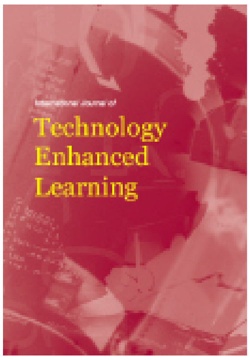

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Higher education students' trust and use of ChatGPT: empirical evidence

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Higher education students' trust and use of ChatGPT: empirical evidence

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Abstract: This paper combines a modified version of the unified theory of acceptance and use of technology (UATAU) with the expectancy value theory (EVT) to examine the variables that influence higher education students' trust and use of ChatGPT. The quantitative method was used, with a structured questionnaire developed to collect data from respondents, which was then analysed using Smart PLS 4. According to the findings, perceived mobility influenced performance and effort expectancy, while social influence and performance expectancy determined students' trust. The three predicted elements that influenced ChatGPT adoption were perceived learning gains, perceived risks, and trust in ChatGPT. The study presented some recommendations for universities.

Keywords: ChatGPT; perceived mobility; trust in ChatGPT; use of ChatGPT.

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1 Introduction

There has been a lot of progress in the study of artificial intelligence (AI) in recent years. And it has imposed a substantial influence on societies and organisations in different contexts (Dwivedi et al., 2023). It has been gaining traction in the education sector, with various applications being developed to improve teaching and learning that can improve student engagement and maximise educational outcomes. As a result, these models have gained popularity among students in higher education institutions who seek efficient and reliable assistance in their academic tasks. Using chatbots to teach is one of the most promising uses of AI. One such chatbot, ChatGPT, has demonstrated encouraging results in the field of higher education. Like Generative Pre-Trained Transformer 3 (GPT-3), ChatGPT is an AI-powered natural language processing version of the GPT tool that was released in November 2022 (Guo et al., 2023). It enables conversational interactions with the chatbot in a variety of contexts (Mijwil et al., 2023). Typically, chatbots respond to user-generated queries using natural language processing (NLP) (Dwivedi et al., 2023). Chatbots have evolved to address numerous NLP-related challenges by incorporating deep learning with language models (Kushwaha and Kar, 2021). The language model can help with things like writing emails, articles, and even programming.

Chatbots like ChatGPT have the potential to significantly impact how we teach and learn in the future, making them a resource worth considering for universities as students in higher education institutions are among the main beneficiaries of these innovations. However, while ChatGPT offers a promising solution, it is crucial to critically evaluate its effectiveness and limitations. The use of AI applications in education is like a double-faced coin as it offers opportunities and imposes concerns (Ramakrishnan Raman, in Dwivedi et al., 2023). Among the main opportunities achieved are:

1 offering educational materials
2 personalised feedback on students' inquiries
3 automation of administrative tasks
4 supporting language learning
5 online education enhancement
6 individualised support.

On the other hand, challenges include:

1 the accuracy of the provided materials
2 ethical consideration
3 security and privacy issues related to students' data
4 limited explanation capabilities
5 understanding the model output
6 the possibility of plagiarism (Cotton et al., 2023).

University students are increasingly choosing to utilise ChatGPT as they engage in their academic assignments, experts raised concerns about the possibility that students misuse ChatGPT to plagiarise their assignments (Bockting et al., 2023) instead of writing them themselves. While ChatGPT can generate solutions to queries, it should be noted that the responses it creates may contain inaccuracies and should not be depended on completely. This is because ChatGPT uses an algorithm to build sentences using data from its database, which has not been updated since 2021 (Mollick, 2022). Trust is often emphasised as a crucial component of the connection between users and AI systems (Carvalho et al., 2019), especially with emerging technologies that are often accompanied by increased complexity and unpredictability, necessitating trust in the systems (Seegebarth et al., 2019). This is because complex machine learning models in the AI sector are not readily understandable or visible. Trust in an AI model involves three parties: the person (P), the AI model (M), and the contract (c). If P considers M to be trustworthy and decides to use it (C), then P is willingly accepting the vulnerability to

M's actions, then P contracts with M in a position of trust. This indicates that by trusting M, P is confident that M is upholding the contract even with uncertain conditions, thus P perceives the availability of risks (Jacovi et al., 2021). Reflecting this scenario on students' use of ChatGPT, students are actively choosing to engage with the system and have certain expectations regarding the outcomes it produces. They anticipate that ChatGPT will provide them with the desired results or information while being aware that there is a possibility of receiving incorrect or inaccurate results.

The widespread of mobile devices and smartphones among higher education students through which they can access and use ChatGPT freely anytime and anywhere is believed to influence them to embrace and utilise advanced tools such as ChatGPT (Hill and Roldan, 2005). The perceived mobility offered by ChatGPT allows students to seamlessly access information, receive feedback, and engage in interactive learning experiences, thereby enhancing their overall academic performance and satisfaction.

This research aims to better understand and assess students' perception of the performance, ease of use, and mobility of ChatGPT, as well as their perception of the expected learning outcomes and the potential risks that may influence their trust level in ChatGPT to provide the desired academic assistance that would ultimately encourage them to continue their use of the model. However, building users' trust in AI technology is crucial to the technology's widespread adoption and use (Choudhury and Shamszare, 2023).

As the release of ChatGPT is relatively recent, few empirical studies were conducted to determine the potential factors that may influence students' trust and use of ChatGPT. Hence, empirically studying the factors that influence students in higher education to trust and use ChatGPT is important and timely since understanding how they perceive and utilise such tools is crucial to leverage their potential effectively. By conducting this study, a contribution is provided to the literature by bringing this topic into the spotlight, raising awareness among practitioners in the field, as well as helping institutions improve student engagement, retention, and personalised learning experiences, as well as meet the growing demand for online learning and AI-based solutions in education. This research focuses on the factors that affect Palestine Technical University-Kadoorie students' adoption and utilisation of ChatGPT.

