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ChatGPT and intrinsic motivation in higher education: a TAM-based study

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Highly evolved and capable, ChatGPT is an intelligent chatbot with great implications for fostering active student learning due to its capacity to respond quickly to academic queries as well as to engage in dynamic interactions with the learner. In the present research which was conducted within the Saudi university context, we studied how intrinsic motivation and factors related to TAM (technology acceptance model) influenced undergraduate students' acceptance of ChatGPT as a tool for learning actively. The study adopted a structural equation approach to investigate the extended TAM model in tertiary education. The results of the revealed that intrinsic motivation, perceived usefulness, and perceived ease of use were found to be significant predictors of behavioral intention. Finally, the study highlights that AI-based tools as user-friendly, beneficial, engaging and intriguing promote students' active learning and enhance their involvement in the learning process and, thus, their acquisition of new knowledge.

KEYWORDS

AI, ChatGPT, teaching acceptance model (TAM), motivation, active learning

Introduction

In the contemporary era, the influence of technology on all aspects of human lives has been tremendous, with such impact extending quite notably to the educational arena (Fanguy et al., 2023; Imran and Almusharraf, 2024; Barbara et al., 2024). Indeed, the educational landscape has also been transformed by the global ingress towards the adoption of the Internet of Things (IoT). The emergence of IoT, or which advancement is known as the fifth generation of the Internet, within education has given rise to a burgeoning interest in how to apply artificial intelligence (AI) in instruction and academic inquiry. In the wake of the emergence of AI engines and chatbots (e.g., Bard, ChatGPT) (Du et al., 2022; Wang et al., 2025) observe that AI has gained prominence as a factor of critical importance vis-à-vis academic inquiry and English as a Second Language teaching, in turn giving rise to the impetus for creating systems to manage learning and authorial tools to support learning. Bonwell and Eison (1991) observe that active learning is underpinned by a pedagogical approach whereby learners participate agentively as well as experientially in their process of learning. Such an approach is not only learner-focused but also tends to be designed around willing and active participation by the learners in lieu of passive listening. Arguing that such a methodology encourages learners to develop autonomy.

The focus of the study is on the use of technology and intrinsic motivation to use newly developed models in higher education. It is highlighted that motivation plays a key role in supporting learners in their quest to learn effectively and successfully (Annamalai et al., 2023; Afzaal et al., 2025; Yating et al., 2025; Younas et al., 2025a). According to Oudeyer et al. (2016), as learners experience the motivation to seek novel or complex information, their curiosity prompts them to retain information more effectively and to enjoy what they are learning. This is of particular importance in the tertiary educational context wherein learners must demonstrate intrinsic motivation (IM) in order to advance their journeys in learning. In this regard, intellectual curiosity, which may be viewed as a form of IM, has a vital role to play in active student-led learning and exploration of information (Oudeyer et al., 2016).

Against this backdrop, ChatGPT has the potential to serve as an effective tool for facilitating the learning of students. In the present era, with the explosion in information available and new knowledge being produced rapidly around the world, students who are either confused or curious while interacting with their course readings have the option to turn to ChatGPT to quickly resolve their academic queries. Additionally, given ChatGPT's user-friendly design, such learners can enter either formally or informally worded prompts to gain the information they need (Aljanabi et al., 2023; Afzaal et al., 2023).

Research Questions:

1 What are the direct and indirect elements that motivate Saudi undergraduates to adopt ChatGPT for engaging in active learning and addressing academic questions?
2 How significantly do these elements influence Saudi undergraduates in making use of ChatGPT for resolving academic issues through active learning?

Literature review

Many studies have highlighted research which suggests that motivation to explore information actively and enjoyment and retention of learning are linked, we turn now to developments in AI which have the potential to advance active student learning to another level. Focusing on AI, which has gained traction in all domains of human enterprise in recent years, Rai et al. (2019) argue that this advancement refers to the capacity of robots to perform thinking tasks which involve the ability to perceive, rationalize, interact and learn, much as human beings do. Akgun and Greenhow (2021) add that AI can be thought of as a technological domain which is focused on establishing systems with the capacity to mimic human cognition as well as behavior, whereby target objectives may be attained. In the educational landscape, it is increasingly being deployed as a writing tool which can foster learners' interest and build up their capacity to write more effectively (Abdelghani et al., 2022; Younas et al., 2025b). Students who are interested in exploring and learning with ChatGPT tend to deploy it for generating information for a wide range of academic assignments. Yilmaz and Yilmaz (2023) suggest that such use of ChatGPT not only expands the scope but also the intensity of learning by students. Research (Halaweh, 2023) highlights that ChatGPT is equipped to perform a wide swath of functions of considerable utility for learners in educational settings, ranging from distilling key ideas within articles, summarizing information, generating practice questions, providing citations as well as furnishing feedback on linguistic aspects of information submitted by the learners.

