Do Academic Stress and Risk Propensity Affect Behavioral Intention to Use ChatGPT among University Students?

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Abstract: The widespread adoption of support tools, such as artificial intelligence, is evident across various fields, including the academic community. Students' attitudes towards using AI tools like ChatGPT significantly impact their utilization. The research employs the Theory of Reasoned Action (TRA) framework, incorporating academic stress and risk propensity as additional constructs to examine students' attitudes toward ChatGPT. The study focuses on college students using AI tools for academic purposes. A survey was conducted across educational institutions, yielding 413 responses. Analysis using the Partial Least Squares – Structural Equation Model revealed that academic stress and peer influence do not positively affect the intention to use ChatGPT. However, academic stress and risk propensity positively impact students' attitudes toward ChatGPT, influencing the intention to use the tool. The study recommends expanding research to include teachers and other professionals, considering diverse cultural settings and employing various research methods. The findings also provide insights for academia to enhance the adoption and integration of AI tools.

Keywords: ChatGPT, Artificial Intelligence Tools, Theory of Reasoned Action (TRA), Academic Stress, Risk Propensity

1. Introduction

Integrating artificial intelligence (AI) technology in the workplace is becoming increasingly prevalent, which paved the way for a new kind of workplace powered by AI, which is set to bring about a revolutionary change in how we manage and operate in the working environments. With the rise of AI-powered technologies, companies and organizations can look forward to a more efficient and productive work environment that can streamline workflows and optimize resources. As such, understanding the potential impact of AI on the future workplace is crucial for institutions, employees, and even students. AI can be a valuable tool in education, reducing the workload of both educators and learners while also providing students with high-quality learning opportunities (Loeckx, 2016). With the advancement of technology, AI in education is becoming increasingly popular and can potentially revolutionize the education sector (Luckin et al., 2016; Xuesong Zhai et al., 2021).

It is evident today that there is a high demand for teaching and learning, which has led to considerable pressure on the education sector. The study of the student-teacher ratio across ASEAN secondary schools (Ancho et al., 2021) showed that the Philippines has the highest number of students per teacher. This means that each teacher's support for each student is significantly reduced, which might compromise students' learning. Dealing with these tremendous realities, the management and experts in the education sector started to embrace the importance of chatbots and related AI-based learning tools such as ChatGPT. It has been argued that an essential benefit of chatbots is their ability to individually provide personalized and focused support to students (Winkler & Söllner, 2018). Computer-based chatbots are becoming more common in our daily lives. They are now essential to various technologies, such as mobile personal assistants, telephone-based technical support, and learning and health interventions (Serban et al., 2017).

While ChatGPT has been generating increasing attention in education, further research on students' perceptions and intentions toward this technology is necessary to prepare for an AI-enabled society. Despite its potential to revolutionize the learning experience, relatively few studies have investigated how students feel about using ChatGPT in educational settings. The study will use TRA as a theoretical framework to analyze the relationships between academic stress, risk propensity, attitudes, and intention toward ChatGPT adoption. Using the Theory of Reasoned Action (TRA) as a lens for analysis, the study intends to provide valuable insights into the existing literature on the factors that drive the adoption of AI-powered learning tools and how individuals' academic stress and risk propensity toward the attitude influence their behavioral intention.

2. Literature Review

According to prior studies (Chassignol et al., 2018; Hwang et al., 2020), AI is a game-changer in education, empowering students with intelligent systems for assessments, data collection, and innovative teaching and learning strategies. This integration of AI is one of the primary research in computers and education, with the potential to transform human knowledge and promote educational reforms (Yang, 2022; Chatterjee & Bhattacharjee, 2020). However, Touretzky et al. (2019) argued that while AI has the potential to revolutionize many areas of society, its use can also have negative consequences. The study of Popenici and Kerr (2017) argued that further research in this field is necessary to develop ethical guidelines and practical implementation strategies to address the drawbacks of this technology for teaching, learning, and administration.

