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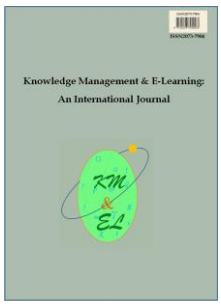

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Assessing the adoption of ChatGPT as a learning tool for college students: An ethical perspective

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Abstract: ChatGPT has experienced remarkable popularity and success in its initial weeks, primarily due to its human-like conversational abilities and its extensive capacity to address a wide array of knowledge domains. However, within the educational context, substantial uncertainties and risks regarding potential misuse pose threats to academic integrity. This study aimed to investigate the determinants of ChatGPT acceptance by integrating constructs from traditional technology acceptance models with those relevant to ethical considerations. A sample of 145 college students was successfully recruited to complete an online survey after using ChatGPT provided by their institution for one month. The analysis, conducted using Partial Least Squares Structural Equation Modeling, revealed several key findings: (1) performance expectancy and social influence were significantly related to the intention to use, which in turn positively influenced actual usage; (2) effort expectancy demonstrated an indirect relationship with the intention to use, mediated by performance expectancy; and (3) among risk perception, risk propensity, and academic dishonesty, only risk perception exhibited an inverse relationship with the intention to use. The study discusses the theoretical and practical contributions of these findings, providing insights into the factors influencing the acceptance and ethical considerations of ChatGPT in educational contexts.

Keywords: Performance expectancy; Social influence; Risk perception; Risk propensity; Academic dishonesty; ChatGPT; College students; Ethics

Biographical notes: Professor Dr. Will W. K. Ma is currently the School of Arts and Humanities' Professor of Teaching and Learning, and the Director of the Centre for Innovative Teaching and Learning (CITL) at Tung Wah College. Professor Ma's research focuses on communication, information systems adoption, education technology, knowledge sharing and knowledge creation. He has publications in international refereed journals, such as Computers and Human Behavior, Computers & Education, Journal of Computer Assisted Learning, Asia Pacific Journal of Teacher Education, Journal of Technology and Teacher Education, Knowledge Management & E-Learning, and Information & Management. He participated and organized international conferences in the technology and learning field, for example, HKAECT International Conference; International Conference on Blended Learning (ICBL), and Engaged Learning & Innovative Teaching in Higher Education (ELITE). He is the series editor of the Educational, Communication and Technology Yearbook series, published by Springer.

1. Introduction

OpenAI released an early demonstration of ChatGPT on 30 November 2022 (Marr, 2023), and the chatbot quickly went viral on social media as users shared examples of what it could do. It quickly gained widespread attention for its natural language abilities, including answering questions, engaging in conversations, and assisting with a variety of tasks. ChatGPT experienced tremendous growth and adoption in a very short period of time after its launch: Within the first 5 days of release, ChatGPT reached 1 million users; in the first two months, it reached over 100 million active users, making it the fastest-growing consumer application in history (Milmo, 2023; UBS, 2023).

On the other hand, there is a lot of uncertainty and risk in the misuse of ChatGPT, like cheating, plagiarism, academic dishonesty, and the potential for ChatGPT to undermine the learning process. In response to this, many universities and schools have banned its students from using it for students' coursework and exams in early 2023 (Johnson, 2023). However, how do users perceive ChatGPT, and would their concerns align with those of regulators when it comes to its usage? Addressing these questions is essential to understanding the potential impact and sustainability of ChatGPT in educational settings.

The remarkable success of ChatGPT has garnered significant interest within the research community, prompting investigations into college students' utilization of ChatGPT specifically, as well as the broader acceptance of technology in educational contexts (e.g., Budhathoki et al., 2024; Strzelecki & ElArabawy, 2024). A quick search of empirical studies revealed that most studies utilized traditional or generic technology acceptance models to explain the ChatGPT user behaviour, such as TAM (e.g., Güner et al., 2024) or UTAUT (e.g., Gulati et al., 2024; Li et al., 2024). Seldom studies examine more relevant contextual factors, such as academic integrity, to explain or to enrich prior models (e.g., Garcia, 2024).

Consequently, it is both timely and relevant to investigate the determinants influencing the use of ChatGPT from an ethical perspective. On one hand, this exploration offers a theoretical contribution by developing a more relevant framework to explain the acceptance of ChatGPT. On the other hand, it furnishes a more comprehensive understanding of ChatGPT's acceptance, thereby providing valuable guidelines for educators. These guidelines can inform the development of training programmes aimed at promoting the proper utilization of ChatGPT, as opposed to its misuse, in the context of enhancing and supporting learning.

The objectives of this study are to:

- Investigate user behaviour regarding the utilization of ChatGPT in higher education.
- Identify the determinants of acceptance, particularly by incorporating factors from an ethical perspective to explain the acceptance behaviours of ChatGPT users.

The research questions are:

RQ1: What factors influence college students' behaviour in their use of ChatGPT?

RQ2: Can determinants from an ethical perspective provide an explanation for college students' behaviour in using ChatGPT?

2. Literature review and hypotheses development

2.1. Performance expectancy

Performance expectancy refers to the degree to which an individual believes that using the system will help him or her to attain gains in job performance (Venkatesh et al., 2003). It origins from a number of prior information system acceptance models and the corresponding construct, including perceived usefulness (Davis, 1989); extrinsic motivation (Davis et al., 1992); job-fit (Thompson et al., 1991); relative advantage (Moore & Benbasat, 1991); outcome expectations (Compeau & Higgins, 1995), etc. A substantial body of research has consistently identified it as the most robust predictor of the intention to use information technology, a conclusion further reinforced by recent studies (e.g., Bower et al., 2020; Molinillo et al., 2023; Uymaz et al., 2024).

