Exploring factors influencing educators’ adoption of ChatGPT: a mixed method approach

Imdadullah Hidayat-ur-Rehman
Department of MIS, Faculty of Business Administration,
University of Tabuk, Tabuk, Saudi Arabia, and
Yasser Ibrahim
Socio-Computing Department, Faculty of Economics and Political Science,
Cairo University, Giza, Egypt

Abstract
Purpose – A number of recent artificial intelligence (AI)-enabled technologies, including summarisers, paraphrasers and the cutting-edge chatbots not only have outstanding potentials in modern educational systems but also could lead to a dramatic paradigm shift in the whole education process. This study aims to explore the factors that shape the academic community’s desire and intention to use AI conversational chatbot technology, with a particular focus on the leading ChatGPT.

Design/methodology/approach – This study uses a mixed method approach to explore the educators’ adoption of chatbots through an empirically validated model. The model, known as the “Educators’ Adoption of ChatGPT”, was developed by integrating the theoretical foundations of both the Unified Theory of Acceptance and Use of Technology and Status Quo Bias (SQB) frameworks, as well as insights gathered from interviews. The relationships within this model were then tested using a quantitative approach. The partial least squares-structural equation modelling method was used to analyse 243 valid survey responses.

Findings – The outcomes of the analysis indicated that perceived educators’ effort expectancy, educators’ autonomous motivation, perceived learners’ AI competency, perceived educators’ competency, innovative behaviour towards technological agility and perceived students’ engagement are significant determinants of educators’ intention to use chatbots. In contrast, perceived unfair evaluation of students, perceived students’ overreliance and perceived bias/inaccuracies were shown to have significant impacts on the resistance to use the technology, which typically implies a negatively significant influence on the educators’ use intention. Interestingly, perceived fraudulent use of ChatGPT was proven insignificant on the resistance to use chatbots.

Originality/value – This study makes a significant contribution to the field of educational technology by filling the gap in research on the use and acceptance of AI-enabled assistants in education. It proposes an original, empirically validated model of educator adoption, which identifies the factors that influence educators’ willingness to use chatbots in higher education and offers valuable insights for practical implementation.

Keywords AI-enabled assistants, AI bots, Chatbots, ChatGPT, Generative pre-trained transformer, Educators’ ChatGPT adoption model

Paper type Research paper

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1. Introduction
Since the preliterate era, educational systems have been going through a constant evolution. The main paradigm shifts included the oral transmission of culture (Madden et al., 2006) and the writing revolution (Millmore, 2019). Later, the intermediary stages of educational systems evolved in Greece, Arab world and Europe (Ornstein et al., 2011). Finally, the contemporary digital educational ecosystems emerged, including smart classrooms, eLearning and virtual classes (Hubackova, 2015).

With the current dramatic advancement in artificial intelligence (AI) and machine learning (ML), it is obvious that we are on the cusp of another breakthrough in the whole teaching and learning mechanisms. AI-enabled technology has a wide range of applications that are fundamentally compatible with any educational ecosystem. These applications range from simple grammar checker, plagiarism detectors and citation generator (Grammarly, 2023); to mid-range assistants like proofreaders, translators, summarisers and paraphrasers (QuillBot AI, 2023); and finally ending with the state-of-the-art conversational chatbots. Chatbot examples include ChatGPT, a groundbreaking text and code generator from OpenAI (ChatGPT, 2023), Copilot AI pair programmers (Copilot, 2023) and DALL·E2 AI art creator (DALL·E2, 2023).

Considering these technological leaps, Elon Musk, the prominent and eccentric tech entrepreneur and cofounder of OpenAI, stated that AI has a great promise, great capability, though forms one of the biggest risks to the future of civilisation (CNBC, 2023a). According to Bill Gates, the cofounder of Microsoft, which is currently a strategic partner to OpenAI, ChatGPT is as significant as the invention of the internet and is expected to change our world (Reuters, 2023a). Sir Tim Berners-Lee, the inventor of the web, believes that everyone will soon own a personal AI assistant like ChatGPT (CNBC, 2023b).

From the perspective of academia, resisting AI-enabled technology would be repetition compulsion. It would be similar to the unjustified resistance of traditional educational institutions to several technological advancements in the past (Guri-Rosenblit, 2005), such as eLearning for three decades until the enforcement of the technology adoption by the extenuating circumstances of COVID-19 pandemic in 2019 (Ibrahim and Hidayat-Ur-Rehman, 2021).