In a recent study by (Bonsu & Baffour-Koduah, 2023), higher education students' perceptions and intentions to use ChatGPT were examined using the Technology Acceptance Model (TAM). The researchers combined two critical constructs from the model, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), into a single variable labeled as "perceptions." The study's findings indicated that perception significantly predicted and influenced the students' intention to use ChatGPT. The survey of Zhai (2022) showed several reports, in both preprint articles and various forms of media, highlighting the advantages of using ChatGPT in educational settings. Other reported studies have argued that ChatGPT can support learning, help students struggling with academic performance, and provide guidelines for using it in physical and virtual classrooms (Mollick & Mollick, 2022). In a recent study conducted by Haque et al. (2022), a Twitter sentiment analysis was performed to investigate public attitudes toward adopting ChatGPT as a technology outside the context of education. The study discovered that users hold divided attitudes toward the technology, with positive and negative sentiments expressed. As the use of ChatGPT in education becomes widespread, it is crucial to conduct research and investigate the potential concerns associated with its adoption and use (Tlili et al., 2023).

Moreover, investigating students' perceptions of ChatGPT, including their attitudes towards its use and the peer influence surrounding its adoption and use, can provide insights into their intentions to use this technology. By understanding these factors, educators and policymakers can design interventions to promote the adoption and effective use of ChatGPT in education. As such, applying and extending the Theory of Reasoned Action or TRA can help guide future research on ChatGPT and inform the development of strategies to enhance its integration in educational settings. This study integrates academic stress and risk propensity as extended constructs TRA to add to the current literature on the adoption and intention to use ChatGPT in educational settings.

3. Theoretical Foundations

The (TRA) Theory of Reason and Action (Ajzen & Fishbein, 1980; Ajzen, 1975) is used to predict individuals' behavior based on their attitudes and behavioral intentions, its demonstrated effectiveness in predicting variability in people's behavior across many contexts, populations, and behaviors (Hager, 2019). Attitude and peer influence are the primary components of understanding a person's behavioral intention. Peer influence refers to the students' view that ChatGPT is appropriate because their peers and attitudes are the students' perceptions that utilizing ChatGPT can promote their academic goals. This theory has been widely used to forecast various human behaviors, including individuals' and organizations' uptake of information systems. It addresses two constructs: "attitude toward behavior" and "peer pressure," strongly emphasizing the person's beliefs.

Academic Stress is widely acknowledged as a relationship between the person and the environment. When an individual's resources are insufficient to handle the demands and stresses of the circumstance, a psychological and physical condition arises (Michie, 2002). The Risk Propensity is an individual factor that could influence risk-taking behavior (Zuckerman et al., 1964), and people will be risk averse when they perceive themselves to be in the domain of gain and risk-seeking in the domain of loss (Kahneman & Tversky, 1979).

Most students reported that academic difficulties were the primary source of stress, followed by physical, social, and emotional factors. Most stressed-out students' self-esteem was low, and almost half had high depression scores (Baste & Gadkari, 2014). According to research findings, higher stress levels are linked to subpar academic performance (Sohail, 2013). Numerous research has shown that stress related to exams, selecting a course of academic study, or a future vocation was linked to parental demands and teachers' expectations (Acharya, 2003; Tangade et al., 2011). The study of Lungu and Sun (2016) determines that students are willing to use technology to decrease their stress.

Risk propensity refers to an individual's willingness to take risks or engage in risky behavior (Gilley et al., 2002). People are ready to take risks for several reasons, including achievement motivation (Atkinson, 1957), which could be why students are willing to take risks. In some cases, risk-seeking behavior reveled in frequently exploited innovative technology. As a result, the study by Tabak and Barr (1999) and Forlani et al. (2002) discovered that a firm's risk-taking proclivity influenced its intention to accept technical innovation, like accepting the new AI tools (ChatGPT).

