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Research article

Investigating influencing factors of learning satisfaction in AI ChatGPT for research: University students perspective

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ABSTRACT

This study investigates the determinants of ChatGPT adoption among university students and its impact on learning satisfaction. Utilizing the Technology Acceptance Model (TAM) and incorporating insights from interaction learning, collaborative learning, and information quality, a structural equation modeling approach was employed. This research collected valuable responses from 262 students at King Faisal University in Saudi Arabia through the use of self-report questionnaires. The data's reliability and validity were assessed using confirmation factor analysis, followed by path analysis to explore the hypotheses in the proposed model. The results indicate the pivotal roles of interaction learning and collaborative learning in fostering ChatGPT adoption. Social interaction played a significant role, as researchers engaging in conversations and knowledge-sharing expressed increased comfort with ChatGPT. Information quality was found to substantially influence researchers' decisions to continue using ChatGPT, emphasizing the need for ongoing improvement in the accuracy and relevance of content provided. Perceived ease of use and perceived usefulness played intermediary roles in linking ChatGPT engagement to learning satisfaction. User-friendly interfaces and perceived utility were identified as crucial factors affecting overall satisfaction levels. Notably, ChatGPT positively impacted learning motivation, indicating its potential to enhance student engagement and interest in learning. The study's findings have implications for educational practitioners seeking to improve the implementation of AI technologies in university students, emphasizing user-friendly design, collaborative learning, and factors influencing satisfaction. The study concludes with insights into the complex interplay between AI-powered tools, learning objectives, and motivation, highlighting the need for continued research to comprehensively understand these dynamics.

1. Introduction

Artificial intelligence (AI) has become a disruptive force in many fields, changing how we interact with technology and enhancing our skills. Artificial intelligence (AI) permeates various aspects of modern life, spanning health, law enforcement, education, and beyond [1,2]. Of particular interest is natural language processing (NLP), which enables computers to understand and generate human language [3]. AI is becoming more and more important in the context of education, helping to improve the quality of learning experiences [1]. As the educational landscape changes, using AI technology becomes essential to meeting students' varied demands and creating a more effective and customised learning environment [2]. The usage of conversational agents, like ChatGPT, has been a key component in the field of AI applications in education. With its robust and clever natural language processing capabilities, ChatGPT is

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an excellent tool for learning and communication [3,4]. These tools address some of the major issues with traditional learning settings, such as the absence of real-time feedback, the difficulty in accessing personalised training, and the insufficient support for a variety of learning styles [1,5].

ChatGPT, a variant of the GPT language model developed by OpenAI, exemplifies the application of AI in natural language processing. Trained on extensive human conversation data, ChatGPT can generate human-like text and engage in discussions on various topics [6]. Widely used in fields such as language translation, chatbots, and NLP, ChatGPT streamlines manual research processes and aids in tasks like summarizing complex concepts and generating scientific reports [6–8]. Large Language Models (LLMs), such as ChatGPT, are advanced artificial intelligence systems proficient in understanding and generating human-like text. ChatGPT, a variant of the GPT model, specializes in conversational interactions, offering assistance and responses akin to human conversation. Leveraging vast amounts of data, these models have been integrated into research and academic settings, showing promise in tasks like literature review assistance and summarizing findings [9,10]. ChatGPT is one well-known application of AI in education. It can write a variety of creative content forms, process and produce text of human calibre, and translate between languages [11]. By helping with tasks like literature reviews, data analysis, and paper drafting, these skills have the potential to significantly transform the field of research [12]. The ChatGPT, created by OpenAI, has amazing promise in a number of domains, including research [2]. Researching is an intricate and challenging process, especially for graduate students who have to deal with time management issues, information overload, and restricted access to fast feedback [13]. ChatGPT presents a viable resolution to these issues by offering assistance with a number of research-related tasks, including 1) Coming up with research questions and theories [13,14]; ChatGPT can help academics come up with creative study questions and ideas by analysing large datasets and finding trends [15]. 2) Assisting with the literature review, ChatGPT can effectively scan and summarise pertinent research publications, making it possible for researchers to rapidly understand the main conclusions and pinpoint significant gaps in the literature [16]. 3) Drafting research papers and proposals: ChatGPT offers structure, topic, and language recommendations to help researchers write research articles and proposals that are understandable and succinct [6,10]. 4) Promoting creativity and teamwork through open-ended conversations; ChatGPT can encourage researchers to consider many viewpoints and come up with original answers to problems in their field of study [10,17]. Researchers extensively explored ChatGPT's potential applications across academic disciplines. Khan et al. (2023) highlighted its significant contributions in medicine and public health education, including case study generation. In language learning, ChatGPT serves as a valuable tool, simulating authentic interactions and motivating skill development [6,7,9,18]. It aids in computer software education by identifying strengths and weaknesses, addressing coding issues, and suggesting best practices. Additionally, ChatGPT supports economics and finance research by generating simulations and scenarios (Dowling & Lucey, 2023). Despite its promising potential, studies indicate ChatGPT is in an early stage of application and has room for improvement [19].

Previous research has looked into how different AI-powered tools affect research [2,20–23], demonstrating how well they work to make knowledge more accessible, encourage critical thinking, and support data analysis. Notably, ChatGPT show great promise for raising productivity and efficiency in research [13,24]. Numerous investigations have looked on the particular uses of ChatGPT in research settings. Lund et al. [25], studied how to utilise LLMs, such as CHatGPT to generate research ideas and hypotheses, showing how they might help with creative research questions by finding patterns and links in massive datasets. Additionally [7], looked at how well ChatGPT supported literature reviews and discovered that they greatly shortened the amount of time needed for scholars to understand important results and pinpoint pertinent research gaps. Specifically, the potential of ChatGPT to promote university students has been the subject of several studies. In their investigation of ChatGPT's use for research paper and proposal drafting, Davis et al. [26]found that it may offer insightful recommendations for enhancing language, structure, and clarity. Dempere et al. [27] examined ChatGPT's (a big language model) possible effects on higher education. They investigated its potential uses in automated grading, improved human-computer interaction, and research assistance. Additionally, Firaina et al. [28] discovered that ChatGPT encouraged university students to investigate other viewpoints and come up with original solutions to research problems by fostering brainstorming and cooperation. Research indicates that ChatGPT has a great deal of promise to improve university students experiences. According to Refs. [28–33], it can offer helpful recommendations for enhancing the language, structure, and clarity of research papers. Furthermore, Huang et al. [10] emphasized how useful ChatGPT is for helping researchers come up with original study ideas and consider a variety of viewpoints. While ChatGPT offers various important benefits, apart from these benefits, some studies also raises some challenges and limitations regarding its reliability, accuracy, and potential biases created by language models including ChatGPT. Few research scholars have cautioned against the over reliance of AI generated text, references due to inaccurate citations, and they suggest that careful verification for authenticity of outputs [6,8,10,34]. Moreover, ethical considerations surrounding the use of AI in research, such as issues of authorship, intellectual property rights, and data privacy, warrant careful examination [35]. Despite these challenges, the adoption of ChatGPT in academic research continues to grow, driven by its potential to augment researchers' capabilities and streamline various aspects of the research process [7].

However, learning satisfaction plays an important role in academic settings. Understanding the factors influencing learning satisfaction is important in academic context, particularly for postgraduates utilizing AI ChatGPT for research purposes. Learning satisfaction directly impacts students' motivation, engagement, and academic performance. Satisfied students exhibit higher levels of persistence and achieve better learning outcomes, adopting a positive learning environment [34,35].

Despite the increasing adoption of AI technologies in education, there remains a gap in understanding the factors that influence learning satisfaction specifically in the context of AI-powered tools like ChatGPT [35]. While previous research has examined the efficacy of AI in improving various aspects of the learning process [36–39], limited attention has been paid to its impact on students' satisfaction with their learning experiences [34,40]. The rationale for using the Technology Acceptance Model (TAM) in this study stems from its established effectiveness in understanding users' acceptance and adoption of new technologies, including AI-based systems [34,35,41]. TAM provides a theoretical framework for examining users' perceptions of a technology's usefulness and ease of use, which are key determinants of their behavioral intentions and actual usage [42]. By applying TAM to investigate students' satisfaction with AI ChatGPT, this research aimed to gain perceptions into the factors that determination their acceptance and usage of this technology in academic research. Additionally, TAM allows us to explore the mediating role of perceived ease of use and perceived usefulness in the relationship between interaction with ChatGPT and learning satisfaction, providing a comprehensive understanding of the underlying mechanisms at play.

1.1. Problem statement

University students face several challenges, including limited time, information overload, and lack of immediate feedback, which can hinder their learning satisfaction and research progress [43]. Traditional research methodologies often require extensive time and effort, leading to feelings of frustration and inadequacy [7,43]. Existing AI-powered research tools, while offering some benefits, often lack the flexibility and personalization needed to effectively address the diverse needs of university students. There is a lack of understanding regarding the specific impact of ChatGPT on learning satisfaction among university students [44]. Despite promising potential in supporting various research tasks, the effectiveness of ChatGPT and its influence on researchers' learning experiences remain unclear. This lack of knowledge hinders the optimal integration of ChatGPT into university students workflows and limits its ability to maximize its potential benefits.

1.2. Research questions

1. To what extent does interaction with ChatGPT influence learning satisfaction among university students?
2. How do perceived ease of use and perceived usefulness of ChatGPT mediate the relationship between interaction with ChatGPT and learning satisfaction?
3. What are the roles of information quality, interaction quality, collaborative learning, and learning motivation in influencing learning satisfaction among university students using ChatGPT?

1.3. Research objectives

1. To examine the factors influencing university students' adoption of ChatGPT for research purposes, focusing on its impact on learning satisfaction.
2. To assess the mediating role of perceived ease of use and perceived usefulness in the relationship between ChatGPT adoption and learning satisfaction among university students.
3. To identify and analyze the effects of information quality, interaction quality, collaborative learning, and learning motivation on learning satisfaction among university students utilizing ChatGPT.

2. Theoretical model

The theoretical model for investigating influencing factors of learning satisfaction in AI ChatGPT for research, from university students, incorporates several key constructs that collectively contribute to understanding the dynamics of learner satisfaction [45]. Each construct reflects a critical aspect of the learner's experience with AI, particularly ChatGPT, and its application in the research context (See Fig. 1 depicting the proposed theoretical model). It is crucial to identify the factors influencing researchers' use of ChatGPT for active learning. Various models in prior literature, including the Unified Theory of Acceptance and Use of Technology (UTAUT), Technology Acceptance Model (TAM), and Extended Expectation Confirmation Model, can help uncover these factors [9]. TAM, especially, has been extensively applied across different countries (e.g., the US, Saudi Arabia, Greece, Indonesia, South Korea, China) and domains (e-learning, remote education, massive open online courses, mobile library applications) to understand the acceptance of technology [46–52]. In this research extend the TAM by adding new constructs such as interaction learning, Information

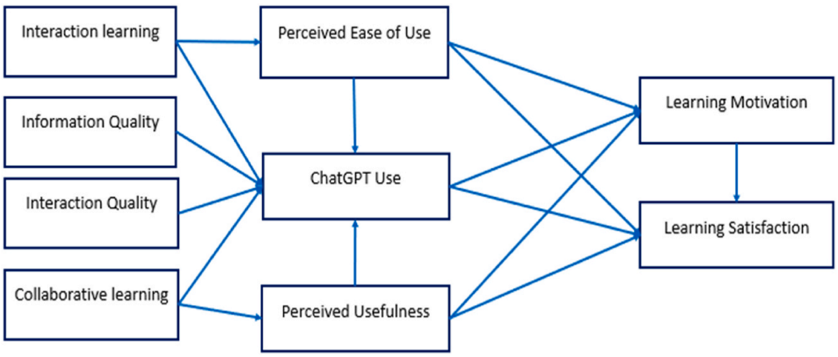

Fig. 1. Proposed model.