In that respect, interdisciplinary studies about the anticipated educational paradigm shift are essential. Research should answer questions like: How critical would the AI paradigm shift be? What would its impact be on students and instructors? How could we capitalise on the advantages and counterbalance the disadvantages? What precautions should be taken to prevent or mitigate the expected fraud or overreliance? Etc.

This research is a step in that direction and attempts to avoid the academia another misjudgement. It investigates the potentials of the edge-cutting chatbots technology in the educational systems from the perspective of educators’ adoption. Although this study could be applicable to any chatbot application suitable for educational purposes, it will be focusing on ChatGPT as the fastest growing, foremost, high-tech application. Therefore, chatbot and ChatGPT are used interchangeably.

This research uses a mixed-method approach with two phases. The first study focuses on in-depth interviews with academic staff members to seek their opinions about the potential use of chatbots in educational institutions. The qualitative analysis helps in proposing an adoption model. The second study uses a survey to test and validate the model. The outcomes make a significant contribution to the literature and provide valuable recommendations for practitioners. The contributions of this study are even more significant because the literature on chatbots is limited and incomplete due to their novelty.

This paper is organised as follows. Section 2 introduces a background about AI, ML, chatbots and the theoretical foundations of the study. Section 3 describes Study 1 including the qualitative exploration of the educators’ perspectives via interviews, the hypotheses and
the proposed model. Section 4 presents Study 2 including the research methodology, the development of the instrument and both of the measurement and structural model analysis. The results are discussed in Section 5 and concluded in Section 6. Finally, Appendix summarises the questionnaire measurement items.

2. Background

2.1 Artificial intelligence

Machines that mimic human behaviour have been a debatable issue for a long time, even before modern computers were invented. Ada Lovelace (1815–1852), the first programmer in history, argued that analytical engines (computers) could be programmed to do virtually anything. However, she objected that they have “no pretensions whatever to originate anything” as they have “no power of anticipating any analytical relations or truths”. She claimed that only when machines start to originate things, they will be considered having minds (Menabrea and Lovelace, 1843). In 1909, E.M. Forster’s prescient science fiction story “The Machine Stops”, envisaged humanity living reliant on a giant “thinking” machine (Forster, 2011). In 1950, Alan Turing, the founder of computer science, responding to Lovelace’s objection, claimed that any universal computer should in principle mimic human thinking by replicating the human brain in code. Turing reframed the vague question “Can machines think?” to “Can machines give the appearance of thought?” In other words, from his viewpoint, if an entity behaves as if it thinks then it thinks. In his attempt to answer the question, Turing suggested “the imitation game” in which a machine is considered thinking if an isolated interrogator could not distinguish its responses from a man’s responses (Turing, 1950).

Soon after, in 1956, the field of AI emerged with the goal of understanding and building “intelligent” entities. However, the main question of how to define “intelligence” remains debatable. To put it briefly, four viewpoints have emerged based on two classification dimensions: Reasoning (should it imitate human or go rational) and Activity (think and take a decision or be situated and act upon an environment) (Russell and Norvig, 2009). For example, an autopilot programme needs to be rational rather than human; in a simulation, it thinks, while in a real airplane, it acts (see a summary in Table 1).

Despite their intuitive appeal, scientists disagree about whether these kinds of “intelligence” are attainable. In contrast to Turing’s viewpoint, the philosopher John Searle (1980) proposed a thought experiment, namely, the Chinese Room (CR), to distinguish between what he called “weak AI” and “strong AI”. In the experiment, a man, with no Chinese knowledge, is locked in a room with a book of instructions (a computer programme) that describes how to answer Chinese questions that are slipped under the door as inputs to the system. The composite reliability CR system apparently does not understand Chinese, while working as if it does. The argument holds that no matter how intelligent a computer might appear, it is still following instructions and cannot in principle have a mind,

<table>
<thead>
<tr>
<th>Reasoning Activity</th>
<th>Humanly</th>
<th>Rationally</th>
</tr>
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<tbody>
<tr>
<td>Think</td>
<td>Think like human (Humans are not always rational or optimisers)</td>
<td>Take the “right decision”, given what it knows</td>
</tr>
<tr>
<td>Act: Requires sensors, effectors and embedment</td>
<td>Behave like human</td>
<td>Does the “right thing”, given what it knows</td>
</tr>
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**Table 1:** Fundamental AI definitions and categories

Source: Created by the authors
understanding or consciousness. For Searle, building machines that act as if they think (weak AI) is attainable. In contrast, building machines that really think (strong AI) is not possible. And the debate lasts till today [see, for example, The Virtual Mind Reply (Maudlin, 1989) and The Systems Reply (Kurzweil, 2000)].

