# Examining students' intention to use ChatGPT: Does trust matter?

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Little knowledge is available on students' attitudes and behavioural intentions towards using ChatGPT, a breakthrough innovation in recent times. This study bridges this gap by adding two relevant less-explored constructs (i.e., perceived enjoyment and perceived informativeness) to the technology acceptance model and illustrating the moderating effect of trust on the acceptance of ChatGPT. Data was collected from 344 private and public university students from Bangladesh, with the analysis done through structural equation modelling. The results highlight the significance of perceived usefulness, perceived ease of use and perceived informativeness in understanding students' attitudes towards using ChatGPT for learning, which subsequently predicts their behavioural intention to use it. Interestingly, students' level of enjoyment was triggered once the trust issue came into play, meaning perceived enjoyment had no substantial impact on attitude unless trust moderates the relationship between perceived enjoyment and attitude towards using ChatGPT.

*Implications for practice or policy*

- Scholars can get first-hand insights into perceived enjoyment and perceived informativeness with perceived usefulness and perceived ease of use in the context of ChatGPT and education.
- Practitioners and educators can comprehensively understand the antecedents affecting students' attitudes in line with their behavioural intention towards ChatGPT.
- Policymakers can design viable strategies to promote the ethical and sustainable usage of ChatGPT in education.

*Keywords:* ChatGPT, education, technology acceptance model, perceived informativeness, perceived enjoyment, trust, educational technology

## Introduction

Technological advancement and increased worldwide connectivity have forced rapid transformations across countries in society, the economy, and the environment. These fast transformations are known as *megatrends*, which are anticipated to continue as the 21st century advances (Haluza & Jungwirth, 2023). A notable example of such advancement is artificial intelligence (AI), which has spurred some ground-breaking innovations like OpenAI's ChatGPT, a state-of-the-art language model (Rudolph et al., 2023). Like other fields (i.e., healthcare, banking, programming, sales and marketing), ChatGPT is predicted to revolutionise the educational landscape (Duong et al., 2023; Liu & Ma, 2023). For instance, this AI-enabled chatbot can generate content from prose, stories and articles and even programming code within a few

seconds (Rudolph et al., 2023). It aims to produce any content indistinguishable from human-written content. Moreover, it can communicate with users effectively, which appears realistic and simple to comprehend.

In the context of modern AI, the Association for the Advancement of Artificial Intelligence and the Computer Science Teachers Association jointly sponsor the Artificial Intelligence (AI) for K-12 initiative, which facilitates national guidelines for AI education for students, instructors and researchers. The initiative includes four big ideas (i.e., perception; representation and reasoning; learning; natural interaction) (Druga et al., 2022). Woodruff et al. (2023) argued that natural interaction (big idea 4) aligns with the concept of ChatGPT representing virtual agents, like chatbots, who must be able to converse in human languages and detect human expression. Students can utilise ChatGPT to facilitate their academic performance (e.g., preparing assignments and reports). Students can even learn a new language through it, as ChatGPT provides customised feedback based on users' capacity (Boubker, 2023; Dwivedi et al., 2023). Thus, it can be concluded that ChatGPT has opened a new window for a more interactive and customised learning platform.

The chatbot concept may appear new to many people, but chatbots started their journey since the first programme named ELIZA was created in 1966 (Weizenbaum, 1966). In the beginning stage, the primary purpose of chatbots was to create simulated human interactions. Nowadays, this technology has been extensively utilised in various fields, such as forecasting, service offerings, individual support, healthcare and education (Følstad & Brandtzaeg, 2017). There are different types of chatbots. According to the report by IBM (Church, 2023), chatbots have five types: menu or button-based chatbots (basic version of a chatbot used by clicking on the button or menu), rules-based chatbots (used in interactive frequently asked questions), AI-powered chatbots (used in an intelligent knowledge base of questions and responses, like Watson Assistant), voice chatbots (used in voice interaction rather than typing, such Apple's Siri), and generative AI chatbots (employed in more interactive and humanly conversation, like ChatGPT). Among these chatbots, ChatGPT has more than 100 million users globally; interestingly, it acquired 1 million users within only 5 days after its launch in November 2022, while Instagram took 2.5 months to achieve that number (Bæk, 2023). Such heightened interest in ChatGPT among people is the blessing of smartphones and internet connectivity.

Young, tech-savvy generations are more likely to use chatbots to access a variety of services. According to the Haptik Team (2021), approximately 40% of millennials connect with chatbots daily. Studies have shown that chatbots' social presence has spurred this rapid adoption among the young generation (Qiu & Benbasat, 2009). In an educational context, many students interact with these AI chatbots, and the trend is increasing notably. This might be due to the deployment of AI technologies emphasised in Education 4.0, the learner-centric educational system (Molnar & Szuts, 2018). Perhaps the ease of use, quick access to resources (e.g., online articles) and time efficiency (e.g., writing any content quickly) are the main reasons driving students towards using AI-based chatbots. To date, several technologies, such as computers, the Internet, social media and virtual reality, have transformed the educational system. However, how stakeholders (e.g., students and teachers) will engage with any new technologies (e.g., ChatGPT) has not received adequate research attention (Rudolph et al., 2023).

With the help of modern technologies like AI, learning and education have become automated. Nevertheless, the usage of ChatGPT has dark sides as well. For example, according to a survey conducted by *USA Today*, 43% of academicians believe that ChatGPT will make their jobs difficult, while one out of four (25%) students cheat on preparing their assignments using ChatGPT (Jimenez, 2023). Similarly, Tech Business News (2023) found that ChatGPT in education has many negative aspects, such as enticing academic dishonesty, diminishing creativity, promoting laziness, and reducing memory retention. However, the positive aspects of using ChatGPT outweigh the negative aspects. For example, ChatGPT can aid academic libraries with basic services, including reference and cataloguing (Adetayo, 2023). It can help users receive accurate climate change forecasts (Biswas, 2023). Dwivedi et al. (2023) have also highlighted multiple learning opportunities for students with ChatGPT:

- Students may use ChatGPT (more convenient than surfing the Internet) to learn deeply about concepts or theories taught during the class lecture.
- Students can generate personalised feedback regarding grammar and content of their academic papers (e.g., assignments, research articles).
- ChatGPT can help students with learning new languages by providing feedback on users' language capacities and encouraging more practice.
- ChatGPT can be an excellent team member helping students with group projects (not simply writing the whole content but giving directions or ideas to explore).
- Non-native speakers can sharpen their English writing skills with ChatGPT.
- Students can better acquaint themselves with technologies like ChatGPT and its uses they might have to capitalise on in their professional life. In fact, ChatGPT could be a good starting point for learning about any issues, topics or concepts.