The study hypotheses are summarized in Figure 1 and are framed into the following statement:

H1: Attitude has a positive and significant influence on the Intention to Use ChatGPT.
H2: Peer Influence has a positive and significant influence on the intention to use ChatGPT.
H3: Academic Stress has a positive and significant influence on attitude towards intention to use ChatGPT
H4: Risk Propensity has a positive and significant influence on attitude towards intention to use ChatGPT
H5: Academic Stress has a positive and significant influence on the intention to use ChatGPT
H6: Risk Propensity has a positive and significant influence on intention to use ChatGPT

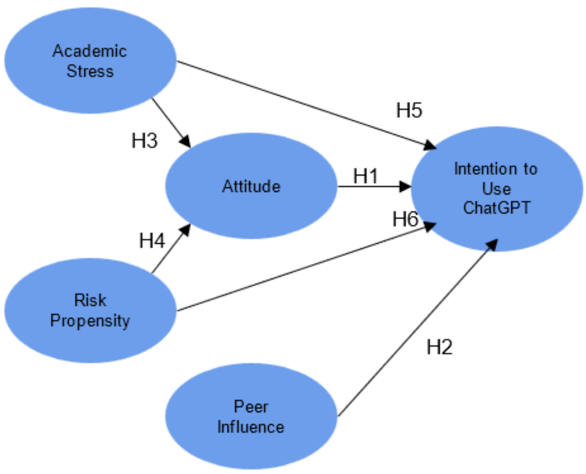

Figure 1. Theoretical Framework and Hypotheses.

4. Methodology

To validate the hypothesis and examine the suitability of the Theory of Reasoned Action (TRA) in the context of ChatGPT, the researcher adapted questions from previous studies and designed a survey instrument to represent the structural model. Three (3) universities in the Philippines were included to gather data from a broad and diverse population. The administrators approved to administer the survey to students. The participants provided informed consent, and no personal identifying information was collected. All participants were above 18 years old. The pilot survey instrument was distributed online using Google Forms as a platform for data collection. This approach allowed the identification of potential issues or flaws with the survey, such as confusing or ambiguous questions, unclear instructions, or technical problems. By testing the instrument in a controlled setting, insights were gathered, and necessary adjustments were made to improve the quality and validity of the data.

To operationalize the construct of academic stress (AS) within our extended TRA model, four (4) questions from the study conducted by Bedewy and Gabriel (2015) were included. In addition, to accurately capture the dimension of the Risk Propensity (RP) construct within the extended TRA model, the proponents included four (4) questions that have been adopted from the research conducted by Agustina and Fauzia (2021) and Koohikamali and Sidorova (2017). Attitude (ATT) with four (4) questions and intention (INT) with three (3) questions are the two primary constructs of the TRA that were included in the studies of Zhang (2007) and Buabeng-Andoh (2018). Finally, to represent the dimension of Peer Influence (PI), five (5) questions were included from the studies of Chang (2014) and Al Mamun et al. (2019).

The results of the pilot testing sample of 34 students, as shown in Table 1, were analyzed using the Partial Least Squares regression method using SmartPLS statistical software. This validation testing analysis ensures the instrument's validity and reliability by meeting the minimum threshold of Cronbach's Alpha (0.70), Average Variance Extracted (0.60), and Composite Reliability (0.70), following Hair et al. (2014) guidelines for establishing instrument reliability and validity.

Table 1. *Instrument Validation*

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Academic Stress	0.893	0.896	0.757
Risk Propensity	0.880	0.885	0.735
Attitude	0.898	0.898	0.765
Peer Influence	0.909	0.918	0.735
Intent to use ChatGPT	0.931	0.931	0.878

The Fornell-Larcker criterion test is widely recognized and trusted for establishing discriminant validity in research studies. It is essential to establish discriminant validity to ensure that the survey instrument accurately measures each construct and does not overlap with other constructs in the study (Hair et al., 2014). To enhance the credibility and reliability of the survey instrument utilized in our research, we conducted a Fornell-Larcker criterion test to evaluate discriminant validity. We examined the results meticulously and found that the square root of the Average Variance Extracted (AVE) for each construct was more significant than the other inter-construct correlation values. The test results, presented in Table 2, showed that the survey instrument was effective in terms of the Fornell-Larcker criterion test, thereby confirming the presence of discriminant validity (Yang et al., 2016; Nelson et al., 2016).