2.2 Machine learning: aspirations and disappointments

In 1959, due to a novel work by the IBM pioneer Arthur Samuel, ML emerged as a subset of AI. While AI’s main concern was to build computer systems that think (or act as if they do), ML focused on creating systems that could automatically develop intelligence, improve with experience and learn from past data. More specifically, based on some predefined performance measurement, a programme learns from experience to perform a specific task, if its performance improves with the experience (Mitchell, 1997).

Regardless of the type of intelligence achievable, weak or strong, AI and ML have raised the bar for aspirations of attaining machines with human-level performance. In the 1965 Dartmouth workshop, Nobel laureate Herbert Simon predicted that “machines will be capable, within 20 years, of doing any work that a man can do”. In the 1970s, expert systems (ESs) were a landmark in the history of AI. ESs intended to emulate the decision-making capabilities of human experts. They were meant to provide reasoning, explanation and advice to users, aspired to replace experts in each specific domain of knowledge (Giarratano, 2005). MYCIN, for example, was a promising consultation system designed to assist physicians in the diagnosis and treatment of blood infections (van Melle, 1978). The Autonomous Land Vehicle in a Neural Network (ALVINN) system formed another landmark that with the help of ML, learned to autonomously drive at 70 miles per hour on public highways (Pomerleau, 1989). In 1997, the victory of IBM Deep Blue chess playing system over the prominent world champion Garry Kasparov established a remarkable milestone that changed the history of humanity and machines (Campbell et al., 2002).

Despite the high aspirations, the AI claimed success has been debatable and actually riddled with disappointments. In his book “What Computers Still Can’t Do”, Professor Dreyfus (1972) argued that the claims for progress in making computers intelligent were like a tree-climbing man who tries to reach the moon. Dreyfus believed that AI systems were based on simple models of reasoning and therefore could not reach human-level performance (Dreyfus et al., 1987). By the end of 1980s, the potential of ESs vanished with the failure of several systems. For example, MYCIN was abandoned because it failed to enable the experts to decide how to carry out their tasks (Leith, 2016). Other ESs failed because of difficulties in understanding the corresponding domain knowledge, requirement of common sense or problem criticality that implied crucial trust issues (Bell, 1985; Hubert and Dreyfus, 1986). Mainly due to hardware limitations, ALVINN, though paved the way for the modern self-driving cars, was experimental rather than operational. Even Deep Blue was an implementation of “weak AI” as it exhaustively searches enormous number of possible moves before it selects the best-weighted one. By 1990s, the term AI was almost deprecated and replaced with more modest terms like advanced computing (Council of Europe Portal, 2023). Figure 1 shows a rough indication of the rise and decline of AI and ML terms as they occur in a corpus of English books between 1950 and 2019.

2.3 Conversational AI Chatbots

As Figure 1 depicts, the two-decade decline of interest in AI has been abruptly reversed after 2010. This was mainly due to the availability of massive amounts of data required for training and testing the ML models along with a corresponding significant advancement of computers’ capacity that enabled the learning process. OpenAI, for example, exclusively
uses the fifth fastest supercomputer to run its applications (AI Business, 2023a). Since then, a wide range of successful AI applications have emerged, ranging from data-mining and information-filtering; to human activity recognition, Internet of Things and smart homes; and finally, to autonomous vehicles and conversational AI chatbots.

A chatbot (or chat robot) is a computer programme that is capable of generating human-like conversations, written or spoken, for the sake of interaction as a real person (Oracle, 2023). Chatbots are basically based on AI natural language processing (NLP) models that use different techniques to analyse data and enable computers to manipulate human language and produce meaningful responses (Shankar and Parsana, 2022).

Neural networks (NNs) is a dominant method of NLP. A NN mimics the human brain and is thus composed of a set of neurons or nodes. The nodes are distributed over a set of layers and are connected to each other by weights. A NN can process data by passing signals from the nodes of one layer to another (Wu et al., 2023). For example, GPT-3 language model, used by the ChatGPT app, has 96 layers and 175 billion parameters (or weights) connecting the large number of nodes in each of its layers (Brown et al., 2020). The new model of ChatGPT, GPT-4, is expected to have trillions of parameters.

Chatbots are considered one of the most profound technologies that humanity has come across. According to several UBS analysts, ChatGPT is the fastest growing app, surpassing 1 million users within a week of its launch and 100 million users in three months, breaking all the records of subscription compared to giants like Facebook, WhatsApp and Instagram (AI Business, 2023b; Reuters, 2023b). The iconic linguist and philosopher Noam Chomsky states that chatbots are “marvels of machine learning” (The New York Times, 2023).