2 Theoretical background

The literature on using ChatGPT is relatively scarce due to the recent release of the model. For example, Kim et al. (2020), who conducted a study in the USA to determine how students perceive AI teaching assistants, are among the researchers who have examined the use of AI in education. The researchers employed TAM to investigate students' perceptions of the utility and accessibility of AI teaching assistants. According to the authors, the two TAM components positively influenced the students' attitudes, which led to their eventual adoption of the system. Similarly, Chatterjee and Bhattacharjee (2020) studied the adoption of AI in higher education utilising a modified version of the unified theory of acceptance and use of technology (UTAUT), their findings showed that perceived risks and effort expectancy were significant in predicting attitudes, attitudes and facilitating conditions together predicted behavioural intention which in turn was significant in predicting the adoption behaviour.

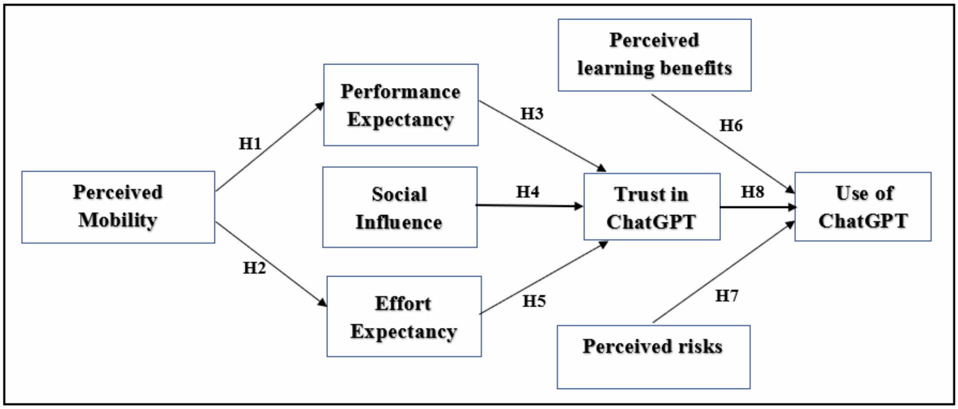
Regarding ChatGPT-related studies, Bonsu and Baffour-Koduah (2023) studied the attitudes and intentions of university students in Ghana for implementing ChatGPT. The authors used a mixed-method approach that included TAM and found that while there was no correlation between students' perceptions and their intention to use ChatGPT, students were open to using and supporting its implementation in education based on their positive experiences, and they experienced more benefits than challenges in implementing it at the university level. Chan and Zhou (2023) conducted a study to see if and how students' expectations affect their adoption of generative AI in the educational setting. According to the results, there was a moderate negative relationship between perceived value and the intent to use generative AI, while a strong positive relationship existed between perceived value and the willingness to use. Users' trust in ChatGPT and how it affects their intent to and actual adoption of the technology was the focus of a study by Choudhury and Shamszare (2023). According to the results, trust is crucial, as it has a direct and substantial effect on users' intent to use ChatGPT and their actual adoption of the technology.

After examining the existing research, the researcher has observed a noticeable absence of a comprehensive theoretical foundation or framework that encompasses various factors associated with the adoption of AI. As potential determinants, these elements include technological concerns, social effects, perceived advantages and disadvantages, and the role of trust. As a result, the goal of this study is to combine a modified version of the UTAUT with the expectancy value theory (EVT) to create a comprehensive framework for studying students' trust in ChatGPT and, ultimately, their use of the system. The justification for this integration could be attributed to several reasons; first, the EVT is a psychological framework that explains and predicts human behaviour including trust behaviour, specifically about decision-making processes. It posits that individuals make choices and engage in behaviours based on the expectation of achieving desired outcomes and the subjective value they place on those outcomes (Wigfield and Eccles, 2000), in the context of higher education, it explores how student confidence in his or her abilities to complete an assignment or reach a goal (i.e., perceived learning benefits) is related to the value they place on completing the task or attaining the goal (i,e perceived risks). Second, the application of the EVT presents a chance to evaluate the compromise between the perceived benefits of learning and the perceived risks in terms of trust towards ChatGPT, as perceived by the students. And third, the inclusion of trust in ChatGPT is justified as students need to trust the technology to rely on its output and make decisions based on its recommendations. The EVT provides a suitable framework to investigate the factors that influence trust formation, such as performance and effort expectancies and social influence, as proposed by the UTAUT model. This theory allows us to examine how these factors interact with trust to shape students' behaviours regarding ChatGPT.

3 The research framework and hypotheses development

Figure 1 depicts the conceptual framework for this study, which is based on the information offered in the previous section.

Figure 1 Research framework (see online version for colours)



3.1 Perceived mobility influence on performance expectancy and effort expectancy

Perceived mobility is the extent to which a person thinks they are free to go about their business at any given time and place thanks to mobile technologies (Hill and Roldan, 2005). Research indicates that individuals who perceive greater levels of mobility associated with a technology or system tend to have heightened expectations regarding its performance benefits, students in higher education are more likely to have optimistic expectations for the performance benefits they can derive from utilising ChatGPT if they believe it is more mobile than competing conversational agents. According to EVT, students' motivation and output are profoundly affected by how certain they are that they will succeed in accomplishing their goals. Increased levels of perceived mobility may lead to increased performance expectancy due to the expectation of greater ease of obtaining information and accomplishing activities. Those students who feel more independent may also think that conversing with a chatbot is easier and more convenient. Students' expectations about the ease of use and the effort necessary to engage with the technology are positively influenced by the fact that they believe ChatGPT to be mobile, which contributes to the idea that the system is accessible and user-friendly. The influence of perceived mobility on performance expectancy and effort expectancy has been tested and verified in several previous studies in different contexts. For example, Alfalah (2023) examined the influencing factors of students' use of mobile learning management systems in Saudi Arabia, the findings revealed that perceived mobility positively influenced performance expectancy. Huang et al. (2007) reported that perceived mobility was a strong predictor of users' perceptions about the usefulness of the m-learning system. Similarly, in mobile banking services, the positive influence of perceived mobility on performance expectancy was reported by Yen and Wu (2016), as well as its positive influence on effort expectancy (Gumussoy et al., 2018).

