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Confidence and trust in artificial intelligence mediate the relationship between performance expectancy and students' behavioral intention to use ChatGPT

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Abstract

This study investigates the factors influencing university students' behavioral intention to use ChatGPT in higher education, focusing on the mediating role of confidence and trust in artificial intelligence (CTAI) as a second-order construct integrating self-efficacy and trust. Using a cross-sectional quantitative design, data were collected from 199 students at the University of Jeddah through purposive sampling and analyzed using covariance-based structural equation modeling (CB-SEM) with AMOS. The results indicate that performance expectancy (PE) and effort expectancy (EE) significantly predict CTAI, while CTAI significantly predicts behavioral intention (BI). However, the direct effects of PE and EE on BI are not significant. Mediation analysis using bootstrapping reveals that CTAI fully mediates the relationship between PE and BI, whereas the indirect effect of EE on BI is not significant. These findings suggest that students' perceptions of performance benefits are associated with their behavioral intention to use ChatGPT through confidence and trust in AI, whereas this mediating mechanism was not supported for effort expectancy. The study contributes to technology acceptance research by conceptualizing CTAI as an integrative higher-order construct and providing initial empirical evidence of its mediating role specifically in the relationship between performance expectancy and behavioral intention.

Keywords Confidence and trust in AI (CTAI) · ChatGPT adoption · Higher education · Behavioral intention

Introduction

The rapid advancement of artificial intelligence (AI) has produced advanced tools, such as ChatGPT, that are increasingly employed in education. Generative AI is maturing and offers much potential for the development of learning experiences. With the use of such tools, the majority of students will look for personalized learning support and assistance in essay writing to better enhance their learning experiences[1]. As technology is so readily available, it is important to be aware of the social factors governing students' behavioral intention (BI) to use such AI tools[2]. However, understanding students' intention to use ChatGPT requires more than identifying conventional technology acceptance predictors. An important unresolved issue is how students' expectancy beliefs,

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particularly performance expectancy (PE) and effort expectancy (EE), are associated with behavioral intention through psychological mechanisms related to their confidence in using AI and trust in AI systems. This study addresses this issue by examining confidence and trust in artificial intelligence (CTAI) as a higher-order mediating construct linking expectancy beliefs with students' behavioral intention to use ChatGPT.

In technology adoption research, the unified theory of acceptance and use of technology (UTAUT) and its extensions have identified the major predictors of user intention, including performance expectancy (PE) and effort expectancy (EE). PE is defined as the extent to which users perceive that using the system is likely to improve their academic results or job performance[3,4]. Studies have established that students' perceived advantages from ChatGPT have a positive effect on their intention to utilize it[1]. EE refers to the perceived ease of using technology. As systems that are easier to use generally have a higher intention to be adopted[3,5], in some cases, EE has negative effects on BI if the AI application is seen to be difficult to use, thus reducing adoption[6].

While PE and EE are clearly significant antecedents (predictors) of BI to utilize AI tools, the underlying psychological reasons behind the relationship merit further exploration. The two important mediating (intervening) variables with regard to technology adoption are self-efficacy (SE) and trust in AI. SE is the belief that users have in their capacity to accomplish specific activities successfully and is a crucial factor in how users approach new technology and interact with it[7]. Prior research has examined self-efficacy as an independent explanatory or mediating factor in technology adoption, with evidence suggesting that greater self-efficacy may strengthen the relationship between technology-related beliefs and behavioral intention[7]. In the present study, however, self-efficacy is incorporated as a first-order dimension of CTAI rather than modeled as a separate mediator.

Trust has also been shown to be a vital factor in the adoption of AI systems. Trust in AI refers to the degree of individuals' confidence in the capabilities of AI, including its accuracy, reliability, and ethical utilization of information[8,9]. Due to issues such as plagiarism and data privacy regarding the availability of AI in academia, trust in the ethical use of data in ChatGPT is influential in determining users' BI[10]. Increased trust in AI results in a greater tendency to accept AI applications[9], as the feeling of being more inclined to use it properly is not just related to attitude but also to actual use[8]. When users know little about a certain AI system, their degree of trust is an important factor which determines whether they will adopt that system[11].

Although PE and EE have already been identified as important in technology acceptance, and SE and trust have been recognized in terms of their importance in technology acceptance, the direct mediation of these factors in students' overall intention to utilize ChatGPT as a whole has not received much attention. Confidence and trust in artificial intelligence (CTAI) is conceptualized as a second-order construct comprising self-efficacy (SE) and trust as distinct but complementary first-order dimensions. By examining CTAI as an integrated mediating construct, we aim to provide a more refined understanding of the psychological processes underlying students' engagement with AI tools.

Despite the extensive use of UTAUT in explaining technology adoption, research on generative AI tools such as ChatGPT remains limited in explaining the underlying psychological mechanisms influencing students' behavioral intention. While PE and EE are well-established predictors, prior studies have largely focused on direct effects, offering limited insight into how cognitive and affective factors jointly shape adoption. Moreover, self-efficacy and trust in AI have often been examined separately, resulting in a fragmented understanding of their combined role. Accordingly, a key research problem remains in understanding how cognitive and affective mechanisms jointly mediate the effects of expectancy beliefs on students' behavioral intention to use generative AI tools. Therefore, this study addresses the following research question: How do confidence and trust in artificial intelligence mediate the relationships between performance expectancy, effort expectancy, and students' behavioral intention to use ChatGPT in higher education?

To address these gaps, this study conceptualizes confidence and trust in artificial intelligence (CTAI) as a higher-order mediating construct integrating self-efficacy and trust. By examining its mediating role between PE, EE, and students' willingness to use ChatGPT, this study extends UTAUT and provides a more comprehensive understanding of AI adoption in higher education.

Literature review

Theoretical framework

Research on the motivational intention of learners to utilize ChatGPT is based on well-established theoretical models of technology adoption and user behavior. In particular, this study is based on the UTAUT. It was modified to include important psychological constructs, such as SE and trust, as determinants.

UTAUT as a foundational framework

The UTAUT represents a more comprehensive framework because it integrates constructs from eight different theories of technology acceptance[1,5]. It has been frequently studied to understand how students utilize ChatGPT in academic context and to show the role of different factors in developing BI and actual use[1,5]. The UTAUT underscores the importance of expectancy beliefs, namely PE and EE, which are established antecedents of BI to utilize technology. PE is the degree to which individuals expect to gain in performance abilities at work or school outcomes from utilizing the system[1]. In this case, a translation of PE into the college or university environment would be that students would have to think that ChatGPT is helpful in providing increased productivity, school standing, or learning processes[1,4]. Studies have indicated that the advantages of ChatGPT for students directly affect their BI to utilize ChatGPT. Ballesteros[1], Emon et al.[6], and Yeoh and Yap[4] found evidence that student expectancy beliefs about ChatGPT influence their propensity to use it. EE indicates the ease of use associated with the entities of technology[6]. This expectancy includes the core elements of perceived complexity and ease of use[6]. If students perceive ChatGPT as easy to learn and use with less hardware difficulty in the area of social engineering of those subscribing to ChatGPT, they will be more intent to use the technology[4]. The general factor has a direct positive influence on BI[2], but some studies have shown elements of a negative functional relationship if users perceive the given technology as complicated, lessening users' intention to utilize and adopt ChatGPT[6]. Recent research further indicates that educational adoption and continued use of generative AI are shaped by mechanisms extending beyond conventional perceptions of technological usefulness and ease of use. For example, Arpaci et al.[12], showed that expectation confirmation and task- and individual-technology fit contribute to students' satisfaction and continuance intention, highlighting the importance of cognitive evaluations and perceived alignment between users, tasks, and AI technologies. Although UTAUT also includes social influence and facilitating conditions, the present study deliberately focuses on PE and EE because its theoretical objective is not to reproduce the full UTAUT model, but to examine the psychological mechanisms associated with expectancy-based evaluations of ChatGPT. PE and EE capture students' evaluations of the expected performance benefits and effort required to use the technology, making them theoretically relevant antecedents for examining how such evaluations are associated with confidence and trust in AI. In contrast, social influence primarily reflects perceived interpersonal expectations, while facilitating conditions concern the availability of organizational and technical resources. These constructs represent theoretically distinct social and contextual mechanisms that fall outside the specific expectancy–CTAI pathway examined in this study. Accordingly, UTAUT is used as a theoretical foundation for selecting expectancy-based antecedents rather than as a complete model to be replicated.