Although human-AI collaboration (e.g., ChatGPT) is predicted as the foreseeable future in education, like any other sector (e.g., business, healthcare), misuse or user resistance to such new technology is clearly evident (Dwivedi et al., 2023). This problem is obvious in developing countries due to the persistent digital divide, where some users have better access to technologies than others. Presumably, many people have learned or even heard about AI for the first time due to ChatGPT. However, stakeholders (e.g., students, teachers, programmers) should make proper use of ChatGPT to augment their potential (as mentioned earlier) and diminish the digital divide across countries (e.g., developing vs developed) and users (e.g., beginner vs tech-savvy). Given that students are heavy users of ChatGPT, measures must be taken to encourage their proper use of it. This begs the understanding of what triggers students to use ChatGPT for learning in a developing country like Bangladesh, which is the main research question this study aimed to answer.

Although a substantial number of studies have been conducted to investigate the role of chatbots in education (e.g., Al-Sharafi et al., 2022; Rudolph et al., 2023), there is still a lack of empirical examination on the acceptance of a specific chatbot like ChatGPT (Bernabei et al., 2023; Bin-Nashwan et al., 2023; Choudhury & Shamszare, 2023). This argument could be further strengthened by Figure 1, which is a keyword co-occurrence network (deeper look into ChatGPT) generated by VOSviewer (van Eck & Waltman, 2010) based on a Scopus bibliographic record of 787 studies on ChatGPT (as of 22 October 2023). The figure shows that the ChatGPT keyword is predominantly linked with chatbots, generative AI and OpenAI. However, no keywords relating to students' adoption or acceptance of ChatGPT, with only one relating to any theoretical models (e.g., technology acceptance model, TAM), are visible. Moreover, Figure 2 (co-authorship network) displays most existing studies on ChatGPT centred on developed countries (e.g., United States of America, United Kingdom), signifying a deficiency of evidence from developing countries like Bangladesh.