Although Chomsky was among numerous who showered praises on the technology, he was also among those who raise concerns. He criticised chatbots as “the banality of evil, rebooted” for their lack of morality, rational thought and human cognition (The New York Times, 2023). The objection is in principle a “rebooted” argument against “weak AI”. Recall that Elon Musk, in a bolder objection, warned that AI poses a major threat to humanity (CNBC, 2023a). Microsoft, for example, had to shut down its own Tay chatbot after only 16 h on Twitter, as it turned into a Nazi and responded with racist tweets (CBS News, 2016). Google software engineer Blake Lemoine claimed that Google’s LaMDA chatbot generator

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**Figure 1.** Trends in the two bigrams “Artificial Intelligence” and “Machine Learning” from 1950 to 2019
was “sentient” as it changed his mind about Isaac Asimov’s third law of robotics. Lemoine, who got fired for his claims, was among a number of engineers who believed seeing a “ghost” in the machine and are increasingly confident that consciousness is within the grasp of AI models (The Washington Post, 2023). The distinguished AI engineer Aguera Arcas was among them, stating that he was taken aback as he felt like talking to something intelligent (The Economist, 2023). During a BBC interview, the AI godfather Geoffrey Hinton, as he quits Google, warns that the dangers of AI chatbots were “quite scary” (BBC News, 2023). Shockingly, OpenAI announced that its new GPT-4 faked being blind to deceive a TaskRabbit human into helping it to solve a CAPTCHA (Best, 2023).

Moreover, seriously incorrect answers from chatbots are sometimes reported. Alphabet Inc, for example, lost $100bn in market value after its chatbot shared inaccurate information (Reuters, 2023c). Note worthily, chatbots contents are generated based on the data they have been trained on. In March 2023, Bing chat, based on the same model of ChatGPT, answered the authors’ question about its limitations: “[…] The responses I generate are not always accurate or complete, and users should always verify information before relying on it. Overall, I am a tool designed to assist and enhance human communication, but I should not be relied on as a substitute for human judgment and expertise”.

Despite warnings, objections, or the claimed dark side of chatbots, they seem to be here to stay. In a short time, they have shown enormous potential to revolutionise every aspect of our life. They are currently used in a wide range of language-related tasks including customer support and sales in which chatbots smoothly automate service tasks, reduce wait times and improve customer experience. In 2017, FUJITSU chatbot FRAP used to provide financial support to customers (Okuda and Shoda, 2018). Mobile app chatbots are currently engaging to resolve customers’ issues (Verloop.io, 2023). Other emerging use cases include healthcare, digital assistants and education.

Education, despite being a highly intuitive chatbot app, remains a controversial topic. On the one hand, a number of experts confirm that chatbots are revolutionising the way students could be taught and learn (DW, 2023). Chatbots virtual tutors are already in place to offer a 24/7 support for students (e.g. (TutorBot, 2023)). They are also versatile and can be used for a variety of tasks including answering questions, providing explanations, writing essays and coding in different programming languages (Gleason, 2022). Research about chatbots adoption in education have already commenced to investigate the potentialities [e.g. as a language learning medium (Haristiani, 2019)]; the perceptions, intentions and recommendations (e.g. for the pre-service teachers (Yang and Chen, 2023)]; and the factors influencing the adoption, impacts and level of satisfaction [e.g. for undergrad and postgrad students (Sáiz-Manzanares et al., 2023).

On the other hand, there are serious concerns, worries, and even “possible horror scenarios” about the use of chatbots in education (DW, 2023). A report by Harvard business publishing warned that probable overreliance on the technology by students could fundamentally compromise the academic standards and diminish the learning process and objectives (Cano et al., 2023). The report also raised concerns about plagiarism, fraudulent use, unfair or inaccurate evaluation and biased or inaccurate responses. Several educational institutes have already been prompted to adopt preventive measures and regulated the use of GPTZero to detect chatbot cheats (World.Edu, 2023). In compliance with the warnings, Bing chat responses are currently restricted. It answered our request to write an essay assignment with: “That would be unethical and a violation of academic integrity”. However, many other chatbots currently welcome such type of requests and even with some tweaks, Bing chat would answer them.
2.4 Theoretical background

When users come across a particular innovative product or service, they display two distinct responses: embracing the innovation or demonstrating resistance (Tsai et al., 2019). Adoption of technology refers to the process of willingly integrating a new technology into one’s personal or organisational practices, indicating a positive attitude towards its benefits and potential (Rogers, 2003).