Quality, Interaction Quality, Collaborative learning, Learning motivation, and learning Satisfaction in the context of research support through ChatGPT. explanation of each construct in this context is given as follows"

2.1. Perceived ease of use (PEU)

The degree to which university students think using ChatGPT for research requires no effort is known as perceived ease of use [53, 54]. It includes how easy and uncomplicated the user feels that interacting with ChatGPT is. This construct represents university students' opinions about how simple it is to understand and use ChatGPT's features [53,54]. This covers the interface's ease of use, the instructions' clarity, and the accessibility of educational materials. Previous research in the field of educational technology has consistently shown that perceived ease of use is a critical determinant of technology acceptance and adoption among students [55,56]. Studies [57–59] have found that students are more likely to use and engage with technology tools that they perceive as easy to use [35, 41]. Therefore, this study's construct of perceived ease of use is aligned with existing literature underscores its importance in understanding students' acceptance and utilization of AI-powered tools like ChatGPT in educational research contexts.

2.2. Perceived usefulness (PU)

The extent to which university students feel ChatGPT improves their efficiency when conducting research is known as perceived usefulness [54,60]. It includes ChatGPT's reported advantages and usefulness for study. This construct reflects the opinions of university students on ChatGPT's usefulness in improving their research methodology [54,60]. This covers how valuable people think ChatGPT is for coming up with pertinent research topics, helping with literature reviews, enhancing research writing, and encouraging teamwork [61]. Studies have demonstrated that students are more likely to adopt and continue using technology tools that they perceive as useful in achieving their academic goals [15,41,55]. By incorporating perceived usefulness as a construct theoretical model, in this research acknowledge its significance in shaping students' attitudes and behaviors towards AI-powered tools like ChatGPT in educational settings.

2.3. ChatGPT use (GPTU)

ChatGPT Use is a measure of how much university students actively use and interact with ChatGPT during their research projects [62,63]. It displays how frequently and thoroughly ChatGPT is used during the study procedure [62]. Previous studies [35,55,56] on technology acceptance and usage behavior have consistently emphasized the importance of actual system usage as a key indicator of technology adoption. Research has shown that students' intention to use technology is strongly influenced by their actual experience with the system [59]. Therefore, by including ChatGPT use as a construct in this research theoretical model, in this research align with existing literature that underscores the significance of actual usage behavior in understanding students' acceptance and utilization of AI-powered tools like ChatGPT [35].

2.4. Interaction with ChatGPT (INL)

The educational benefit gained from interacting with ChatGPT in an interactive manner is known as interaction learning. The dynamic and responsive character of the engagement facilitates the development of information and skills. The level to which university students use ChatGPT for different research activities, such as idea development, literature review, research paper writing, and collaborative learning, is represented by this construct. The amount and duration of ChatGPT usage, the variety of activities performed using ChatGPT, and the degree of interaction with the feedback and information offered may all be used to gauge this construct. While existing literature may not directly address this construct in the context of ChatGPT, studies on computer-mediated communication and online learning have highlighted the importance of interaction and engagement in facilitating effective learning experiences [64–66]. Therefore, this research inclusion of interaction learning in the theoretical model is from the broader literature on the significance of interaction and engagement in online learning environments.

2.5. Information quality (INQ)

The trustworthiness, relevance, and correctness of the data produced by ChatGPT are all reflected in the information quality. It evaluates the degree to which university students think ChatGPT's material is reliable and beneficial. This term describes the precision and applicability of the data that ChatGPT offers. This covers the extent to which data are factually accurate, current, compliant with research guidelines, and pertinent to the particular subject of study. INQ may be assessed by contrasting ChatGPT's material with data from reputable sources and determining how well it answers research queries.

Information quality in online environments has emphasized the importance of reliable and relevant information for facilitating effective decision-making and problem-solving [67–70]. By incorporating Information Quality as a construct in this research theoretical model, we recognize the critical role of information reliability and relevance in shaping users' perceptions and behaviors in online contexts, highlighting the importance of high-quality information in facilitating effective learning and research outcomes among university students.

2.6. Interaction quality (IQ)

Interaction Quality describes how well a user interacts with ChatGPT overall [71]. Communication efficacy, coherence, and responsiveness are some of its components. The user experience and responsiveness that ChatGPT provides are reflected in this architecture [71]. This comprises ChatGPT's capacity to comprehend customer inquiries, offer succinct, understandable solutions, and adjust to various learning preferences. The effectiveness of ChatGPT's feedback, the speed and precision of its replies, and the general level of user interface pleasure may all be used to gauge IQ.

2.7. Collaborative learning (CL)

The extent to which university students collaborate while utilizing ChatGPT for research is known as collaborative learning [72]. It evaluates the cooperative elements of sharing and creating knowledge [47,72,73]. This concept describes how university students may work together and share information more easily by using ChatGPT. This includes ChatGPT's capacity to facilitate communication between researchers and experts, colleagues, and pertinent research communities. It also offers resources for idea exchange, brainstorming, and discussion of research findings. The frequency of ChatGPT-facilitated collaborative activities, the intensity of discussion participation, and the perception of the influence of collaboration on research advancement are indicators of CL. Existing research on collaborative learning in online environments has highlighted its benefits for promoting critical thinking, problem-solving skills, and social interaction [70,74–76]. By incorporating CL into the research theoretical model, we can explore how ChatGPT supports collaborative knowledge creation, communication, and research advancement among university students. This study contribute to the existing body of literature on CL, highlighting the potential of ChatGPT to facilitate effective collaboration and knowledge exchange among users.

2.8. Learning motivation (LM)

This concept captures the innate drive of university students to advance their knowledge and abilities in research [77]. This comprises their degree of curiosity, openness to investigating novel ideas, and dedication to lifelong learning [78]. Literature on motivation theory in education underscores the significance of intrinsic motivation for promoting engagement, persistence, and learning outcomes [79–82]. This study explores the impact of Learning Motivation on students' experiences with ChatGPT, focusing on how motivation shapes their research interactions, highlighting the crucial role of intrinsic motivation in fostering a supportive and productive learning environment for university students.

2.9. Learning satisfaction (LS)

The degree to which university students are satisfied with ChatGPT for research-related learning is indicated by their overall level of learning satisfaction [83,84]. It incorporates the effects of several elements on the overall happiness of the students. This construct reflects the general level of pleasure that university students have with their experience learning via research. This covers how much they love conducting research, how much they think the learning exercises are worth doing, and how they feel about themselves overall. studies on satisfaction in educational settings have highlighted its importance for fostering positive attitudes, engagement, and academic achievement [40,83,84], By integrating Learning Satisfaction into our research theoretical model, we investigate how satisfaction influences students' attitudes and behaviors when utilizing ChatGPT for research purposes, shedding light on its impact on their overall learning experience.

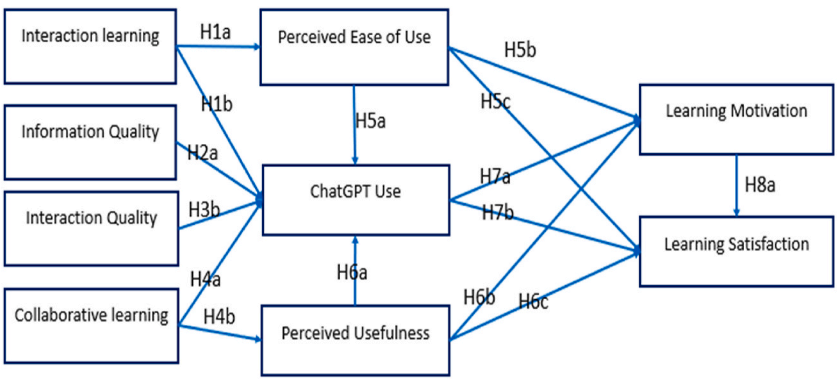

Fig. 2. Constructs and their paths.

2.10. Hypothesis

Based on the proposed theoretical model, Fig. 2 depicts the relationships between the following constructs, leading to the formulation of several hypotheses.

H1a. Interaction learning (INL) has a significant effect on perceived ease of use (PEU) of ChatGPT.

H1b. Interaction learning (INL) has a significant effect on ChatGPT use (GPTU).

H2a. Interaction quality (IQ) has a significant effect on ChatGPT use (GPTU).

H3a. Information quality (INQ) has a significant effect on ChatGPT use (GPTU).

H4a. Collaborative learning (CL) has a significant effect on ChatGPT use (GPTU).

H4b. Collaborative learning (CL) has a positive effect on perceived usefulness (PU) of ChatGPT.

H5a. Perceived ease of use (PEU) has a significant effect on ChatGPT use (GPTU).

H5b. Perceived ease of use (PEU) has a significant effect on learning motivation (LM).

H5c. Perceived ease of use (PEU) has a significant effect on learning satisfaction (LS).

H6a. Perceived usefulness (PU) has a significant effect on ChatGPT use (GPTU).

H6b. Perceived usefulness (PU) has a significant effect on learning motivation (LM).

H6c. Perceived usefulness (PU) has a significant effect on learning satisfaction (LS).

H7a. ChatGPT use (GPTU) has a significant effect on learning motivation (LM).

H7b. ChatGPT use (GPTU) has a positive effect on learning satisfaction (LS).

H8a. Learning motivation (LM) has a significant effect on learning satisfaction (LS).

The established links in the TAM framework and the extra components that are particularly pertinent to the study setting serve as the basis for these hypotheses. To gain a better understanding of ChatGPT's potential to improve university students experiences, more study is needed to determine the veracity of these ideas.

3. Research methodology

The effect of ChatGPT on university students' learning satisfaction was examined in this study using a quantitative research methodology. The study specifically used Partial Least Squares Path Modelling (PLS-SEM), a structural equation modelling (SEM) approach, to analyze the intricate interactions between many constructions [85]. This method was selected because it can estimate both direct and indirect effects and is appropriate for handling complicated models with latent variables.

3.1. Instrument development and survey administration

Translation Process: Ensuring your questionnaire reaches Arabic speakers effectively requires a careful translation process. This excursion transforms your English questionnaire into a clear, accurate, and culturally relevant tool see appendix A.