Vis-à-vis its potential applications across a spectrum of academic subjects, ChatGPT appears to have impacted multiple epistemic domains to a significant extent. This AI tool has been used to generate information as well as case studies in medicine and public health to further students' learning (Khan et al., 2023). In computing education, ChatGPT has been harnessed to analyze the pros and cons of scripting language, tackle coding conundrums and identify best approaches for developing software. In the domain of reading and writing, this AI tool with its capacity for simulating authentic interactions is viewed as being well-equipped to motivate writers to advance their language skills (Liu and Ma, 2023). Kohnke et al. (2023) explain that ChatGPT offers not only access to a dictionary but also defines words according to context. In addition, it clarifies and corrects linguistic errors, creates texts in a range of genres, and produces appropriate translations (Kohnke et al., 2023).

Moving on, we look at how ChatGPT fosters active learning by activating students' ability to self-regulate their learning. Pintrich (2000) defines self-regulation as the capacity of learners to independently regulate their processes of learning with a view to accomplishing their target objectives. The value of learners' motivation, "engagement in learning" and "self-efficacy" in the mechanism of "self-regulation" has been well-documented (Lai et al., 2023; Yu et al., 2022; Afzaal et al., 2024). During forethought, learners analyze their learning tasks, set objectives, and come up with strategies which can help them to attain their learning targets. At this point, the process is mobilized by the learners' enthusiasm and helps to activate their learning techniques. With reference to this initial phase, there is potential for the ChatGPT to aid learners in expressing their objectives, honing in on the topic they wish to investigate, and in benchmarking their process of learning, thus capacitating them to take responsibility for their own learning at the very outset of an academic task.

Drawing upon earlier research, Ernst et al. (2014) point out that learners' negative or positive attitudes towards different kinds of learning (Mager, 1968) effectively predict their actual use of new forms of learning. Research has also highlighted how learners perceive and accept emergent technologies influences effective learning (e.g., McLoughlin and Lee, 2010; Ahmad et al., 2024) and how these perceptions also impact learners' decision to undertake self-directed learning (Liaw et al., 2007). Earlier studies have investigated student motivation in the utilization of technologies to a considerable extent (Davis, 1986). TAM is distilled from the idea of rationalized action which is premised on the notion that how individuals behave is shaped by their intended behavior or Behavioral intention (BI). TAM is made up of two basic dimensions, namely Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). This model suggests that (PU) and (PEOU) shape the attitudes of individuals, whereas BI can be predicted by PU and attitudes pertaining to technology according to Alharbi and Drew (2014). It is hypothesized by Davis et al. (1989) that BI has a direct effect on PU as shown in Figure 1.

Extended efforts have been undertaken to utilize the TAM in tertiary education in order to gain insights into the significant beliefs and actions of learners when it comes to their receptivity to learning technologies. A dependent variable in the Technology Acceptance Model (TAM), Business Intelligence (BI) refers to a user's intention to carry on making use of the technology in the future, as defined by Alharbi and Drew (2014). Based on Davis et al. (1989), PEOU quantifies how individuals perceive the level of ease related to deploying a specific system. When users consider systems as user-friendly, this is likely to enhance their utilization.