The previous results suggest and support that regarding ChatGPT use by higher education students, their perceptions of their mobility have a favourable positive effect on their expectations for future performance and ease of use.

H1 Perceived mobility positively influences performance expectancy.

H2 Perceived mobility positively influences effort expectancy.

3.2 Performance expectancy influence on trust in ChatGPT

Performance expectancy refers to individuals' beliefs and perceptions regarding the extent to which utilising technology would enhance their performance and help them achieve their desired goals (Davis, 1989). In the case of higher education students using ChatGPT, individuals who perceive greater levels of performance of the technology generate a higher level of trust in its capability to deliver desired outcomes, including enhanced efficiency, convenience, and access to information or services. Consequently, individuals are more inclined to hold higher expectations for performance, as they believe that the technology will enhance their productivity and effectiveness. According to the technology adoption model (TAM), the perceived utility of technology influences its adoption and utilisation by individuals (Davis, 1989). Prior research approved its positive effect on trust in technology adoption across a variety of circumstances. For example, research on e-government services (Abu-Shanab, 2019) and mobile banking (Ramos et al., 2018) revealed evidence that performance expectancy had a favourable influence on trust. Performance expectancy, as a crucial component of perceived usefulness, adds to users' belief in the technology's potential to provide the promised advantages. As a result, higher education students who have higher performance expectations for ChatGPT are more likely to establish faith in the system. These results justify proposing that performance expectancy positively influences trust in ChatGPT.

H3 Performance expectancy positively influences trust in ChatGPT.

3.3 Social influence impact on trust in ChatGPT

According to the social information processing theory's central premise (Salancik and Pfeffer, 1978), an individual with limited knowledge about a specific entity or trust target may rely on information about other people's ongoing interactions with that target as an indication of its trustworthiness. The impact of social elements such as peers, instructors, or experts on individuals' attitudes, beliefs, and actions toward technology adoption is referred to as social influence (Venkatesh et al., 2003). Higher education students who get good suggestions, endorsements, or support from their social networks are more likely to establish higher levels of trust in the system in the setting of ChatGPT. When the student perceives that the influential individuals in their social circle hold positive views regarding trust in and adoption of new technologies based on their dependability, legitimacy, and fit for their requirements, they are more likely to adopt similar opinions and share the same convictions. Previous research has indicated that social influence plays a significant role in shaping users' intentions to trust and adopt technology systems in different contexts. For example, Hooda et al. (2022), Mensah (2019) and Abu-Shanab (2019) reported that social influence positively influenced the trust level in e-government services of African students in China. Similarly, Beldad and Hegner (2018) explored the factors that influence German users' willingness to keep using a fitness app. They discovered that social norms influenced users' trust level in using the app. In addition, research by Chaouali et al. (2016) on Tunisian users of m-banking services found that the level of trust and intent to utilise the service was significantly influenced by the users' social networks. Namahoot and Jantasri (2023) reported the positive influence of social influence on trust in the cashless payment system. Additionally, social networks, forums, discussion groups, and social media platforms influence trust in ChatGPT as positive comments or successful ChatGPT use in these networks can boost users' confidence. So H4 reads as:

H4 Social influence positively influences trust in ChatGPT.

3.4 Effort expectancy influence on trust in ChatGPT

It is common to classify innovations as either simple or complex in terms of their usability (Rogers, 1995). Venkatesh et al. (2003) defined 'effort expectancy' as the degree to which a user believes a system requires little to no work on their part. As a result, the adoption rates of complex innovations are lower than those of simple ones (Yuen et al., 2020). It is hypothesised in this research that college students will find ChatGPT to be a helpful and time-saving study tool. If they perceive ChatGPT to be user-friendly and easy to navigate, it instils trust in them regarding the efforts exerted by the designers of the innovation. This ease of use reflects the competence of the innovation, which, in turn, influences users' satisfaction with it (Alkhateeb and Abdalla, 2021), and ultimately their trust in using the system (Khan et al., 2021). The positive significant influence of effort expectancy on trust has been examined and approved by previous research. For example, Khan et al. (2021), Abu-Shanab (2019), Xie et al. (2017) and Abu-Shanab (2017) reported positive influences on the level of ease of the systems and its users' trust level in it in the context of e-government services. Namahoot and Jantasri (2023) revealed a strong and favourable influence on individuals' trust in Thailand's cashless payment system. Similarly, Raman et al. (2023) investigated five variables as determinants of intention to use ChatGPT among university students, and one of the significant ones was the simplicity of use. Hence, the following hypothesis is suggested:

H5 Effort expectancy positively influences trust in ChatGPT.