The first step involves a skilled bilingual translator fluent in both English and Arabic. Ideally, this expert also possesses knowledge of the questionnaire's topic to ensure accurate translation of any technical terms.

Next, a team of experts reviews the translated version. These experts typically include linguistic, subject matter experts and cultural experts who understand the research study being conducted, translation experts who can identify difficult phrasing in Arabic, and cultural experts who ensure the questionnaire avoids offensive language or concepts and resonates with the target audience. This review panel meticulously examines the translated version for accuracy, clarity, and cultural appropriateness. They discuss any disagreements or ambiguities until they reach a consensus on the best wording for the Arabic audience.

Following the expert review process, a second bilingual translator, distinct from the initial translator, is engaged to perform the back-translation of the Arabic version into English. This translator is proficient in both languages and possesses expertise in translation techniques. They ensure the fidelity of the back-translation by accurately rendering the Arabic text into English, aiming to capture the original meaning as closely as possible [86].

We considered the Linguistic and cultural equivalence as key goals throughout this process. Linguistic equivalence guarantees the Arabic version conveys the same information and meaning as the original English version. Cultural equivalence ensures the questionnaire is phrased in a way that's understandable and relevant to the Arabic audience, avoiding cultural biases or offensive language.

Finally, a pilot test is conducted with a small group of Arabic speakers. They take the translated questionnaire to assess its clarity, whether the questions make sense within their cultural context, and its overall cultural relevance. Based on their feedback highlighted issues such as technical language complexity, cultural insensitivity, and inaccuracies in translation, the Arabic version receives any necessary adjustments to ensure it is clear, accurate, and culturally appropriate for the target audience. This multi-step process ensures your questionnaire delivers accurate and reliable data from your Arabic-speaking participants.

The Final survey questionnaire consisted of fourty two items designed especially to gauge the following constructs such as learning satisfaction, collaborative learning, quality of information, perceived usefulness, perceived ease of use, and utilization of ChatGPT.

Out of 42 items, 15 were adapted from studies that developed the TAM, TAM2, and TAM3 Model [59,87,88], while the sources of adaptation for the remaining items are provided in Table 1. Additionally, the Likert scale was utilized to rate each construct, with 5 indicating strong agreement and 1 indicating strong disagreement [89,90]. Prior to the primary data collection phase, the questionnaire underwent piloting among a small group of thirty undergraduate students of Scientific College, at King Faisal university to ensure clarity, relevance, and internal consistency of the items [91]. Important input from this pilot testing was incorporated into the final draft of the questionnaire. First, Cronbach's alpha coefficient was used to assess the internal consistency of the questionnaire, with values ranging from 0.75 to 0.90 across different constructs as highlighted in Table 1, aligning with previous studies [86,92].

Second, Participants provided feedback on the questionnaire's clarity, relevance, and cultural appropriateness. For instance, one participant suggested simplifying a question inquiring about the ease of using AI ChatGPT by proposing, "Using AI ChatGPT makes my research tasks easier." Additionally, another participant noted the need for further explanation of the term "collaborative environment" in the questionnaire, ensuring universal understanding across diverse cultural backgrounds. These examples showcase how participant feedback guided minor modifications to enhance the questionnaire's readability and cultural relevance. Overall, the pilot testing phase helped refine the questionnaire and ensured its suitability for the target population. All constructs achieved Cronbach's alpha values exceeding this threshold, confirming the reliability of the data for subsequent analysis then final questionnaire was electronically distributed to university students at King Faisal University. Participation was voluntary and anonymous, and data collection continued until a sufficient sample size was obtained to ensure the generalizability of the findings [92]. The collected data underwent thorough analysis to exclude outliers, incomplete replies, and unnecessary data points, ensuring data quality [98]. In managing missing data, the SPSS 21v application was utilized, employing appropriate methods such as mean imputation or deletion [92]. Mean imputation was chosen as the preferred method for handling missing data, as it helps to preserve sample size and maintain statistical power [68]. This approach was justified based on its effectiveness in minimizing bias and maintaining the integrity of the dataset [69].

3.2. *Measurement and structural model analysis*

In accordance with well-established two-step PLS-SEM analysis procedures [92], the present study utilized SmartPLS 4.0 for structural modeling. The first stage focused on developing, converging, and evaluating the measurement model. This entailed assessing both the reliability and validity of the constructs [85].

3.2.1. *Measurement model Evaluation*

Internal consistency reliability was established through Cronbach's alpha and composite reliability, exceeding the recommended thresholds of 0.7 [98]. Convergent validity was confirmed by examining average variance extracted (AVE) values exceeding 0.5 and factor loadings exceeding 0.5 for each indicator, indicating adequate convergent validity [86]. Discriminant validity was verified using both the Fornell-Larcker criterion and cross-loadings analysis, ensuring that each construct demonstrated greater variance shared with its own indicators compared to other constructs [92].

3.2.2. *Structural model Evaluation*

The structural model was assessed based on key PLS-SEM criteria: path coefficients signifying the direction and strength of relationships between constructs [98], R-squared values indicating the proportion of variance explained in each endogenous construct [92], and path coefficients and their associated p-values used to test the formulated hypotheses [92]. This study aims to interpret the impact of ChatGPT on learning satisfaction among university students. The mediating roles of perceived ease of use and perceived usefulness will be further explored and discussed. Based on the empirical results, the theoretical model will be refined and strengthened to provide deeper insights into this emerging field of research.

Table 1
Key Constructs information.

Constructs	No. of Items	Piloting Results	Source of adoption
Perceived Ease of Use (PEU)	5	0.85	[62,63,77]
ChatGPT Use (GPTU)	5	0.80	[62,63,77]
Perceived Usefulness (PU)	5	0.88	[49,63,77,93]
interaction learning (INL)	5	0.75	[94–96]
Information Quality (INQ)	5	0.82	[53,68]
Interaction Quality (IQ)	4	0.79	[56,97]
Collaborative learning (CL)	3	0.81	[47,62,73]
Learning Motivation (LM)	5	0.90	[77]
Learning Satisfaction (LS)	5	0.87	[63,96]

4. Results and analysis

4.1. Demographics data analysis

Table 2 shows the demographic analysis of the study participants. The demographic analysis of the dataset, comprising 262 participants, revealed a gender distribution where 66.79 % identified as male (175), and 33.21 % as female (87). Regarding age distribution, the majority of respondents fell within the 23–26 age range (59.54 %, 156), followed by the 18–22 age group (12.98 %, 34). Other age categories included 27–30 (6.49 %, 17), 31–34 (10.31 %, 27), and more than 35 (10.69 %, 28). In terms of academic level, 58.40 % identified as undergraduate students (153), while 41.60 % were pursuing postgraduate studies (109). The participants represented diverse fields of study, with 16.41 % from scientific colleges (43), 51.53 % from humanities colleges (135), and 32.06 % from medical colleges (84).

4.2. Assessment of the research model

A. Descriptive analysis (Mean, SD)

The factor loadings for all constructs, including Perceived Ease of Use (PEU), Perceived Usefulness (PU), Interaction Learning (INL), Interaction Quality (IQ), Information Quality (INQ), Collaborative Learning (CL), and ChatGPT Use (GPTU), consistently surpassed the recommended threshold of 0.70 [92,98]. These robust factor loadings indicate a strong association between individual items and their respective constructs, affirming the reliability and validity of this research measurement model. Specifically, items within constructs such as PEU, PU, INL, and CL demonstrated factor loadings ranging from 0.804 to 0.924 (see Table 3 for factor loading), emphasizing the coherence and significance of these constructs. The high factor loadings observed across all constructs contribute to the overall robustness of this research instrument, ensuring the accurate measurement of the intended theoretical constructs [92,98].

B. Reliability and Convergent Validity Analysis

In accordance with established criteria for evaluating the reliability and validity of this research measurement model, in this research examined Cronbach's alpha, Average Variance Extracted (AVE), and Composite Reliability (CR) for each construct as shown in Table 4 [92,98]. The reliability analysis reveals strong internal consistency across all constructs. Cronbach's alpha values range from 0.878 to 0.934, exceeding the recommended threshold of 0.7. This indicates that the items within each construct are highly reliable and consistently measure the underlying construct. Convergent validity, assessed through AVE, signifies the extent to which the items within a construct converge. The AVE values range from 0.888 to 0.938, surpassing the threshold of 0.5 [92,98]. This suggests that a substantial portion of the variance in the constructs is captured by their respective items, confirming the convergent validity of the measurement model. Composite Reliability (CR), an indicator of internal consistency and reliability, demonstrates robust values ranging from 0.710 to 0.838. All constructs surpass the threshold of 0.7 [92,98]., reinforcing the reliability of the measurement model. The findings collectively underscore the strong reliability and validity of this research measurement model. These results instill confidence in the accuracy and consistency of the constructs, affirming their suitability for evaluating the factors influencing learning satisfaction in the context of AI ChatGPT for research from university students.

Table 5 presents the R-squared values and adjusted R-squared values for all endogenous latent variables in the structural model.

The R-squared values indicate the proportion of variance in each endogenous variable explained by the model. As shown, ChatGPT Use (GPTU) demonstrates the highest R-squared value of 0.677, indicating that the model explains 67.7 % of the variance in this construct. Learning Satisfaction (LS) follows with an R-squared value of 0.719, suggesting that the model explains 71.9 % of the variance in this key outcome variable. The R-squared values for Perceived Ease of Use (PEU) and Perceived Usefulness (PU) are 0.449 and 0.424, respectively, indicating that the model explains 44.9 % and 42.4 % of the variance in these constructs. Finally, the R-

Table 2
Information of participants.

Demographic Questions		Overall Total	
Items	Characteristic	Count	%
Gender	Female	87	33.21
	Male	175	66.79
Age(Years)	18–22	34	12.98
	23–26	156	59.54
	27–30	17	6.49
	31–34	27	10.31
	More than 35	28	10.69
Academic Level	Undergraduate	153	58.40
	Postgraduate	109	41.60
Field of Study	Scientific Colleges	43	16.41
	Humanties Colleges	135	51.53
	Medical Collges	48	32.06

Table 3
Factor loading results.

Constructs	Item	Factor loading
Perceived Ease of Use (PEU)	PEU1	0.850
	PEU2	0.911
	PEU3	0.924
	PEU4	0.886
	PEU5	0.822
Perceived Usefulness (PU)	PU1	0.858
	PU2	0.899
	PU3	0.857
	PU4	0.902
	PU5	0.858
interaction learning (INL)	INL1	0.804
	INL2	0.842
	INL3	0.867
	INL4	0.856
	INL5	0.845
Interaction Quality (IQ)	INQ1	0.905
	INQ2	0.894
	INQ3	0.888
	INQ4	0.900
	INQ5	0.863
Information Quality (INQ)	IQ1	0.847
	IQ2	0.874
	IQ3	0.832
	IQ4	0.865
Collaborative learning (CL)	CL1	0.916
	CL2	0.910
	CL3	0.919
ChatGPT Use (GPTU)	GPTU1	0.855
	GPTU2	0.878
	GPTU3	0.891
	GPTU4	0.877
	GPTU5	0.891
Learning Motivation (LM)	LM1	0.855
	LM2	0.892
	LM3	0.904
	LM4	0.883
	LM5	0.854
Learning Satisfaction (LS)	LS1	0.798
	LS2	0.872
	LS3	0.819
	LS4	0.812
	LS5	0.824

Table 4
Convergent validity results (Cronbach's alpha, AVE, and CR).