In this study, performance expectancy is defined as the degree to which a learner believes that using ChatGPT will help him or her to attain gains in their studies. ChatGPT's ability to assist with a wide range of academic tasks, such as research, writing, problem-solving, and analysis, can be a significant driver of adoption and use. Students may perceive ChatGPT as a valuable tool that enhances their academic performance and productivity. Therefore, we test the following hypothesis:

> ***H1:*** Performance expectancy of a learner is significantly related to the intention to use ChatGPT for his or her studies.

2.2. Effort expectancy

Effort expectancy is defined as the degree of ease associated with the utilization of a system (Venkatesh et al., 2003). This construct originates from several established models of information technology acceptance, encompassing related concepts such as perceived ease of use, complexity, and ease of use (Davis, 1989; Moore & Benbasat, 1991; Thompson et al., 1991). Extensive empirical research has substantiated the role of effort expectancy in influencing the intention to utilize an information system (e.g., Bower et al., 2020; Joa & Magsamen-Conrad, 2022). Furthermore, numerous empirical studies have demonstrated that effort expectancy does not have a direct correlation with the intention to use technology; rather, it influences intention indirectly through performance expectancy or other mediating factors that serve as full mediators (e.g., Malanga et al., 2022; Molinillo et al., 2023).

In this study, effort expectancy is defined as the degree of ease associated with the use of ChatGPT. It is argued that the seamless integration of ChatGPT into the students' existing academic tools and platforms can affect its adoption and use. If ChatGPT can be easily incorporated into the students' research, writing and study processes, it may increase the chance of adoption and use. However, as indicated by earlier studies, there is only an indirect relationship between effort expectancy and intention to use via performance expectancy. The lower the effort is expected, the higher the performance gain is expected and hence, the higher the chance of intention to use ChatGPT as a learner for his or her studies.

In this study, effort expectancy is defined as the degree of ease associated with the utilization of ChatGPT. It is posited that the seamless integration of ChatGPT into students' existing academic tools and platforms can significantly influence its adoption and use. If ChatGPT can be effortlessly incorporated into students' research, writing, and study

processes, it may enhance the likelihood of its adoption and utilization. Nevertheless, as indicated by previous research, the relationship between effort expectancy and the intention to use ChatGPT is indirect, fully mediated by performance expectancy. Specifically, the lower the anticipated effort, the higher the expected performance gains, which in turn increases the likelihood of students' intention to use ChatGPT for their academic endeavours. Therefore, we test the following hypothesis:

> ***H2:*** Effort expectancy is significantly related to performance expectancy of the learner towards the use of ChatGPT for his or her studies.

2.3. Social influence

Social influence is referred to as the degree to which an individual perceives that important others believe he or she should use the new system (Venkatesh et al., 2003). Similarly, the construct originates from various acceptance models and the corresponding constructs, including subjective norm, social norms, social factors, and image (Fishbein & Ajzen, 1975; Mathieson, 1991; Moore & Benbasat, 1991; Taylor & Todd, 1995; Thompson et al., 1991). Empirical studies confirmed the importance of social influence towards intention to use an information system on the rationale that important others' recommendations can shape perceptions of its utility and credibility, and thereby influence their decision to adopt the technology. The impact of social influence on the intention to use has been empirically examined across various contexts, technologies, and participant groups, demonstrating a significant relationship (e.g., Chen et al., 2022; Forgas-Coll et al., 2023; Malanga et al., 2022).

In this study, social influence is defined as the extent to which a learner perceives that significant others believe he or she should utilize ChatGPT. Within the context of higher education institutions, ChatGPT is provided to students as a tool to support their learning endeavours. The endorsement of ChatGPT by the institution and, more specifically, by instructors, can significantly shape learners' perceptions of the utility and credibility of ChatGPT. Consequently, such endorsements can influence learners' decisions to adopt ChatGPT for academic purposes. Therefore, we test the following hypothesis:

> ***H3:*** Social influence is significantly related to the intention to use ChatGPT for his or her studies.

2.4. Ethical concerns

While ChatGPT represents an innovative technology, the decision to use it should not be viewed solely through the lens of technological adoption. Rather, users' perceptions of the ethical implications associated with using ChatGPT can significantly impact their willingness to engage with the application. In the educational context, students' perceptions of employing ChatGPT to assist with learning, complete assignments, and support assessments may raise concerns regarding academic integrity (e.g., Farhi et al., 2023; Tenakwah et al., 2025). The potential misuse of ChatGPT for cheating or plagiarism constitutes a substantial barrier to its adoption. Students may be reluctant to use ChatGPT if they perceive it as a threat to academic integrity and their own intellectual property.

Furthermore, the ethical implications of using ChatGPT, including issues related to accountability, transparency, and its impact on human cognition, may influence student adoption. Students who prioritize these ethical considerations may exhibit a lower

propensity to adopt ChatGPT. If students defend strong ethical concerns, such as the potential for academic dishonesty, these concerns could outweigh the perceived benefits of the technology, leading to reduced adoption rates even in the presence of other favourable factors.

A review of the literature has identified several constructs relevant to the use of ChatGPT from an ethical perspective, including risk perception, risk propensity, and academic dishonesty.