Although prior UTAUT-based research has established PE and EE as important antecedents of technology acceptance, evidence from generative AI contexts suggests that their relationships with behavioral intention may not be uniformly direct. Generative AI differs from conventional educational technologies because students must evaluate not only whether the technology is useful and easy to use but also whether they are capable of interacting with it effectively and whether its outputs can be trusted. Consequently, examining PE and EE solely as direct predictors of behavioral intention may provide an incomplete account of students' responses to generative AI. This creates a theoretical basis for examining whether expectancy-based evaluations are associated with behavioral intention through psychological mechanisms involving both user-directed confidence and system-directed

trust. The present study addresses this gap by examining CTAI as a higher-order mechanism through which PE and EE may be associated with students' behavioral intention to use ChatGPT.

PE and students' BI to utilize ChatGPT

PE is a fundamental model construct for technology acceptance, defined as the extent to which users believe that using a system will assist them in receiving benefits in their job performance or attaining specified outcomes[5]. In the academic context, it refers to the belief of students that using AI applications (e.g., ChatGPT) will improve their productivity, academic performance, or learning processes[1]. In sum, PE captures users' perceived benefits and usefulness of a technology[3]. Some studies have confirmed that PE has a powerful influence on students' BI to adopt and use educational technologies and AI applications[13].

EE and students' intention to use ChatGPT

EE refers to the perceived ease of using a system or a technology[3,5]. In the case of ChatGPT, EE is the students' perception of the ease of use of chatbots[3]. This factor is important because it considers how the technology is perceived by users with regard to its ease of use and understanding when doing their homework[4]. As EE decreases, the BI to use the technology increases as it uses more technologies with lower cognitive needs and less technical skills[1]. On the contrary, if it is perceived to be used with great effort or cumbersome despite its benefits, this factor will be rejected or will have less intention to be used[14]. This is acknowledged in technology acceptance, as it is common among potential users due to a complex interface or long learning schedule if the technology has no instant superior benefits or offerings to possible users (technological utility)[15]. Therefore, to obtain the correct educational effort expectancy, it is important to introduce a correct design and adequate support for learning from an educational perspective[1].

SE in AI

SE refers to users' confidence regarding their potential to successfully implement specific operations and reach certain goals[16]. In terms of the technology and tools of AI, mainly ChatGPT, this concept applies to the confidence people have in their potential to effectively interface with the AI, apply it according to its purposes, and produce answers to relevant tasks to help them reach their educational and learning goals[4]. With high SE, people can confidently use the latest technological aids and realize that these aids can strengthen their capabilities rather than supplant them[9,17]. This confidence will affect the motivation and persistence of those who want to gain information and skills and give them value[4]. For example, when students see themselves as possessing superior abilities to handle difficult problem-solving and critical thinking tasks, they will have a high SE in using ChatGPT in complex academic assignments[9]. This cognitive assessment indicates the entire approach to AI and determines whether the inputs will be confidently and critically used. In short, confidence in oneself affects learners' eagerness to practice using AI, critical examination of its answers, and revision of the parameters to produce the best answers. Thus, the outcome is a mediating variable that affects learners' thought outcomes regarding AI, especially the aims of its use. That is, the feeling of SE will affect the expectation of the performance results of AI, which will decide the intention of the outcome of the actions concerning AI. In the present study, self-efficacy is not modeled as an independent mediator between expectancy beliefs and behavioral intention. Rather, it is conceptualized as a first-order dimension of the higher-order CTAI construct. Self-efficacy captures the user-directed component of CTAI by reflecting students' confidence in their capability to interact effectively with ChatGPT, whereas trust captures the complementary system-directed component. Accordingly, references to self-efficacy in the present framework should be understood as contributing to the broader CTAI construct rather than representing a separate mediating mechanism.

Trust in AI

Trust in AI refers to users' confidence level in the accuracy, reliability, and ethicality of the AI tool when using data[10], on which the AI system can be relied to fulfill its roles and functions as expected without compromising users' interests or integrity[3]. This trust is important in educational settings in which the issues of data privacy, biases in algorithms, and integrity can influence students' willingness to adopt these applications[8]. For this reason, in view of the ethical issues that plague academia regarding AI, trust assumes an important role in influencing students' BI to utilize these tools in that it diminishes the perceived risk presented by misinformation when using them or depending on them[10]. A relationship exists between the perceived capabilities of AI and the level of trust, as this affects how the products of AI are perceived in terms of their intelligence level and utility[9]. No empirical research has examined the relationship between ethical concerns, the possible misuse of AI applications, and the effect of adopting generative AI instruments on education, pointing to a deficiency in research[10].

Trust in AI is a multidimensional concept that may encompass perceptions of reliability, accuracy, transparency, privacy, and ethical conduct. However, the present study operationalizes trust more narrowly through the three items included in the measurement instrument. Accordingly, the trust dimension examined here should not be interpreted as comprehensively representing all facets of trust in generative AI, particularly specific concerns related to privacy, transparency, and ethicality. Rather, it captures the aspects of trust reflected in the adopted measurement items within the broader CTAI construct.

CTAI as a second-order mediator

To develop a thorough understanding of students' intention to utilize ChatGPT, the study proposes CTAI as an integrative, second-order mediating construct. This construct embodies two important psychological constructs: SE, which relates to users' belief in their own ability to utilize AI tools successfully, and trust, which denotes users' belief in the ability of AI tools to deliver consistent, reliable, accurate, ethical, and transparent information.

Conceptualizing CTAI

CTAI combines SE and trust in AI. SE refers to users' belief in their capability to utilize ChatGPT efficiently, solve problems with it, and achieve good results in the academic context[4]. It is the sense of mastery and capability that users have obtained with regard to AI tools. Trust in AI refers to users' confidence in ChatGPT's results (correctness, reliability), behavior (ethics, data privacy), and ease of understanding (transparency)[10]. This refers to external users' trust in the AI system itself. Although self-efficacy and trust are conceptually distinct, they represent complementary dimensions of students' psychological assurance when engaging with AI. Self-efficacy is user-directed, reflecting confidence in one's own capability to interact effectively with ChatGPT, whereas trust is system-directed, reflecting confidence in the reliability, integrity, and performance of the AI system. Their higher-order conceptualization does not imply that these dimensions are interchangeable; rather, CTAI represents the broader psychological assurance arising from confidence in both the user's capability and the system's trustworthiness. Accordingly, CTAI is modeled as a second-order construct to capture the shared higher-order dimension underlying these two theoretically distinct first-order components while preserving their conceptual distinction. By combining these two components, CTAI exhibits a more integrative psychological context. It shows that users' intention to deploy an AI tool is contingent not only on their beliefs about the tool's external features (trust) or internal capacities (i.e., SE) but also on the combination of both. Students might trust the results produced by ChatGPT but might not have the SE to perform well with it, and vice versa. Accordingly, self-efficacy and trust are conceptualized as distinct but complementary first-order dimensions of CTAI. Their integration within the higher-order construct reflects the proposition that both user-directed confidence and system-directed trust contribute to a broader form of psychological assurance toward AI use. However, this conceptualization does not imply that either dimension is individually necessary or sufficient for behavioral intention. Rather, the present

study examines whether the higher-order CTAI construct is statistically associated with students' behavioral intention and mediates the proposed expectancy–intention relationships.