3.5 Perceived learning benefits influence on trust in ChatGPT

According to the diffusion of innovation theory (DOI), relative advantage (RA) as a main component of DOI refers to the extent to which people perceive innovation as superior to the conventional way (Rogers, 1995). As a result, deriving from the global definition of relative advantage, perceived learning benefits in the current study are like the relative advantage concept, it refers to students' thoughts and views about the benefits and good results they expect to obtain from adopting a specific technology, such as ChatGPT, that is superior to traditional procedures and can improve their future performance (Almaiah et al., 2022). A student's perception of the amount to which he or she will benefit from using a given technology is known as 'benefits' (Kim et al., 2008). These benefits may include gaining new knowledge, boosting skills, increasing efficiency, or promoting a more interesting and effective learning experience. Kasneci et al. (2023) discussed the opportunities and challenges of ChatGPT, they argued that large language models aid research, writing, critical thinking, and problem-solving. These models create book summaries and outlines to help students grasp key themes and structure their writing. In addition, they help students acquire research abilities by giving information, resources, and suggestions of unexplored areas and current research topics to help them grasp and analyse the content. These opportunities and benefits have a substantial impact on people's attitudes, motives, and intentions to use technology for learning (Almaiah et al., 2022). Baber (2020) pointed out that perceived learning benefits positively influenced students' satisfaction with online learning. Three of four perceived benefits were found to have a substantial impact on the propensity to utilise e-commerce, according to research by Ahmad et al. (2020). Similarly, Gilbert et al. (2004) reported that perceived relative benefits had a significant influence on the willingness to use e-government technology, Terblanche and Taljaard (2018) investigated the influence of six benefits on the use and loyalty to travel agents, finding that four out of six benefits were significant. Students' beliefs in technology's ability to assist learning and improve educational outcomes are enhanced by their perception of learning benefits which is a fundamental component of perceiving the system's usefulness (Alfalah, 2023). As a result, university students who perceive greater levels of learning gains using ChatGPT are expected to have higher levels of usage of the system.

Thus, H6 reads as:

H6 Perceived learning benefits positively influence students' use of ChatGPT.

3.6 Perceived risks influence on trust in ChatGPT

Prior the unknown outcome of behaviour is related to perceived risk (Bauer, 1960). The influence of perceived risks as a determinant of technology adoption has been examined in previous research. For example, the amount of perceived risk associated with the use of technology is among the many elements that influence people's trust in e-government, and their plans for using the technology (Ejdys et al., 2019; Karavasilis et al., 2016). In the same vein, Hanafizadeh et al. (2014) argued that the level of overall risk associated with adopting mobile technology correlates negatively with adoption rates.

The user's perception of the overall risk has acted as an obstacle to the sustained utilisation of mobile shopping as well (Grob, 2016). According to Alalwan et al. (2017), customers are more likely to suffer financial or privacy-related losses when pursuing desirable outcomes while using internet banking. However, despite these results, other researchers pointed out that the negative influence of perceived risk on the continuance usage of mobile shopping applications was not supported (Chopdar and Sivakumar, 2019). Risk avoidance plays a major effect in how people feel and act when it comes to adopting new technologies. In the context of ChatGPT, college students who perceive greater risks from conversing with the conversational agent are more likely to have a negative impression of it. Concerns about privacy, data security, information accuracy, and possible adverse effects on academic performance are some of the types of risks that students may perceive. Kasneci et al. (2023) argued that another potential risk is the overuse of the application, as the easily generated information may impair critical thinking and problem-solving. The paradigm simplifies knowledge acquisition, which can increase laziness and discourage learners from investigating and solving problems on their own. The influence of perceived risk is usually supposed to impose a negative influence on the use of technology. Hence, university students who consider ChatGPT as riskier are anticipated to use it less:

H7 Perceived risks negatively influence students' use of ChatGPT.

3.7 Trust in ChatGPT influence on trust in ChatGPT use

McKnight et al. (2011) defined trust as the propensity of an individual to rely on another party due to that party's characteristics. It plays a crucial role in facilitating the adoption, retention, and efficient rollout of new AI technologies (Kim et al., 2021). Usually, people are more likely to rely on technology, share private information, and speak openly and honestly when they have trust in it. When it comes to the use of ChatGPT, trust is of the utmost importance (Choudhury and Shamszare, 2023). The findings of Choudhury and Shamszare's (2023) research offered a new understanding of the forces pushing forward chatbot technologies like ChatGPT. According to the authors, user trust is paramount to the success of ChatGPT. Students' perception of ChatGPT's competence, dependability, and capability of delivering their demands is projected to improve as their expectations for the technology rise. Nguyen et al. (2021) surveyed 359 people about their continuance intention toward using chatbot services provided by the banks in Thailand, they found that users' trust in the chatbot was the most important factor in determining whether they would continue utilising chatbot services. Similarly, users' trust in chatbots as conversational agents was shown to be the deciding element in Laumer et al. (2019) study on the acceptability of chatbots in healthcare for disease diagnosis. As a result, university students who have a higher level of trust in ChatGPT are more likely to use the system. Hence:

H8 Trust in ChatGPT positively influences students' use of ChatGPT.

4 Research methodology

The current study adopts a quantitative technique since it aligns with the study's structure, which is based on a literature review and theoretical rationale (Sekaran and Bougie, 2019). A questionnaire with three sections is used to collect data. The first section asked the respondent whether he/she is aware of AI applications such as ChatGPT. If the respondent was not aware of these applications, the corresponding response was excluded. The justification for the exclusion is that the current study is interested in investigating the determinants of the actual use of ChatGPT, hence students who are not aware of them are not actual users. The second part gathered participant demographics, while the third contained the study instruments used to evaluate the various factors. These items were drawn from current literature, and their validity and reliability have been rigorously investigated and confirmed as listed in the Appendix. Although the items were drawn from earlier studies, they were changed to fit the specific setting of the current study. In addition, to accommodate the respondents' local language, the questions were back-to-back translated into Arabic. Data for both exogenous and endogenous variables were acquired from the same individuals (using the same method and source), hence it is possible for there to be common method variance (CMV). Tehseen et al. (2017) suggest that the presence of CMV may have an effect on the constructs' validity and increase bias. CMV was avoided or minimised through cautious item selection and wording (Podsakoff et al., 2003). Furthermore, appropriate statistical analyses were used to check for CMV in the data analysis.

The research focuses on the population of enrolled students at PTUK, which consists of 7,018 individuals. G-Power 3.9.1.7 software was used to calculate the suitable sample size. The program requires four crucial elements: statistical power, effect size, significance level, and the greatest number of arrows pointing to an external, mediating, or endogenous latent variable in the model. The statistical power of 80%, the effect size of 0.15, and the significance level of 5% are commonly the maximum of five recommended parameters for social science studies (Hair et al., 2017). Given that the proposed model has 3 arrows pointing to trust in ChatGPT and use of ChatGPT, the software suggested that the current study requires a sample size of 77.