Recent research has investigated factors influencing the implementation of IT by expanding the Technology Acceptance

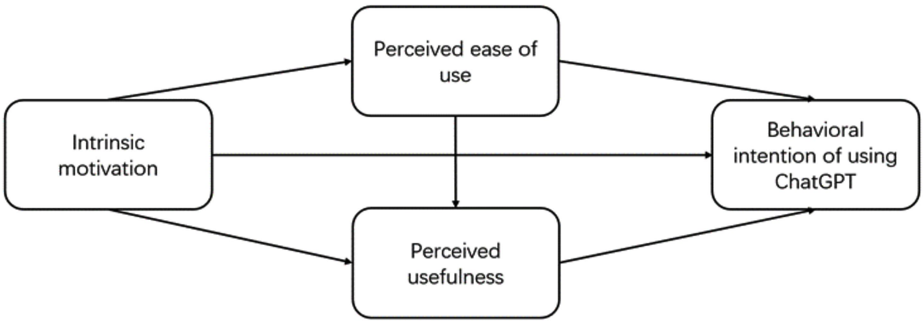

FIGURE 1
Study model.

Model (TAM) with Independent Motivation (IM). Examining factors that affected the adoption of mobile augmented reality in education, Papakostas et al. (2023) helped to expand TAM by discovering that positive correlations were identifiable between PU and PEOU and the students' playfulness and output quality. In another context, Wang et al. (2023) investigated variables that influence individuals' engagement in online education. Wang et al. (2023) expanded the Technology Acceptance Model (TAM) by proposing that the perception of fun is directly linked to the perceived usefulness (PU) of online education. The hypothesis proposed that the perception of playfulness would have a positive correlation with participation, attitudes, and intentions. Their research results confirmed Wang et al. (2023) hypothesis, accept the negligible correlation between perceived fun and participation attitudes. While previous studies have expanded the Technology acceptability Model (TAM) by including elements of playfulness or enjoyment, a survey of literature reveals that there is a dearth of studies that have investigated the combination of Intrinsic motivation (IM) and TAM factors in the context of ChatGPT acceptability.

Further, earlier research did not involve users experiencing frequent interactions with systems like online libraries, online learning technology, mobile learning or library applications, or other types of chatbots (Zhou et al., 2022). On the other hand, ChatGPT presents potential infringements of privacy for learners seeking to acquire knowledge. Furthermore, the utilization of user responses to train ChatGPT has given rise to substantial privacy issues in relation to OpenAI's handling of user data.

This advances the discussion to the Technology Acceptance Model (TAM). Originally advanced as a model by Davis et al. (1989), TAM comprises an instrument which can help to predict the extent to which a new technology will find acceptance within any group or organization (Kowalska-Pyzalska, 2023). Noting that TAM is underpinned by theory of planned behavior (TPB), Turner et al. (2010) point out that the model, over its many evolutions, has come to comprise a key heuristic for comprehending factors which predict learners' attitudes vis-à-vis acceptance or rejection of any new technology.

As part of its evolution, TAM has changed over time to incorporate multiple external dimensions, including the impact of society, user experience, stress and anxiety as well as user self-efficacy and satisfaction (Guner and Acarturk, 2020). These intentions are influenced by the advantages anticipated by the users as well as the level of convenience offered to them by the technology understanding of which can enable technology application developers to design digital tools in such a way that user attitudes towards the technology are influenced positively. Research suggests that TAM is a well-tested theoretical framework which enables researchers to systematically examine user attitudes towards digital learning and tools (Saade et al., 2007).

While existing studies have looked at how teachers interact with and behave in digital learning environments, the present study inquiries into the learners' acceptance of AI ChatGPT as well as their behaviors and intentions to make use of AI tools and applications in their academic matters. Focusing on Saudi undergraduate L2 learners' acceptance of newly developed AI technology, this study examines factors which influence ChatGPT adoption by the students as well as their inclination towards active learning in tackling academic concerns. In addition to identifying both direct and indirect aspects which affect students' willingness to deploy ChatGPT as a tool to foster academic engagement, the study strives to gauge the significance of these factors in influencing students' intentions to deploy ChatGPT for addressing academic issues via active learning. The comprehension of these factors will contribute to the study's findings on how to effectively integrate advanced AI technologies in higher education and transform the educational experiences of students in similar contexts.

Figure 1 illustrates a model of how intrinsic motivation influences the behavioral intention to use ChatGPT. It shows that intrinsic motivation can directly impact a user's intention to use ChatGPT, and that this relationship is also mediated by two factors: perceived ease of use and perceived usefulness. Specifically, if a user is intrinsically motivated, they are more likely to find ChatGPT easy to use and useful, which further increases their intention to use the tool. Perceived ease of use and perceived usefulness each independently contribute to shaping the behavioral intention to adopt ChatGPT. Thus, the following research questions and hypotheses (adopted from Lai et al., 2023) have been developed to examine the direct effects:

Research Hypotheses (adopted from Lai et al., 2023):

> *H1*: IM positively affects BI when ChatGPT is used to answer academic questions.
>
> *H2*: IM positively affects the PEOU of ChatGPT for answering academic inquiries.