Research gap and hypothesis development

Based on the integrated theoretical framework, expectancy beliefs are proposed to influence behavioral intention both directly and indirectly through CTAI, reflecting the role of cognitive and affective mechanisms in AI adoption.

Hypothesis development

Based on the theoretical framework and the identified research gap, the following hypotheses are proposed:

H1: PE positively affects students' BI to utilize ChatGPT.
H2: EE positively affects students' BI to utilize ChatGPT.
H3: PE positively affects CTAI.
H4: EE positively affects CTAI.
H5: CTAI positively affects students' BI to utilize ChatGPT.
H6: CTAI mediates the relationship between PE and students' BI to utilize ChatGPT.
H7: CTAI mediates the relationship between EE and students' BI to utilize ChatGPT.

Conceptual model

Figure 1 shows the proposed research model.

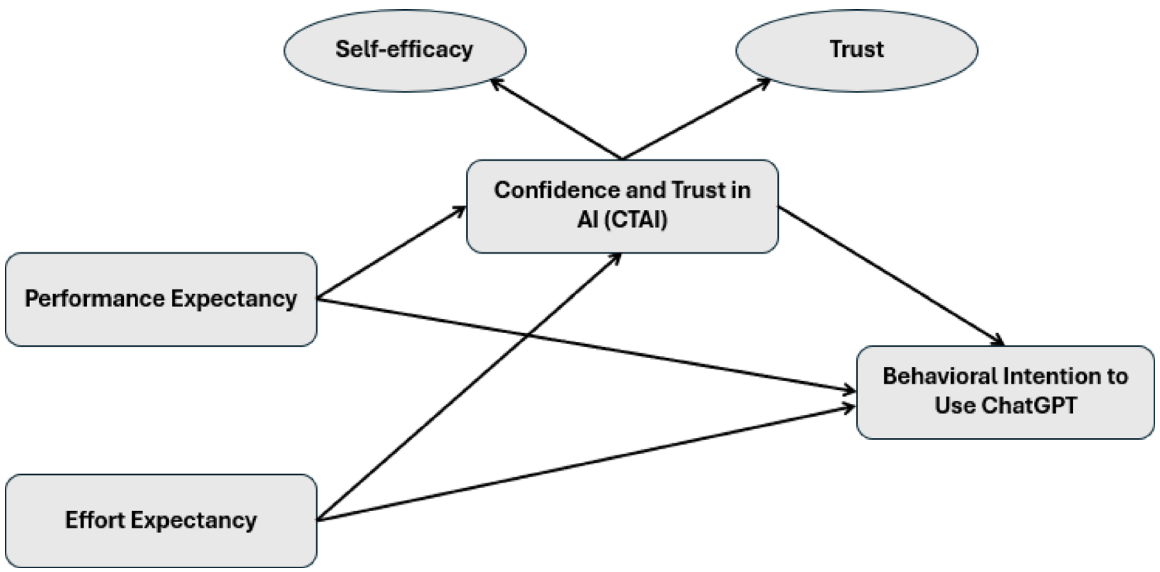

Fig. 1 The proposed research model.

Methodology

Research design

To investigate the mediating roles of CTAI in PE, EE, and students' BI to utilize ChatGPT, this study employed a cross-sectional quantitative design. SEM was the main analytical tool used. It allows for the strong possibility of testing complex theoretical models involving several latent constructs and their hypothesized relationships[5]. SEM is ideally suited to the following aspects:

- Assesses the direct and indirect effects between constructs.
- Estimates the mediating roles of constructs, such as CTAI, within the same causal pathway.
- Involves measurement errors in observable variables, thereby allowing for more accurate estimates of the theoretical relationships.
- Establishes the fitness of the suggested conceptual model to the empirical data, thereby allowing for a thorough estimation of the theoretical framework.

This ensured a thorough investigation of how students' initial perceptions of PE and EE toward ChatGPT led to their intention to use it through the psychological mechanism of their CTAI. As the study employs a cross-sectional design, the findings should be interpreted as associative rather than strictly causal relationships.

Participants

The sample comprised 199 students from the University of Jeddah, selected through purposive sampling. A total of 310 students were invited to participate in the study, of whom 199 completed the questionnaire and were included in the final analysis, yielding a response rate of 64.2%. Responses were screened for completeness and eligibility before analysis. No responses were excluded from the completed questionnaires, resulting in a final analytical sample of 199 participants. Although purposive sampling from a single university ensured data relevance, it may limit the representativeness of the sample and introduce potential sampling bias. This non-probability sampling approach was appropriate as the study targeted participants with prior experience using ChatGPT in educational contexts, ensuring the relevance and validity of the collected data. In most studies exploring technology acceptance in education, purposive sampling techniques are the most widely adopted to obtain information from available students[8]. The sample ensured the relevance of the participants using the universal criterion of the participants being university students who possess previous knowledge of or experience in using ChatGPT in an educational context[1,5]. The adequacy of the sample for SEM is justified in the literature, which indicates that certain thresholds for the number of participants are considered in the general requirements. For example, in terms of the SEM analysis[18], considered the minimum number of participants to be 5–10 per item in a survey instrument[9]. For example, for a study with 18 items, a sample size of 180 participants and above is considered adequate. Thus, given a sample size of $n = 199$, the present study meets the SEM requirements to provide a thorough analysis of meaningful relationships in this method and to test the model ramifications. The sample included undergraduate students from diverse academic disciplines, providing variability in experience and perspectives toward AI tools.

Instruments and measurement

Prior to the main data collection, the questionnaire was pretested with 20 students from the target population to assess the clarity, relevance, comprehensibility, and contextual appropriateness of the items. Based on the pretest feedback, minor wording adjustments were made to improve clarity and comprehensibility; however, no changes were made to the underlying conceptual meaning or dimensional structure of the original measures. All constructs were measured using previously validated scales drawn from the relevant literature, with contextual adaptations to reflect the use of ChatGPT in higher education. Specifically, the wording of the original items was adapted to

the ChatGPT context while maintaining their original meaning and theoretical consistency. The survey instrument contained 18 items covering five latent constructs: PE, EE, SE, trust, and BI. Respondents indicated their responses using a five-point Likert scale, with higher scores indicating greater agreement with each statement.