Risk perception is defined as an individual's assessment of how risky a situation is based on probabilistic estimates of situational uncertainty, the controllability of that uncertainty, and confidence in those estimates. Risk propensity, on the other hand, is defined as an individual's current tendency to take or avoid risks (Sitkin & Weingart, 1995). Building on this foundational work, subsequent empirical studies have extended the application of risk perception and risk propensity to various situational contexts to explain risky decision-making. For instance, these constructs have been applied to Internet shopping (e.g., Jarvenpaa et al., 2000) and peer-to-peer sharing software (e.g., Xu et al., 2005), where these new technologies were initially perceived as risky, uncertain, and fraught with ethical concerns. The concepts of risk attitude and risk perception have been further applied to the study of food purchasing decisions, revealing that risk attitude significantly affects purchase intentions for genetically modified foods and other food products (e.g., Ma & Zhang, 2023; Sun & Meng, 2022).

In the field of education, the most prominent ethical issue relates to academic integrity, with academic dishonesty being a persistent challenge among college students. According to Krienert et al. (2022), "*more than half of students report engaging in cheating behavior while in college*." Academic dishonesty includes any form of cheating associated with formal academic activities, such as plagiarism, fabrication, deception, and sabotage (Whitley & Keith-Spiegel, 2002). McCabe and Trevino (1993) conducted a comparative analysis of academic dishonesty levels between colleges with honour codes and those without. In a subsequent study (1997), they examined the effects of individual and contextual factors on self-reported academic dishonesty. More recent research has explored factors contributing to academic dishonesty (e.g., Malesky et al., 2022), while other studies have investigated whether online instruction during the COVID-19 pandemic has led to an increase in academic misconduct, such as cheating and plagiarism (e.g., Ives & Cazan, 2024). These prior studies underscore the importance of understanding ethical considerations, such as academic integrity, in the context of ChatGPT adoption and use.

In light of the initial responses from universities regarding the prohibition of ChatGPT usage, it is evident that these institutions perceive ChatGPT as a potentially hazardous tool that could be misused and thereby compromise academic integrity. There exists an inherent uncertainty concerning whether students would utilize the tool appropriately. Consequently, permitting students to use ChatGPT is perceived as fraught with risk and uncertainty. Similarly, students are likely to share this perception of ChatGPT during its nascent stage. The decision to use ChatGPT is viewed as risky, with significant uncertainty surrounding its proper and ethical application.

From an ethical standpoint, the inter-relationship among risk perception, risk propensity, and academic dishonesty plays a critical role in shaping the intention to use ChatGPT. Academic dishonesty, often driven by the desire to achieve success with minimal effort, is influenced by an individual's risk propensity, which reflects their willingness to engage in risky behaviours despite potential consequences (Nicholson et al.,

2005). Individuals with high-risk propensity are more likely to perceive lower risks and ethical concerns associated with using ChatGPT for dishonest purposes, viewing the potential benefits as outweighing any negative repercussions (Weber et al., 2002). This perceived low-risk attitude can increase their intention to use such applications unethically. Conversely, individuals with low-risk propensity are more likely to recognize and heavily weigh the ethical implications and potential academic consequences, resulting in a cautious approach and a reduced intention to misuse ChatGPT (Floridi & Cowls, 2019). Therefore, we test the following hypothesis:

H4: Academic dishonesty of a learner is significantly related to the intention to use ChatGPT for his or her studies.

H5: Risk propensity of a learner is significantly related to the academic dishonesty of him or her.

H6: Risk propensity of a learner is significantly related to the intention to use ChatGPT for his or her studies.

H7: Risk perception of a learner towards ChatGPT is significantly related the academic dishonesty of him or her.

H8: Risk perception of a learner towards ChatGPT is significantly and inversely related to the intention to use ChatGPT for his or her studies.

2.5. Intention to use

Prior studies have suggested that the intention to use a technology serves as a reliable predictor of actual usage. Numerous empirical investigations have substantiated this relationship (e.g., Legris et al., 2003). The underlying argument is that if an individual is motivated and exhibits a higher intention to use ChatGPT for their studies, the likelihood that they will actually engage in this behaviour increases correspondingly. Therefore, it is proposed to test,

H9: Intention to use ChatGPT of a learner is significantly related to the actual usage of ChatGPT for his or her studies.

The hypotheses were summarized in the Fig. 1.

3. Method

3.1. Background

A local Hong Kong self-financing tertiary institution provided ChatGPT services to all students and staff through the college website on 1 Sept 2024 for free. Students would have a free quota of 200 credits while staff would have 300 credits in the academic year 2024-2025. This is the first time the College has provided the service to all staff and students. This study aims to collect students' opinions on the use of ChatGPT to understand the determinants to intention to use. The institution provides a blended learning educational model, wherein the majority of courses are delivered in-person within lecture halls and classrooms. Students participate in smaller group sessions for tutorials and laboratory exercises. Concurrently, the Learning Management System (LMS), Blackboard, is accessible for all courses on a 24/7 basis. Course instructors utilize the LMS to administer classes, collect and grade assessments, while students interact with the platform to access

teaching materials and engage in various pedagogical activities, such as group discussions and quizzes.