Table 2. *Fornell-Larcker Criterion Discriminant Validity*

Construct	Academic Stress	Attitude	Intent to use ChatGPT	Peer Influence	Risk Propensity
Academic Stress	**0.870**				
Attitude	0.619	**0.875**			
Intent to use ChatGPT	0.596	0.750	**0.937**		
Peer Influence	0.686	0.748	0.665	**0.857**	
Risk Propensity	0.659	0.655	0.722	0.698	**0.857**

Upon conducting the Fornell-Larcker test, compelling evidence was obtained that the constructs used in our study effectively represented the variables in our structural model for the validity and reliability test. The Fornell-Larcker discriminant validity test has long been a widely adopted method for examining the degree to which constructs in a study measure distinct and unrelated concepts (Henseler et al., 2014). Recent developments in the literature have proposed more advanced techniques for assessing discriminant validity by implementing the Heterotrait-Monotrait (HTMT2) test (Roemer et al., 2021). Despite the growing popularity of the HTMT test, the Fornell-Larcker test remains a widely accepted method for assessing discriminant validity in information systems research. However, the HTMT test offers additional validation and can provide more nuanced insights into the relationships between constructs (Benitez et al., 2020; Ab Hamid et al., 2017; Hair et al., 2016).

Table 3 shows the Heterotrait-Monotrait Validity Test (HTMT) criterion values from the Partial Least Squares regression (PLS) algorithm using SmartPLS. It is worth noting that all constructs, except for the measures of attitude and intention, which have scores of 0.858 and 0.893, respectively, are below 0.85, suggesting discriminant validity. However, Benitez et al. (2020) argued that values above 0.85 but below 0.90 are acceptable for quantitative studies in information systems research using PLS-SEM, thereby suggesting the distinctiveness of the measures for each of the study model's constructs.

Table 3. *Heterotrait-monotrait-ratio (HTMT) Validity*

Construct	Academic Stress	Attitude	Intent to use ChatGPT	Peer Influence	Risk Propensity
Academic Stress					
Attitude	**0.688**				
Intent to use ChatGPT	0.652	**0.820**			
Peer Influence	0.758	0.824	**0.719**		
Risk Propensity	0.744	0.733	0.796	**0.778**	

Bootstrapping is a powerful statistical technique that can be employed to test the significance of various PLS-SEM results, including path coefficients, Cronbach's alpha, HTMT, and R^2 values (Ringle et al., 2022). The technique is nonparametric; thereby, it does not require any assumptions about the underlying distribution of the data. Instead, bootstrapping involves resampling the original data multiple times to create a series of new datasets representative of the population (Ringle et al., 2022). To test our hypotheses, the researchers used a bootstrapping technique (Ringle et al., 2022; Hair et al., 2022) to better approximate the collected responses. One of the reasons why we employed this technique was due to the relatively small sample size of our study, as noted in the literature (Ringle et al., 2022; Hair et al., 2022; Schmidheiny, 2021; Benitez et al., 2020). In Table 4, we presented the results of the path analysis based on our proposed model, including the T statistics values for each path. A T-Statistics value above 1.96 indicates a significant relationship between variables (Hair et al., 2014).

Table 4. *Structural Model Test Results: Attitude and Factors Influencing Intention to Use ChatGPT*

Hypotheses	VIF Inner Values	Path coefficients Values	T statistics	Decision
H1: Attitude -> Intention	2.507	0.450	**7.459**	Supported
H2: Peer Influence -> Intention	3.019	0.037	0.642	Not Supported
H3: Academic Stress -> Attitude	1.766	0.331	**5.951**	Supported
H4: Risk Propensity -> Attitude	1.766	0.437	**8.300**	Supported
H5: Academic Stress -> Intention	2.183	0.049	1.044	Not Supported
H6: Risk Propensity -> Intention	2.332	0.368	**6.071**	Supported

To check the potential for common method bias in the study, the inner variance inflation factors (VIFs) were examined using the PLS-SEM algorithm feature of SmartPLS for each of the constructs used in our structural model. The VIFs represent a measure of the degree of multicollinearity among the indicators of each construct, with higher values indicating a greater risk of CMB (Heale & Forbes, 2013; Kock, 2015). In Table 4, it is indicated that none of the extracted VIFs exceeded a value of 3.3, which is well below the commonly accepted threshold of 5 for identifying high levels of multicollinearity. This indicates no evidence of CMB in the data collected from our online survey.