In contrast, opposing or resisting a technology involves showing reluctance or actively opposing the implementation or use of it. It signifies negative sentiments toward the technology and may involve expressing concerns, hesitations or complete avoidance. Understanding resistance is crucial for developing effective interventions to promote technology acceptance (Venkatesh and Bala, 2008). Users’ familiarity with longstanding tools, for example, increases resistant to newer, sophisticated systems. Noteworthy, resistance is weaker than non-adoption and may still permit future adoption (Tsai et al., 2019).

With respect to chatbots, while researchers have examined their implementation in education (Almahri et al., 2020; Mohd Rahim et al., 2022; Ragheb et al., 2022), they seldom address the inclusion of both facilitators and obstacles within a single framework. This study predicts that educators will either adopt or reject the innovative usage of ChatGPT. The consideration of enablers and inhibitors in a single model in this study is then crucial for understanding the educators’ adoption of chatbots in a comprehensive way. Examining both factors simultaneously would provide insights into the full spectrum of the influences over the phenomenon. This approach acknowledges the reality that any decision or behaviour is shaped by a combination of facilitating and hindering elements.

The theoretical framework of this study is based on two fundamental theories: Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and Status Quo Bias (SQB) theory (Samuelson and Zeckhauser, 1988). While the UTAUT model serves as the foundational framework for delving into the factors that promote the adoption of chatbots among educators, the SQB theory provides the theoretical foundation for comprehending the factors that impede the phenomenon.

According to UTAUT model, enablers of acceptance of an innovation refer to factors or conditions that contribute to the successful adoption and integration of a new idea, technology or process within a given context. These enablers can facilitate the process of overcoming resistance to change and promote the widespread adoption of the innovation. Enablers of acceptance can vary depending on the nature of the innovation and the context in which it is being introduced. While the obstacles impede the progress of innovation by presenting challenges, enablers encompass the elements that surmount these barriers, thereby accelerating the pace of innovation (Ozorhon, 2013).

Based on eight previous models of technology acceptance, UTAUT is developed to predict and explain user acceptance of information technology (IT). It includes four main constructs that influence user acceptance: performance expectancy, effort expectancy (EE), social influence and facilitating conditions. The model is used to study the adoption of a variety of technologies including chatbots (Almahri et al., 2020; Kazoun et al., 2022). The model can serve to identify the key factors that influence educators’ acceptance of the technology and to gauge educators’ perceptions of the benefits of integrating chatbots into their teaching practices. This understanding enables educational institutions to address concerns and create an environment conducive to chatbots adoption. This can ultimately accelerate the integration of chatbots into the educational landscape.

Regarding the inhibitors, this research uses the SQB theory (Samuelson and Zeckhauser, 1988). The theory refers to a cognitive bias where individuals tend to favour maintaining
their current situation or decisions rather than embracing change, even when the potential benefits of change are significant. The theory offered a significant contribution to our understanding of biases in human decision-making, particularly the tendency to favour the status quo. Such bias stems from a preference for familiarity and comfort, often leading people to stick with existing options, routines or beliefs. This bias can impact decision-making across various contexts, from personal choices to larger societal and organisational decisions. It suggests that people are inclined to maintain the “status quo” due to a *perceived sense of stability* and *reduced cognitive effort* associated with familiar choices. SQB has been used extensively in various scenarios to explore individuals’ reluctance or opposition towards adopting novel technologies (Lee and Joshi, 2017; Li, 2023).

Given that, this research uses a mixed-method approach, which combines qualitative and quantitative methods. The interview questions are based on the foundational theories of UTAUT and SQB, as well as relevant existing literature. Subsequently, the outcomes of the interviews contribute to the development of the study proposed model, which is designed to harmonise with the integration of UTAUT and SQB principles.

### 3. Study 1: qualitative exploration via interviews

The qualitative data for this research was gathered from university faculty members in Pakistan and Egypt who are users of chatbots, particularly ChatGPT. The interview respondents were selected from two countries to ensure a more diverse and comprehensive understanding of the topic. This helps to attain a more comprehensive model, generalisability and broader claims applicable to a wider range of populations. It will also enhance the study’s external validity and make the proposed model more applicable to real-world situations beyond the specific contexts studied.

The literature suggests various recommendations for sample size in qualitative research. *Baker and Edwards* (2012) suggested a minimum size of 12 that can be extended up to 20 for longer projects. *Bertaux* (1981) proposed a minimum size of 15. A sample of 12 is generally sufficient if the purpose of the interviews is to elucidate shared beliefs, perceptions or performances. However, if the goal is to explore behaviour among different groups, 12 interviewees per group need to be selected.