Constructs	Reliability	AVE	CR
Collaborative learning (CL)	0.903	0.907	0.838
ChatGPT Use (GPTU)	0.926	0.928	0.772
interaction learning (INL)	0.898	0.904	0.710
Interaction Quality (IQ)	0.934	0.938	0.792
Information Quality (INQ)	0.878	0.888	0.730
Learning Motivation (LM)	0.925	0.926	0.770
Learning Satisfaction (LS)	0.884	0.889	0.681
Perceived Ease of Use (PEU)	0.926	0.927	0.773
Perceived Usefulness (PU)	0.924	0.926	0.766

squared value for Learning Motivation (LM) is 0.428, suggesting that the model explains 42.8 % of the variance in this construct. Adjusted R-squared values, which consider the model complexity and penalize for adding additional variables, show similar trends. They are slightly lower than the R-squared values but remain within acceptable ranges. Overall, these R-squared values suggest that the proposed model provides a good fit to the data and explains a significant proportion of the variance in the investigated constructs.

C. Discriminant Validity Analysis

Discriminant validity assesses the degree to which constructs are distinct from each other, ensuring that they measure separate

Table 5
Model fitness score -**R2** of the endogenous latent variables.

Variables	R-square	R-square adjusted
ChatGPT Use (GPTU)	0.677	0.669
Learning Motivation (LM)	0.428	0.421
Learning Satisfaction (LS)	0.719	0.714
Perceived Ease of Use (PEU)	0.449	0.447
Perceived Usefulness (PU)	0.424	0.422

concepts. This study employed two methods to assess discriminant validity: the Heterotrait-Monotrait (HTMT) ratio and the Fornell-Larcker criterionTwo distinct methods, the Heterotrait-Monotrait (HTMT) ratio and the Fornell-Larcker Criterion, were employed to assess discriminant validity across the constructs in this study [52,73]. Table 6 presents the HTMT ratios for all construct pairs. The values range from 0.534 to 0.971, with all values falling below the recommended threshold of 0.85 [99]. This indicates that the constructs in the model are sufficiently distinct from each other and capture unique dimensions of the research domain. The research results demonstrate that all constructs meet this criterion, confirming satisfactory discriminant validity. Notably, the highest HTMT ratio is 0.971, indicating strong discriminant validity among the constructs.

Table 7 presents the Fornell-Larcker criterion values for all construct pairs. The diagonal elements represent the square root of the AVE for each construct, while the off-diagonal elements represent the correlations between constructs. All diagonal elements are greater than the corresponding off-diagonal elements, demonstrating satisfactory discriminant validity according to the Fornell-Larcker criterion [100]. In this study, all constructs meet this criterion, with the square root of the AVE consistently higher than the correlations, indicating robust discriminant validity. Both the HTMT ratio and the Fornell-Larcker Criterion consistently support the discriminant validity of the constructs in this study.

In conjunction, these results provide convincing evidence that the constructs in the model are distinct and capture unique aspects of the research domain. This ensures that the findings and interpretations based on these constructs are reliable and valid for further analysis in the context of investigating influencing factors in AI ChatGPT for research from university students.

D. Hypotheses Testing (Path analysis of the structural model)

The structural equation model analysis was conducted using Smart PLS, applying the maximum likelihood estimation approach to explore the interrelationships among various theoretical constructs within the structural model [69,72,75]. The hypothesis testing results unveiled significant relationships among the identified constructs as highlighted in Table 8, offering crucial insights into the factors influencing learning satisfaction in the context of AI ChatGPT for research from university students. Interaction learning (INL) exhibited a substantial impact on both Perceived Ease of Use (PEU) ($T = 13.512$, $p = 0.000$) and ChatGPT Use (GPTU) ($T = 5.172$, $p = 0.000$), supporting H1a and H1b. These results suggest that heightened interaction learning experiences positively contribute to the perceived ease of using ChatGPT and its actual usage among university students.

Information Quality (INQ) and Collaborative Learning (CL) significantly influenced ChatGPT Use (GPTU) ($T = 4.104$, $p = 0.000$) and Perceived Usefulness (PU) ($T = 14.065$, $p = 0.000$), respectively, affirming H3a and H4b. This implies that the quality of information and collaborative learning experiences strongly contribute to the adoption of ChatGPT for research purposes and enhance its perceived usefulness among university students.

Perceived Ease of Use (PEU) emerged as a pivotal factor, significantly impacting ChatGPT Use (GPTU) ($T = 7.204$, $p = 0.000$), Learning Motivation (LM) ($T = 2.495$, $p = 0.013$), and Learning Satisfaction (LS) ($T = 1.932$, $p = 0.023$), supporting H5a, H5b, and H5c. These findings suggest that university students' perceptions of the ease of using ChatGPT not only influence their usage patterns but also play a crucial role in shaping their motivation to learn and overall satisfaction with the learning experience.

Perceived Usefulness (PU) significantly influenced Learning Motivation (LM) ($T = 4.750$, $p = 0.000$) and Learning Satisfaction (LS) ($T = 3.931$, $p = 0.000$), supporting H6b and H6c. This indicates that university students who perceive ChatGPT as useful are more motivated in their learning endeavors and experience higher satisfaction with their learning outcomes.

ChatGPT Use (GPTU) demonstrated a significant positive influence on Learning Motivation (LM) ($T = 2.138$, $p = 0.033$), supporting H7a. This implies that university students who actively use ChatGPT in their research activities experience heightened motivation in

Table 6
Discriminant Validity (HTMT ratio).

	CL	GPTU	INL	INQ	IQ	LM	LS	PEU	PU
CL									
GPTU	0.676								
INL	0.638	0.754							
INQ	0.801	0.647	0.705						
IQ	0.884	0.623	0.726	0.971					
LM	0.684	0.596	0.579	0.680	0.671				
LS	0.811	0.689	0.688	0.813	0.806	0.860			
PEU	0.658	0.820	0.729	0.721	0.749	0.634	0.731		
PU	0.710	0.665	0.753	0.854	0.870	0.636	0.752	0.731	

Table 7
Discriminant Validity (Furnell larker Criterion).

	CL	GPTU	INL	INQ	IQ	LM	LS	PEU	PU
CL	0.915								
GPTU	0.619	0.878							
INL	0.582	0.694	0.843						
INQ	0.741	0.606	0.649	0.890					
IQ	0.794	0.570	0.646	0.885	0.855				
LM	0.627	0.555	0.534	0.634	0.609	0.878			
LS	0.729	0.628	0.613	0.739	0.713	0.795	0.825		
PEU	0.603	0.760	0.670	0.672	0.677	0.588	0.660	0.879	
PU	0.651	0.617	0.688	0.797	0.783	0.592	0.677	0.677	0.875

Table 8
Hypothesis testing (Path, T-Value, and P-value).

Relationships	Original sample	T statistics	P values	Decision
H1a = Interaction learning (INL) →Perceived Ease of Use (PEU)	0.670	13.512	0.000	Supported
H1b = interaction learning (INL) →ChatGPT Use (GPTU)	0.290	5.172	0.000	Supported
H2a = Interaction Quality (IQ) →ChatGPT Use (GPTU)	0.114	1.254	0.210	Rejected
H3a = Information Quality (INQ) →ChatGPT Use (GPTU)	−0.336	4.104	0.000	Supported
H4a = Collaborative learning (CL) → ChatGPT Use (GPTU)	0.292	3.797	0.000	Supported
H4b = Collaborative learning (CL)→ Perceived Usefulness (PU)	0.651	14.065	0.000	Supported
H5a = Perceived Ease of Use (PEU)→- > ChatGPT Use (GPTU)	0.500	7.204	0.000	Supported
H5b = Perceived Ease of Use (PEU)→ Learning Motivation (LM)	0.234	2.495	0.013	Supported
H5c = Perceived Ease of Use (PEU)→Learning Satisfaction (LS)	0.116	1.932	0.023	Supported
H6a = Perceived Usefulness (PU)→ ChatGPT Use (GPTU)	0.060	0.891	0.373	Rejected
H6b = Perceived Usefulness (PU)→ Learning Motivation (LM)	0.324	4.750	0.000	Supported
H6c = Perceived Usefulness (PU) →Learning Satisfaction (LS)	0.211	3.931	0.000	Supported
H7a = ChatGPT Use (GPTU)→Learning Motivation (LM)	0.177	2.138	0.033	Supported
H7b = ChatGPT Use (GPTU)→Learning Satisfaction (LS)	0.109	1.691	0.091	Rejected
H8a = Learning Motivation (LM) - > Learning Satisfaction (LS)	0.542	12.867	0.000	Supported

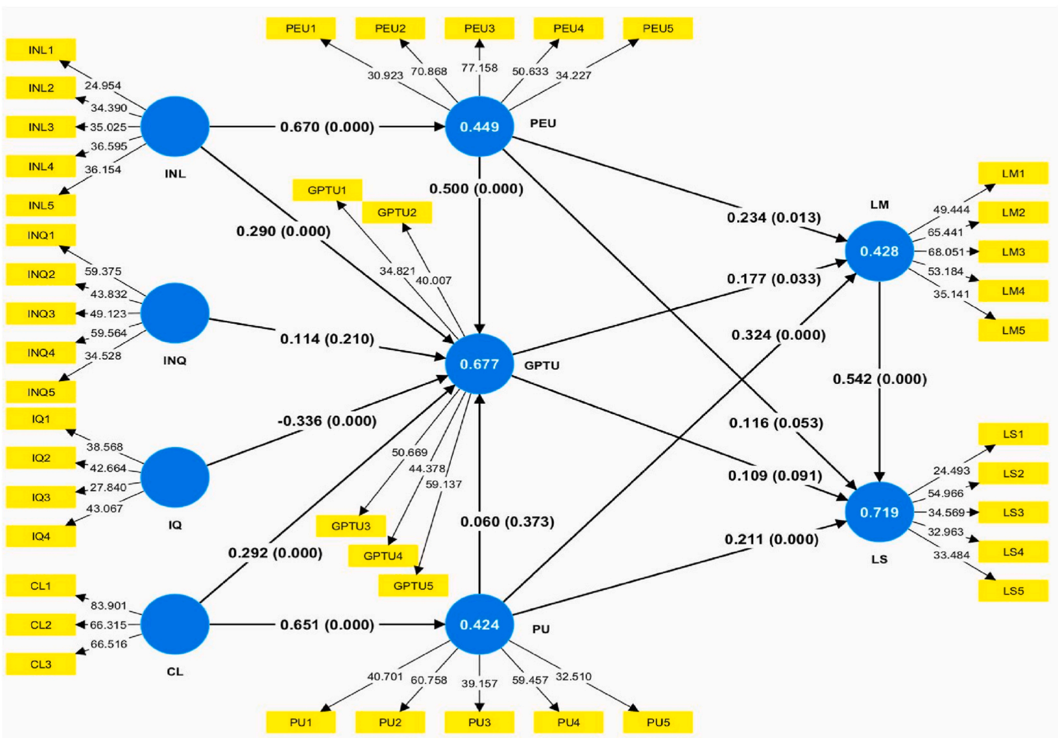

Fig. 3. Structural model (path coefficients).

their learning pursuits.