> *H3*: IM of ChatGPT for answering academic inquiries positively affects PU.
>
> *H4*: PEOU positively affects BI when using ChatGPT to answer academic inquiries.
>
> *H5*: PEOU positively affects the PU of ChatGPT for answering academic inquiries.
>
> *H6*: The PU of ChatGPT positively affects BI when using ChatGPT to answer academic inquiries.

This study addresses the gaps in research by incorporating the TAM with the Intrinsic Motivation (IM) in order to investigate how these variables, influence the learners' Behavioral Intention (BI) in using ChatGPT while considering the digital tool's intensive interactions and associated hazards. Therefore, the study introduces the following research model (Figure 2) for path analysis to investigate the direct impacts.

Methodology

In the present study, we tested the hypotheses and measured the validity and reliability with the help of Smart PLS 4.0. SEM was employed that needed to be measured in relation to constructs featured in the multivariate environment and due to the need to simultaneously identify how dependent and independent factors were associated. Making use of confirmatory factor analysis (CFA) while deploying PLS, we examined the measurement model to establish how the observed and unobserved variables were linked.

Next, we look at additional factors of significance that influence learners' desire to make use of ChatGPT, such as the PEOU and PU within the specific setting of this AI tool. This is likely to enhance their cognition as well as academic performance. Furthermore, the present study provides a valuable addition to the limited empirical research on the utilization of AI chatbots by proposing a novel model which sheds light on the intention underlying the use of ChatGPT. We conduct a thorough analysis of the TAM, self-determination theory (SDT), and motivation model to investigate how these three aspects are interconnected. The study also investigates the interrelationships between Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Intention to Use (IM) and their influence on the utilization of ChatGPT. The present study provides valuable insights for university teachers as well as AI developers in regard to the key components essential to promoting the use of ChatGPT by undergraduate learners seeking to undertake active learning.

Data collection and questionnaire

In April 2024, we conducted a study using a quantitative cross-sectional survey. Carrying out a case study with 257 students, we distributed the questionnaire to undergraduate students at 11 Saudi universities (adopted from Lai et al., 2023). Adopting a convenience sampling strategy, we used a Google form to distribute the questionnaires. The students were free to take part in the study as well as to refuse to participate or to leave the study at any point in time. We calculated the required sample size by making use of the minimum sample size estimation method in PLS-SEM (Peng and Lai, 2012; Noor et al., 2022). Three hundred and thirty-nine questionnaires were filled out and returned to us. Of these, only 257 respondents (75.8%) indicated their experience of using ChatGPT. As our study was focused on ChatGPT, we included only those responses which addressed the ChatGPT experience. With an eye to the estimated minimum of respondents in a survey, we considered 160 respondents to be adequate for our purpose. The demographic details are presented in Table 1. The age distribution reveals that the majority of participants (64.2%) are aged between 18 and 20 years, while 29.6% fall within the 21 to 24-year-old category, and a minority (6.2%) are older than 24. Gender representation within the sample is relatively balanced, with females comprising 51.4% of the participants and males comprising 48.6%. Regarding academic majors, 58.0% of the participants are enrolled in Science and Technology disciplines, whereas 42.0% of the