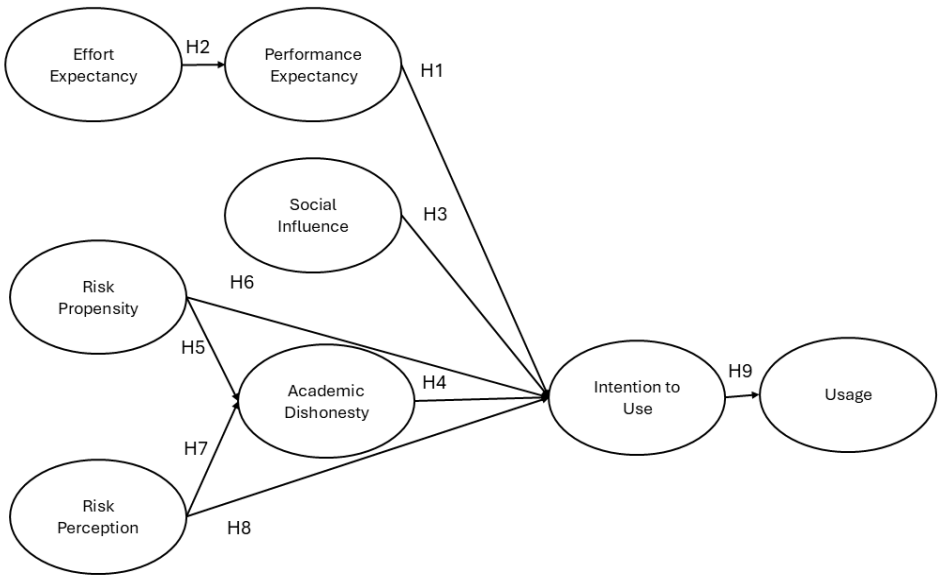

Fig. 1. Model framework and hypotheses

3.2. Subject

The study targeted the population of college students. College students continue attracting attention from researchers to understand user behaviour in general (e.g., Kim & Khang, 2014) while college students are also to be heavy users of ChatGPT to generate content and knowledge in the learning process. All students were contacted through internal email to invite them to complete an online survey about their use of ChatGPT. Finally, 145 students completed and returned the online survey.

3.3. Measurement

The online survey was separated into two parts. The first part asked about the demographics of the participants and their use of ChatGPT in the first month of the launch of the service.

The second part collected participants' opinions on the potential determinants and the intention to use. The measured instrument was adapted from prior validated scales, with minor changes to wordings to suit the context of this study (see Appendix I). Accordingly, there were 4 items in performance expectancy, 4 items in effort expectancy, 4 items in social influence and 3 items in intention to use (Venkatesh et al., 2003). There were two items in risk perception and 2 items in risk propensity (Jarvenpaa et al., 2000; Xu et al., 2005). All of these were statements measured by a Likert scale ranged from 1 (strongly disagree) to 7 (strongly agree).

Moreover, 12 items in academic dishonesty (McCabe & Trevino, 1997) were measured by a 5-point scale (never = 1; once = 2; a few times = 3; several times = 4; many

times = 5). This scale measured students' attitudes and behaviours related to academic dishonesty, including cheating, plagiarism, and unauthorized collaboration. A composite measure would be constructed by adding these together, with 12 representing no self-reported academic dishonesty and 60 representing frequent cheating of many kinds. Prior studies (McCabe & Trevino, 1997) also found that the academic dishonesty variable is highly skewed, and the standard assumption of normality is violated. It was because, in reality, academic dishonesty rarely happened, and most of the time, the class discipline was in order. Accordingly, a log transformation of the variable was used to achieve a closer to normal distribution for statistical analyses.

3.4. Data collection

The study collected data in the first month of use. In the last week of September 2024, an email was sent to all students in the College. The email invited students to click the link to participate in an online survey on the use of ChatGPT. The link directed participants to the survey, which started with an informed consent explaining the research purposes, data collection process and confidentiality details. The participants agreed to proceed with the online survey. Or else, they would leave the online survey without any penalty. On average, the online survey took 10 minutes to complete. The survey was anonymous and did not collect any identifying information from the participants. The survey lasted for three weeks. Two reminder emails were sent in the second and third week, respectively.

Ethics approval was sought from the Ethics Review Committee of the College at the end of August 2024, before data collection started at the end of September 2024.

3.5. Data analysis

The descriptive analysis provided a comprehensive summary of the sample demographics and usage behaviour, in addition to detailing the means and standard deviations of the determinant constructs. The measurement models were rigorously validated to ensure both reliability and validity. Structural equation modeling was conducted using SmartPLS 4.0, employing partial least squares to estimate the structural model and rigorously test the proposed hypotheses.

4. Findings

4.1. Descriptive analysis of respondents

4.1.1. System log statistics

There were 4457 full-time students by the time of the study for AY2024-2025. By the first month of use (from 1 to 30 Sept), the system log recorded 813 total student logins and 580 total number of student users. There were 14 users who asked more than 150 questions; 27 users asked more than 100 questions, while 67 users asked more than 50 questions. The total number of questions asked was 12,873. Students were allocated 200 credits for the academic year, where in the first month, 719 student users used less than 50 credits, 5 users used 50-100 credits, 1 user used 100-150 credits, and 1 user used up all the 200 credits.

4.1.2. Survey participants

There were 145 students who completed the online survey, where 44 (30.3%) were male, and 101 (69.7%) were female. Student respondents came from all programmes offered by the College, where the top three most included 80 (55.2%) from Nursing, 11 (6.2%) from Physiotherapy, and 7 (4.8%) from Health Information & Services Management, respectively. The first two were comparable to the student intake composition. Other information was summarized in Table 1 below.