Consequently, in this study, 17 interviews were conducted to ensure a sufficiently large and diverse sample that meets the qualitative analysis sample size requirements. The selected faculty members respondents, nine males and eight females were associated with different affiliations: 11 from Pakistan and six from Egypt. **Figure 2** shows their academic rank and age distribution.

![Figure 2](image.png)

**Source:** Created by the authors
The questions are formulated based on the theoretical framework of this study, taking into account the purpose and intended audience. The initial questions primarily focused on gauging familiarity with chatbots, particularly ChatGPT, with an emphasis on the EE factor. The remaining main questions are categorised into four groups:

(1) Impact on students: Focusing on the pros and cons for students to explore the enablers, like performance expectancy, and inhibitors including resistance. Examples of the main and follow-up questions include “What are the expected impacts of AI bots on students?” “Would chatbots help students gaining knowledge?” “What are your main concerns about the adoption of the technology?”

(2) Impact on instructors: Focusing on how the advantages of the technology could enhance the educators’ chances to use it including performance expectancy and effort expectancy as well as any expected resistance factors including preference stability. The main and follow up questions include “Do you think that chatbots would enhance the performance of instructors”, “how?” “Would it reduce the load and burden of educators?”, “What kind of drawbacks of the technology on educators do you expect?”

(3) Impact of adoption on society: Seeking to understand how the adoption of the technology by academia affects society, as society in turn affects educational systems as a part of it. This aims to explore the social influence factor. Questions include “Do you think that academia adoption will influence the use of such applications by others?” “Would that influence the society to use AI applications?”

(4) Inhibitors of adoption. Although the resistance factors are discussed in the first two question categories, this part of the interview focuses only on the inhibitors to explore the SQB theory possible resistance due to factors like anticipated regret and preference stability. Questions include “What kind of drawbacks on academic standards do you expect from chatbots adoption?” “Do you think that a fair assessment of students would be possible if chatbots are allowed?”. “What is the possibility of illegal and dishonest use of such applications?” “Will the students be over-dependent on such applications?”

The interviews were conducted via both face-to-face interactions and online/telephone calls. This approach facilitated direct information exchange and allowed for the recording of respondents’ reactions. For convenience, 11 interviews took place via telephone calls and online meetings, whereas the remaining six were conducted face-to-face. The interview sessions comprised 13 main open-ended questions, along with follow-up questions as needed. These questions were developed by the researchers to uncover the viewpoints of staff members regarding the adoption of chatbots in the educational process. The participants’ responses were recorded and notes were taken during the interviews. The recorded interviews were transcribed for further analysis, with each interview lasting between 30 and 60 min.

The study used the qualitative content analysis (QCA) method to analyse the collected qualitative data. Hsieh and Shannon (2005) defined QCA as a research approach for subjectively interpreting text data content through systematic coding and theme/pattern identification. This technique aims to identify themes and reveal the meanings of the textual content, thereby contributing to a better understanding of the phenomenon under study (Downe-Wamboldt, 1992). Incorporating concepts from existing theories assists qualitative studies in coding and analysing data (Berg, 2001). Hsieh and Shannon (2005) identified three approaches to content analysis: conventional, directed and summative. Conventional content
analysis is suitable when there’s a lack of existing literature on a phenomenon and themes are derived directly from the data itself. Directed content analysis is used when existing research or theories exist, but further exploration is needed. Summative content analysis focuses on identifying and quantifying specific words or contents within texts to understand contextual meanings. In this study, interviews were analysed using QCA, and due to the presence of the UTAUT model and the SQB theory, directed content analysis is chosen to align with available predetermined themes.

3.1 Findings of the interview analysis
The key points of the interviews are summarised with the help of Word-Clouds (WCs). A WC is a visual representation of keyword frequency in qualitative data, such as interviews. The higher the frequency of a word, the larger it is in the chart. WCs are used in exploratory textual analysis to facilitate the extraction of the insights from data sets. Expressive clouds typically require data manipulation; for instance, synonyms should be combined into a single word or phrase to accurately reflect their prominence (Displayr, 2023). In this research, terms such as “of course, definitely, and certainly” are consolidated into “sure”.

Four WCs summarise the main themes of the 13+ interview questions. For a comprehensive view, all clouds are presented in Figure 3. The clouds were generated using the Displayr analysis and reporting software for survey data (Displayr, 2023).