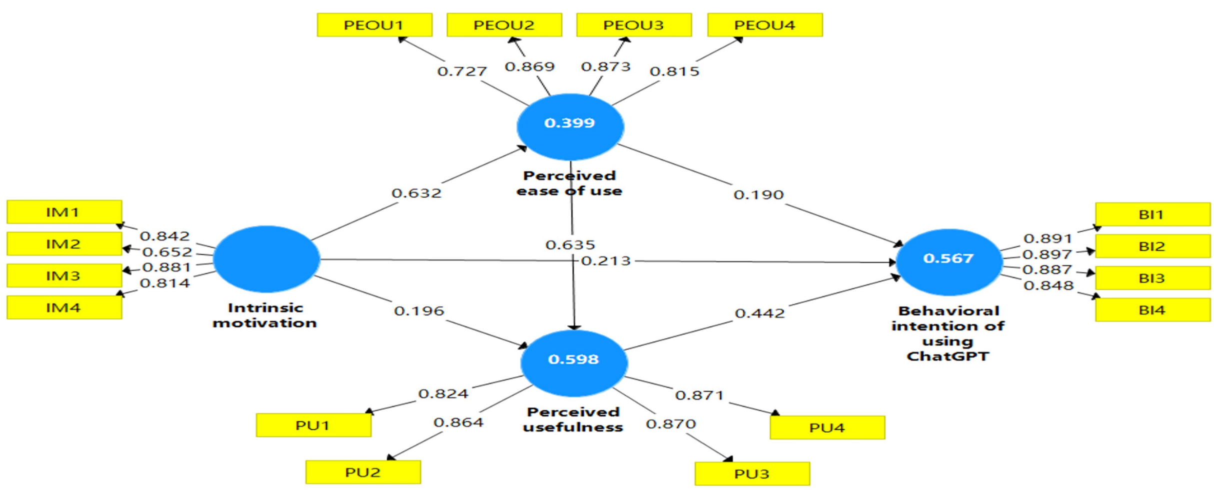

FIGURE 2
Path analysis model.

TABLE 1 Statistical results ($N = 257$).

Construct	Item	Factor loading	AVE	CR	Cronbach's alpha
Intrinsic motivation	IM1	0.842	0.644	0.877	0.815
	IM2	0.652			
	IM3	0.881			
	IM4	0.814			
Perceived ease of use	PEOU1	0.727	0.677	0.893	0.839
	PEOU2	0.869			
	PEOU3	0.873			
	PEOU4	0.815			
Perceived usefulness	PU1	0.824	0.736	0.917	0.88
	PU2	0.864			
	PU3	0.87			
	PU4	0.871			
Behavioral intention	BI1	0.891	0.776	0.933	0.904
	BI2	0.897			
	BI3	0.887			
	BI4	0.848			

participants are pursuing studies in Humanities and Social Sciences as shown in Table 2.

Analysis procedure

Adopting a vigorous statistical technique used to model complex intersections among observed and latent variables, we made use of PLS-SEM. As part of our analysis, we began by coding the questionnaire items as revelatory indicators. Assessing the measurement model entailed evaluating indicator reliability, reliability (Composite Reliability, and Cronbach's Alpha), convergent validity (Average Variance Extracted, AVE), and discriminant validity (using the Fornell-Larcker criterion).

Measures

We developed a questionnaire by adapting items (Lai et al., 2023) from scales which had been validated in earlier studies (Teo, 2009). In 16 items linked to the four constructs covered in the present study, we asked for the participants' demographic information. Four items each were assigned to PU, PEOU, IM and BI, respectively.

Results and discussion

Confirmatory factor analysis (CFA)

This study uses CFA to assess the constructs regarding their reliability as well as convergent validity, assessing reliability by deploying Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE).

TABLE 2 Demographic profile of participants ($N = 257$).

Variable	*N*	%
Age		
18–20	165	64.2
21–24	76	29.6
Above 24	16	6.2
Gender		
Female	132	51.4
Male	125	48.6
Major		
Science and technology	149	58.0
Humanities and social sciences	108	42.0

As shown in Table 1, all 16 items evidenced factor loadings, greater than 0.5, adequately represented corresponding constructs. The Average Variance Extracted (AVEs), ranging from 0.644 to 0.776, beyond the minimum requirement of 0.5, while the Composite Reliability values, from 0.877 to 0.933, exceeded the recommended level of 0.60, so indicating that the measurement model was trustworthy. Cronbach's alpha values, between 0.815 and 0.904, surpassed the 0.7 criterion.

Additionally, we explored discriminant validity using Fornell and Larcker's (1981) criterion which states that the square root of the AVE for each construct should be greater than the correlations between that construct and any other construct. The results confirmed that this criterion was met, thus providing further evidence of discriminant validity.