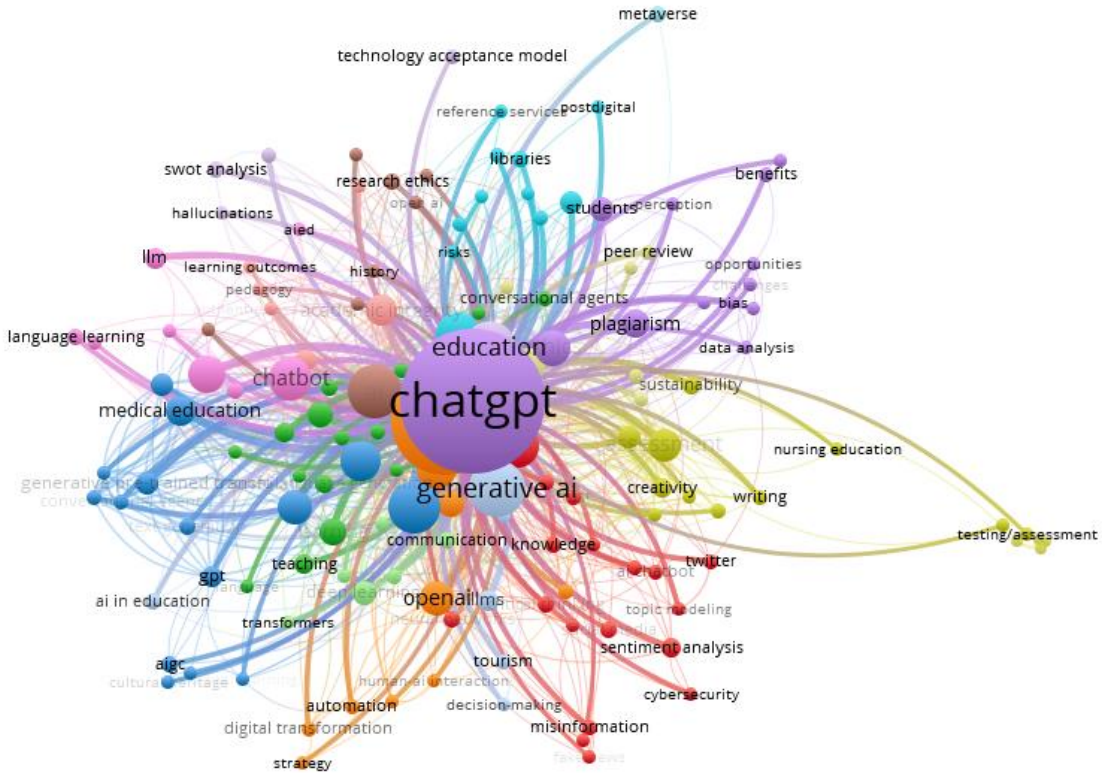


*Figure 1.* Keyword co-occurrence network developed using VOSviewer

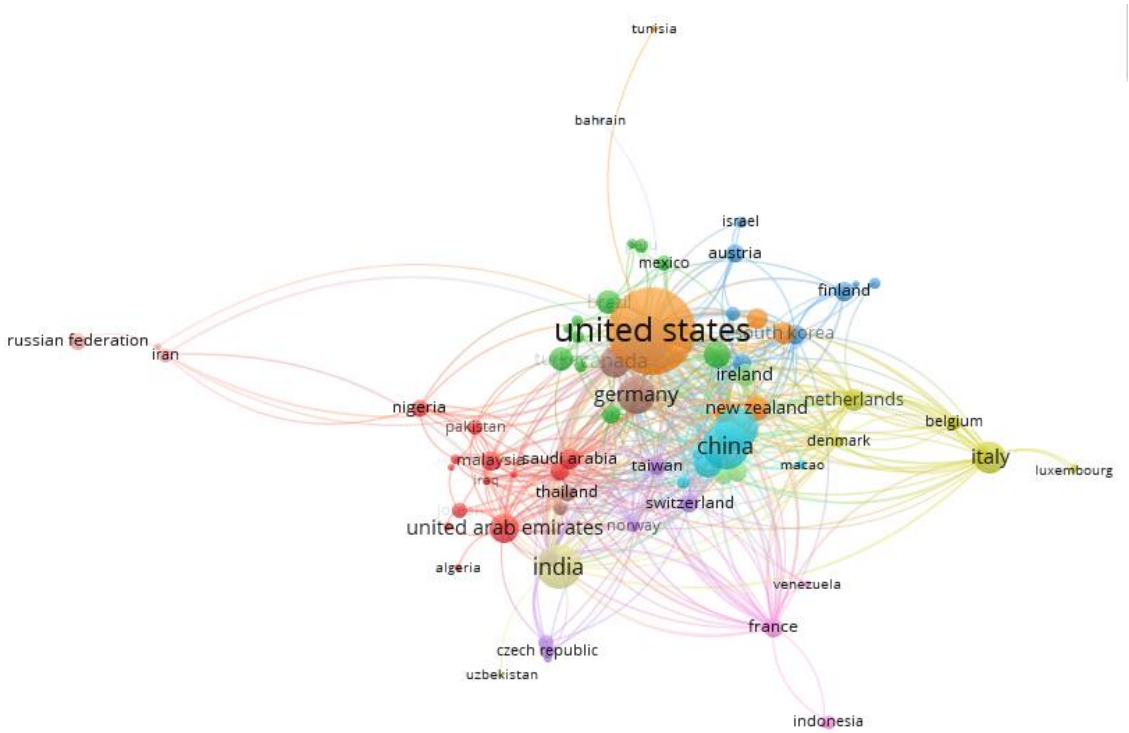


*Figure 2.* Co-authorship network (countries) developed using VOSviewer

Even though many studies are available based on relevant technologies, such as virtual reality and cloud computing (Sestino & D'Angelo, 2023), the adoption of new technologies might vary across technologies and cultures (Ashraf et al., 2019). Besides, most studies (e.g., Al-Sharafi et al., 2022; Chatterjee & Bhattacharjee, 2020) have overlooked the interrelations (e.g., moderation and mediation effects) among constructs to predict a specific technology adoption behaviour. However, researchers (e.g., Senali et al., 2022) have opined that moderators and mediators help to comprehensively understand the relationship among variables and better predict an outcome (e.g., acceptance of new technology). This study bridges the research gaps by adding two relevant less-explored constructs (i.e., perceived enjoyment and perceived informativeness) to TAM (Davis, 1989), hypothesising the moderating effect of trust on the acceptance of ChatGPT and testing the extended TAM (Venkatesh & Davis, 2000) in a developing country context (i.e., Bangladesh).

## Theoretical framework and hypothesis development

Technology acceptance theories, including the TAM (Davis, 1989), the extended TAM (Venkatesh & Davis, 2000), the model combining the TAM and the theory of planned behaviour (Taylor & Todd, 1995) and the unified theory of acceptance and use of technology (Venkatesh et al., 2003), are well-accepted theories to examine users' technology adoption intention and behaviour. In fact, these models are frequently used across disciplines to study how users interact with various technologies. In line with this, the current study considered the variables of TAM (e.g., perceived usefulness and perceived ease of use) and two relevant variables, perceived informativeness and perceived enjoyment, with trust as a moderator to understand the determinants influencing attitudes towards adopting ChatGPT by university students.

Holdack et al. (2022) emphasised perceived informativeness and enjoyment to investigate consumers' wearable technology adoption behaviour and called for further investigation into these determinants. In the context of avatar marketing, Miao et al. (2022) affirmed that consumers' cognitive responses, like perceived informativeness, can play a crucial role in determining consumers' purchase intention. Moreover, several studies have extended TAM, such as Sabbir et al. (2020), which incorporated perceived enjoyment in the technology adoption domain. Jan and Contreras (2011) used TAM to predict students' technology acceptance behaviour. In order to predict older adults' mobile payment adoption, Yang et al. (2023) employed the extended TAM to examine the influential predictors of attitudes and use intention. Therefore, the utilisation of TAM to explain users' technology adoption behaviour is well established (Sabbir et al., 2020; Yang et al., 2023). Yet, research gaps exist in explaining users' (e.g., students) technology adoption behaviour as such behaviours vary with new technologies. Accordingly, Dwivedi et al. (2023) called for further research attention on how hedonic (e.g., enjoyment) and utilitarian (e.g., informativeness and trust) factors influence users to use ChatGPT. In light of this evidence and considering the informativeness and enjoyment perspective with ChatGPT, including perceived informativeness, perceived enjoyment and trust in the current research model is reasonable. In fact, ChatGPT is a quick source of relevant information, and many users have fun with ChatGPT by asking playful questions (e.g., "What name you would like to have if you were a human?").

### Perceived usefulness

Perceived usefulness is the degree to which people believe using new technology will improve their ability to accomplish their jobs (Lee, 2006). The usefulness of any information technology is considered essential for acceptability and popularity. For instance, in mobile shopping, usability strongly influences behavioural intention to purchase mobile devices (H. P. Lu & Su, 2009). If users believe there is something to benefit from a new technology, they are more likely to adopt it. However, in TAM, perceived usefulness and perceived ease of use do not equally affect a user's behavioural intention (Worthington & Burgess, 2021). Worthington and Burgess demonstrated that students' adoption intention of online therapy might be influenced by the perception that it is useful, while they might not perceive it as easy to use. Similarly, students may find a new technology easy to use but not substantially useful. In several studies, perceived usefulness was identified as an important factor that promotes using a specific technology (Tiwari et al., 2023; J. H. Wu & Wang, 2005). Generally, if users believe that a technology like a virtual assistant is useful,

they will embrace it (Hussain et al., 2019). In line with this, it would be interesting to study how attitudes towards using ChatGPT for learning are influenced by perceived usefulness. Although ChatGPT can offer several learning opportunities, including flexibility, convenience and time saving, it is crucial to understand how it is effective in a least-developing country. Based on this discussion, we postulated the following hypothesis:

**H1:** Perceived usefulness has a positive and significant effect on the attitude to use ChatGPT.

### Perceived ease of use

The extent to which a person feels that utilising a certain information system will be devoid of mental effort is known as the perceived ease of use of that technology (Davis, 1989). Davis asserted that user-friendliness is a sign of technological acceptability. In the context of education, students are more inclined to use chatbots for information acquisition if the technological infrastructure is already in place (Malik et al., 2021). Such infrastructure includes user-friendly interfaces and messaging programmes that can work with different Internet-enabled phones. In order to make the infrastructure easy and manageable, organisations reduce the entrance barrier, making it simple for customers to use technology (Svendsen et al., 2013). In other words, potential users of a particular technology will be ready to adopt it if it is simple to comprehend and utilise. Several researchers (e.g., Jan & Contreras, 2011) have shown that people who utilise technologies may have preconceived notions about how simple or complex technology would be to use.