However, Interaction Quality (IQ) did not significantly influence ChatGPT Use (GPTU) (T = 1.254, p = 0.210), leading to the rejection of H2a. Similarly, ChatGPT Use (GPTU) did not significantly influence Learning Satisfaction (LS) (T = 1.691, p = 0.091), resulting in the rejection of H7b. These results provide a nuanced understanding of the intricate relationships among various constructs in the proposed model, offering a comprehensive view of the factors influencing learning satisfaction in the utilization of AI ChatGPT for research from university students.

The results showed a number of important connections. The study found that both ChatGPT use and perceived ease of use were favourably impacted by interaction and collaborative learning, underscoring the significance of these learning strategies in promoting technology adoption. The usage of ChatGPT was also significantly impacted by the quality of the content, indicating that user engagement is greatly impacted by having access to high-quality information. Learning motivation and learning satisfaction were positively influenced by perceived ease of use and perceived usefulness, indicating their mediation roles in the link between ChatGPT interaction and learning outcomes. Notably, ChatGPT use improved learning motivation, indicating that it may be used as a technique to increase students' drive to study. Ultimately, learning motivation was found to have a considerable and beneficial impact on learning satisfaction, indicating its significance in attaining favourable learning results. Some hypotheses, meanwhile, were not validated. The lack of a significant relationship between interaction quality and ChatGPT use suggests that other factors may be more important than interaction quality. Furthermore, ChatGPT use was not directly impacted by perceived usefulness, suggesting that other characteristics, such as perceived ease of use, may moderate ChatGPT's influence on learning outcomes. Finally, ChatGPT use did not directly affect learning satisfaction, showing that technology use and learning outcomes may be complicated and impacted by other factors. These data shed light on ChatGPT uptake and learning outcomes. Interaction learning, collaborative learning, information quality, perceived simplicity of use, and perceived utility can improve learning outcomes using this technology, according to the research. The results also suggest that ChatGPT may motivate learners, but more study is needed to understand the complicated interaction between technology use and learning outcomes, see Fig. 3.

5. Discussion

This study investigated the factors influencing university students' adoption of ChatGPT for research purposes and its subsequent impact on learning satisfaction, supporting primary research objectives. The research analysis was guided by three key objectives: firstly, to explore the determinants of ChatGPT adoption among students; secondly, to assess the mediating role of perceived ease of use and perceived usefulness in the relationship between ChatGPT adoption and learning satisfaction; and thirdly, to identify and analyze the effects of information quality, interaction quality, collaborative learning, and learning motivation on learning satisfaction among students utilizing ChatGPT. By systematically examining these objectives, this research aimed to contribute to a deeper understanding of AI adoption in education and its implications for learning outcomes. ***First objective****: Factors influencing university students' adoption of ChatGPT for research purposes:* this study aimed to investigate the factors influencing university students' adoption of ChatGPT for research purposes and its impact on learning satisfaction. The findings revealed several key determinants of ChatGPT adoption among students. Interaction learning and collaborative learning emerged as significant factors influencing the adoption of ChatGPT for research support context [10,25,44]. Students who engaged in conversations and shared experiences with colleagues regarding ChatGPT reported increased comfort and confidence in using the tool, highlighting the importance of social interaction in technology adoption [10,25,44]. Additionally, information quality played a crucial role in students' choice to continue using ChatGPT [14]. Students were less inclined to rely on ChatGPT for their research needs when they encountered inaccurate or irrelevant information, consistent with prior studies emphasizing the role of information quality in technology adoption [34,101,102].

Second objective: *Mediating role of perceived ease of use and perceived usefulness.* This study also assessed the mediating role of perceived ease of use and perceived usefulness in the relationship between ChatGPT adoption and learning satisfaction among university students. The results confirmed the intermediate function of perceived ease of use and perceived usefulness in this relationship, consistent with the Technology Acceptance Model (TAM) [42,59]. Students reported heightened satisfaction with their learning experience when they found ChatGPT to be user-friendly and beneficial for their research and learning activities. Enhancing ChatGPT's user-friendliness and perceived usefulness emerged as important choices for improving its impact on learning outcomes [25,103]. The results further confirm the intermediate function of perceived ease of use and perceived usefulness in the connection between engagement with ChatGPT and satisfaction with learning, consistent with the Technology Acceptance Model [42,59]. However, few hypotheses proposing a positive relationship between perceived usefulness and ChatGPT Use was rejected. This finding contradicts some previous research indicating that perceived usefulness significantly impacts technology usage [15]. However, it aligns with studies suggesting that perceived usefulness may not always directly translate into actual usage behavior [57]. One possible explanation could be that while students may perceive ChatGPT as useful, they may encounter barriers or lack sufficient motivation to incorporate it into their research activities. Another poistive relationships linking ChatGPT Use to Learning Satisfaction was also rejected. This result challenges the notion that increased technology usage necessarily leads to greater learning satisfaction. While previous studies have demonstrated positive associations between technology usage and learning outcomes, the research findings suggest a more nuanced relationship. It's possible that other factors, such as the quality of interaction or the relevance of information provided by ChatGPT, play a more significant role in shaping learning satisfaction. This underscores the complexity of the relationship between technology usage and learning outcomes, emphasizing the need for a multifaceted approach when examining the impact of AI adoption on learning satisfaction.

Third Objective: *Effects of information quality, interaction quality, collaborative learning, and learning motivation on learning satisfaction.* Furthermore, this study identified and analyzed the effects of information quality, interaction quality, collaborative learning, and learning motivation on learning satisfaction among university students utilizing ChatGPT. The results demonstrated the significant impact of these factors on learning satisfaction. Higher levels of learning satisfaction were associated with high-quality information provided by ChatGPT, effective interaction experiences, collaborative learning activities, and increased learning motivation among students. These findings contribute to a deeper understanding of the factors influencing learning satisfaction in the context of AI adoption in education. The study found that the information quality given by ChatGPT had a substantial impact on researchers' choice to continue using it. Researchers were less inclined to depend on ChatGPT for their research requirements when they came across erroneous or irrelevant material. This aligns with previous studies that highlight the significance of information quality in the adoption and utilization of technology [70,104]. This underscores the necessity for ongoing enhancement in the precision and pertinence of information delivered by ChatGPT to guarantee its enduring viability in research settings. The results of the study showed a strong positive correlation between using ChatGPT and learning motivation, indicating that using ChatGPT may stimulate a person's desire to learn. This result builds on other studies investigating the potential for AI-powered educational tools to motivate students [25,103]. The capacity of ChatGPT to provide innovative material, offer tailored feedback, and enable interactive learning sessions can all help to pique interest, build a feeling of achievement, and eventually increase motivation to study more about research subjects. The results indicate an indirect impact mediated by learning desire, despite the study's failure to uncover a direct correlation between ChatGPT use and learning satisfaction. This suggests that although using ChatGPT by itself would not directly result in enhanced learning satisfaction, it might be able to do so by encouraging learners to be more motivated to study. This result emphasizes the intricate relationship that exists between learning results, motivation, and technology use. It also emphasizes the need for more study to completely comprehend the processes by which AI-powered tools might affect learning satisfaction. The results of the study demonstrate how several factors that affect ChatGPT adoption and learning outcomes are interrelated. Users became more comfortable and confident using ChatGPT as a result of interaction learning and collaborative learning, which enhanced use. Maintaining user involvement was largely dependent on the quality of the information provided, highlighting the ongoing need to improve the relevance and accuracy of the content. Higher levels of learning pleasure were translated from ChatGPT interaction through the mediating effects of perceived utility and simplicity of use. Lastly, the application of ChatGPT improved learning motivation, indicating that it has the ability to raise student involvement and promote deeper learning.

Apart from all success, there is the hypothesis stating a positive relationship between Interaction Quality (IQ) and ChatGPT Use (GPTU) was rejected. This finding challenges some existing literature suggesting that higher interaction quality leads to increased technology usage [64–66]. While previous studies have highlighted the importance of interaction quality in fostering technology adoption, results suggest that in the context of ChatGPT, other factors such as ease of use or perceived usefulness might have a stronger influence on usage behavior. This discrepancy underscores the need for further investigation into the specific factors driving technology adoption in different educational contexts.

Comparing findings with existing literature in the field, this study aligns with previous research highlighting the importance of social interaction, information quality, and perceived ease of use in technology adoption [15,34,35,52,67,105–107]. However, this study extends this understanding by specifically examining the adoption of ChatGPT for research purposes and its impact on learning satisfaction among university students. By integrating insights from the TAM and theories of collaborative learning, in this research provided a comprehensive analysis of the factors influencing AI adoption and its effects on learning outcomes. Overall, this study contributes to the current understanding of AI adoption and its impact on learning satisfaction by identifying key determinants and mediating mechanisms in the context of ChatGPT. These findings have implications for educators, researchers, and policymakers seeking to enhance technology adoption and improve learning outcomes in educational settings.

5.1. Implications

The results of this study have important consequences for both the academic community and educational professionals regarding the use of AI ChatGPT by university students for research purposes. The significance of user-friendly interfaces and interactive learning experiences in promoting the usage of ChatGPT is shown by the favourable impact of perceived ease of use and interaction learning. These findings may be utilized by educational practitioners to improve the usability of AI technologies, guaranteeing a smooth and instinctive user experience for university students involved in research activities. These key findings are aligned with existing theories, particularly the Technology Acceptance Model (TAM) and collaborative learning theories. The results indicate that both ChatGPT use and perceived ease of use are positively influenced by interaction and collaborative learning experiences, echoing the TAM's emphasis on the importance of perceived ease of use and perceived usefulness in technology adoption (Davis, 1989). Moreover, the significant impact of information quality on ChatGPT use underlines the role of collaborative learning in promoting technology adoption and enhancing user engagement, consistent with collaborative learning theories emphasizing knowledge construction through social interaction [108]. These findings contribute to a deeper understanding of technology adoption and collaborative learning in educational contexts, highlighting relationships between technology use, learning motivation, and satisfaction. Additionally, the study reveals the mediating roles of perceived ease of use and perceived usefulness in the relationship between ChatGPT interaction and learning outcomes, highlighting the importance of considering these factors in educational interventions for AI technologies. Furthermore, the observed beneficial effect of collaborative learning on the perceived utility underscores the importance of collaborative settings in promoting the perceived value of AI ChatGPT for research purposes. Educational institutions and instructors can strategically include collaborative learning activities into research methodology, therefore fostering information sharing and cooperative involvement. This approach is consistent with collaborative learning theories [109] and frames AI technologies as tools that support collaborative research activities, improving the educational experience for university students.