Table 1
Descriptive statistics of respondents

Age	17 to 49 years old (M: 22.54, SD: 6.064)
Last GPA	1.93-4.00 (M: 2.99, SD: .446) (75 replied)
Study Year	• Year 1: 69 (47.6%) • Year 2: 28 (19.3%) • Year 3: 24 (16.6%) • Year 4: 19 (13.1%) • Year 5: 5 (3.4%)
Entry Year	Year 1: 118 (81.4%); Senior Year: 27 (18.6%)
Join student societies	No: 125 (86.2%); Yes: 20 (13.8%)
How often did you use ChatGPT in the last four weeks?	• Never: 17 (11.7%) • Once a month or less: 25 (17.2%) • A few times a month: 30 (20.7%) • Once a week: 14 (9.7%) • A few times a week: 35 (24.1%) • Once a day: 5 (3.4%) • Several times a day: 19 (13.1%)
Usually use ChatGPT for	1. Research and information gathering: 114 (78.6%) 2. Study and revision: 79 (54.5%) 3. Homework help: 77 (53.1%) 4. Essay writing and editing: 48 (33.1%) 5. Language practice: 28 (19.3%) 6. Others: advanced reading (1); creative ideas (1); entertainment (1); summarize notes (1)

4.2. Descriptive analysis of variables

The minimum values, maximum values, means, and standard deviations were listed in Table 2 below. For academic dishonesty, it was the summation of all 12 items for a composite score. Moreover, as suggested by prior literature (McCabe & Trevino, 1997) and discussed in the method measurement section earlier, the logarithm value of it was used for further analysis (AD).

4.3. Reliability and validity

The reliability of the constructs refers to the consistency and stability of the measure. It was assessed by two widely used indicators, including Cronbach's alpha and Composite Reliability (CR) in this study (see Table 3). Noted that academic dishonesty was a single composite item, and reliability was not assessed. Cronbach's alpha is a measure of internal

consistency, which indicates how closely related a set of items is as a group. As shown below, all the alpha values for each construct were either higher than 0.8 or 0.9; they were considered good to excellent reliability (Hair et al., 2010). Composite Reliability (CR) is another measure of internal consistency. It is considered a more accurate estimate of reliability in the context of structural equation modeling (SEM) because it takes into account the different loadings of items on the construct. From the table below, the Composite Reliability values for all the constructs were above 0.8, showing that they exhibited good reliability (Fornell & Larcker, 1981). Combining the results, the constructs were ensured to be measured reliably, providing confidence in the findings and further interpretations.

Table 2
Descriptive statistics of variables

	Min	Max	*M*	*SD*
Performance Expectancy (PE)				
PE1	1	7	5.54	1.264
PE2	1	7	5.52	1.202
PE3	1	7	5.43	1.317
PE4	1	7	5.29	1.384
Effort Expectancy (EE)				
EE1	1	7	5.26	1.275
EE2	1	7	5.11	1.365
EE3	1	7	5.48	1.167
EE4	1	7	5.39	1.226
Social Influence (SI)				
SI1	1	7	4.68	1.437
SI2	1	7	4.60	1.460
SI3	1	7	4.82	1.368
SI4	1	7	4.97	1.351
Risk Perception (RA)				
RA1	1	7	4.48	1.405
RA2	1	7	4.28	1.534
Risk Propensity (RP)				
RP1	1	7	5.08	1.286
RP2	1	7	5.08	1.360
Intention to Use (INT)				
INT1	1	7	5.31	1.498
INT2	1	7	5.40	1.488
INT3	1	7	5.28	1.470
Academic Dishonesty (AD)				
AD	2.48	3.87	2.67	.3116

Table 3
Reliability assessments

	Cronbach's alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
PE	.944	.945	.856
EE	.902	.906	.772
SI	.864	.866	.709
RA	.818	.832	.845
RP	.818	.818	.846
INT	.965	.965	.934

Convergent validity refers to the extent to which a set of indicators or items that are intended to measure a particular construct actually converge or share a high proportion of variance in common. In this study, it was assessed by Average Variance Extracted (AVE), which is a key measure used to assess the convergent validity of a construct in structural equation modeling (SEM). As shown in the above table, all the AVE values were above 0.5, indicating that the constructs exhibited good convergent validity. This means that more than 50% of the variance of the indicators is accounted for by the construct, suggesting that the indicators are well representative of the construct (Fornell & Larcker, 1981).

Evaluating the discriminant validity of constructs is essential to ensure that the constructs in a model are distinct and do not measure the same concept. In this study, three methods to assess discriminant validity were included: the Heterotrait-Monotrait (HTMT) ratio of correlations, the Fornell-Larcker criterion, and cross-loadings.

The HTMT ratio is the average of the heterotrait-heteromethod correlations (correlations between different constructs) relative to the geometric mean of the average monotrait-heteromethod correlations (correlations with the same construct). As shown in the below HTM matrix (see Table 4), the HTMT ratio for each pair of constructs is listed. They were compared with the commonly used thresholds of 0.85 (for conceptually distinct constructs). The HTMT ratio is below the threshold; discriminant validity is established (Henseler et al., 2015).

Table 4
HTMT matrix

	PE	EE	SI	RA	RP	AD	INT	USE
PE	1.000							
EE	.840	1.000						
SI	.777	.759	1.000					
RA	.047	.118	.174	1.000				
RP	.281	.332	.325	.266	1.000			
AD	.049	.087	.094	.157	.041	1.000		
INT	.762	.666	.675	.099	.282	.013	1.000	
USE	.326	.305	.252	.195	.071	.037	.454	1.000

Fornell-Larcker criterion is based on the average variance extracted (AVE). According to the criterion, discriminant validity is established if the square root of the AVE of each construct is greater than the highest correlation between that construct and any other construct. From Table 5 below, the diagonal elements (square root of AVE) were compared with the off-diagonal elements (correlations). It was found that the diagonal elements were all greater than the off-diagonal elements in the corresponding rows and columns. Discriminant validity was established (Fornell & Larcker, 1981).

Cross-loadings involve examining the factor loadings of each indicator on all constructs. From Table 6 shown below, all the indicators' loadings on their intended construct are higher than their loadings on any other constructs. Discriminant validity is established (Chin, 1998).