To understand users' expectations, researchers must investigate how easy users consider a system to use. The simplicity of use significantly impacts users' adoption of technical products, and thus it should be carefully taken into account while designing a product (N. Wang et al., 2023). For example, in app-based technology, if users can simply add a contact to their standard messaging applications, like WhatsApp, Facebook, without difficulty, they are more likely to adopt the technology. Although ChatGPT has an app version to use easily with any smartphones, tablets and laptops, it can still be accessed in the browser across all web-responsive devices without many hazards. Besides, as discussed earlier, the characteristic of natural interaction highlights ChatGPT's greater levels of usability with ease, which may foster users' positive attitudes towards ChatGPT. Thus, the contexts above helped to formulate the following hypothesis:

**H2:** Perceived ease of use has a significant positive influence on attitude towards ChatGPT.

### Perceived enjoyment

Perceived enjoyment is connected with an individual's personal behaviour (T. S. H. Teo et al., 1999). According to S. H. Kim (2008), users like to adopt technology if they find enjoyment or satisfaction in doing so. In other words, perceived enjoyment is one of the most important factors in users deciding whether they will engage in online activities such as mobile games, online learning and online purchasing (Ha et al., 2007). T. Teo (2009) found that perceived enjoyment plays an influential role in the desire to use the Internet for activities like surfing, texting and even downloading any online content. Accordingly, the impact of perceived enjoyment on users' attitudes has been demonstrated in several studies, especially in technology adoption contexts (Jeon et al., 2021; Sabbir et al., 2020). In particular, for Internet users who want to get services online, their attitudes are affected notably by perceived enjoyment (H. P. Lu & Su, 2009). In an educational aspect, it seems that the more a person appreciates utilising ChatGPT for learning, the more likely they will continue the behaviour. Therefore, the above circumstances suggested the following hypothesis:

**H3:** Perceived enjoyment has a significant and positive influence on attitude towards ChatGPT.

### Perceived informativeness

Perceived informativeness is the extent to which an individual perceives that an entity can deliver pertinent, in-depth and accurate information on any problem, attribute or policy (Holzwarth et al., 2006). Online users prefer websites or even virtual entities that can offer crucial and up-to-date information since it helps them make wise decisions, given that buying products online does not provide a touch-feel trial (Reddy & Chalam, 2013). The context of the informativeness of a virtual entity in terms of product, pricing and promotion information has been emphasised by Pandey and Chawla (2016). In the case of online learning through ChatGPT, a person is expected to form a positive attitude when they find that the chatbot is effective in providing the desired information. From this point of view, we assumed that:

> **H4:** Perceived informativeness has a positive and significant impact on attitude towards ChatGPT.

### Attitudes and intentions to use

People have a psychological system for evaluating the effects of a given act, which is commonly known as attitude (Athiyaman, 2002). In brief, attitude is a set of beliefs, emotions and behaviours that a person possesses towards any object, event or person, and it directly impacts behavioural intention to initiate any action (Davis, 1989). Attitude has been broadly studied under TAM and the theory of reasoned action (Fishbein & Ajzen, 1975). Students' attitudes towards ChatGPT for education can be positive or negative. Scholars have argued that individuals' attitudes might vary due to multiple factors, such as age, gender and occupation (Sabbir et al., 2020; Wilkes et al. 2008). In the context of technology adoption, Kerschner and Ehlers (2016) affirmed that consumers do not have similar attitudes while adopting a technology. For instance, students might feel positive about adopting a wearable technology but might hold negative attitudes towards ChatGPT as it involves ethical usage. Even the theory of reasoned action and TAM illustrate that individuals' attitudes towards behaving in a certain way are significantly influenced by what they believe will happen due to their actions. Both models illustrate that attitudes have an influential impact on individuals' intentions for actions. Hence, the inclusion of students' attitudes towards ChatGPT in the current study is worthy for determining its influential role.

In the context of technology adoption, including e-banking (Ahmad et al., 2020), smart homes (Shuhaiber & Mashal, 2019) and mobile payment systems (Park et al., 2019), the association between attitude and intention has been investigated and shown to be positively significant. Accordingly, the current study anticipated that students' attitude towards using ChatGPT for learning has a substantial effect on their behavioural intention, and we postulated the following hypothesis:

> **H5:** Attitudes towards ChatGPT have a significant positive influence on the intention to use.

### Moderation of trust

Trust is known as the arbitrary possibility that users believe an online service entity will carry out a certain transaction according to their confident anticipation (D. J. Kim, 2008). Customers who make purchase decisions online cannot touch and feel items, which is possible offline. Thus, customers always take some risk when making purchases online. Indeed, trust is not required in a situation when there is no threat. However, as uncertainty adds risk to the purchase process, trust may be useful in preparing for an uncertain future and minimising risk (D. J. Kim, 2008).

Numerous studies have looked into the relevance of trust in online transactions and purchasing behaviour to achieve the intended outcomes (Yousafzai et al., 2003). Gefen et al. (2003) identified that trust has a fundamental influence on a customer's belief system and has a direct impact on purchasing any goods and services. The results of studies show that individuals' attitudes are significantly influenced by trust (Chen & Tan, 2004). According to Y. Lu et al. (2019), individuals' level of confidence in a new technology varies depending on how much knowledge and trust they have in this. When deciding whether to use a new system, people consider if they can trust it. As a result, their trust propensity acts as a key factor in

such choices (Chiu et al., 2009; Furner et al., 2022). Talwar et al. (2020) found that trust has a favourable impact on online business transactions. I. L. Wu and Chiu (2018) noted that when people lack familiarity with a system, their level of trust plays a key role in their adoption decisions. Those with low trust are less inclined to use the system, as a lack of trust creates a sceptical impression of a new system (Gu et al., 2015). However, no studies have considered the interactions of trust in the relationships from perceived usefulness, perceived ease of use, perceived informativeness and perceived enjoyment to attitude within the context of a novel technology like ChatGPT. Building on the above discussion, this study assumed that the impact of perceived usefulness, perceived ease of use, perceived informativeness and perceived enjoyment on ChatGPT may vary based on the users' trust in the system. Hence, we put forward the following hypothesis:

> **H6:** Trust positively moderates the impacts of (a) perceived usefulness, (b) perceived ease of use, (c) perceived enjoyment and (d) informativeness on attitudes towards ChatGPT.

Figure 3 presents our conceptual framework.