As a result, a minimum of 77 responses are necessary to validate the study framework. The researcher used stratified random sampling to assure a representative sample from every school because data for the full population is available and the percentage of students in each college compared to the total population varies among colleges. A Google Form was constructed and published on the colleges' official pages and forums to collect the essential data. IBM SPSS 28.0 and Smart PLS 4.0 were used to analyse the gathered data (Ringle et al., 2022). This software was chosen because of its capacity to investigate both the measurement and structural model, as well as it does not require a normal distribution, which is beneficial for survey-based research because it frequently deviates from a normal distribution (Chin et al., 2003).

5 Data analysis

The data were collected during May and June of 2023. There were 247 answers in all. However, after filtering the responses based on the respondents' awareness of ChatGPT, surprisingly, 120 respondents were not aware of ChatGPT, consequently they were not actual users of the AI application, so these responses were excluded. The remaining 127 responses were used for further analysis.

5.1 Descriptive statistics

The respondents' profile is summarised in Table 1.

Table 1 Respondents profile

Demographic characteristic	*Category*	*Frequency*	*Percent %*
Gender	Male	69	54.3
	Female	58	45.7
	Total	127	100.0
Age (years)	18–20 years	60	47.2
	21–23 years	54	42.5
	>23 years	13	10.2
	Total	127	100.0
Academic program	Diploma	23	18.1
	Bachelor	90	70.9
	Postgraduate	14	11.0
	Total	127	100.0

Table 1 Respondents profile (continued)

Demographic characteristic	*Category*	*Frequency*	*Percent %*
Faculty	Faculty of Graduate Studies	13	10.2
	Palestine Technical College	20	15.7
	Faculty of Business and Economics	10	7.9
	Faculty of Applied Sciences	19	15.0
	Faculty of Information Technology	14	11.0
	Faculty of Engineering and Technology	26	20.5
	Faculty of Agricultural Science and Technology	6	4.7
	Faculty of Art and Educational Sciences	9	7.1
	Faculty of Physical Education and Sport Sciences	10	7.9
	Total	127	100.0
Academic level	1st year	43	33.9
	2nd year	37	29.1
	3rd year	14	11.0
	4th year	23	18.1
	>4th year	10	7.9
	Total	127	100.0
Mobile use duration	<1 year	10	7.9
	1–3 years	40	31.5
	>3 years	77	60.6
	Total	127	100.0

5.2 Measurement models assessment

As suggested by Hair et al. (2017), convergent validity and discriminant validity should be examined to assess the reflective measurement models.

5.2.1 Convergent validity

The assessment of convergent validity of the reflective measurement models consists of examining three criteria: factor loadings, composite reliability (CR), and average variance extracted (AVE). These values are summarised in Table 2.

Initial loadings of the items were above the cut-off value of 0.708 (Hair et al., 2017) except for two items: PeRisk3 and Trust2 as their loadings were 0.699 and 0.588 respectively. However, as all items with loadings between 0.4 and 0.6 should be maintained if the composite reliability (CR) and average variance extracted (AVE) of the construct are sustained, they were not deleted (Hair et al., 2017). All CR and AVE of all variables were above the acceptable levels of 0.7 and 0.5 respectively as suggested by Hair et al. (2019), Hence, the measurement model's convergent validity is ensured in this way.

Table 2 Initial loadings, CR and AVE

Variable	*Item*	*Initial loading*	*CR*	*AVE*
Effort expectancy	EfExp1	0.811	0.887	0.724
	EfExp2	0.897		
	EfExp3	0.842		
Perceived learning benefits	PeBen1	0.761	0.874	0.700
	PeBen2	0.867		
	PeBen3	0.876		
Performance expectancy	PeExp1	0.824	0.898	0.746
	PeExp2	0.876		
	PeExp3	0.889		
Perceived mobility	PeMob1	0.785	0.819	0.602
	PeMob1	0.804		
	PeMob1	0.738		
Perceived risk	PeRisk1	0.786	0.842	0.642
	PeRisk2	0.905		
	PeRisk3	0.699		
Social influence	SoInf1	0.833	0.821	0.606
	SoInf2	0.748		
	SoInf3	0.752		
Trust in ChatGPT	Trust1	0.876	0.832	0.630
	Trust2	0.588		
	Trust3	0.881		
Use of ChatGPT	Use1	0.808	0.925	0.805
	Use2	0.936		
	Use3	0.942		

5.2.2 Discriminant validity

Heterotrait-monotrait ratio (HTMT) is used for the assessment of discriminant validity as recommended by Henseler et al. (2015) and Franke and Sarstedt (2019). All the values of HTMT ratios between the variables are less than the stricter criterion of 0.85 (Henseler et al., 2015; Franke and Sarstedt, 2019). This indicates that discriminant validity is obtained. Table 3 lists the HTMT ratios in which a 95% confidence interval with a bootstrapping of 5,000 was used.

5.3 Common method bias

Taking into account that the data came from a single repository, we first assessed the degree to which the variables were correlated by following the procedures outlined by Kock and Lynn (2012). Each variable was analysed by regression using IBM SPSS, and all variables were regressed against random variable and their Variance Inflation Factors (VIFs), and are presented in Table 4.