As the questionnaire was administered in Arabic, the measurement items were translated from English into Arabic to ensure their accessibility and comprehensibility for the target participants. A translation and back-translation procedure was employed to preserve the conceptual equivalence of the original measures. The English items were first translated into Arabic, after which the Arabic version was independently back-translated into English. The original and back-translated versions were compared to identify and resolve discrepancies in wording and meaning. Minor linguistic adjustments were made where necessary to ensure clarity and contextual appropriateness while preserving the intended meaning of the original constructs. The psychometric properties of the adapted measures were subsequently evaluated through confirmatory factor analysis (CFA), convergent validity, and discriminant validity assessments, as reported in the measurement model results. The complete wording of all measurement items used in this study is provided in Appendix A. Table 1 presents the details of the constructs and measurements.

CTAI was specified as a reflective second-order construct comprising two first-order dimensions: self-efficacy (SE) and trust in AI. In this specification, the higher-order CTAI factor was conceptualized as accounting for the shared variance between SE and trust, while the individual measurement items loaded on their respective first-order constructs. This specification is theoretically consistent with the conceptualization of CTAI as a broader psychological assurance construct comprising a user-directed dimension (SE) and a system-directed dimension (trust). The two dimensions were therefore retained as conceptually distinct first-order factors rather than treated as interchangeable individual indicators.

The second-order model was identified by applying standard identification constraints used in CFA, including fixing the scale of the latent factors and estimating the relationships between CTAI and its first-order dimensions. The adequacy of the higher-order specification was evaluated using the overall measurement-model fit indices and the standardized loadings of the first-order dimensions on CTAI. The purpose of combining SE and trust at the higher-order level was not to imply that they are identical or individually necessary for behavioral intention, but to model their shared variance as complementary dimensions of a broader psychological construct.

Data collection

Data were collected through an online survey designed using Google Forms. This method ensured a broad demographic range to be examined and accessibility to a vast population comprised mostly of college students, similar to the methods employed by other studies on technology acceptance[6]. The questionnaires were disseminated electronically during the first semester of 2025 through university mailing lists and other means, such as LMS, within the University of Jeddah. Although the survey invitation was distributed through university mailing lists and the LMS, participation was restricted to students who met the study's eligibility criteria. Eligible participants were students enrolled at the University of Jeddah who had prior experience using ChatGPT for educational or academic purposes. Accordingly, the recruitment strategy was considered purposive because participation targeted students with experience relevant to the phenomenon under investigation. Furthermore, ethics approval was obtained from the Ethics Committee of the University of Jeddah before data collection. All participants gave their written informed consent prior to the start of the survey. At the beginning of the questionnaire, an introductory

Table 1 Specific constructs and their measurement details.

Construct	Number of items	Source(s)
PE	4 items	19
EE	4 items	19
SE	4 items	20,21
Trust	3 items	10,11
BI	3 items	19

paragraph clearly outlined the study objectives and the participants' rights. The participants were also informed that their involvement was voluntary and that they could withdraw at any point without penalty. A mandatory question or explicit option to consent was used to ensure that the participants actively agreed to participate. To ensure confidentiality and anonymity, measures were implemented so that survey respondents' identities would not be revealed. Before analysis, responses were screened for eligibility and completeness. Responses would have been excluded if participants did not meet the study eligibility criteria, did not provide informed consent, or failed to complete the questionnaire. Because informed consent and all questionnaire items were mandatory in Google Forms, no completed responses were excluded during the final screening. Consequently, all 199 completed eligible responses were retained for analysis, and no missing-data imputation was required. All questionnaire items were configured as mandatory in Google Forms; therefore, the final dataset contained no item-level missing values, and no missing-data imputation was required. The participants' responses were entirely anonymous, and no private information was stored that could link the responses back to the participants. All methods were performed following the Declaration of Helsinki.

Data analysis

The collected data were analyzed using SEM through AMOS software. Specifically, covariance-based SEM (CB-SEM) was employed, as it is suitable for theory testing and confirmation of hypothesized relationships. This approach is suitable for confirming theoretical relationships and testing complex models involving latent constructs. The analytical procedure followed the established guidelines for CB-SEM. The data analysis was conducted using a two-step approach. First, as an initial step, confirmatory factor analysis (CFA) for the measurement model assessment was used to assess validity and reliability. Second, a structural model assessment was conducted to examine the research hypothesis, such as through path analysis and mediation effects. Bootstrapping with 5,000 resamples was used to assess the significance of indirect effects. This analytical approach enabled systematic assessment of the measurement and structural models and examination of the hypothesized relationships. However, the analytical approach does not eliminate limitations associated with the cross-sectional, self-report design, sampling strategy, or potential common method bias, which are acknowledged in the limitations section.

Results

Demographic information

As shown in Table 2, the study involved 199 participants, with the majority being female (72.4%, $n=144$) compared with males (27.6%, $n=55$). In terms of academic level, the participants were distributed fairly evenly between bachelor's and diploma programs. Bachelor's degree students represented 43.7% ($n=87$) of the sample, while diploma students comprised a slightly larger proportion, at 44.2% ($n=88$). Students pursuing higher education degrees accounted for only 12.1% ($n=24$). The participants were drawn from different colleges. The largest representation came from applied college (36.2%, $n=72$), followed by science (26.6%, $n=53$) and education (21.6%, $n=43$). Computer science and engineering students made up 12.1% ($n=24$) of the sample, while the languages and translation students accounted for the smallest representation, at 3.5% ($n=7$). The majority of the participants (92.5%, $n=184$) reported previous experience using AI for learning, while 7.5% ($n=15$) indicated no prior experience. This suggests a highly AI-aware and experienced sample group, which is relevant for a study focusing on adopting AI tools, such as ChatGPT.

Table 2 Demographic information.

		Frequency	Percentage
Gender	Male	55	27.6
	Female	144	72.4
Academic level	Bachelor	87	43.7
	Diploma	88	44.2
	Higher education	24	12.1
Colleges	Applied college	72	36.2
	Education	43	21.6
	Science	53	26.6
	Computer science and engineering	24	12.1
	Languages and translation	7	3.5
Previous experience in using AI for learning	Yes	184	92.5
	No	15	7.5
	Total	199	100.0