Table 5
Fornell-Larcker criterion

	PE	EE	SI	RA	RP	AD	INT	USE
PE	.925							
EE	.781	.879						
SI	.705	.676	.842					
RA	–.023	.096	.143	.919				
RP	.247	.285	.273	.222	.92			
AD	–.047	–.084	.086	.142	.03	1.000		
INT	.728	.622	.619	–.08	.25	.009	.966	
USE	.317	.289	.233	–.176	–.064	.037	.446	1.000

Table 6
Cross-loadings table

	PE	EE	SI	RA	RP	AD	INT	USE
PE1	.923	.691	.638	–.036	.169	–.054	.697	.352
PE2	.934	.703	.639	.009	.251	–.043	.663	.294
PE3	.932	.705	.632	–.023	.236	–.057	.635	.242
PE4	.911	.785	.694	–.033	.256	–.021	.695	.286
EE1	.729	.896	.615	.080	.210	–.114	.540	.279
EE2	.695	.861	.578	.052	.212	–.082	.578	.210
EE3	.590	.872	.505	.138	.243	–.051	.509	.264
EE4	.715	.885	.661	.077	.337	–.043	.556	.264
SI1	.593	.569	.852	.042	.203	.101	.506	.242
SI2	.564	.545	.827	.110	.204	.078	.479	.200
SI3	.652	.592	.870	.147	.236	.026	.565	.200
SI4	.560	.568	.818	.177	.274	.089	.528	.146
RA1	.007	.058	.102	.932	.248	.126	–.022	–.151
RA2	–.053	.124	.166	.906	.152	.136	–.134	–.174
RP1	.285	.310	.287	.191	.918	–.007	.237	–.020
RP2	.170	.216	.216	.217	.921	.061	.223	–.098
AD	–.047	–.084	.086	.142	.030	1.000	.009	.037
INT1	.712	.614	.615	–.042	.269	–.006	.973	.429
INT2	.705	.595	.605	–.088	.234	.025	.964	.451
INT3	.695	.595	.574	–.103	.221	.007	.963	.412
USE	.317	.289	.233	–.176	–.064	.037	.446	1.000

4.4. Structural model

The structural model was analysed, and the path coefficients were estimated using SmartPLS 4.0. SmartPLS is an application used for structural equation modeling (SEM) using partial least square (PLS) path modeling. In this study, Partial Least Squares Structural Equation Modeling (PLS-SEM) was deemed to be suitable as the research objective is prediction-oriented, the model is complex with many constructs and indicators, the data is non-normally distributed and has a small sample size (Hair et al., 2017; Sarstedt et al., 2017). Moreover, it is particularly useful in exploratory research where the primary

goal is theory development rather than theory testing, as in this study. The model testing results were summarized in Table 7 and in Fig. 2.

For hypothesis H1: It was supported that performance expectancy was positively and significantly related to intention to use ($\beta = .540$, $p < .001$).

For hypothesis H2: It was supported that effort expectancy was positively and significantly related to intention to use ($\beta = .781$, $p < .001$).

For hypothesis H3: It was supported that social influence was positively and significantly related to intention to use ($\beta = .234$, $p < .01$).

For hypothesis H7: It was supported that perceived risk attitude was positively and significantly related to academic dishonesty ($\beta = .143$, $p < .05$).

For hypothesis H8: It was supported that perceived risk attitude was negatively and significantly related to intention to use ($\beta = –.137$, $p < .05$).

For hypothesis H9: It was supported that intention to use was positively and significantly related to actual usage ($\beta = .446$, $p < .001$).

For hypotheses H4, H5 and H6: There could not find significant relationship between academic honesty and intention to use, risk propensity and academic dishonesty, as well as risk propensity and intention to use.

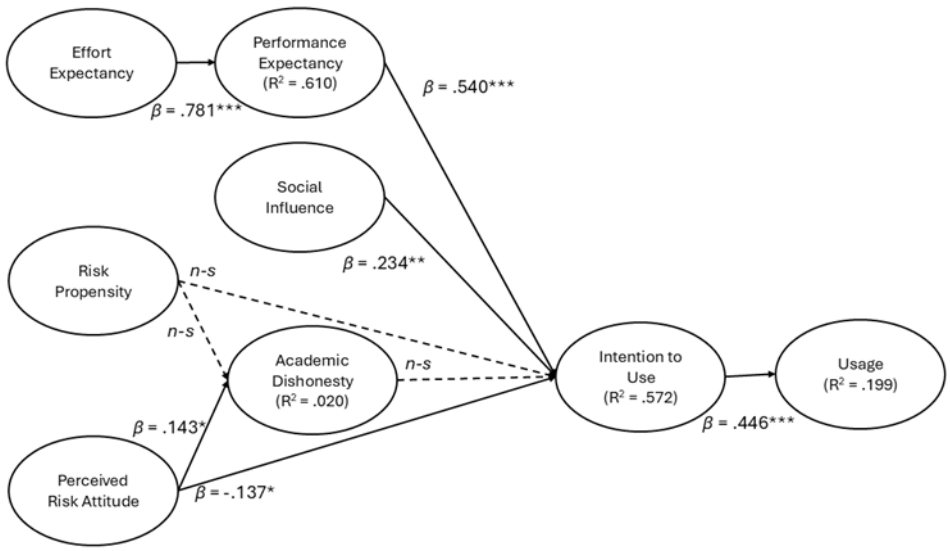

Fig. 2. Model testing results

The R-square for academic dishonesty was low ($R^2 = .020$). On the other hand. The R-square for actual usage ($R^2 = .020$), intention to use ($R^2 = .572$) and performance expectancy ($R^2 = .610$) were from moderate to high. In the other words, for the increase of one standard unit of all the determinants, there would be an increase of .572 standard unit of intention to use, or all the determinants together explained 57.2% variance of intention to use.