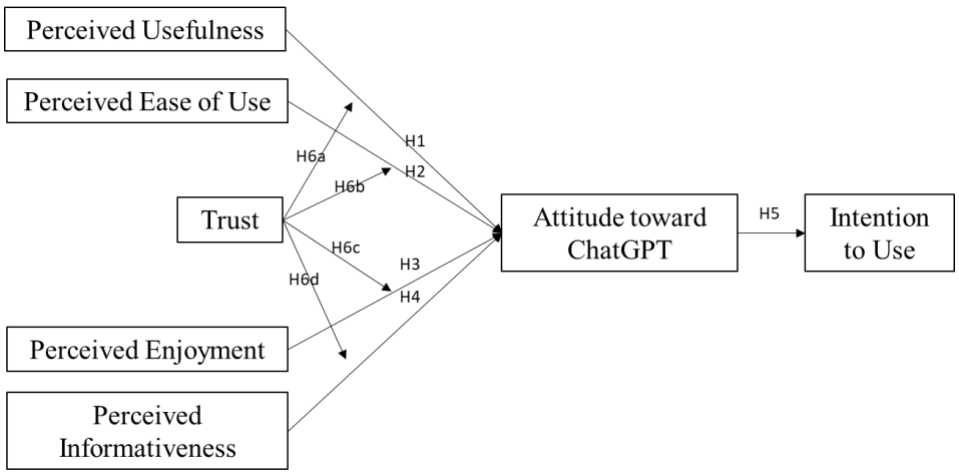


*Figure 3.* Conceptual framework

## Methodology

### Participants and procedures

Students use several information communication technologies (ICTs) daily to make their studies convenient and enjoyable. This study considered private and public university students in Bangladesh as participants who know ChatGPT and have access to it for learning. The reason for selecting university students is that they are expected to have a deep awareness and knowledge of e-learning. Also, as members of the digital age, they are more accustomed to using the Internet and accessing online learning materials.

This study used Google Forms to gather responses with an online questionnaire from April 10 to June 14, 2023. A snowball sampling technique was employed to collect data. In the context of education-related studies, researchers such as Freiberg et al. (2021) and Chhetri et al. (2021) used this non-probability sampling technique to examine students' behaviour. Snowball sampling is a referral-based sampling method that follows a referral chain (Biernacki & Waldorf, 1981). In fact, the unknown population of ChatGPT users drove us to use this method. A message entailing the study objectives with a Google Form link was shared among prospective respondents using social networking platforms, including Facebook, WhatsApp and LinkedIn. As the usage of ChatGPT is emerging, not everyone may know or have used it. To sort out the target respondents, a couple of screening questions (i.e., "I have heard the name ChatGPT", "I know about ChatGPT") were set to find whether the participants had any knowledge of

ChatGPT. Responses were excluded from the study if the participants had no knowledge regarding ChatGPT. The objective – examining students' intention to use ChatGPT for learning – was clearly indicated in an introductory paragraph at the beginning of the questionnaire. The learning purposes include using ChatGPT for learning about new concepts or theories, generating personalised feedback on the quality of their academic papers, getting help learning new languages or sharpening English writing skills. Moreover, the research was exempt from the need for ethical clearance since it focused on the investigation of human behaviour rather than any experimentation involving humans and animals.

The questionnaire was categorised into two parts: the first comprised demographic variables and screening questions; the second included the measurement items of constructs employed in the study. A total of 636 responses were received; however, 234 of them were excluded due to the respondents' no awareness or knowledge of ChatGPT. In addition, 58 responses excluded due to missing data. Finally, a total of 344 responses were selected for data analysis. Table 1 presents the demographic details of the participants. The sample consisted of 212 males and 132 females aged between 18 and 33 years. Among 344 participants, 224 were bachelor students, 116 were master students, and 4 reported others. Among them, 102 were from the science and engineering stream, 82 were from arts and humanities, 117 were from the business stream and 43 were from other fields. The majority of the participants (214) were from private universities, whereas public universities and others reported 116 and 14, respectively.

Table 1
*Respondents' demographic details (N = 344)*

| Variables or dimensions | Frequency | Percentage |
|---|---|---|
| Gender | | |
| Male | 212 | 62 |
| Female | 132 | 38 |
| Age | | |
| 18–21 | 121 | 35 |
| 22–25 | 154 | 45 |
| 26–29 | 45 | 13 |
| 30–33 | 24 | 7 |
| Education level | | |
| Bachelor | 224 | 65 |
| Master | 116 | 34 |
| Other | 4 | 1 |
| Concentration | | |
| Business | 117 | 34 |
| Science and Engineering | 102 | 30 |
| Arts and Humanities | 82 | 24 |
| Others | 43 | 12 |
| Institution type | | |
| Private | 214 | 62 |
| Public | 130 | 38 |

## Measures

The measurement items of the questionnaire (see the Appendix) were chosen from multiple studies with direct and modified forms. The items of perceived usefulness and perceived ease of use were adopted from Davis (1989), perceived enjoyment from Davis et al. (1992), perceived informativeness from Buaprommee and Polyorat (2016), trust from Chong et al. (2012), attitude from Taylor and Todd (1995) and intention to use from Kordzadeh (2019). All the constructs of the study were examined using a 5-point Likert scale.

### Data analysis

The two-stage (i.e., measurement and structural) structural equation modelling (SEM) approach with the analysis of moment structures (AMOS v. 23 software) was employed to analyse the collected data. Hair et al. (2010) have illustrated SEM as a well-known multivariate analysis technique for behavioural and psychological studies. In addition, Kline (2011) suggested using SEM for determining any complex relationships among latent constructs, as SEM runs multiple regression equations while accounting for measurement error in the observed variables.

## Results

### Reliability and validity

To determine whether the collected data were suitable for analysing SEM, they were examined through several multivariate tests. In order to proceed with further analysis, Hair et al. (2010) noted that the data should be free of outlier issues and multi-collinearity issues, indicating data are normally distributed. We used both Pearson's skewness and kurtosis benchmark values to determine whether the collected data were normally distributed. Kline (2015) suggested that the threshold values for data normality range from less than 3 to not more than 10. Table 2 presents the descriptive statistics, showing both skewness and kurtosis values and suggesting that data were normally distributed.