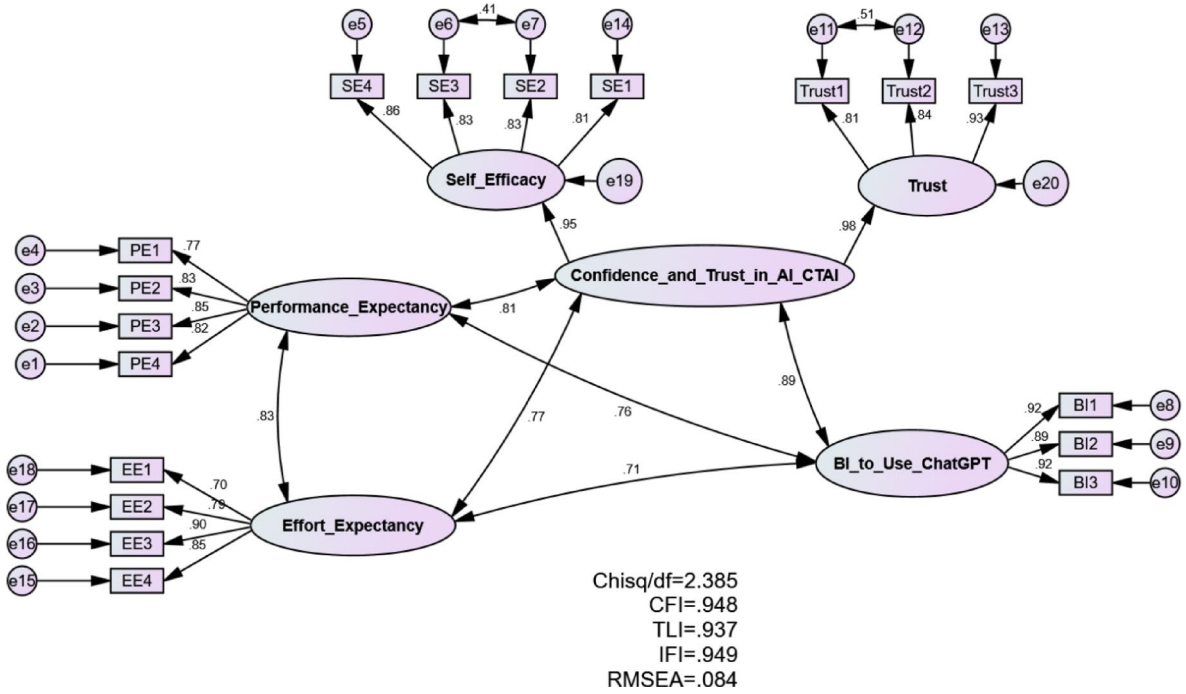

Fig. 2 CFA Output.

CFA

CFA was employed to assess the construct, convergent, and discriminant validities of the measurement model. Construct validity is established when the model's fit indices meet the accepted threshold values, such as a chi-square/df ratio of below 3.0, CFI and TLI values of above 0.90, and RMSEA of below 0.08 (Awang, 2015). In this study, the CFA results indicated generally acceptable model fit ($\chi^2/df = 2.385$, CFI = 0.948, TLI = 0.937, and IFI = 0.949). However, the RMSEA value (0.084) was slightly above the conventional 0.08 criterion, indicating marginal fit for this index. Overall, the pattern of fit indices was considered adequate for subsequent structural model assessment. Figure 2 presents the CFA output.

The measurement model demonstrated generally acceptable fit, as shown in Table 3 ($\chi^2/df = 2.385$, CFI = 0.948, TLI = 0.937, and IFI = 0.949). The RMSEA value of 0.084 was slightly above the conventional 0.08 criterion and

Table 3 Model fit indices.

Fit index	Accepted threshold	Obtained value	Reference	Decision
χ^2/df	≤ 3.00	2.385	Awang (2015)	Within acceptable range
CFI	≥ 0.90	0.948	Awang (2015),[18]	Acceptable
TLI	≥ 0.90	0.937	Awang (2015),[18]	Acceptable
IFI	≥ 0.90	0.949	[18]	Acceptable
RMSEA	≤ 0.08	0.084	Awang (2015), Byrne (2016)	Marginal; slightly above the recommended threshold

Table 4 CR and AVE values.

	CR	AVE
Effort_Expectancy	0.885	0.659
Performance_Expectancy	0.889	0.667
BI_to_Use_ChatGPT	0.938	0.834
Confidence_and_Trust_in_AI_CTAI	0.964	0.930

Table 5 Discriminant validity.

	Effort expectancy	Performance expectancy	Behavioral intention	Confidence and trust in AI
Effort expectancy	**0.812**			
Performance expectancy	0.834	**0.817**		
Behavioral intention	0.709	0.765	**0.913**	
Confidence and trust in AI	0.768	0.810	0.887	**0.964**

therefore indicated marginal rather than optimal fit. Accordingly, the overall pattern of fit indices was considered adequate for proceeding with structural model assessment, while the RMSEA result was interpreted cautiously.

To assess convergent validity, the CR and AVE values were assessed for all constructs. Convergent validity is achieved when the CR is greater than 0.60 and the AVE is greater than 0.50 (Awang, 2015), indicating that the items consistently measure the related latent construct and share an adequate proportion of the variance. All constructs passed the recommended minimum tests, as shown in Table 4, with CR values of 0.885–0.964 and AVE values of 0.659–0.930. Overall, these results provide evidence of high internal consistency and adequate convergent validity across the latent constructs. However, the exceptionally high CR and AVE values observed for CTAI warrant additional consideration.

Although the CR (0.964) and AVE (0.930) values for CTAI indicate very high internal consistency and convergent validity, these values should be interpreted cautiously. Given that CTAI is represented by the closely related first-order dimensions of self-efficacy and trust, the exceptionally high values may also indicate substantial shared variance and potential measurement redundancy or construct narrowness. Therefore, these results are not interpreted as unequivocal evidence of superior measurement quality. Future research should further examine the breadth of CTAI and compare alternative measurement specifications to determine whether its dimensions capture sufficiently distinct aspects of the higher-order construct.

The Fornell–Larcker results generally supported discriminant validity; however, an exception was observed for performance expectancy (PE) and effort expectancy (EE). The correlation between PE and EE (r = 0.834) was slightly higher than the square roots of the AVE for EE (0.812) and PE (0.817), indicating potential conceptual overlap between these two expectancy constructs. Accordingly, the Fornell–Larcker criterion was not fully satisfied for this construct pair. Complementary assessment using HTMT showed a PE–EE value of 0.84, which remained below the adopted threshold of 0.90. Taken together, these findings provide qualified rather than unequivocal support for discriminant validity and suggest that the conceptual proximity between PE and EE should be considered when interpreting the structural results Table 5.

Discriminant validity was further assessed using the heterotrait–monotrait ratio (HTMT). As shown in Table 6, all HTMT values were below the recommended threshold of 0.90[22], providing general support for discriminant validity. However, some values approached this threshold, particularly trust–BI (0.89) and SE–trust (0.88), indicating substantial conceptual proximity among these constructs and warranting cautious interpretation. Accordingly, when considered alongside the Fornell–Larcker results, the evidence provides qualified rather than unequivocal support for discriminant validity.

Normality assessment

The normality of the data was assessed using skewness and kurtosis values. The results indicated that skewness values ranged from −1.518 to −0.541, while kurtosis values ranged from −1.011 to 2.535. These univariate values were within commonly recommended thresholds for SEM (Awang, 2015), suggesting no substantial violations of univariate normality. However, the multivariate kurtosis results indicated some departure from multivariate normality. Because CB-SEM with maximum likelihood estimation can be sensitive to multivariate non-normality, this departure was considered when interpreting the model estimates. In addition, bootstrapping with 5,000 resamples was employed for the mediation analysis to obtain bias-corrected confidence intervals for the indirect effects, thereby reducing reliance on normal-theory assumptions for mediation inference. Accordingly, the results were interpreted with appropriate caution rather than assuming strict multivariate normality.

Common method bias (CMB)

Common method bias was initially assessed using Harman's single-factor test. The results showed that the first factor accounted for 41% of the total variance, below the conventional 50% threshold, suggesting that no single factor dominated the variance in the measures. However, Harman's single-factor test has limited sensitivity for detecting common method bias. Therefore, the possibility of common method bias cannot be completely ruled out, particularly given the cross-sectional and self-reported nature of the data, and the findings should be interpreted with appropriate caution.

Standardized estimates

Running standardized estimates in the CFA is essential for assessing factor loadings, R^2 values, and the strength of relationships among constructs. Standardized estimates indicate how well each observed variable represents its latent construction and how strongly the constructs are related (Awang, 2015). Factor loadings above 0.50 are acceptable, while values exceeding 0.70 reflect strong reliability. In this study, all standardized loadings met the recommended thresholds, confirming that the measurement model demonstrated satisfactory reliability and validity. Figure 3 presents a structural model with standardized estimates.