Table 7
Summary of path coefficients and hypothesis testing

Hypotheses	Paths	Path coefficients	Significance (p-values)	Supported (Y/N)
H1	PE → INT	.540	.000 < p = .001***	Y
H2	EE → PE	.781	.000 < p = .001***	Y
H3	SI → INT	.234	.009 < p = .01**	Y
H4	AD → INT	.032	.477 > p = .05 (n-s)	N
H5	RP → AD	.000	.998 > p = .05 (n-s)	N
H6	RP → INT	.079	.202 > p = .05 (n-s)	N
H7	RA → AD	.143	.034 < p = .05*	Y
H8	RA → INT	– .137	.029 < p = .05*	Y
H9	INT → USE	.446	.000 < p = .001***	Y

5. Discussion

5.1. Key findings

Performance expectancy and social influence were found to be significantly and positively correlated with the intention to use, which was significantly and positively related to the actual usage of ChatGPT. Conversely, risk perception exhibited a significant but negative relationship with the intention to use. Specifically, elevated levels of performance expectancy and social influence corresponded with increased intentions to use ChatGPT, thereby enhancing actual usage. However, even in contexts where other factors were favourable, heightened risk perception served to diminish the intention to use and, consequently, actual usage. Furthermore, effort expectancy demonstrated an indirect effect on the intention to use, mediated through performance expectancy. Higher levels of effort expectancy were associated with greater performance expectancy, which in turn led to a higher intention to use ChatGPT. No significant relationship was identified between academic dishonesty and risk propensity with regard to the intention to use ChatGPT.

5.2. Performance expectancy and effort expectancy

In this study, performance expectancy and effort expectancy emerged as the two most influential determinants of the intention to use, a finding that aligns with the results of more recent studies (e.g., Al-Okaily et al., 2025; Hsu & Silalahi, 2024; Marinas et al., 2025). Performance expectancy was observed to exert a direct effect on the intention to use (β = .540, p < .001), whereas effort expectancy had an indirect effect mediated through performance expectancy (β = .781 × .540 = .422, p < .001). Specifically, the more students perceived that ChatGPT could enhance their academic performance, the more inclined they were to use it. Furthermore, a lower perceived effort in using ChatGPT was associated with higher perceived usefulness, thereby increasing the likelihood of its usage.

The study revealed that students who recognized ChatGPT's potential to assist in various academic activities (e.g., Bachiri et al., 2025; Kohnke & Ulla, 2024) – such as research and information gathering (78.6%), study and revision (54.5%), homework help (53.1%), essay writing and editing (33.1%), and language practice (19.3%) – were most motivated to adopt the tool. The intuitive nature of ChatGPT, resembling human

conversation, makes it easy and effortless for students to use by simply typing their queries. As students become more adept at crafting precise and specific prompts, they are likely to find ChatGPT even more beneficial, thus further enhancing their academic performance.

5.3. Social influence

Social influence is significantly associated with the intention to use ChatGPT ($\beta = .234$, $p < .01$), a finding that is supported by and consistent with recent empirical studies (e.g., Acquah et al., 2024; Zaim et al., 2024).

Within the context of ChatGPT usage among college students, both peers and influential figures, such as instructors and institutional authorities, exert considerable influence. Although students may initially express reservations about adopting new technology, they are more likely to experiment with ChatGPT if it is endorsed by these significant individuals. This finding offers practical implications for the development of institutional policies and guidelines aimed at promoting effective AI integration, while recognizing that social influence is a key determinant in the intention to use ChatGPT.

5.4. Ethical concerns

In this study, it was hypothesized that risk perception, risk propensity, and academic dishonesty would influence the intention to use ChatGPT. The results revealed that only risk perception was inversely related to the intention to use ($\beta = -.137$, $p < .05$), while no significant relationships were identified for risk propensity and academic dishonesty. These findings align with some prior studies on the relationships among these ethics-related factors. For instance, in this study, perceived risk attitude was positively and significantly related to academic dishonesty ($\beta = .143$, $p < .05$), which is comparable to the findings of Huang and colleagues (2025). Although ethical concerns are considered relevant to the use of ChatGPT in education, researchers address the issue through various concepts, such as perceived ethics (e.g., Farhi et al., 2023), ethics (e.g., Mustofa et al., 2025), personal ethics, cheating (e.g., Huang et al., 2025), religion-related ethics (e.g., Elbaz et al., 2024), as well as risks and perceived threats (e.g., Hsu & Silalahi, 2024), highlighting the complex dynamics of the issue. Each study tries to contribute to a better understanding of the topic, and further research is warranted to develop a comprehensive and holistic perspective.

The underlying assumption is that ChatGPT is not merely a technology designed to enhance efficiency and productivity; it also raises substantial ethical concerns. Particularly within the educational context, the misuse of ChatGPT could lead to issues such as cheating, plagiarism, and breaches of academic integrity. This concern is reflected in the varied responses to ChatGPT's implementation in higher education, ranging from complete bans to cautious allowances with comprehensive guidelines to govern proper use.

The uncertainty and perceived risks associated with ChatGPT are mirrored in the worries of many educators regarding its potential for misuse by students. Even students themselves may have doubts about ChatGPT's potential and may lack awareness of appropriate usage practices. Risk perception and risk propensity have been validated in the context of other emerging technologies, such as online shopping and peer-to-peer file sharing, which also involve significant uncertainties and ethical considerations during their early stages of development.