Table 2
*Data normality test (skewness - kurtosis criterion)*

| Construct | Mean | SD | Variance | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|---|
| | Statistic | Statistic | Statistic | Statistic | SE | Statistic | SE |
| PU1 | 3.866 | 0.8397 | 0.705 | -1.140 | 0.131 | 2.075 | 0.262 |
| PU2 | 3.855 | 0.7801 | 0.609 | -1.223 | 0.131 | 2.568 | 0.262 |
| PU3 | 3.767 | 0.8354 | 0.698 | -1.170 | 0.131 | 2.156 | 0.262 |
| PU4 | 3.826 | 0.8357 | 0.698 | -1.049 | 0.131 | 1.720 | 0.262 |
| PEU1 | 3.872 | 0.8266 | 0.683 | -1.097 | 0.131 | 2.011 | 0.262 |
| PEU2 | 3.898 | 0.8285 | 0.686 | -0.860 | 0.131 | 1.133 | 0.262 |
| PEU3 | 3.913 | 0.8696 | 0.756 | -1.168 | 0.131 | 2.031 | 0.262 |
| PEU4 | 3.895 | 0.8157 | 0.665 | -1.069 | 0.131 | 1.973 | 0.262 |
| PEU5 | 3.759 | 0.8855 | 0.784 | -0.952 | 0.131 | 1.201 | 0.262 |
| TR1 | 3.631 | 0.8573 | 0.735 | -0.858 | 0.131 | 1.158 | 0.262 |
| TR2 | 3.741 | 0.8739 | 0.764 | -1.027 | 0.131 | 1.716 | 0.262 |
| TR3 | 3.663 | 0.8688 | 0.755 | -0.899 | 0.131 | 1.296 | 0.262 |
| TR4 | 3.637 | 0.8323 | 0.693 | -0.913 | 0.131 | 1.475 | 0.262 |
| TR5 | 3.657 | 0.8495 | 0.722 | -0.829 | 0.131 | 1.159 | 0.262 |
| PE1 | 3.564 | 0.8410 | 0.707 | -0.691 | 0.131 | 0.902 | 0.262 |
| PE2 | 3.555 | 0.8756 | 0.767 | -0.733 | 0.131 | 0.945 | 0.262 |
| PE3 | 3.555 | 0.8347 | 0.697 | -0.645 | 0.131 | 0.778 | 0.262 |
| PI1 | 3.863 | 0.8479 | 0.719 | -1.150 | 0.131 | 2.132 | 0.262 |
| PI2 | 3.843 | 0.8698 | 0.757 | -1.348 | 0.131 | 2.651 | 0.262 |
| PI3 | 3.942 | 0.8517 | 0.725 | -1.284 | 0.131 | 2.397 | 0.262 |
| AT1 | 3.741 | 0.7787 | 0.606 | -0.818 | 0.131 | 1.216 | 0.262 |
| AT2 | 3.733 | 0.8214 | 0.675 | -0.771 | 0.131 | 0.957 | 0.262 |
| AT3 | 3.692 | 0.7775 | 0.604 | -0.975 | 0.131 | 1.636 | 0.262 |
| AT4 | 3.645 | 0.8022 | 0.644 | -0.703 | 0.131 | 0.845 | 0.262 |
| IU1 | 3.858 | 0.8365 | 0.700 | -1.049 | 0.131 | 1.786 | 0.262 |
| IU2 | 3.901 | 0.8616 | 0.742 | -0.991 | 0.131 | 1.504 | 0.262 |
| IU3 | 3.901 | 0.8684 | 0.754 | -1.151 | 0.131 | 1.989 | 0.262 |

*Note*. PU = perceived usefulness; PEU = perceived ease of use; TR = trust; PE = perceived enjoyment; PI = perceived informativeness; AT = attitude towards ChatGPT; IU = intention to use.

The study performed a two-phase confirmatory factor analysis (CFA) with the maximum likelihood method. The first phase includes testing the measurement model with the reliability, validity and model fit. The second phase comprises the structural model to examine the hypothesised relationships among the variables. The measurement model results show that all the fit indices were satisfactory [$\chi 2 = 456.563$, $\chi 2/DF = 1.507$, goodness of fit index (GFI) = 0.913, comparative fit index (CFI) = 0.982, root mean square error of approximation (RMSEA) = 0.038, standardised root mean residual (SRMR) = 0.0281] (Byrne, 1994). The reliability of the measurement model was confirmed with the factor loadings, showing that the minimum value is within the recommended range (Hair et al., 2014). The measurement model was also used to examine two validity tests: convergent and discriminant validity. Convergent validity was estimated by calculating factor loadings, composite reliability (CR) and average variance extracted (AVE). Table 3 shows that individual items' factor loadings (0.748 to 0.939) are more than the threshold value of 0.70 (Hair et al., 2014). Moreover, all constructs' CR and AVE are above the cut-off value of 0.60 (Bagozzi & Yi, 1988) and 0.50 (Fornell & Larcker, 1981), respectively. Table 3 also displays that Cronbach's alpha values are above 0.70, demonstrating the internal validity of the measurement items (Hinton et al., 2014).

Table 3
*Item loadings of the constructs with CR, AVE and Cronbach's alpha values*

| Construct | Item | Estimate | CR | AVE | Cronbach's alpha |
|---|---|---|---|---|---|
| Perceived usefulness (PU) | PU4 | 0.854 | 0.910 | 0.716 | 0.908 |
| | PU3 | 0.857 | | | |
| | PU2 | 0.870 | | | |
| | PU1 | 0.803 | | | |
| Perceived ease of use (PEU) | PEU5 | 0.748 | 0.917 | 0.689 | 0.915 |
| | PEU4 | 0.858 | | | |
| | PEU3 | 0.880 | | | |
| | PEU2 | 0.837 | | | |
| | PEU1 | 0.822 | | | |
| Trust (TR) | TR5 | 0.842 | 0.923 | 0.705 | 0.922 |
| | TR4 | 0.827 | | | |
| | TR3 | 0.868 | | | |
| | TR2 | 0.864 | | | |
| | TR1 | 0.794 | | | |
| Perceived enjoyment (PE) | PE3 | 0.916 | 0.947 | 0.855 | 0.946 |
| | PE2 | 0.919 | | | |
| | PE1 | 0.939 | | | |
| Perceived informativeness (PI) | PI3 | 0.844 | 0.893 | 0.736 | 0.893 |
| | PI2 | 0.893 | | | |
| | PI1 | 0.835 | | | |
| Attitude (AT) | AT4 | 0.801 | 0.899 | 0.691 | 0.899 |
| | AT3 | 0.817 | | | |
| | AT2 | 0.826 | | | |
| | AT1 | 0.878 | | | |
| Intention to use (IU) | IU3 | 0.877 | 0.913 | 0.778 | 0.913 |
| | IU2 | 0.881 | | | |
| | IU1 | 0.888 | | | |

Table 4
*Discriminant validity (Fornell-Larcker criterion)*

| | PI | PU | PEU | TR | PE | AT | IU |
|---|---|---|---|---|---|---|---|
| PI | 0.858 | | | | | | |
| PU | 0.810*** | 0.846 | | | | | |
| PEU | 0.820*** | 0.829*** | 0.830 | | | | |
| TR | 0.763*** | 0.774*** | 0.799*** | 0.839 | | | |
| PE | 0.634*** | 0.694*** | 0.642*** | 0.604*** | 0.925 | | |
| AT | 0.803*** | 0.770*** | 0.771*** | 0.727*** | 0.596*** | 0.831 | |
| IU | 0.787*** | 0.745*** | 0.810*** | 0.776*** | 0.586*** | 0.774*** | 0.882 |

*Note.* PI = perceived informativeness; PU = perceived usefulness; PEU = perceived ease of use; TR = trust; PE = perceived enjoyment; AT = attitude towards ChatGPT; IU = intention to use.
****p < 0.01.*

The Fornell and Larcker (1981) standard was used to determine the discriminant validity of the constructs (see Table 4). The discriminant validity represents that the square root of AVE for each construct must be higher than its correlations with other constructs (Fornell & Larcker, 1981). In this regard, the study has no inter-item correlations that are greater than the square root of the corresponding AVE.