The R^2 value for BI was 0.79, indicating that the structural model accounted for 79% of the variance in students' behavioral intention to use ChatGPT within the present sample. This represents substantial explanatory power for the estimated model. However, given the cross-sectional and self-report design, the R^2 value should be interpreted as explained variance within the sample rather than evidence of out-of-sample predictive capability. Moreover, because the constructs were measured through self-report within the same survey and some constructs

Table 6 Discriminant validity assessment using HTMT.

Constructs	PE	EE	SE	Trust	BI
PE	–	0.84	0.79	0.78	0.80
EE	0.84	–	0.82	0.80	0.79
SE	0.79	0.82	–	0.88	0.87
Trust	0.78	0.80	0.88	–	0.89
BI	0.80	0.79	0.87	0.89	–

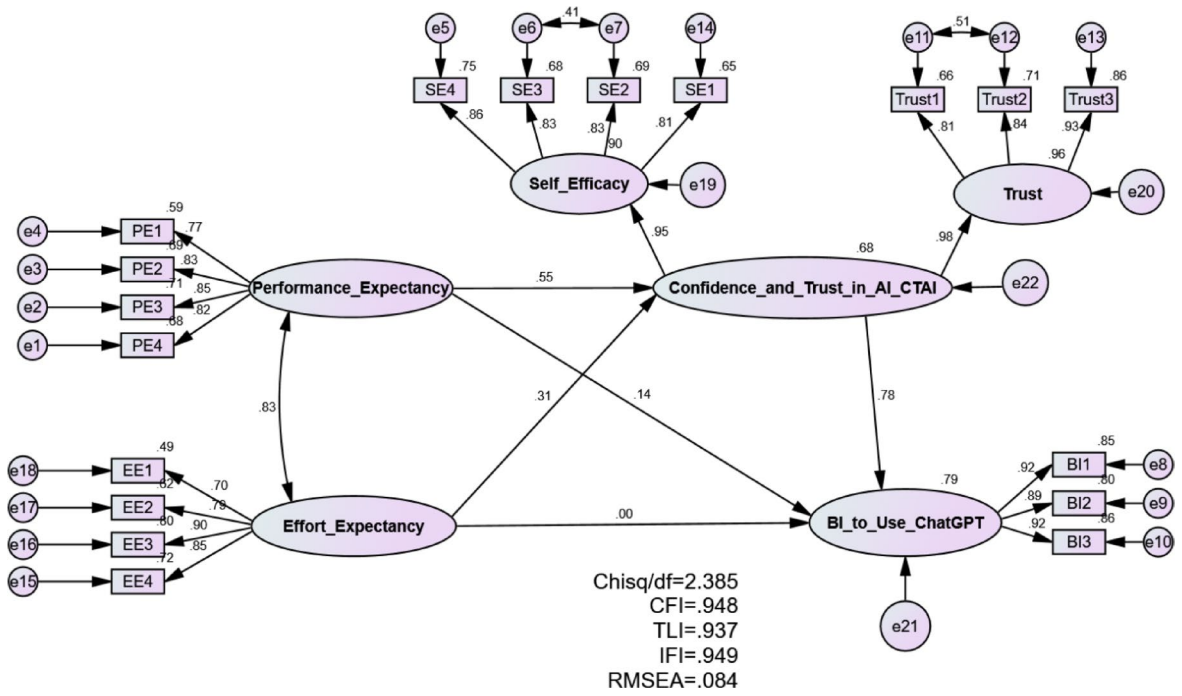

Fig. 3 Standardized estimates.

exhibited relatively high intercorrelations, the magnitude of R^2 should be interpreted cautiously, as shared measurement characteristics and construct overlap may have contributed to the explained variance.

Unstandardized estimates

Unstandardized estimates are crucial in SEM for assessing the critical ratios (C.R.) and regression weights (true B values) used to test the research hypotheses. These estimates represent the direct effects on constructs in their original measurement scales and are evaluated for statistical significance when C.R. > ± 1.96 at the 0.05 level (Awang, 2015). In this study, unstandardized estimates were generated, and their output, as presented in Fig. 4, illustrates the regression weights and significance of the hypothesized relationships within the proposed model. Figure 4 presents the structural model with its unstandardized estimates.

Regression weight analysis

The regression weight results from the SEM are presented in Fig. 4; Table 7. As shown, PE had a significant positive association on CTAI (B = 0.658, $p < 0.001$), supporting H3. Similarly, EE had a significant positive effect on CTAI (B = 0.414, $p = 0.007$), thereby supporting H4. CTAI significantly predicted BI to utilize ChatGPT (BI) (B = 0.687, $p < 0.001$), thus confirming H5.

Conversely, the direct paths from PE (B = 0.143, $p = 0.222$) and EE (B = −0.002, $p = 0.985$) to BI were not significant, indicating that H1 and H2 were not supported. The findings suggest that students' performance and effort beliefs do not directly influence their intention to utilize ChatGPT but instead operate through psychological mechanisms, such as CTAI.

In addition, the paths from CTAI to its subdimensions of SE (B = 0.895, $p < 0.001$) and trust (B = 1.000) were strong and significant, confirming that the higher-order construct (i.e., CTAI) adequately represents its first-order dimensions. Overall, the model demonstrated strong internal consistency and statistically meaningful pathways, consistent with the proposed conceptual framework.

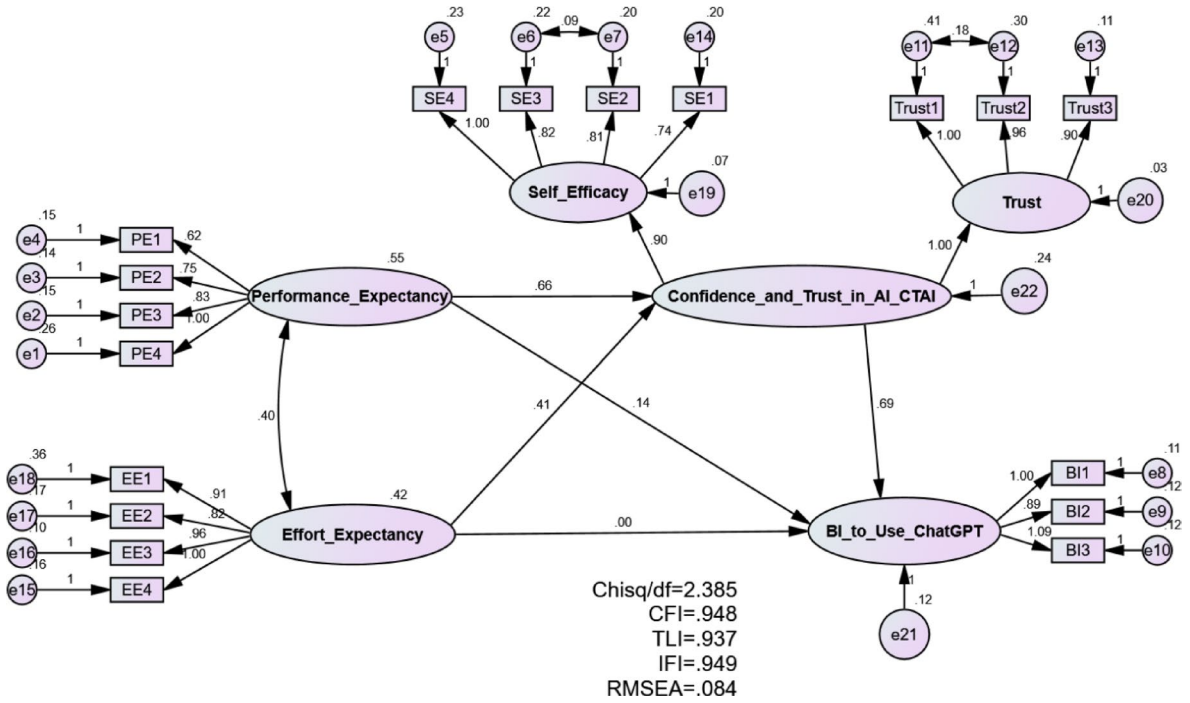

Fig. 4 Unstandardized estimates.