The consequences pertain to the assessment of learning satisfaction, wherein the favourable effects of perceived ease of use, perceived utility, and learning motivation underscore the interdependence of these elements in moulding the happiness of university students using AI ChatGPT. Educational practitioners may utilise these observations to create interventions that target the highlighted characteristics, prioritising user-friendly interfaces, highlighting perceived utility, and encouraging active involvement to improve overall satisfaction levels. This is consistent with overarching ideas of user pleasure and motivation in the field of educational technology, as discussed by Refs. [110,111].

Moreover, the surprising results about the absence of statistical significance between the use of ChatGPT and the level of pleasure with learning necessitate thoughtful examination. Educational practitioners should recognize the distinct attributes of AI ChatGPT and university students environments, acknowledging that the correlation between technology use and contentment may be impacted by subtle circumstances. This underscores the necessity for customised interventions and more study to reveal the complex dynamics of technology use in advanced educational environments.

6. Conclusion

This study set out to investigate the factors influencing university students' adoption of ChatGPT for research purposes and its subsequent impact on learning satisfaction, aligning with primary research objectives. This research employed a structural equation modelling approach to assess the relationships based on a well specified theoretical model that included constructs like perceived usefulness, perceived ease of use, interaction learning, information quality, collaborative learning, and their interactions. The use of Smart PLS for structural equation modelling (SEM) enhanced theoretical model's resilience even more. The reliability and validity of study were confirmed by the careful examination of the data gathered using a structured questionnaire, which provided a strong framework for the investigation of the elements that influence the learning experience. The research analysis was guided by three key objectives: firstly, to explore the determinants of ChatGPT adoption among students; secondly, to assess the mediating role of perceived ease of use and perceived usefulness in the relationship between ChatGPT adoption and learning satisfaction; and thirdly, to identify and analyze the effects of information quality, interaction quality, collaborative learning, and learning motivation on learning satisfaction among students utilizing ChatGPT. Addressing first objective, findings revealed several crucial determinants of ChatGPT adoption among students. Interaction learning and collaborative learning emerged as significant factors influencing ChatGPT adoption, emphasizing the importance of social interaction in technology adoption. Additionally, the quality of information provided by ChatGPT significantly influenced students' decisions to continue using the tool, underscoring the importance of information quality in technology adoption. Moving on to second objective, this study confirmed the mediating role of perceived ease of use and perceived usefulness in the relationship between ChatGPT adoption and learning satisfaction. Students reported heightened satisfaction with their learning experience when they found ChatGPT to be user-friendly and beneficial for their research and learning activities. Furthermore, this study addressed the effects of information quality, interaction quality, collaborative learning, and learning motivation on learning satisfaction among students utilizing ChatGPT, as outlined in third objective. The results demonstrated the significant impact of these factors on learning satisfaction, highlighting the importance of providing high-quality information, fostering effective interaction experiences, promoting collaborative learning activities, and enhancing learning motivation among students. This study contributes to the current understanding of AI adoption and its impact on learning satisfaction by identifying key determinants and mediating mechanisms in the context of ChatGPT. These findings have implications for educators, researchers, and policymakers seeking to enhance technology adoption and improve learning outcomes in educational research settings. This study advances the field of AI adoption and learning satisfaction research.

6.1. Limitations

In this research must note many intrinsic limitations in study, which might possibly impact the extent and generalizability of findings. The exclusive focus of research on university students in the Saudi Arabian educational system may restrict the generalizability of findings to other cultural or institutional contexts. The distinct socio-cultural elements specific to Saudi Arabia may have impacted the way participants responded and perceived things, in a way that may not be representative of other educational settings. Furthermore, the use of a cross-sectional methodology in study limits capacity to establish causal linkages between variables, therefore making it difficult to fully capture the dynamic character of AI ChatGPT adoption and its influence on learning satisfaction over a period of time. Additionally, the use of self-reported data obtained through a questionnaire adds possible biases, including social desirability and response bias, which can affect the accuracy of participant replies. This study primarily examined AI ChatGPT, and the results may not be immediately applicable to other AI technologies or educational chatbots, which restricts the range of technical representation in this research.

6.2. Future work

In order to overcome these constraints and enhance the comprehension of AI ChatGPT in educational environments, next research endeavours should explore several routes. Longitudinal studies would provide a more thorough investigation of the time-related patterns of AI ChatGPT adoption, documenting alterations in user attitudes and experiences over a prolonged duration. Conducting comparative analyses in various educational settings and with different student demographics would improve the capacity to apply the findings to a wider range of situations, taking into account cultural and contextual differences. Integrating qualitative research approaches, like as interviews or focus group discussions, can offer more comprehensive insights into the experiences of university students with AI ChatGPT, complementing quantitative data. Furthermore, delving into the ethical aspects linked to AI in education, including concerns about privacy, data security, and the appropriate utilization of AI, will enhance comprehensive comprehension of the consequences of using AI technology in academic environments. Future research might explore the collective influence of various AI technologies on learning satisfaction, taking into account the changing AI landscape in education and providing insights into the wider technology environment that affects educational methods. Future study can enhance comprehension of the intricate relationship between artificial intelligence and education by taking into account these factors.

Data availability statement

Data will be made available on request to corresponding authors.

Ethical approval statement

The research study mentioned above involved the collection of data from King Faisal University, Saudi Arabia, and prior ethical approval was duly obtained, under Reference No. Ethical Approval (KFU-REC-2023-DEC-ETHICS1820)/Dated: 20-12-2023.

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CRediT authorship contribution statement

Mohammed Abdullatif Almulla: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Questionnaire

Please rate your agreement with the following statements on a scale from 1 to 5, where 1 represents "Strongly Disagree" and 5 represents "Strongly Agree".

Constructs	Items
Perceived Ease of Use (5 items)	1. Interacting with AI ChatGPT for research purposes is easy for me.
	2. I find it simple to navigate and use AI ChatGPT in my research activities.
	3. Learning to use AI ChatGPT for research is simple.
	4. Using AI ChatGPT enhances the ease of conducting research tasks.
	5. I feel confident in my ability to use AI ChatGPT effectively for research purposes.
ChatGPT Use (5 items)	6. I actively use AI ChatGPT as a research tool.
	7. AI ChatGPT is an integral part of my research workflow.
	8. I consistently use AI ChatGPT in various aspects of my research.
	9. AI ChatGPT is a significant factor in my research efforts.
	10. I utilise AI ChatGPT as a primary tool for conducting research.
Perceived Usefulness (5 items)	11. AI ChatGPT enhances the efficiency of my research tasks.
	12. Using AI ChatGPT improves the quality of my research outputs.
	13. AI ChatGPT adds value to my research process.
	14. I perceive AI ChatGPT as a valuable resource for achieving research objectives.
	15. The use of AI ChatGPT positively impacts the outcomes of my research projects.
Interaction Learning (5 items)	16. Interacting with AI ChatGPT enhances my learning experience in the context of research.
	17. AI ChatGPT facilitates a more interactive and engaging learning process in my research activities.
	18. I find that interaction with AI ChatGPT enhances my understanding of research concepts and methodologies.
	19. AI ChatGPT contributes positively to my ability to grasp complex research ideas.
	20. The interactive nature of AI ChatGPT enhances my overall learning satisfaction in research endeavors.
Information Quality (5 items)	21. The information provided by AI ChatGPT for research is accurate and reliable.
	22. AI ChatGPT provides high-quality information that is relevant to my research objectives.
	23. I trust the information provided by AI ChatGPT in my research projects.
	24. AI ChatGPT enhances the overall quality of information available for my research.

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(*continued*)

Constructs	Items
	25. The information derived from AI ChatGPT significantly contributes to the rigor of my research outcomes.
Interaction Quality (4 items)	26. The interactions with AI ChatGPT are pleasant and user-friendly.
	27. AI ChatGPT provides a seamless and enjoyable user experience in my research activities.
	28. The interactions with AI ChatGPT are effective in addressing my research inquiries.
	29. I find the interaction with AI ChatGPT to be satisfying and conducive to my research tasks.
Collaborative Learning (3 items)	30. AI ChatGPT supports collaborative learning efforts within my research team.
	31. Collaborating with AI ChatGPT enhances the synergy among research team members.
	32. AI ChatGPT fosters a collaborative environment conducive to shared research insights.
Learning Motivation (5 items)	33. Interacting with AI ChatGPT motivates me to actively participate in my research tasks.
	34. The use of AI ChatGPT enhances my motivation to achieve meaningful outcomes in my research.
	35. AI ChatGPT contributes positively to my overall motivation in the pursuit of research excellence.
	36. I feel more motivated to engage in research activities with the support of AI ChatGPT.
	37. Interacting with AI ChatGPT stimulates my motivation for conducting rigorous and insightful research.
Learning Satisfaction (5 items)	38. Overall, I am satisfied with the learning experience facilitated by AI ChatGPT in my research endeavors.
	39. The use of AI ChatGPT enhances my satisfaction with the research process.
	40. I find that AI ChatGPT contributes significantly to my overall satisfaction with research-related activities.
	41. The learning opportunities provided by AI ChatGPT contribute to my overall satisfaction as a postgraduate researcher.
	42. I am highly satisfied with the learning outcomes and experiences facilitated by AI ChatGPT in my research journey.

