their university studies

^a $p < .001$ indicating a statistically significant collection between the factors. ^b Factors: EU = Perceived Ease of Use; PU = Perceived Usefulness; AT = Attitude, SN = Subjective Norms, BI = Behavioral Intentions

The model highlights the statistically significant relationship between the variables. To sum up, there is a statistically significant correlation ($p < .001$) for all relationships within the model, and therefore, all six hypotheses are confirmed and thus can be accepted. Furthermore, the observed correlation between the six variables demonstrated a moderate strength varying between 0.484 to 0.630.

Figure 2.

The result of the regression analysis indicates the strength of the relationship among the variables



Discussion and implications

The objective of this study was to analyze how different factors—perceived usefulness, perceived ease of use, attitude, and subjective norm—intersect to influence the behavioral intentions of university students in utilizing ChatGPT within an educational context. All the pair-wise correlations, ranging from 0.484 to 0.630, fall within the moderate strength category. This suggests that each of these constructs has a meaningful and moderate influence on each other (Benesty et al., 2009). The strongest relationship is observed between perceived usefulness (PU) and attitude (AT) with an R-value of 0.630. This shows that students' perceptions of the usefulness of ChatGPT play a significant role in shaping their attitudes towards it. In this case, students notice its distinct advantages. This leads them to develop

a more positive view of the platform. To support this statement, a hospitality and tourism management student mentioned in the open comment field of the survey that “it can be useful in terms of processing the pattern of idea in many different ways in Chat GPT. Unlike Google [search], Chat GPT is more likely to give a clearer answer”. This sentiment is in line with the principles of the Technology Acceptance Model (Kamal et al., 2020) which suggests that the way users see the usefulness of a technology can directly impact their willingness to use it. In essence, when students see the benefits of ChatGPT in their academic journey, their eagerness to engage with it increases. Highlighting the tangible benefits of such technologies becomes crucial in promoting a positive user perspective.

The evident connection between perceived usefulness (PU) and attitude (AT) suggests a broader implication: Students likely perceive ChatGPT as a tool that can significantly enhance their learning journey. This perception is likely rooted in ChatGPT’s capabilities to offer immediate, comprehensive, and tailored feedback, transforming the learning process into a more dynamic and immersive experience (Fitria, 2023; Fuchs, 2022). Echoing this sentiment, a male student remarked, “I might use ChatGPT to assist with a wide range of tasks, such as answering questions, brainstorming ideas, generating content, learning new topics, practicing language skills, and more. It is a versatile tool that can provide helpful insights and information in a conversational manner.” Such firsthand accounts underscore the potential of ChatGPT as a multifaceted educational aid, aligning with broader research on the benefits of interactive learning tools (Saleem et al., 2022).

Transparency and ethical awareness are paramount in the integration of AI technologies like ChatGPT into higher education (Rios-Campos et al., 2023). To effectively address these considerations, educational institutions must establish clear ethical guidelines that explicitly define the scope and limitations of AI usage within academia (Rios-Campos et al., 2023). Such guidelines should encompass issues related to academic integrity, privacy, and responsible AI utilization (Cathrin & Wikandaru, 2023). Simultaneously, institutions should actively promote ethical awareness and open discussions within the

academic community. By openly acknowledging the capabilities and limitations of ChatGPT and other NLP models, universities foster a culture of transparency, ensuring that both educators and students comprehend the role of AI in education fully. This transparency enables students to make informed decisions regarding their engagement with AI technologies and sets clear expectations for responsible usage.

Moreover, there are other implications deriving from the study. It is noteworthy to mention that the findings from this study contribute to the existing literature on the Technology Acceptance Model (TAM) by reaffirming the enduring importance of perceived usefulness and perceived ease of use as pivotal determinants in influencing behavioral intentions. The study's findings underscore the robustness of these foundational TAM constructs in the context of ChatGPT adoption within higher education. Moreover, the study identifies the critical role of social norms (as introduced through the Extended Technology Acceptance Model) in shaping technology acceptance and behavioral intentions. These theoretical implications not only enhance our understanding of the core TAM constructs but also advocate for the continued examination of the evolving socio-cultural factors that play a crucial role in shaping technology acceptance behaviors, thus fostering a more comprehensive and dynamic framework for studying technology adoption in the modern era.

Conclusion and future research

The study aimed to investigate university students' Chat Generative Pre-Trained Transformer (ChatGPT) adoption intentions within higher education using an Extended Technology Acceptance Model (eTAM). Key findings underscore the enduring significance of perceived usefulness and ease of use in influencing students' attitudes toward ChatGPT. The inclusion of subjective norms in the eTAM highlights the pivotal role of social influences on technology acceptance within education. These insights emphasize the importance of a holistic approach to technology adoption, considering both technical and socio-cultural factors. Moreover, the limitations of this study offer

potential areas for future research. For instance, comparative studies conducted in different geographical settings could better assess the impact of social norms on perceived behavioral intention toward ChatGPT adoption. Understanding how cultural factors shape technology acceptance can inform tailored strategies for AI integration in diverse educational contexts. Future research should strive for larger and more diverse samples, ensuring enhanced generalizability of findings to a broader student population and strengthening the foundation for informed decision-making in the realm of AI technology adoption within academia. Lastly, the statistical analysis conducted on the survey instrument affirms its reliability and validity. Such robustness in the instrument's design and structure ensures that the findings derived from it are trustworthy and can be used confidently to draw meaningful conclusions. Future studies can also consider using this instrument, given its demonstrated reliability and validity, to explore similar research questions or contexts.

Etichal Aspects

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