Table 7 Regression analysis.

			Estimate	S.E.	C.*R*.	*P*	Result
Confidence_and_Trust_in_AI_CTAI	<---	Performance_Expectancy	0.658	0.142	4.648	***	Significant
Confidence_and_Trust _in_AI_CTAI	<---	Effort_Expectancy	0.414	0.155	2.677	0.007	Significant
BI_to_Use _ChatGPT	<---	Performance_Expectancy	0.143	0.117	1.222	0.222	Not significant
BI_to_Use _ChatGPT	<---	Confidence_and_Trust _in_AI_CTAI	0.687	0.092	7.425	***	Significant
BI_to_Use _ChatGPT	<---	Effort_Expectancy	−0.002	0.117	−0.019	0.985	Not significant
Self_Efficacy	<---	Confidence_and_Trust _in_AI_CTAI	0.895	0.070	12.800	***	-
Trust	<---	Confidence_and_Trust _in_AI_CTAI	1.000		-		-

Mediation analysis

The mediating effects of CTAI were examined using the bootstrapping method by selecting 5,000 samples and the bias-corrected confidence intervals. The results revealed that CTAI fully mediated the relationship between PE and BI. Specifically, the indirect effect was significant (B = 0.452, p = 0.004, 95% CI [0.183, 0.838]), while the direct effect of PE on BI was not significant (B = 0.143, p = 0.297). This finding supports H6 and indicates that students' perceived usefulness of ChatGPT influenced their BI to utilize it primarily through increased CTAI.

Conversely, the mediating role of CTAI between EE and BI was not significant (indirect B = 0.284, p = 0.065, 95% CI [−0.018, 0.661]), and the direct path was also not significant (B = −0.002, p = 0.914). Although EE had a significant positive effect on CTAI (B = 0.414, p = 0.007), its indirect effect on BI through CTAI was not significant (p = 0.065). This suggests that while students who perceived ChatGPT as easy to use tended to develop

Table 8 Mediation analysis.

Path	Effect type	Effect type	Estimate (β)	*P*-value	95% BC CI	Mediation type
PE → CTAI → BI	Direct 0.143 $p=0.297$ Insignificant	Indirect	(0.452)	($p=0.004$) Significant	[0.183, 0.838]	Full Mediation
EE → CTAI → BI	Direct −0.002 $p=0.914$ Insignificant	Indirect	(0.284)	($p=0.065$) Insignificant	[−0.018, 0.661]	No Mediation

greater CTAI, this enhanced psychological assurance does not necessarily translate into a stronger BI to utilize it. Thus, H4 was supported, but the mediated relationship (H7) was not confirmed.

Overall, the results offer strong empirical support for the full mediation of CTAI in the relationship between PE and BI, underscoring its critical psychological role in shaping students' adoption of ChatGPT. Table 8 presents the results of the mediating analysis.

Discussion

This study aimed to examine the factors influencing students' BI to utilize ChatGPT, with a particular focus on the mediating role of CTAI, conceptualized as a second-order construct. The empirical findings offer nuanced insights into the determinants of technology adoption in the context of generative AI.

This study revealed that PE had a positive and significant effect on CTAI, indicating that students who regard ChatGPT as beneficial for their academic performance or academic learning outcomes are also more likely to have higher levels of confidence in their own abilities to utilize AI and trust in the AI system itself. This is consistent with the findings of previous research indicating that the PE of a technology is a crucial determinant of user confidence and trust[5].

EE was significantly and positively associated with CTAI (B = 0.414, $p = 0.007$), indicating that students who perceived ChatGPT as easier to use tended to report greater confidence and trust in AI. However, EE was not significantly associated with BI either directly or indirectly through CTAI. This pattern suggests that perceived ease of use may contribute to students' confidence and trust in AI without necessarily translating into stronger behavioral intention. One possible explanation is that ease of use may be less salient among students who are already familiar with digital technologies. However, because digital competence and technology familiarity were not directly measured in this study, this interpretation remains tentative and should be examined in future research.

In addition, a significant positive relationship was found between CTAI and students' BI to utilize ChatGPT. This indicates the important role that the combined perception of SE in interacting with AI and trust in AI capabilities plays in influencing intentions related to adoption[8]. Previous literature has consistently supported the characteristics related to trust in AI, which are indicators of users' intention to engage with AI applications[8,9]. Students who feel able to integrate AI into their interactions and feel confident in its reliability are more inclined to incorporate such means into their learning activities.

Contrary to H1, the direct relationship between PE and BI was not statistically significant. This finding indicates that, within the present sample, perceiving ChatGPT as beneficial for academic performance was not independently associated with stronger behavioral intention when CTAI was included in the model. Although this finding differs from the conventional UTAUT expectation of a direct PE–BI relationship, it does not imply that PE is unimportant. Rather, PE was significantly associated with CTAI, and its indirect association with BI through CTAI was statistically significant. Thus, H1 was not supported, whereas the findings provided support for the indirect PE–BI relationship proposed through CTAI.

The mediation analysis further showed that the indirect relationship between PE and BI through CTAI was statistically significant, whereas the direct PE–BI relationship was not significant. This pattern is consistent with an indirect-only mediation effect, suggesting that, within the present sample, the association between perceived performance benefits and behavioral intention was primarily observed through confidence and trust in AI. Similar mediation patterns have been reported in technology acceptance research[23,24]. However, given the cross-sectional nature of the study, this mediation finding represents an indirect statistical association and should not be interpreted as establishing a necessary or causal sequence.

EE was significantly and positively associated with CTAI (B = 0.414, $p = 0.007$), indicating that students who perceived ChatGPT as easier to use tended to report greater confidence and trust in AI. However, contrary to H2, the direct relationship between EE and BI was not statistically significant. Moreover, the indirect relationship between EE and BI through CTAI was not significant; therefore, H7 was not supported. These findings suggest that although perceived ease of use was associated with students' confidence and trust in AI, this association did not translate into a statistically significant direct or indirect relationship with behavioral intention in the present sample. One possible explanation is that ease of use may be less salient for some users of generative AI; however, factors such as digital literacy, prior technology experience, and AI competence were not directly assessed as explanatory mechanisms in this study. Therefore, explanations based on these factors remain tentative and should be examined empirically in future research.

Theoretical implications

These findings offer several theoretical implications for technology acceptance research in the context of generative AI. By conceptualizing CTAI as a second-order mediating construct, this study extends the UTAUT-based framework by incorporating an integrated psychological mechanism comprising students' confidence in their ability to use AI and their trust in the AI system. The significant mediation of CTAI in the relationship between PE and BI suggests that perceived performance benefits may be associated with behavioral intention through students' confidence and trust in AI. This finding extends the conventional emphasis on expectancy beliefs by highlighting the potential role of psychological factors that reflect both user-related confidence and system-related trust in understanding generative AI adoption.