References

[1] U.A. Khan, A. Alamäki, Harnessing AI to Boost Metacognitive Learning in Education, 2023.
[2] U.A. Khan, The Unstoppable March of Artificial Intelligence: the Dawn of Large Language Models, 2023.
[3] E. Sabzalieva, A. Valentini, ChatGPT and Artificial Intelligence in Higher Education: Quick Start Guide, 2023.
[4] B. Foroughi, M.G. Senali, M. Iranmanesh, A. Khanfar, M. Ghobakhloo, N. Annamalai, B. Naghmeh-Abbaspour, Determinants of intention to use ChatGPT for educational purposes: findings from PLS-SEM and fsQCA, Int. J. Human–Computer Interact (2023) 1–20.
[5] S.F. Ahmad, M.K. Rahmat, M.S. Mubarik, M.M. Alam, S.I. Hyder, Artificial intelligence and its role in education, Sustainability 13 (2021) 12902.
[6] J. Huang, M. Tan, The role of ChatGPT in scientific communication: writing better scientific review articles, Am. J. Cancer Res. 13 (2023) 1148.
[7] Z.N. Khlaif, A. Mousa, M.K. Hattab, J. Itmazi, A.A. Hassan, M. Sanmugam, A. Ayyoub, The potential and concerns of using AI in scientific research: ChatGPT performance evaluation, JMIR med, Educ. Next 9 (2023) e47049.
[8] A. Strzelecki, To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology, Interact. Learn. Environ. (2023) 1–14.
[9] C.Y. Lai, K.Y. Cheung, C.C. Seng, Exploring the role of intrinsic motivation in ChatGPT adoption to support active learning: an extension of the technology acceptance model, Comput. Educ. Artif. Intell. (2023) 100178.
[10] H. Huang, O. Zheng, D. Wang, J. Yin, Z. Wang, S. Ding, H. Yin, C. Xu, R. Yang, Q. Zheng, ChatGPT for shaping the future of dentistry: the potential of multi-modal large language model, Int. J. Oral Sci. 15 (2023) 29.
[11] G. Cooper, Examining science education in chatgpt: an exploratory study of generative artificial intelligence, J. Sci. Educ. Technol. 32 (2023) 444–452.
[12] F. Joublin, A. Ceravola, J. Deigmoeller, M. Gienger, M. Franzius, J. Eggert, A glimpse in ChatGPT capabilities and its impact for AI research, ArXiv Prepr. ArXiv2305 (2023) 06087.
[13] A.A.Q. Mohammed, A. Al-ghazali, K.A.S. Alqohfa, Exploring ChatGPT uses in higher studies: a case study of arab postgraduates in India, J. English Stud. Arab. Felix 2 (2023) 9–17.
[14] T. Rasul, S. Nair, D. Kalendra, M. Robin, F. de Oliveira Santini, W.J. Ladeira, M. Sun, I. Day, R.A. Rather, L. Heathcote, The role of ChatGPT in higher education: benefits, challenges, and future research directions, J. Appl. Learn. Teach. 6 (2023).
[15] J.M. Romero Rodríguez, M.S. Ramírez-Montoya, M. Buenestado Fernández, F. Lara Lara, Use of ChatGPT at University as a Tool for Complex Thinking: Students' Perceived Usefulness, 2023.
[16] Y. Liu, T. Han, S. Ma, J. Zhang, Y. Yang, J. Tian, H. He, A. Li, M. He, Z. Liu, Summary of chatgpt-related research and perspective towards the future of large language models, Meta-Radiology (2023) 100017.
[17] F. Fui-Hoon Nah, R. Zheng, J. Cai, K. Siau, L. Chen, Generative AI and ChatGPT: applications, challenges, and AI-human collaboration, J. Inf. Technol. Case Appl. Res. 25 (2023) 277–304.
[18] E. Vázquez-Cano, J.M. Ramirez-Hurtado, J.M. Saez-Lopez, E. Lopez-Meneses, ChatGPT: the brightest student in the class, Think. Ski. Creat. 49 (2023) 101380.
[19] A. Korinek, Generative AI for economic research: use cases and implications for economists, J. Econ. Lit. 61 (2023) 1281–1317.
[20] J.-C. Lee, Y. Tang, S. Jiang, Understanding continuance intention of artificial intelligence (AI)-enabled mobile banking applications: an extension of AI characteristics to an expectation confirmation model, Humanit, Soc. Sci. Commun. 10 (2023) 1–12.
[21] G. Orrù, A. Piarulli, C. Conversano, A. Gemignani, Human-like problem-solving abilities in large language models using ChatGPT, Front. Artif. Intell. 6 (2023) 1199350.
[22] C.-N. Bran, E.-C. Balas, Metacognitive regulation and in-depth learning. A study on the students preparing to become teachers, Procedia-Social, Behav. Sci. 11 (2011) 107–111.
[23] M. Losinski, Y. Cuenca-Carlino, M. Zablocki, J. Teagarden, Examining the efficacy of self-regulated strategy development for students with emotional or behavioral disorders: a meta-analysis, Behav. Disord. 40 (2014) 52–67.
[24] Y. Dai, S. Lai, C.P. Lim, A. Liu, ChatGPT and its impact on research supervision: insights from Australian postgraduate research students, Australas, J. Educ. Technol. 39 (2023) 74–88.
[25] B.D. Lund, T. Wang, N.R. Mannuru, B. Nie, S. Shimray, Z. Wang, ChatGPT and a new academic reality: artificial Intelligence-written research papers and the ethics of the large language models in scholarly publishing, J. Assoc. Inf. Sci. Technol. 74 (2023) 570–581.
[26] J. Davis, J. Davis, Probing the gap between policy and practice in initial early childhood teacher education in Australia in relation to education for sustainability, Asia-Pacific, J. Teach. Educ. 49 (2021) 550–565.
[27] J. Dempere, K.P. Modugu, A. Hesham, L. Ramasamy, The impact of ChatGPT on higher education, Dempere J, Modugu K, Hesham A Ramasamy LK impact ChatGPT high, Educ. Front. Educ 8 (2023) 1206936.
[28] R. Firaina, D. Sulisworo, Exploring the usage of ChatGPT in higher education: frequency and impact on productivity, Bul. Edukasi Indones. 2 (2023) 39–46.
[29] M. Sullivan, A. Kelly, P. McLaughlan, ChatGPT in Higher Education: Considerations for Academic Integrity and Student Learning, 2023.
[30] P.S. Aithal, S. Aithal, Application of ChatGPT in higher education and research–A futuristic analysis, Int. J. Appl. Eng. Manag. Lett. 7 (2023) 168–194.
[31] R. Baskara, Exploring the implications of ChatGPT for language learning in higher education, Indones. J. English Lang. Teach. Appl. Linguist. 7 (2023) 343–358.

[32] F. Fauzi, L. Tuhuteru, F. Sampe, A.M.A. Ausat, H.R. Hatta, Analysing the role of ChatGPT in improving student productivity in higher education, J. Educ. 5 (2023) 14886–14891.
[33] C. Song, Y. Song, Enhancing academic writing skills and motivation: assessing the efficacy of ChatGPT in AI-assisted language learning for EFL students, Front. Psychol. 14 (n.d.) 1260843.
[34] N.A. Dahri, N. Yahaya, W.M. Al-Rahmi, M.S. Vighio, F. Alblehai, R.B. Soomro, A. Shutaleva, Investigating AI-based academic support acceptance and its impact on students' performance in Malaysian and Pakistani higher education institutions, Educ. Inf. Technol. (2024) 1–50.
[35] N.A. Dahri, N. Yahaya, W.M. Al-Rahmi, A. Aldraiweesh, U. Alturki, S. Almutairy, A. Shutaleva, R.B. Soomro, Extended TAM based acceptance of AI-Powered ChatGPT for supporting metacognitive self-regulated learning in education: a mixed-methods study, Heliyon 10 (8) (2024) e29317.
[36] K.G. Srinivasa, M. Kurni, K. Saritha, Harnessing the power of AI to education, in: Learn. Teaching, Assess. Methods Contemp. Learn. Pedagog. Digit. Gener., Springer, 2022, pp. 311–342.
[37] P. Pandey, A.K. Rai, Consumer adoption of AI-powered virtual assistants (AIVA): an integrated model based on the SEM–ANN approach, FIIB Bus. Rev. (2023) 23197145231196064.
[38] A. Ni, A. Cheung, Understanding secondary students' continuance intention to adopt AI-powered intelligent tutoring system for English learning, Educ. Inf. Technol. 28 (2023) 3191–3216.
[39] S. Na, S. Heo, W. Choi, C. Kim, S.W. Whang, Artificial intelligence (AI)-Based technology adoption in the construction industry: a cross national perspective using the technology acceptance model, Buildings 13 (2023) 2518.
[40] M. Ashfaq, J. Yun, S. Yu, S.M.C. Loureiro, I. Chatbot, Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents, Telemat. Informatics 54 (2020) 101473.
[41] I. Baroni, G.R. Calegari, D. Scandolari, I. Celino, AI-TAM: a model to investigate user acceptance and collaborative intention in human-in-the-loop AI applications, Hum. Comput. 9 (2022) 1–21.
[42] S.Y. Yousafzai, G.R. Foxall, J.G. Pallister, Technology acceptance: a meta-analysis of the TAM: Part 1, J. Model. Manag. 2 (2007) 251–280.
[43] P. Mohd Isa, Y. Ahmad, Scrutinizing the issues and challenges faced by postgraduate students: an effort to design specific programs to inculcate research culture, J. Adm. Sci. 15 (2018).
[44] C.K. Lo, What is the impact of ChatGPT on education? A rapid review of the literature, Educ. Sci. 13 (2023) 410.
[45] F. Ouyang, L. Zheng, P. Jiao, Artificial intelligence in online higher education: a systematic review of empirical research from 2011 to 2020, Educ. Inf. Technol. 27 (2022) 7893–7925.
[46] H. Rafique, A.O. Almagrabi, A. Shamim, F. Anwar, A.K. Bashir, Investigating the acceptance of mobile library applications with an extended technology acceptance model (TAM), Comput. Educ. 145 (2020) 103732.
[47] A.M. Al-Rahmi, A. Shamsuddin, U. Alturki, A. Aldraiweesh, F.M. Yusof, W.M. Al-Rahmi, A.A. Aljeraiwi, The influence of information system success and technology acceptance model on social media factors in education, Sustainability 13 (2021) 7770.
[48] W.M. Al-Rahmi, M.S. Othman, M.A. Musa, The improvement of students' academic performance by using social media through collaborative learning in Malaysian higher education, Asian Soc. Sci. 10 (2014) 210.
[49] M.M. Alamri, W.M. Al-Rahmi, N. Yahaya, A.M. Al-Rahmi, H. Abualrejal, A.M. Zeki, Q. Al-Maatouk, Towards adaptive e-learning among university students: by applying technology acceptance model (TAM), E-Learning 7 (2019).
[50] M.M. Alamri, M.A. Almaiah, W.M. Al-Rahmi, The role of compatibility and task-technology fit (TTF): on social networking applications (SNAs) usage as sustainability in higher education, IEEE Access 8 (2020) 161668–161681.
[51] A.M. Al-Rahmi, W.M. Al-Rahmi, U. Alturki, A. Aldraiweesh, S. Almutairy, A.S. Al-Adwan, Acceptance of mobile technologies and M-learning by university students: an empirical investigation in higher education, Educ. Inf. Technol. (2022) 1–22.
[52] N.A. Dahri, W.M. Al-Rahmi, A.S. Almogren, N. Yahaya, M.S. Vighio, Q. Al-maatuok, A.M. Al-Rahmi, A.S. Al-Adwan, Acceptance of mobile learning technology by teachers: influencing mobile self-efficacy and 21st-century skills-based training, Sustainability 15 (2023) 8514.
[53] I.Y. Alyoussef, Acceptance of e-learning in higher education: the role of task-technology fit with the information systems success model, Heliyon 9 (2023) e29317.
[54] W.M. Al-Rahmi, N. Yahaya, A.A. Aldraiweesh, M.M. Alamri, N.A. Aljarboa, U. Alturki, A.A. Aljeraiwi, Integrating technology acceptance model with innovation diffusion theory: an empirical investigation on students' intention to use E-learning systems, IEEE Access 7 (2019) 26797–26809.
[55] V. Venkatesh, M.G. Morris, G.B. Davis, F.D. Davis, User acceptance of information technology: toward a unified view, MIS Q. (2003) 425–478.
[56] M.A. Almaiah, M.A. Jalil, M. Man, Extending the TAM to examine the effects of quality features on mobile learning acceptance, J. Comput. Educ. 3 (2016) 453–485.
[57] B. Rahmi, B. Birgoren, A. Aktepe, A meta analysis of factors affecting perceived usefulness and perceived ease of use in the adoption of e-learning systems, Turk. Online J. Dist. Educ. 19 (2018) 4–42.
[58] L.C. Gumbo, D. Halimani, M. Diza, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as Key Drivers of Mobile Banking Adoption: a Case of Zimbabwe, 2017.
[59] F.D. Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, MIS Q. (1989) 319–340.
[60] W.M. Al-Rahmi, N. Yahaya, M.M. Alamri, I.Y. Alyoussef, A.M. Al-Rahmi, Y. Bin Kamin, Integrating innovation diffusion theory with technology acceptance model: supporting students' attitude towards using a massive open online courses (MOOCs) systems, Interact. Learn. Environ. 29 (2021) 1380–1392.
[61] S.-S. Liaw, H.-M. Huang, Perceived satisfaction, perceived usefulness and interactive learning environments as predictors to self-regulation in e-learning environments, Comput. Educ. 60 (2013) 14–24.
[62] W.M. Al-Rahmi, N. Yahaya, U. Alturki, A. Alrobai, A.A. Aldraiweesh, A. Omar Alsayed, Y. Bin Kamin, Social media–based collaborative learning: the effect on learning success with the moderating role of cyberstalking and cyberbullying, Interact. Learn. Environ. 30 (2022) 1434–1447.
[63] I.Y. Alyoussef, E-Learning acceptance: the role of task–technology fit as sustainability in higher education, Sustainability 13 (2021) 6450.
[64] K. Swan, Learning effectiveness online: what the research tells us, Elem. Qual. Online Educ. Pract. Dir. 4 (2003) 13–47.
[65] W.G. Anderson, Interaction and Control in Asynchronous Computer-Mediated Communication in a Distance Education Context, The Pennsylvania State University, 2003.
[66] A.L. Whiteside, A.G. Dikkers, K. Swan, Social Presence in Online Learning: Multiple Perspectives on Practice and Research, Taylor & Francis, 2023.
[67] A. Raven, C.W. Park, Information quality as a determinant of task-technology fit in using communication technology for simple task, Issues Inf. Syst. 16 (2015).
[68] X. Li, W. Zhu, System quality, information quality, satisfaction and acceptance of online learning platform among college students in the context of online learning and blended learning, Front. Psychol. 13 (2022) 1054691.
[69] A.A. Arain, Z. Hussain, W.H. Rizvi, M.S. Vighio, Extending UTAUT2 toward acceptance of mobile learning in the context of higher education, Univers. Access Inf. Soc. 18 (2019) 659–673.
[70] N.A. Dahri, M.S. Vighio, J. Das Bather, A.A. Arain, Factors influencing the acceptance of mobile collaborative learning for the continuous professional development of teachers, Sustainability 13 (2021) 13222.
[71] C. Pelau, D.-C. Dabija, I. Ene, What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry, Comput. Human Behav. 122 (2021) 106855.
[72] N. Alalwan, W.M. Al-Rahmi, O. Alfarraj, A. Alzahrani, N. Yahaya, A.M. Al-Rahmi, Integrated three theories to develop a model of factors affecting students' academic performance in higher education, IEEE Access 7 (2019) 98725–98742.
[73] N.A. Dahri, M.S. Vighio, M.H. Dahri, A survey on technology supported collaborative learning tools and techniques in teacher education, in: 2019 Int. Conf. Inf. Sci. Commun. Technol., IEEE, 2019, pp. 1–9.
[74] J. Kelly, Collaborative learning: higher education, interdependence, and the authority of knowledge by Kenneth Bruffee: a critical study, J. Natl. Coll. Honor. Counc. Arch. (2002) 82.
[75] A.A. Gokhale, Collaborative learning enhances critical thinking, Fall 1995 7 (1) (1995).