Table 3 shows the statistics of the Average Variance Extracted (AVEs) was greater than the constructs, thus confirming presence of validity. This bias has the potential to increase the route coefficients, which can result in type I errors. Further, the results indicate that variables include statistics and also include shared differences, which leads to increased collinearity among latent variables. Elevated levels of collinearity can lead to inflated path coefficients. When the relationships between hidden variables get stronger, the average variance extracted (AVE) also increases. The VIF can be used to detect this simultaneous increase. A Variance Inflation Factor (VIF) exceeding 3.3 indicates the presence of pathological collinearity, which suggests that the model is affected by common method bias. All Variance Inflation Factors (VIFs) in this investigation were ≤ 3.3, with a range of 1.4 to 3.3.

Answering hypotheses

The results of hypotheses show that the variables IM and BI ($\beta = 0.213$; $t = 2.59$; $p < 0.05$) was noteworthy. This suggested that IM

TABLE 3 Results of average variance.

Constructs	BI	IM	PEOU	PU
BI	0.881			
IM	0.597	0.802		
PEOU	0.66	0.632	0.823	
PU	0.713	0.597	0.759	0.858

and BI were positively related. Likewise, the PEOU and BI path coefficient was notable ($\beta = 0.19$; t = 2.088; $p < 0.05$), thus showing that PEOU and BI were positively related. Moreover, IM and PU were also observed as significant ($\beta = 0.196$; t = 2.615; $p < 0.01$), suggesting that IM positively affects perceived usefulness (PU). The results further showed that PU and PEOU were highly significant (t = 11.746; $\beta = 0.635$; $p < 0.001$), indicating a strong positive relationship between PEOU and PU. Similarly, the effect of PU on BI was highly significant ($\beta = 0.442$; t = 4.98; $p < 0.001$), indicating that PU positively influences BI. Furthermore, the indirect effect of IM on BI through PU was significant ($\beta = 0.086$; t = 2.078; $p < 0.05$), suggesting that PU mediates the relationship between IM and BI.

The results of the study support for all the proposed hypotheses: H1 (IM - > BI), H2 (IM - > PEOU), H3 (IM - > PU), H4 (PEOU - > BI), H5 (PEOU - > PU), H6 (PU - > BI), H7 (IM - > PU - > BI), and H8 (IM - > PEOU - > BI) as shown in Table 4.

Discussion

Overall, the study identified that Intrinsic motivation (IM) and (PU) significantly affect the participants' Behavioral Intention (BI). We also found that intrinsic motivation (IM) strongly predicted the (PEOU) and yielded a moderate impact on (PU).

These results are corroborated by a study carried out by Chang et al. (2022) which found that the utilization of chatbots tended to result in heightened self-reported self-efficacy, involvement, and acquisition of knowledge. Based on analysis of the results, we found that while using instant messaging (IM), the participating students learnt proactively, taking control of the interaction and posing questions to ChatGPT. This aligns with the results of a comparable study undertaken by Hobert et al. (2023) and Younas et al. (2024), which found that educational chatbots effectively delivered instructional material and promoted active learning. The study has highlighted that learners are intrinsically motivated to actively explore new and complex aspects of ChatGPT, with their curiosity helping them to learn actively and to enhance their ability to retain information (Duan et al., 2020). When learners are inherently driven to utilize ChatGPT for enjoyment and fulfilment, they are inclined to disregard the costs linked to its usage. Consequently, they are more inclined to consider the utilization of ChatGPT as being effortless. Research by Huang et al. (2022) found that the presence of PI, like IM, increased the perceived ease of use (PEOU) for Internet-based learning because when learners were engaged and interested in learning through the Internet, they were less likely to view it as being difficult.

The study showed that ChatGPT is capable of generating responses even for fragmented or partial questions, learners are likely to find it effortless to utilize ChatGPT for answering their queries. The influence of Intrinsic motivation (IM) on Perceived Usefulness (PU) is favorable and substantial. Our results align with findings in earlier empirical research, which supports the notion that perceived usefulness (PU) is associated with intention to use (IM) since it is influenced by external factors which go beyond the individual or the job. Individuals may engage in a particular activity or behavior just because they believe it will be beneficial for attaining desired objectives or preventing unfavorable consequences (Davis et al., 1992; Imran and Almusharraf, 2023).