Although EE was significantly associated with CTAI, neither its direct association with BI nor its indirect association with BI through CTAI was statistically significant. This finding suggests that effort expectancy may contribute to students' confidence and trust in AI without necessarily translating into stronger behavioral intention. Accordingly, the mediating role of CTAI should not be generalized across all expectancy pathways, as significant mediation was observed for PE but not for EE. Overall, this study contributes to the literature by conceptualizing CTAI as a higher-order construct in the context of generative AI adoption and by providing initial empirical evidence of its mediating role specifically in the relationship between performance expectancy and students' behavioral intention to use ChatGPT.

Practical implications

The findings offer several practical considerations for AI developers, higher education institutions, and policymakers. Given the significant indirect association between PE and BI through CTAI, institutions may consider addressing students' confidence and trust alongside communicating the potential academic benefits of ChatGPT and similar generative AI applications. Potential initiatives may include workshops, tutorials, and guidance designed to support students' self-efficacy in using AI effectively and responsibly. In addition, developers and institutions may consider emphasizing the reliability, transparency, capabilities, and limitations of AI systems, while clear institutional guidelines concerning responsible and ethical AI use may contribute to a more informed environment for educational AI adoption.

The findings also suggest that students' confidence and trust may warrant consideration alongside usability when institutions develop strategies for integrating generative AI into higher education. However, these implications should be interpreted cautiously. The present study examined behavioral intention rather than actual AI use, learning outcomes, training effectiveness, policy effectiveness, or the impact of specific institutional interventions. Therefore, the proposed initiatives should be regarded as practical considerations derived from the observed associations rather than as empirically validated strategies. Future research should directly evaluate whether such interventions contribute to students' actual use, responsible adoption, or educational outcomes.

Limitations and future research

While this study offers meaningful insights into students' adoption of ChatGPT, several limitations should be acknowledged. First, the cross-sectional design restricts causal inference and does not permit conclusions regarding the temporal ordering of the observed relationships. Although SEM enabled examination of the hypothesized associations, longitudinal research is needed to assess how these relationships develop and change over time. Future studies could therefore employ longitudinal designs to examine how CTAI develops over time and whether changes in CTAI are associated with changes in behavioral intention.

Second, because participants were recruited through purposive, non-probability sampling from a single Saudi university, the possibility of self-selection bias cannot be excluded, and the findings should be generalized to students from other institutions, regions, and cultural contexts with caution. The gender imbalance in the sample, with female students representing 72.4% of participants, may further restrict representativeness. Future studies should examine the proposed model using larger, multi-institutional and culturally diverse samples and, where feasible, probability-based sampling with more balanced demographic representation.

Third, the study examined students' behavioral intention rather than their actual use of ChatGPT or subsequent learning outcomes. Therefore, the observed relationships should not be interpreted as evidence of actual adoption behavior or educational effectiveness. Future research should incorporate behavioral measures of AI use and relevant educational outcomes to determine whether the observed associations with behavioral intention extend to actual adoption and educational practice.

Fourth, although the measurement items were adapted from validated instruments, the second-order CTAI construct warrants further psychometric validation. The relatively high associations among some constructs, the failure of the Fornell–Larcker criterion to fully distinguish PE from EE, and the very high CR and AVE values observed for CTAI indicate potential construct overlap or measurement redundancy that should be examined further. Future research should compare alternative measurement specifications, including models in which SE and trust are represented separately, and evaluate the stability and distinctiveness of CTAI across independent and more diverse samples.

Fifth, the nonsignificant indirect EE–CTAI–BI relationship indicates that the mediating role of CTAI should not be generalized across all expectancy pathways. Although EE was significantly associated with CTAI, its indirect association with BI through CTAI was not statistically significant. Future research should investigate the conditions under which effort expectancy may be associated with behavioral intention and examine whether other psychological or contextual mechanisms account for this relationship. Additional mediators or moderators, such as perceived risk, ethical awareness, social influence, or AI-related competence, may also be considered in future studies.

Finally, because the study relied on self-reported data collected through a single questionnaire, common method bias cannot be completely excluded. Although Harman's single-factor test indicated that no single factor dominated the observed variance, this test alone provides limited evidence regarding common method bias. Future studies should employ stronger procedural and statistical approaches, such as temporal separation, multiple data sources, or appropriate marker-variable techniques, to assess and minimize potential common method variance.

Conclusion

This study assessed the determinants of students' BI to use ChatGPT, with particular emphasis on the mediating role of CTAI. The findings indicated that PE and EE were positively and significantly associated with CTAI, while CTAI was positively and significantly associated with students' BI to use ChatGPT. However, neither PE nor EE was directly associated with BI at a statistically significant level. Although PE had a significant indirect association with BI through CTAI, the indirect association of EE with BI through CTAI was not statistically significant. Overall, CTAI emerged as a significant mediating mechanism in the relationship between PE and BI in the present sample but did not significantly mediate the relationship between EE and BI. These findings suggest that confidence and trust may help explain how perceived performance benefits are associated with students' behavioral intention to use ChatGPT, while the cross-sectional design precludes causal or necessity-based conclusions. The study extends technology acceptance research by integrating self-efficacy and trust within the higher-order CTAI construct and provides initial empirical evidence of its mediating role in the relationship between performance expectancy and behavioral intention. From a practical perspective, the findings suggest that higher education institutions may consider supporting students' confidence in using AI and fostering appropriately calibrated trust in AI systems alongside efforts to demonstrate their academic usefulness. Such implications should be interpreted cautiously, as the present study examined behavioral intention rather than actual use or the effectiveness of specific institutional interventions.

Appendix A. measurement items

All items were measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Performance expectancy (PE)

PE1. I would find ChatGPT useful for my academic learning.
PE2. Using ChatGPT enables me to accomplish my academic tasks more quickly.
PE3. Using ChatGPT increases my academic productivity.
PE4. Using ChatGPT improves my academic performance and learning outcomes.

Effort expectancy (EE)

EE1. My interaction with ChatGPT for academic learning is clear and understandable.
EE2. It would be easy for me to become skillful at using ChatGPT for academic purposes.
EE3. I would find ChatGPT easy to use for academic learning.
EE4. Learning to operate ChatGPT for my studies would be easy for me.

Academic self-efficacy (SE)

SE1. I am confident in my ability to use ChatGPT to understand academic content.
SE2. I can successfully complete my academic assignments with the help of ChatGPT.
SE3. Even if my academic tasks are difficult, I believe I can succeed with the support of ChatGPT.
SE4. I am confident that I can rely on ChatGPT to improve my academic performance.

Trust in artificial intelligence

TR1. I feel confident relying on ChatGPT for academic learning.

TR2. I trust ChatGPT to perform reliably in academic contexts.
TR3. I believe ChatGPT will act in my best academic interest.

Behavioral intention (BI)

BI1. I intend to use ChatGPT for my academic learning in the coming months.
BI2. I predict that I will use ChatGPT for my academic learning in the coming months.
BI3. I plan to use ChatGPT for my academic learning in the coming months.

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Data availability The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

Declarations

Competing interests The authors declare no competing interests.

Ethical approval All procedures involving human participants were conducted in accordance with the ethical standards of the institutional research committee and the principles outlined in the Declaration of Helsinki. Informed consent was obtained from all participants prior to their inclusion in the study. Participation was anonymous, and no personally identifiable information was collected.

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