Table 3 The HTMT ratios of the variables

	Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1	Effort expectancy								
2	Perceived benefits	0.456							
3	Perceived risks	0.142	0.119						
4	Performance expectancy	0.374	0.544	0.172					
5	Social influence	0.237	0.558	0.189	0.503				
6	Trust	0.303	0.474	0.088	0.700	0.705			
7	Use of ChatGPT	0.348	0.602	0.260	0.452	0.508	0.549		
8	Perceived mobility	0.544	0.797	0.160	0.692	0.557	0.674	0.684	

Table 4 The VIF values of the constructs

Variable	*VIF*
Effort expectancy	1.267
Perceived benefits	1.780
Perceived risks	1.097
Performance expectancy	1.686
Social influence	1.513
Trust	1.710
Use of ChatGPT	1.717
Perceived mobility	2.007

All values are less than 3.3 (Diamantopoulos and Siguaw, 2006), these values indicate that the dataset is clear of critical collinearity-related issues.

5.4 Structural models assessment

5.4.1 Collinearity analysis

The analysis of lateral collinearity is the first phase in the structural model evaluation process. When two variables with a hypothesised causal relationship really measure the same underlying notion, we have lateral collinearity (Kock and Lynn, 2012). Using PLS-calculated VIF values from the inner model, the collinearity between the constructs was evaluated. All VIF values are <3.3 (Diamantopoulos and Siguaw, 2006), indicating that there is no critical level of lateral collinearity as shown in Table 5.

5.4.2 Normality check

The data distribution's normality was determined using multivariate skewness and kurtosis, as proposed by Hair et al. (2017). WebPower's website was used for the evaluation (WebPower, n.d.). The multivariate skewness was ($\beta = 13.902$, $p < 0.01$) and kurtosis was ($\beta = 93.6768$, $p<0.01$) values for Mardia. When these values are compared to the Kline (2015) thresholds (skewness 3; multivariate kurtosis 20), the data does not follow a normal distribution. As a result, a non-parametric test should be used to assess the importance of the weight, loadings, and path coefficient. Hair et al. (2017) used the bootstrapping technique with 5,000 sample resamples to accomplish this.

Table 5 Lateral collinearity analysis results

	Effort expectancy	*Performance expectancy*	*Trust*	*Use of ChatGPT*
Effort expectancy			1.111	
Perceived benefits				1.158
Perceived risks				1.004
Performance expectancy			1.295	
Social influence			1.185	
Trust				1.162
Perceived mobility	1.000	1.000		

5.4.3 Direct relationships between perceived mobility and performance expectancy and effort expectancy

The first and second structural models relate to perceived mobility and performance expectancy and effort expectancy. Since the p-value criterion alone has been questioned (Hahn and Ang, 2017), the researchers used confidence intervals and effect magnitude (substantial significance) to evaluate significance, as suggested by Sullivan and Feinn (2012). Cohen (1988) recommended 0.02 for minor effects, 0.15 for medium effects, and 0.35 for large effects. The findings related to these relationships are summarised in Table 6.

Perceived mobility shows direct positive significant influences on performance expectancy and effort expectancy as the p-values are <0.01, and the confidence intervals do not straddle zeros, this leads to support H1 and H2. Furthermore, the effect sizes are large and medium respectively as the $f^2 = 0.354$ and 0.215. The explanatory power of the change in performance expectancy was 26.2%, and the change in effort expectancy was 17.7%.

Table 6 Performance expectancy model findings

Hypothesis	*Relationship*	*Beta*	*St. dev.*	*T value*	*P value*	*BCI LL*	*BCI UL*	*f^2*	*Effect size*	*Decision*
H1	Perceived mobility → performance expectancy	0.512	0.086	5.959	0	0.367	0.646	0.354	Large	Supported
H2	Perceived mobility → effort expectancy	0.421	0.077	5.461	0	0.300	0.552	0.215	Medium	Supported

5.4.4 Direct relationships with trust in ChatGPT

Three predictors in the proposed model directly influenced trust in ChatGPT. The findings about these hypotheses are summarised in Table 7.

Table 7 Trust in ChatGPT model findings

Hypothesis	*Relationship*	*Beta*	*St. dev.*	*T value*	*P value*	*BCI LL*	*BCI UL*	*f^2*	*Effect size*	*Decision*
H3	Performance expectancy → trust	0.432	0.069	6.244	0	0.317	0.545	0.255	Medium	Supported
H4	Social influence → trust	0.341	0.063	5.369	0	0.241	0.452	0.173	Medium	Supported
H5	Effort expectancy → trust	0.039	0.09	0.429	0.334	–0.115	0.184	0.002	No effect	Not supported

Two variables performance expectancy and social influence showed significant positive influences on trust in ChatGPT as their p-value <0.01, and confidence intervals do not straddle zero, and their effect size is not marginal. Performance expectancy and social influence had small effects on trust in ChatGPT ($0.02 < f^2 < 0.35$), hence supporting H3 and H4, respectively. On the other hand, effort expectancy is not significant as its p-value is 0.334, and the confidence intervals straddle a zero, thus H5 is not supported. All these variables were responsible for R^2 = 43.5% of the change in trust in ChatGPT.

5.4.5 Direct relationships with use of ChatGPT

Three predictors in the proposed model directly influenced the use of ChatGPT. The findings about these hypotheses are summarised in Table 8.

Table 8 The use of ChatGPT model findings

Hypothesis	*Relationship*	*Beta*	*St. dev.*	*T value*	*P value*	*BCI LL*	*BCI UL*	*f^2*	*Effect size*	*Decision*
H6	Perceived benefits → use of ChatGPT	0.41	0.082	5.008	0	0.275	0.546	0.236	Medium	Supported
H7	Perceived risks → use of ChatGPT	–0.225	0.089	2.534	0.006	–0.358	–0.104	0.082	Small	Supported
H8	Trust → use of ChatGPT	0.273	0.09	3.031	0.001	0.120	0.419	0.104	Small	Supported

The three variables perceived benefits, perceived risks, and trust in ChatGPT had significant positive influences on the use of ChatGPT as their p-value <0.01, confidence intervals did not straddle zero, and their effect sizes were meaningful. Perceived risks and trust had small effects ($f^2 < 0.15$), while perceived benefits has a medium effect size ($0.15 < f^2 < 0.35$) supporting H6, H7, and H8 respectively. All these variables were responsible for $R^2 = 38.5\%$ of the change in the use of ChatGPT.