The lack of significant relationships between risk propensity, academic dishonesty, and the intention to use ChatGPT may be attributed to several factors. Some students may lack AI literacy and thus have a limited understanding of what ChatGPT is, while others may not associate ChatGPT with unethical use. These aspects warrant further examination in future studies to better understand the dynamics at play.

5.5. Theoretical contributions

This study has validated key determinants of ChatGPT acceptance, specifically performance expectancy, effort expectancy, and social influence. Additionally, constructs from ethical perspectives, including risk perception, risk propensity, and academic dishonesty, were integrated into the analysis. The findings confirmed a significant and inverse relationship between risk perception and the intention to use ChatGPT. By incorporating these ethical considerations, this study has developed a comprehensive acceptance framework that enhances our understanding of ChatGPT adoption.

5.6. Practical contributions

This study has offered a more comprehensive model for explaining ChatGPT adoption by incorporating an ethical perspective. It provides practical guidelines for developing training programmes aimed at fostering the proper use of ChatGPT, thereby benefiting college students. This enhanced theoretical basis supports universities in promoting the responsible use of ChatGPT. During the initial phases of ChatGPT implementation, some institutions, such as Harvard University (2024), have refrained from imposing campus-wide bans. Instead, they have encouraged faculty to guide students on appropriate usage and have advocated for the responsible integration of ChatGPT into coursework.

5.7. Limitations and future research

This study has several limitations. Firstly, the online survey was conducted using convenience sampling rather than true random sampling. Secondly, the sample size is relatively small, which may affect the robustness of the findings. Thirdly, certain variables, particularly academic dishonesty, exhibited high skewness. This skewness could be attributed to the infrequent occurrence of academic dishonesty in real-life practices, leading to a non-normal distribution of the variable. Consequently, the findings of this study may have limited generalizability.

Moreover, this study did not find significant relationships between academic dishonesty, risk propensity, and the intention to use ChatGPT. Future research should consider exploring other factors related to ethical concerns to provide a more comprehensive understanding of the determinants influencing the adoption of ChatGPT.

6. Conclusion

This exploratory study examines the factors influencing the adoption of ChatGPT among college students. The research builds upon established determinants of technology acceptance, incorporating ethical concerns that are related to the utilization and nature of this emerging technology. The findings affirm significant correlations between key acceptance determinants – namely, performance expectancy, effort expectancy, and social influence – and both the acceptance of and intention to use ChatGPT. Furthermore, the study indicates that risk perception is negatively correlated with the intention to use

ChatGPT. Although other ethical concerns, such as risk propensity and academic dishonesty, were investigated, no significant association with the intention to use ChatGPT was identified. The results of this study expand the existing theoretical framework of technology acceptance, demonstrating its applicability to the novel technology represented by ChatGPT. Furthermore, the study provides significant practical implications for its application, especially regarding ethical considerations within higher education, including institutional policies and guidelines for encouraging the appropriate use of ChatGPT in educational contexts.

Author Statement

The authors declare that there is no conflict of interest.

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Appendix I

Measurement

	Performance Expectancy (Venkatesh et al., 2003)
PE1	I would find ChatGPT useful in my study.
PE2	Using ChatGPT enables me to accomplish tasks more quickly.
PE3	Using ChatGPT increases my productivity.
PE4	If I use ChatGPT, I will increase my chances of getting better academic performance.
	Effort Expectancy (Venkatesh et al., 2003)
EE1	My interaction with ChatGPT would be clear and understandable.
EE2	It would be easy for me to become skillful at using ChatGPT.
EE3	I would find ChatGPT easy to use.
EE4	Learning to operate ChatGPT is easy for me.
	Social influence (Venkatesh et al., 2003)
SI1	People who influence my behavior think that I should use ChatGPT.
SI2	People who are important to me think that I should use ChatGPT.
SI3	The senior management of this business has been helpful in the use of ChatGPT.
SI4	In general, the organization has supported the use of ChatGPT.
	Risk perception (Jarvenpaa et al., 2000; Xu et al., 2005)
RA1	There is too much uncertainty associated with using ChatGPT to learn.
RA2	Compared with other ways of learning, using ChatGPT would be more risky.
	Risk propensity (Jarvenpaa et al., 2000; Xu et al., 2005)
RP1	I avoid risky things.
RP2	I would rather be safe than sorry.
	Intention to use (Venkatesh et al., 2003)
INT1	I intend to use ChatGPT in the next 4 weeks.
INT2	I predict I would use ChatGPT in the next 4 weeks.
INT3	I plan to use ChatGPT in the next 4 weeks.
	Academic dishonesty (McCabe & Trevino, 1997)
AD1	Using crib notes (cheat sheets) on a test
AD2	Copying from another student during a test
AD3	Using unfair methods to learn what was on a test before it was given
AD4	Copying from another student during a test without their knowledge
AD5	Helping someone else to cheat on a test
AD6	Cheating on a test in any other way
AD7	Copying material and turning it in as your own work
AD8	Fabricating or falsifying a bibliography
AD9	Turning in work done by someone else
AD10	Receiving substantial, unpermitted help on an assignment;
AD11	Collaborating on an assignment when the instructor asked for individual work
AD12	Copying a few sentences of material from a published source without footnoting

Note. All measured in 7-point Likert scale (strongly disagree = 1, neutral = 4; strongly agree = 7) except academic dishonesty in 5-point scale (never = 1; once = 2; a few times = 3; several times = 4; many times = 5).