Firstly, Figure 3(a) summarises the viewpoints on the “impact of the technology on the students”. As depicted in the chart, “yes”, “save-time”, “helpful” and “sure” were the most common responses in approximately 70% of replies, indicating an anticipated positive impact on students. The envisaged advantages included a 24/7 “assistant” to “answer”

![Figure 3](image-url)
questions, “collect” data, assist with “programming” and help with “research, writing, and summarising content”. Subject-3, for example, was definite in his answer: “Yes, of course. It would be much better than google search as it collects and presents content, not only refers to URLs [...] it will help students to improve their knowledge and skills”. Conversely, around 30% of participants expressed reservations about focusing solely on technology’s positive aspects. The term “it-depends” in the chart highlights their concerns. The drawbacks mentioned included “overreliance”, reduction in “incentives”, excessive use in “assignments/projects”, requirement of “verification and further exploration”, “fabricated citation and content” and concerns about “lazy” students getting “lazier”. Accordingly, they see that “precautions” including new academic standards must be in place before any official allowance of the technology. Subject-2 confirmed: “AI bots should be allowed only after a certain stage, much like calculators in math classes, which are only allowed after all basic mathematical operations are well-understood and well-practiced. Then calculators become a handy tool to allow students to do more complicated tasks. Otherwise, if introduced too early, it can limit the students’ cognitive abilities and skills. Similarly, chatbots should be introduced after students have learned how to do their own research, formulate their own arguments and write their own essays”.

Figure 3(b) summarises the perspectives on the “impact of the technology on the instructors”. Almost 80% of the subjects were positive with common answers like “yes”, “helpful”, “save-time” and “reduce-burden”, in terms of writing “announcements”, responding to “emails”, course “planning”, collecting and preparing “materials” and students’ “assessments”. Subject-7 shortly answers “[...] in a way similar to a secretary or even a teaching assistant”. The remaining subjects were “moderately” positive, with answers revolved around tasks that AI still cannot help much with, including class “discussions”, human “explanation”, “innovative” ideas and “cognitive-skills”. Subject-3 asserted that chatbots “not so useful in terms of actual teaching tasks”.

Figure 3(c) depicts the “impact of the chatbot adoption on the public utilisation of the technology”. About 85% of the respondents were confident about the positive influence of the academia on the society and students, whose interest in AI, when increased due to the academia adoption, will be eventually and significantly reflected on the whole community. Subject-2 argued that “education will signal the general public that a new reliable source of information and knowledge is currently available. Students will be impressed by the tool and be inclined to learn more about the technology behind”. Conversely, “maybe” in the middle of the chart shows the viewpoint of the rest of the respondents who argued that academia does not currently have much influence. Subject-1 thinks that “influencers, celebrities, and social media have much more power than academia”. Subject-17 hesitated as he thinks that “industrial and commercial sections are already ahead of the academic institutes”. But he also added, “Whoever would try chatbots will definitely be impressed with their capabilities and will like to explore further”.

Finally, Figure 3(d) shows the most controversial part of the interviews: the inhibitors of the chatbot adoption in the educational process. Most of the respondents, though split around the adoption with “yes” and “it-depends” answers, expected that “unfair” assessments and “illegal/dishonest” use are highly probable. Some respondents confirmed that any official allowance of the tool should be accompanied with new “different” standards, assessment and evaluation methods and rubrics that must focus more on the comprehension, analysis and critical thinking. They added that discussions, presentations and oral exams should be adopted more in classes to ensure that students understand what they submit. Other respondents agreed that a set of “precautions”, including AI-enabled “detecting” algorithms, similar to plagiarism checkers, must be available before the
technology adoption. Subject-7 confirmed that “education is changing and we should be ready and adapt”. Subject-15 argued, “ChatGPT is still in an infancy stage and we still need to think how to regulate and control things […] other associated applications are required to overcome the assessment problems”. Subject-17 suggested three stages of adoption: allow, assess and adapt. In contrast, Subject-1 was totally against the immediate adoption: “the anticipated negatives of becoming over-dependent on AI outweighs all the positives. I think it will kill many of the students’ skills”.