## Hypothesis testing

This section illustrates the structural model. The model reveals that five of the nine hypotheses were supported, as displayed in Table 5. In addition, the fit indices of the structural model reflect a good model fit ($\chi2$= 536.625, $\chi2$/DF = 1.742, GFI = 0.898, CFI = 0.973, RMSEA = 0.047, SRMR = 0.0442) to the data, according to the recommended thresholds by Byrne (1994).

As seen in Table 5, PU (β = 0.17; t = 2.017; $p < 0.05$ [significant]), PEU (β = 0.21; t = 2.500; $p < 0.05$ [significant]), and PI (β = 0.39; t = 4.825; $p < 0.001$ [significant]) strongly affect students' AT towards using ChatGPT. In addition, AT towards ChatGPT (β = 0.83; t = 15.289; $p < 0.001$ [significant]), has the most influential impact on students' IU of ChatGPT. However, PE (β = 0.03; t = 0.535; p > 0.05 [insignificant]) has no impactful influence on AT. Therefore, H1, H2, H4, and H5 are supported while H3 is not.

According to Table 5, H6c is statistically supported, indicating that TR significantly moderates the relationship between PE and AT. On the contrary, TR is found to have no moderating effect on the paths from PU to AT, PEU to AT, and PI to AT. These outcomes indicate that H6a, H6b and H6d are not statistically supported.

Table 5
*The standardised estimation of the structural model with hypotheses testing*

| Hypotheses | Relationships | | Estimate (standardised) | SE | *t* values | *p* value | Decision |
|---|---|---|---|---|---|---|---|
| H1 | PU | → AT | 0.169 | 0.074 | 2.017 | 0.044* | Yes |
| H2 | PEU | → AT | 0.213 | 0.081 | 2.500 | 0.012* | Yes |
| H3 | PE | → AT | 0.026 | 0.040 | 0.535 | 0.593 | No |
| H4 | PI | → AT | 0.391 | 0.071 | 4.825 | 0.000*** | Yes |
| H5 | AT | → IU | 0.832 | 0.066 | 15.289 | 0.000*** | Yes |
| H6a | PU*TR | → AT | -0.191 | 0.065 | -1.354 | 0.176 | No |
| H6b | PEU*TR | → AT | 0.153 | 0.065 | 1.095 | 0.273 | No |
| H6c | PE*TR | → AT | 0.216 | 0.055 | 2.159 | 0.031* | Yes |
| H6d | PI*TR | → AT | -0.194 | 0.066 | -1.392 | 0.164 | No |

**p* < 0.05. ****p* < 0.0001.

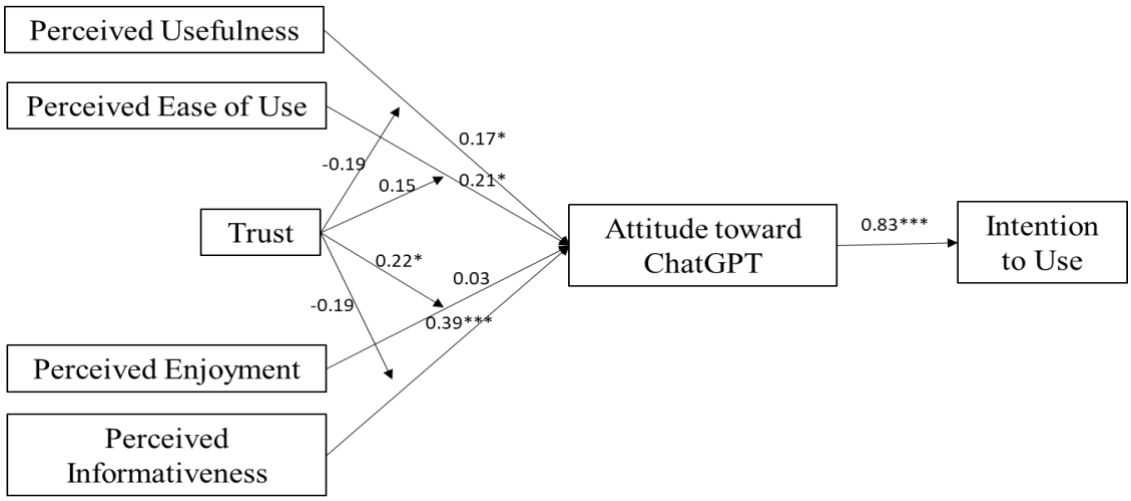


*Figure 4.* Results of the conceptual model
*$p$ < 0.05. ***$p$ < 0.0001.

Figure 4 presents the significant effect of TR on the association between PE and AT towards adopting ChatGPT. The results indicate that the students with high TR enjoy more and form a positive attitude towards ChatGPT compared to those with low TR levels. This occurs especially for students who perceive that ChatGPT might not cause any privacy problems or other detrimental effects while using it.

## Discussion

With the aim of investigating the factors that affect students' intention to use ChatGPT for learning, this study tested the extended TAM framework. More specifically, the study integrated two well-accepted TAM constructs (PU and PEU) with PE and PI. According to the outcomes of this study, PU positively affects students' AT towards ChatGPT, which is consistent with the results of Malik et al. (2021) and Indarsin and Ali (2017), who found that PU is a significant driver that helps to form positive attitudes and influences to adopt new technology. This result also indicates ChatGPT's superiority in overall responsiveness, convenience and efficiency in providing information, which plays a robust role in affecting students' AT. In contrast, the result is not in line with the findings of Kwangsawad and Jattamart (2022), who found that PU is ineffective for chatbot users who have technology usage experience as they are aware of the utilities and benefits of the technology. In such cases, Kwangsawad and Jattamart (2022) recommended focusing on those who have not yet used the technology or novice users of the technology, which is consistent with this study's context. Furthermore, the association between PEU and AT was significant, signifying that PEU positively influences students' AT to adopt ChatGPT. This result is similar to that of studies (Chocarro et al., 2023; Kasilingam, 2020), indicating that if students find ChatGPT easy to use, and understandable and matches their skills, they tend to show positive AT towards it.

However, the relationship between PE and AT was not significant, illustrating that when students use ChatGPT, they do not find it fun and enjoyable. It might be the case that new users with no or little experience of using ChatGPT might suffer from privacy and security issues, which have an impact on their PE. This finding contradicts the results of De Cicco et al. (2021), who asserted that the young generation loves having fun while using a chatbot, which positively influences their AT.