Conclusion

Investigating the intrinsic motivation of Saudi learners in using AI tools in their academic inquiry tasks and their behavior towards the ChatGPT, we found that the advanced AI tools have the potential to facilitate students in their academic tasks. ChatGPT serve as crucial elements of active learning as they have the ability to make the learning process engaging and to stimulate learner curiosity. Student motivation plays a key role in attaining learning objectives as it is linked to increased engagement and more favorable attitudes. In addition, we also found that that chatbots can help to augment learners' motivation and engagement by delivering personalized assistance, providing real-time feedback, and promoting self-directed learning. In contrast, the lack of motivation reduces learners' inclination to incorporate chatbots into their academic matters.

Based on our findings, we suggest that undergraduates will welcome the use of ChatGPT as part of their learning when they perceive its ease of use and usefulness, and also when they develop intrinsic motivation towards the use of this novel Chatbot. Hence, it is highly recommended for university educators to support their students while using ChatGPT to address academic questions. Explicit instruction of how this chatbot can best serve students' needs is required. Additionally, students should be engaged in teacher-facilitated activities to develop their knowledge of the benefits as well as the limitations of ChatGPT. Clear policies are also needed to

TABLE 4 Results of path coefficients.

Hypotheses	Paths	Path coefficients	*p* values	*t*-values	Findings
H1	IM - > BI	0.213	0.010	2.59	Supported
H2	IM - > PEOU	0.632	0.000	15.599	Supported
H3	IM - > PU	0.196	0.009	2.615	Supported
H4	PEOU - > BI	0.19	0.037	2.088	Supported
H5	PEOU - > PU	0.635	0.000	11.746	Supported
H6	PU - > BI	0.442	0.000	4.98	Supported
H7	IM - > PU - > BI	0.086	0.0380	2.078	Supported
H8	IM - > PEOU - > BI	0.12	0.0330	2.137	Supported

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

regulate the use of this tool and ensure that students can use it positively and ethically. As for the developers of ChatGPT, it is important to increase its accessibility for undergraduates with different levels of technical and academic competence. It is also important to make efforts to obviate the ChatGPT's hallucinations and erroneous and fabricated output in order to increase students' trust in the tool and, hence, boost their intrinsic motivation to use it.

It must be noted that the results of the current study need to be interpreted with some caution due to three limitations. First, the number of Saudi undergraduates who participated in the study is relatively small although it successfully met the statistical requirements for analysis. A larger sample from diverse Saudi regions and types of post-secondary educational institutions will allow better generalizations of the results. Hence, it is highly recommended to replicate the study on a larger scale in Saudi Arabia as well as in other countries around the world to enhance our understanding of undergraduates' perceptions of this important AI-based Chatbot. Second, the results reflect the perceptions of the undergraduate students in Saudi Arabia, but these may not extend to the wider Saudi population of students in other stages of education. It is thus advisable to conduct further studies to understand how students of other educational stages, such as the elementary and secondary stages, perceive the use of ChatGPT. With the current technological revolution and the extensive focus on digital transformation in the Saudi Vision 2030, the use of such AI-based tools is expected to increase and spread across all the educational spectrums. Third, our study relied on the use of a questionnaire based on a 5-point Likert scale, and our results are, therefore, purely quantitative. It will be intriguing for future researchers to combine quantitative with qualitative measures while examining the learners' perceptions towards this use of such AI-innovated technologies. The use of qualitative measures, such as focus groups and interviews, will enrich our data and will subsequently boost our comprehensive understanding of learners' perspectives.

Research implications

The research highlights important implications for the integration of AI-based tools like ChatGPT in higher education. By demonstrating that intrinsic motivation, perceived usefulness, and perceived ease of use significantly predict students' intention to use ChatGPT, the study suggests that educational technology developers and institutions should focus on enhancing these factors to promote active student engagement and learning. Tailoring AI tools to be user-friendly and beneficial can encourage more students to adopt such technologies for academic purposes, ultimately supporting self-regulated learning and knowledge acquisition. These insights can inform future policies and strategies aimed at fostering the effective use of AI-driven educational resources in diverse academic settings.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by Ethics Review Board of Prince Sultan University. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

MA: Project administration, Formal analysis, Writing – original draft. AB: Writing – review & editing, Data curation, Methodology. MY: Data curation, Methodology, Writing – original draft. DE-D: Conceptualization, Writing – review & editing, Data curation, Supervision.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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