5. Results and Discussion

In the structural model test, researchers conducted a path analysis using SmartPLS' bootstrapping method. We extracted T statistics and P values as significance measures, as shown in Table 4 - Structural Model Test. H1, H3, H4, and H6 were supported, as their respective T statistics were above the threshold value of 1.96. H2 and H5 were not supported, as their respective T statistics were below the threshold value. H1, which posited a positive relationship between Attitude and Intention to use ChatGPT, was supported with a T statistic of 7.459 and a P value of 0.000. H3 and H4, which proposed positive relationships between Academic Stress and Attitude and Risk Propensity and Attitude, were also supported with T statistics of 5.951 and 8.300 and P values of 0.000 each. H6, which proposed a positive relationship between Risk Propensity and Intention to use ChatGPT, was also supported with a T statistic of 6.071 and a P value of 0.000. On the other hand, H2, which posited a positive relationship between Peer Influence and Intention to use ChatGPT, and H5, which proposed a negative relationship between Academic Stress and Intention to use ChatGPT, were not supported, as their respective T statistics were 1.044 and 0.297, indicating that the relationships were not significant.

Based on the statistical analysis (H1) result, it has been highlighted that having a favorable attitude towards technology (ChatGPT) is strongly associated with using technology as a learning tool. This finding is consistent with prior studies and reinforces the significance of a positive perception of ChatGPT as a determinant of behavioral intention (Haque et al., 2022; Al Mamun et al., 2019; Buabeng-Andoh, 2018). In Table 4, the statistical analysis revealed a T-Statistic value of 7.459 for H1, indicating a significant and positive influence on the intention to use ChatGPT among university students (Buabeng-Andoh, 2018; Hair et al., 2014). These results suggest that a positive attitude toward ChatGPT can motivate students (individuals) to incorporate it as a learning tool, emphasizing the importance of promoting positive perceptions towards ChatGPT as a viable resource for learning.

The statistical analysis of the relationship between peer influence (social norms) and the intention to use ChatGPT (H2) yielded a T-Statistics value of 0.642. This value does not support hypothesis H2 and contradicts previous studies conducted by Gómez-Ramirez et al. (2019) and Kucuk et al. (2020). However, the current findings align with Azizi and Khatony's (2019) study, which reported no significant relationship between peer influence (subjective norm) and the intention to use ChatGPT. Negative perceptions or influence shared by peers (negative peer influence) about ChatGPT could create a bias against it, which could influence an individual's (student) own perception and intention to use such tools (Karakos, 2014). For example, if a peer shared negative perceptions or reviews about ChatGPT, this could potentially impact students' beliefs about its (ChatGPT) effectiveness as a learning tool. In addition, peers may not have accurate knowledge about ChatGPT or may misunderstand its purpose and potential benefits. This lack of knowledge can lead to negative perceptions and, in turn, affect an individual's intention to use ChatGPT. Moreover, students may hesitate to use ChatGPT if they fear being judged or stigmatized by their peers for using an AI-powered learning tool. Thereby, while peer influence (subjective norm) may have a negative significant impact on the intention (Azizi & Khatony, 2019) to use ChatGPT, as highlighted in this study, it is essential to note that individual attitudes and beliefs can also play a significant role in shaping an individual's intention to use ChatGPT.