The results of the study show that PI positively and significantly influences students' AT towards ChatGPT. This finding suggests that students who use Chatbot get the desired information to make decisions. For example, when a student asks ChatGPT to write an essay or prose, it responds within a few seconds. This reduces students' search time and efforts to prepare any content. The positive association between PI and AT is consistent with the findings of Mo et al. (2023), who affirmed that PI is an influential antecedent of AT in the context of technology adoption. The relationship between AT and IU is also supported, illustrating that AT has the most significant impact (β = 0.83) on IU in the context of ChatGPT. This result

is in line with the findings by Malik et al. (2021) and Kwangsawad and Jattamart (2022), who found that if users have positive AT towards any technology, this directly affects their IU.

In regard to the moderating effect, TR positively and significantly moderates the relationship between PE and AT. Although the direct association of PE with AT is insignificant, with TR as a moderator, the interaction (PE*TR) significantly impacts AT. This finding is interesting, suggesting that students' level of enjoyment is triggered only when TR issue comes into play. Accordingly, students' PE of using ChatGPT strengthens their AT towards using ChatGPT positively once they trust this new technology and the relationship between PE and AT weakens when students do not trust the technology. However, the other interactions (i.e., PU*TR, PEU*TR and PI*TR) have no significant moderating effect. Perhaps this relates to the fact that students find ChatGPT substantially useful, easy and informative, and therefore TR does not make a big difference in this context.

## Theoretical and practical contributions

This study contributes to knowledge in various ways. For example, it integrates two contextual factors (PE and PI) with the core constructs of TAM. The results of the extended framework suggest that PU, PEU and PI have a strong association with AT in the context of a new technology like ChatGPT in an education setting. To the best of our knowledge, this is the first study that integrates PE and PI with PU and PEU in the context of ChatGPT and education, while most researchers (e.g., T. Wang et al., 2023; Zafar et al., 2023) have considered PE and PI separately. Besides, the study is the first, to our knowledge, which shows the moderating effect of TR in the context of ChatGPT. As ChatGPT is a new addition to technological advancement, most of the research in this domain is qualitative. However, empirical studies to date inspected only the direct influence of contextual and personal factors, yet the potential interactions have received scarce attention. Unlike past studies, the current study confirms the moderation of TR in the relationship between PE and AT in adopting ChatGPT.

Apart from the theoretical contributions, this study provides some notable practical implications for policymakers, online education service providers, and chatbot-based service providers. The results will help service providers and policymakers identify influential factors and shape students' AT towards adopting ChatGPT in the context of learning. Therefore, the insights will help service providers design and develop more education-friendly, attractive, effective, convenient and secure AI chatbots. Along with service providers, governments can play a crucial role in accelerating AI-based chatbot adoption, emphasising ethical and sustainable usage. The results show that PU and PEU significantly affect students' AT towards ChatGPT. Service companies should highlight the benefits and simplicity of using AI chatbots to attract potential users. Moreover, to promote ChatGPT or related technology, marketers should focus on building users' trust in the technology, as people welcome new technologies if they perceive they will be safe and cause no privacy concerns.

## Conclusions, limitations and directions for future research

This study aimed to investigate the factors triggering students' intention to adopt ChatGPT from an academic perspective. The findings are robust in understanding and promoting the ethical and sustainable use of such AI tools for practitioners, scholars and educators. Although the research provides significant implications for practice, it has multiple limitations that show potential research gaps could be filled by conducting future research. First, the participants of this study were limited to Bangladeshi university students. Although the moderation of trust enhances the generalisation of the outcomes, the proposed model could be examined in other countries. Second, the study investigated behavioural intention; thus, the findings may not apply to actual usage and post-usage behaviour. We recommend research on users' usage and post-usage behaviour so as to comprehend their actual behaviour more deeply. Third, the study used trust as a single moderator; hence, we suggest undertaking research by incorporating other variables, such as age, gender and e-word of mouth, as moderators. Finally, the study excluded any mediation analysis. Therefore, future studies could be undertaken by considering relevant mediating effects. Testing moderation and mediation provide insights that help marketers customise their marketing strategies effectively.

## Author contributions

**Author 1**: Conceptualisation, Investigation, Writing – original draft, Writing – review and editing; **Author 2**: Formal analysis, Methodology, Writing – original draft, Writing – review and editing; **Author 3**: Writing – review and editing; **Author 4**: Writing – review and editing; **Author 5**: Writing – review and editing.

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# Appendix

## List of measures

| Measures with items | Sources |
|---|---|
| Perceived usefulness<br>1. Using ChatGPT for learning enables me to achieve learning objectives effectively.<br>2. Learning from ChatGPT improves my performance.<br>3. Using ChatGPT is useful to provide access to information.<br>4. Using ChatGPT for learning will increase my productivity. | Davis (1989) |
| Perceived ease of use<br>1. Using ChatGPT, learning becomes easy.<br>2. Using ChatGPT for learning requires less mental effort.<br>3. Learning is easy and understandable with ChatGPT.<br>4. I can easily become skillful at using ChatGPT for learning.<br>5. I think I will be able to learn using ChatGPT without the help of an expert. | Davis (1989) |
| Trust<br>1. I believe learning through ChatGPT is secure.<br>2. I believe information exchange through ChatGPT will be secure.<br>3. I believe my personal information will be kept confidential while using ChatGPT.<br>4. I am confident regarding the security measurements offered by ChatGPT.<br>5. The privacy of ChatGPT is well protected. | Chong et al. (2012) |
| Perceived enjoyment<br>1. I find using ChatGPT for learning enjoyable.<br>2. The actual process of using ChatGPT for learning is pleasant.<br>3. I will have fun while using ChatGPT for learning. | Davis et al. (1992) |
| Perceived informativeness<br>1. Learning through ChatGPT will give me quick and easy access to large scales of in-depth information.<br>2. I am likely to learn a lot from ChatGPT.<br>3. ChatGPT can give me extensive information. | Buaprommee & Polyorat (2016) |
| Attitude<br>1. It would be very desirable to use ChatGPT for learning.<br>2. Using ChatGPT is better than using any other e-learning application.<br>3. I like to use ChatGPT learning for academic purposes.<br>4. It is desirable to use ChatGPT compared to any other applications. | Taylor & Todd (1995) |
| Intention to use<br>1. I intend to use ChatGPT for learning.<br>2. I believe using ChatGPT is valuable for learning.<br>3. During the next 6 months, I intend to use ChatGPT for learning. | Kordzadeh (2019) |