5.5 *Predictive relevance of the models*

For the assessment of these models' prediction accuracy, the researcher used Geisser (1974) and Stone (1974) blindfold testing. The Q^2 value was used when its value of the reflected endogenous variable was greater than zero, the model provided accurate predictions (Hair et al., 2017). The four structural models have predictive powers: for effort expectancy, $Q^2 = 14.9\%$; for performance expectancy $Q^2 = 23.6\%$; for trust in ChatGPT $Q^2 = 30.0\%$; and for the use of ChatGPT $Q^2 = 32.7\%$. Furthermore, item-level predictive potential assessments are also recommended by Shmueli et al. (2019). Predictive relevance cannot be confirmed if all PLS-LM item differences are greater than zero; moderate predictive power is indicated if half or more are less than zero; and low predictive power is indicated if the minority is less than zero. Table 9 shows item-level predictive relevance.

Table 9 Item level predictive relevance

Item	*PLS RMSE*	*LM RMSE*	*PLS-LM*	*Q^2_predict*	*Prediction Power*
EfExp1	0.969	0.987	–0.018	0.149	High predictive power
EfExp2	0.923	0.939	–0.016		
EfExp3	0.893	0.898	–0.005		
PeExp1	0.914	0.935	–0.021	0.236	Medium predictive power
PeExp2	0.96	0.936	0.024		
PeExp3	0.982	0.984	–0.002		
Trust1	1.063	1.084	–0.021	0.303	High predictive power
Trust2	1.176	1.234	–0.058		
Trust3	1.007	1.054	–0.047		
Use1	1.182	1.266	–0.084	0.327	High predictive power
Use2	0.915	0.944	–0.029		
Use3	0.856	0.867	–0.011		

Three models (effort expectancy, trust in ChatGPT, and use of ChatGPT) had high predictive power, whereas the fourth model of performance expectancy had a medium predictive power.

6 Discussion

This research investigated PTUK students' trust in and use of ChatGPT to shed insight on the determining factors of their trust and use of ChatGPT by examining eight hypotheses.

The study's conclusions showed that all the proposed factors in the research model had a substantial impact aside from effort expectancy on trust in ChatGPT.

As for perceived mobility's influence on performance expectancy and effort expectancy, the two relationships were supported by a larger impact on performance expectancy. These results ensure the importance of perceived mobility as an external determinant of the performance and level of ease associated with the use of a certain technology. Since students can use the technology freely without constraints related to time or place, this helps in raising their expectations about the performance and productivity of ChatGPT. In addition, as mobility saves time and boosts productivity, it enhances the efficiency of the technology which promises improved results. As ChatGPT can be used on mobile devices, this makes it more intuitive than desktop computers. When students have a good mobile platform experience, they perceive it to be more useful for them as it enables them to accomplish their education-related tasks more professionally, easily, and successfully. These results matched the findings of previous studies such as Alfalah (2023), Gumussoy et al. (2018), Yen and Wu (2016) and Huang et al. (2007).

On the other hand, for the three proposed determinants of students' trust in ChatGPT, performance expectancy, and social influence impacts were supported, whereas effort expectancy influence on trust in ChatGPT was not supported. The positive influence of performance expectancy on trust was supported in previous studies (i.e., Abu-Shanab, 2019; Ramos et al., 2018). This indicates that as students perceive ChatGPT as reliable in providing them with correct, helpful, dependable information, and quick responses, it builds trust in the system. Additionally, when ChatGPT functions effectively, users don't have to check the system's responses. Lack of double-checking boosts system correctness and dependability and fosters trust in it.

Similarly, regarding the impact of social influence on trust in ChatGPT that was approved, as students observe others, particularly colleagues or important ones for them placing trust in ChatGPT and relying on its responses, they are more likely to do the same. This instils confidence in the AI system's credibility and nurtures trust, as users perceive the collective opinion of others as a sign of dependability. Besides, with the recent release of ChatGPT, many positive press coverages can influence public opinion including students. Hence, positive media coverage boosts students' trust in the AI system. These results are in line with the findings of many previous studies including Hooda et al. (2022), Mensah (2019) and Abu-Shanab (2019) and others.

In contrast, effort expectancy did not impose a positive influence on students' trust in ChatGPT as was anticipated. This result contradicts the reported findings of Raman et al. (2023), Khan et al. (2021), Abu-Shanab (2019), and others. A possible justification would be that although students' perceptions of ChatGPT can be affected by their effort expectations, but this may not necessarily translate to a higher level of trust in the underlying AI. This is attributed to the fact that many higher education students are familiar with using technological applications and are getting familiar with them, hence they may not consider the level of ease in using a certain technology to be a good indicator of whether to trust ChatGPT. Performance, openness, and social influence are only a few of the many aspects that contribute to trust's complex nature. AI systems that successfully gain and keep users' confidence over time require an understanding of the complex interplay of these aspects.

Considering the determinants of the use of ChatGPT, the findings support that the three proposed factors (perceived benefits, perceived risks, and trust in ChatGPT) positively influence the use of ChatGPT. Perceived benefits such as quick responses that save time; the novelty of engaging with ChatGPT might be interesting to users and pique their interest in learning more about its capabilities that may lead to continued usage as consumers discover further perceived benefits during their interactions; and its availability all the time is a huge benefit over human specialists. Users become more reliant on the service due to its constant availability. Students are more inclined to adopt and use ChatGPT for their daily academic work because of its advantages. These findings are consistent with those of other prior research efforts, including those of Baber (2020) and Terblanche and Taljaard (2018).