Academic stress (H3) and risk propensity (H4) positively influence students' attitudes towards intention to ChatGPT. These findings are supported by the T-statistics values of 5.951 and 8.300, respectively, which are well above the minimum threshold of 1.96 (Hair et al., 2014) for statistical significance. Additionally, this paper showed significant relationships between academic stress, risk propensity, and attitude toward ChatGPT, which confirms the acceptance of the H3 and H4 hypotheses. In our third hypothesis (H3), like the findings of previous studies (Procentese et al., 2020; Wang et al., 2020; Brand and Schoonheim-Klein, 2009), students who experienced academic stress may have a more positive attitude towards using technology and artificial intelligence tools like ChatGPT to help them cope with that stress. In prior studies, people who are comfortable and familiar with technology may be more likely to use educational apps or learning tools (Buabeng-Andoh, 2018) like ChatGPT to help them with academic work (Candra & Jeselin, 2022; Menon, 2022). Additionally, students who feel they are not getting enough support (academic-related stress) from other sources such as teachers, friends, or family may be more likely to develop a positive attitude towards ChatGPT to get the needed help. In the context of using ChatGPT on H4, students with a positive level of risk propensity can impact their attitude toward using the platform, consistent with the findings of Koohikamali et al. (2017) and Tabak and Barr (1999). Students with a high-risk propensity are likelier to embrace new technologies and experiences, including tools like ChatGPT (Tabak & Barr, 1999; Zhang et al., 2019; Koohikamali et al., 2017). Their willingness to take risks and explore novel options may lead them to use ChatGPT more readily. Conversely, students with a low level of risk propensity tend to be more cautious and hesitant about trying new things, which could make them less inclined to adopt ChatGPT.

The study has unveiled a significant relationship between risk propensity and the student's behavioral intention to use and adopt ChatGPT technology (H6). This finding is supported by a T-Statistic value of 6.071, demonstrating a strong relationship between these two variables. In addition, it is consistent with prior literature that individuals' risk propensity positively influences their intention to use or adopt potential technological innovations such as ChatGPT (Tabak & Barr, 1999; Zhang et al., 2019). Moreover, our study provides insights that students with a higher propensity for risk-taking tend to be more inclined to use ChatGPT, which indicates that risk-taking behavior may positively influence the adoption and use of innovative technologies such as ChatGPT. The finding that risk propensity positively influences the use and adoption of ChatGPT and related technology can also be relevant in the workplace, where new technologies are constantly being introduced and deployed. By understanding the factors influencing technology adoption, organizations can develop strategies to encourage and support individuals to adopt new technologies, increasing productivity, efficiency, and competitiveness. The findings for H5 corroborate the Setiakarnawijaya et al. (2022) study, which failed to establish a positive association between academic stress and the intention to use technology for educational purposes such as ChatGPT. It is plausible that technology may not be perceived as an effective means of addressing academic stress, as individuals may prefer other coping mechanisms (Joseph et al., 2021). Alternatively, academic stress may reduce students' motivation to engage with learning technology such as ChatGPT due to competing demands on their academic situations and stress-related reasons.

6. Conclusion and Recommendations

This study explores the factors influencing students' intention to use ChatGPT, reinforcing the applicability of the Theory of Reasoned Action (TRA) in understanding these areas. The findings validate four hypotheses (H1, H3, H4, and H6), while hypotheses H2 and H5 are not supported by the T-Statistics values. The results indicate that academic stress and risk propensity positively influence students' attitudes towards using ChatGPT, with both attitude and risk propensity emerging as strong predictors of the intention to use the tool. However, the study reveals that academic stress and peer influence do not significantly impact students' intention to use ChatGPT. Despite experiencing pressure from significant others and academic stress, students do not necessarily turn to ChatGPT to meet their academic needs. This outcome may reflect recent shifts in how universities perceive and integrate ChatGPT into academic environments.

In the future, researchers could explore this further. Increasing the sample size could enhance the generalizability of the study's findings and help determine whether the student-to-teacher ratio influences the intention to use ChatGPT. Although the findings are primarily based on university students' perspectives, it would be valuable to investigate whether these insights apply to professionals and educators, particularly those with low-risk propensity or under significant academic pressure. Additionally, it would be intriguing to compare these findings across different cultural contexts. Finally, the study could be expanded to examine the moderating effects of student gender and age on the behavioral intention to use ChatGPT.

The TRA effectively assesses students' intentions to use AI tools. The study shows academic stress and risk propensity influence students' intentions to use ChatGPT. These factors should be considered when integrating AI into the classroom. Recognizing what influences students' intentions can help promote AI's safe and ethical use in education, guiding educators and administrators in developing appropriate guidelines.

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