[76] W.M. Al-Rahmi, A.M. Zeki, A model of using social media for collaborative learning to enhance learners' performance on learning, J. King Saud Univ. Inf. Sci. 29 (2017) 526–535.
[77] K. Li, Determinants of college students' actual use of AI-based systems: an extension of the technology acceptance model, Sustainability 15 (2023) 5221.
[78] R.H. Shroff, C.J. Keyes, A proposed framework to understand the intrinsic motivation factors on university students' behavioral intention to use a mobile application for learning, J. Inf. Technol. Educ. Res. 16 (2017) 143.
[79] C.P. Niemiec, R.M. Ryan, E.L. Deci, The path taken: consequences of attaining intrinsic and extrinsic aspirations in post-college life, J. Res. Pers. 43 (2009) 291–306.
[80] R.M. Ryan, E.L. Deci, Intrinsic and extrinsic motivation from a self-determination theory perspective: definitions, theory, practices, and future directions, Contemp. Educ. Psychol. 61 (2020) 101860.
[81] P. Pintrich, T. García, Intraindividual differences in students' motivation and selfregulated learning, Ger. J. Educ. Psichol. 7 (1993) 99–107.
[82] P.R. Pintrich, A motivational science perspective on the role of student motivation in learning and teaching contexts, J. Educ. Psychol. 95 (2003) 667.
[83] M.Q. Memon, Y. Lu, A.R. Memon, A. Memon, P. Munshi, S.F.A. Shah, Does the impact of technology sustain students' satisfaction, academic and functional performance: an analysis via interactive and self-regulated learning? Sustainability 14 (2022) 7226.
[84] M.A. Alqahtani, M.M. Alamri, A.M. Sayaf, W.M. Al-Rahmi, Exploring student satisfaction and acceptance of e-learning technologies in Saudi higher education, Front. Psychol. 13 (2022) 939336.
[85] J.F. Hair, M. Sarstedt, C.M. Ringle, J.A. Mena, An assessment of the use of partial least squares structural equation modeling in marketing research, J. Acad. Mark. Sci. 40 (2012) 414–433.
[86] J.F. Hair Jr., M. Sarstedt, L. Hopkins, V.G. Kuppelwieser, Partial least squares structural equation modeling (PLS-SEM) an emerging tool in business research, Eur. Bus. Rev. 26 (2014) 106–121.
[87] V. Venkatesh, Determinants of perceived ease of use: integrating control, intrinsic motivation, and emotion into the technology acceptance model, Inf. Syst. Res. 11 (2000) 342–365.
[88] V. Venkatesh, H. Bala, Technology acceptance model 3 and a research agenda on interventions, Decis. Sci. 39 (2008) 273–315.
[89] T.A. Brown, Confirmatory Factor Analysis for Applied Research, Guilford publications, 2015.
[90] B. Williams, A. Onsman, T. Brown, Exploratory factor analysis: a five-step guide for novices, Australas. J. Paramed. 8 (2010).
[91] T.R. Hinkin, A review of scale development practices in the study of organizations, J. Manage. 21 (1995) 967–988.
[92] J.F. Hair, J.J. Risher, M. Sarstedt, C.M. Ringle, When to use and how to report the results of PLS-SEM, Eur. Bus. Rev. 31 (2019) 2–24.
[93] F.D. Davis, R.P. Bagozzi, P.R. Warshaw, User acceptance of computer technology: a comparison of two theoretical models, Manage. Sci. 35 (1989) 982–1003.
[94] S. King, J. Boyer, T. Bell, A. Estapa, An automated virtual reality training system for teacher-student interaction: a randomized controlled trial, JMIR Serious Games 10 (2022) e41097.
[95] D. Menon, K. Shilpa, "Chatting with ChatGPT": analyzing the factors influencing users' intention to Use the Open AI's ChatGPT using the UTAUT model, Heliyon 9 (2023) e29317.
[96] A.S. Almogren, N.A. Aljammaz, The integrated social cognitive theory with the TAM model: the impact of M-learning in King Saud University art education, Front. Psychol. 13 (2022) 1050532.
[97] L. Zhou, S. Xue, R. Li, Extending the Technology Acceptance Model to explore students' intention to use an online education platform at a University in China, Sage Open 12 (2022) 21582440221085260.
[98] J. Hair, C.L. Hollingsworth, A.B. Randolph, A.Y.L. Chong, An updated and expanded assessment of PLS-SEM in information systems research, Ind. Manag. Data Syst. 117 (2017) 442–458.
[99] J. Henseler, C.M. Ringle, M. Sarstedt, A new criterion for assessing discriminant validity in variance-based structural equation modeling, J. Acad. Mark. Sci. 43 (2015) 115–135.
[100] C. Fornell, D.F. Larcker, Evaluating structural equation models with unobservable variables and measurement error, J. Mark. Res. 18 (1981) 39–50.
[101] C.C. Tossell, N.L. Tenhundfeld, A. Momen, K. Cooley, E.J. de Visser, Student perceptions of ChatGPT use in a college essay assignment: implications for learning, grading, and trust in artificial intelligence, IEEE Trans. Learn. Technol. 17 (2024), 1069-108.
[102] N. Omrani, G. Rivieccio, U. Fiore, F. Schiavone, S.G. Agreda, To trust or not to trust? An assessment of trust in AI-based systems: concerns, ethics and contexts, Technol, Forecast. Soc. Change 181 (2022) 121763.
[103] J.H. Al Shamsi, M. Al-Emran, K. Shaalan, Understanding key drivers affecting students' use of artificial intelligence-based voice assistants, Educ. Inf. Technol. 27 (2022) 8071–8091.
[104] K. Candrawati, A. Nuvriasari, E. Yulianto, K.D. Adijaya, N. Farizy, The role of information quality on task technology fit and student academic performance, in: Entrep. Econ. Bus. Int, . Conf., 2023.
[105] Z. Du, X. Fu, C. Zhao, Q. Liu, T. Liu, Interactive and collaborative e-learning platform with integrated social software and learning management system, in: Proc. 2012 Int. Conf. Inf. Technol. Softw. Eng. Softw. Eng. Digit. Media Technol., Springer, 2013, pp. 11–18.
[106] M.S. Kumar, D.S.G. Krishnan, Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Behavioural Intension to Use (BIU): Mediating Effect of Attitude toward Use (AU) with Reference to Mobile Wallet Acceptance and Adoption in Rural India, 2020.
[107] R. Pillai, B. Sivathanu, B. Metri, N. Kaushik, Students' adoption of AI-based teacher-bots (T-bots) for learning in higher education, Inf. Technol. People 37 (1) (2023) 328–355.
[108] J.A. Jaramillo, Vygotsky's sociocultural theory and contributions to the development of constructivist curricula, Education 117 (1996) 133–141.
[109] P. Dillenbourg, What Do You Mean by Collaborative Learning?, 1999.
[110] V. Viswanath, User acceptance of information technology: toward a unified view, MIS Q. 27 (2003) 425–478.
[111] G.-Y. Lin, C.-C. Jhang, Y.-S. Wang, Factors affecting parental intention to use AI-based social robots for children's ESL learning, Educ. Inf. Technol. (2023) 1–28.