According to the findings of the study, perceived risks had a negative impact on the adoption and use of ChatGPT. These findings supported prior studies by Ejdys et al. (2019) and Karavasilis et al. (2016), indicating that individuals, even students in this situation, are aware of the possible risks associated with utilising ChatGPT. Perceived risks had a small effect on their actual use of the device. It is worth noting that the effect size of perceived risks was found to be smaller than that of perceived benefits which was medium. This means that, despite being aware of the risks, students judged that the benefits they obtained from utilising ChatGPT surpassed the potential negative repercussions of its use. These findings support the idea that, while identifying risks is crucial, students' positive impressions of a technology's benefits might be a deciding factor in its acceptance and sustained use. It implies that the perceived benefits functioned as a driving force that exceeded the students' worries about potential risks, eventually encouraging them to embrace and adopt ChatGPT into their routines or learning processes.

Finally, the results show that there is a strong positive correlation between their trust in ChatGPT and their actual use of it. It was recognised that students' ability to trust one another would go far toward easing ChatGPT's acceptance and incorporation into their academic lives. Students were more likely to use ChatGPT, seek assistance from it, and embrace it as a beneficial tool in their educational activities when they had a high level of trust in it. The findings emphasised the significance of trust as a critical component in the effective implementation of ChatGPT. ChatGPT, as an AI-based technology, functions in a situation in which users must rely on its capabilities and replies. Students were more likely to entrust ChatGPT with academic work and decision-making processes when they were confident in its accuracy and dependability. This result is like the results of many previous studies such as Nguyen et al. (2021) and Laumer et al. (2019).

7 Conclusions

This research studied what makes PTUK students trust while using ChatGPT, providing vital insights into their beliefs and behaviours regarding this AI system. The study's findings indicated that, except for effort expectancy, the recommended components in the research model strongly influenced confidence in ChatGPT. Perceived mobility emerged as an important external predictor, improving performance and effort expectancies, and thus favourably influencing students' trust in the system. The favourable connections between performance expectancy and social influence on trust were consistent with prior research, emphasising the relevance of dependability and social validation in trust formation.

Students' decision to include ChatGPT in their academic activities was influenced by the perceived benefits of quick responses, novelty, and constant availability. Perceived hazards, on the other hand, served as a disincentive to usage. Furthermore, the study emphasised the importance of trust in encouraging students to use ChatGPT. Building and sustaining trust in the AI system is critical for its effective implementation. Students' trust in ChatGPT not only enhances their likelihood of using it but also motivates them to seek its assistance and incorporate it into their academic lives. This emphasises the significance of technical proficiency, ethical issues, and transparency in maintaining trust and adoption of ChatGPT.

For universities in general and PTUK in specific, they may gain knowledge about ChatGPT trust and usage through the study. They can better integrate AI technologies into their educational systems using this knowledge. They may carefully prepare ChatGPT deployment and integration into academic support services. In addition, the results provide institutions with important data for fully realising the benefits of AI technologies like ChatGPT. Universities may build a more supportive, individualised, and technologically sophisticated learning environment that benefits both students and the institution by utilising these insights. Students' familiarity with and practice with AI technologies like ChatGPT can better prepare them for the AI-driven future as AI becomes increasingly pervasive in society and the workforce. Students can benefit greatly from gaining an understanding of AI tools and how to use them ethically because of this.

Lastly, larger implications for technology adoption in general are demonstrated, as the study stresses the need of understanding users' opinions of a technology's benefits and drawbacks. It also emphasises the importance for developers to identify and mitigate perceived risks while also promoting perceived benefits to enable widespread and beneficial technology adoption.

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Appendix

Items for measuring the variables

Variable	*Measuring items*	*Source*
Perceived mobility	I perceive ChatGPT's mobile accessibility as a valuable feature that encourages me to use it regularly.	Yu (2009)
	ChatGPT enables users to perform chatting at any location and time	
	ChatGPT is a more time-efficient alternative to traditional search methods.	
Performance expectancy	I believe that ChatGPT will help me accomplish tasks more efficiently and effectively	Venkatesh et al. (2003)
	Using ChatGPT will enhance my productivity by providing accurate and relevant information	
	ChatGPT can deliver high-quality responses and solutions to my queries or problems.	Moon and Kim (2001)
Trust in AI-based systems	ChatGPT is trustworthy in the sense that it is dependable and credible	Choudhury and Shamszare (2023)
	ChatGPT will not cause harm, manipulate its responses, create negative consequences for me	
	ChatGPT is reliable in providing consistent and dependable information	
Social influence	The recommendations and positive opinions of others influence my intention to use ChatGPT	Venkatesh et al. (2003)
	I am more likely to use ChatGPT if I see others around me using it	
	The influence of influential individuals in my network positively affects my intention to use ChatGPT	
Perceived risks	Using ChatGPT might lead to negative psychological consequences, such as a loss of control over the conversation or a feeling of dependence on technology	Bauer (1960)
	Using ChatGPT raises concerns about the security and privacy of my personal information	Doolin et al (2005)
	I am concerned about potential financial risks, such as unexpected charges or unauthorised access to my financial information	Carter and Bélanger (2005)

Items for measuring the variables (continued)

Variable	*Measuring items*	*Source*
Perceived learning benefits	Using ChatGPT can help me acquire new knowledge and learn about a wide range of topics	Venkatesh et al. (2003)
	ChatGPT helps me stay updated with the latest information and developments in different fields.	Davis et al. (1989)
	I believe that using ChatGPT will broaden my understanding of complex concepts and ideas	
Effort expectancy	Learning how to utilise ChatGPT is easy for me.	Davis et al. (1989)
	It is easy for me to get proficient with ChatGPT	
	I expect my experience with ChatGPT is clear.	
Continue to use	I see myself using ChatGPT over an extended period of time	Venkatesh et al. (2003)
	I am likely to keep using ChatGPT in the future due to its usefulness	
	Based on my past experience, I am inclined to keep using ChatGPT	