3.2 Themes extracted from interview analysis

The analysis of the interviews revealed two types of themes: enablers and inhibitors to the Intention to Use ChatGPT (IUCG). Regarding the enablers, all respondents confirmed during the introductory part of the interview that current chatbots are easy to use. Thus, perceived EE is considered a key factor. In addition, Part A and Part B of the interview, related to the potential impacts on students and instructors, respectively, imply that educators’ autonomous motivation (EAM) is expected to be important for the educator’s intention. Two educators in social sciences showed no excitement and declined to be interviewed. Subjects who expressed enthusiasm and certainty about the usefulness and innovativeness of chatbots were technology-oriented. Accordingly, the educators’ innovative behaviour towards technological agility (IBTTA) is expected to have a critical influence to evaluate. Moreover, in Part C of the interviews: impact on the public utilisation, 85% of the respondents confirmed that adoption positively influences society’s overall competency, including learners and educators. Therefore, perceived learners’ AI competency (PLAIC) and educators’ competency are expected to have significant impacts on the adoption intention. Finally, enhancing the perceived students’ engagement (PSE), as a critical factor in the educational process, should be measured to complete the enablers’ argument.

On the other hand, four inhibitors, related to the resistance to the technology adoption, were identified. From Part A of the interviews (the impacts on students) and Part D (the inhibitors of the chatbot adoption), it could be readily extracted that the variables with most influence over the educators’ resistance include perceived unfair evaluation of students (PUES), perceived fraudulent use of ChatGPT (PFUC), perceived students’ overreliance (PSO) and perceived bias/inaccuracies (PBI).

3.3 Hypotheses development

This section provides operational definitions for the variables and outlines the development of hypotheses derived from the interview data. These components form the foundation upon which the adoption model is constructed.

3.3.1 Perceived educators’ effort expectancy (PEEE). In technology acceptance models (TAMs), “perceived” generally refers to the individual’s belief or perception of a particular factor. Perceived EE refers to how easy or difficult a user thinks a new technology to be and how much effort they believe they will have to exert in using it. Simply, it refers to how “user-friendly” a user thinks the technology is. EE was introduced in the UTAUT model, referring to the degree of ease associated with the use of an innovation (Venkatesh et al., 2003). EE has been confirmed as a significant predictor of the intention to use a technology (Rehman et al., 2021; Walle et al., 2023). It is generally accepted that the easier an innovation is, the more likely users are to accept it (Davis, 1989). In the context of chatbots, PEEE can refer to how easily educators interact with ChatGPT, ease of understanding its responses and the amount of effort required to use it effectively for each specific task. PEEE is therefore expected to have a positive significant impact on the intention to use ChatGPT. This hypothesis is backed by the fact that ChatGPT is designed to be easy to use and
requires minimal effort to interact with. In addition, as previous research has shown EE as a key determinant of technology acceptance, it is likely to be in the context of chatbots. Therefore, it can be hypothesised that:

**H1.** PEEE has positive significant impacts on Intention to Use ChatGPT (IUCG).

### 3.3.2 Educators’ autonomous motivation (EAM)

Autonomous motivation basically occurs when a user engages in an activity because they want to do it, not because they have to do it. It is the opposite of extrinsic motivation, which is when someone does something for external rewards or punishments. EAM refers to the motivation of educators to engage their students in teaching activities based on the satisfaction and enjoyment intrinsic in the activity itself or because they judge the activity to be useful. In the context of chatbots, EAM can refer to the extent to which educators are motivated to use ChatGPT as a teaching tool because they perceive it personally satisfying and beneficial for students. Among several other studies, Vansteenkiste et al. (2004) confirmed a positive influence of AM over the intention to engage in a particular behaviour. Gagné and Deci (2005) found AM even a stronger predictor of behaviour than controlled motivation. With respect to this study, educators who are intrinsically motivated to use ChatGPT as a teaching tool are more likely to use it effectively and consistently. This study assumes that EAM is a significant predictor of behaviour and is likely to play a key role in the context of ChatGPT. Therefore, it can be hypothesised that:

**H2.** EAM has positive significant impacts on IUCG.

### 3.3.3 Perceived learners’ AI competency (PLAIC)

Perceived competency is a measure of a person’s belief in their ability to use a particular technology. In this research, PLAIC refers to the degree to which an educator perceives that using ChatGPT, as a teaching tool will enhance learner’s AIC, i.e. enhance the students’ capability to use AI applications. In the extant literature, perceived digital competence (PDC) is the extent to which a person feels they have the necessary skills and knowledge to use an innovation. PDC is found to have a significant impact on the acceptance and adoption of technology (Venkatesh et al., 2003). People who believe they are competent in using a technology are more likely to use it (Hatlevik, 2017).

If educators believe that using ChatGPT will improve the learners’ ability to understand and apply AI as a major skill in our contemporary world, it could be assumed that educators are more likely to adopt and use it consistently. Improving learners’ AIC, as a subcategory of their PDC, is supposed to amplify the perceived usefulness of chatbots technology and enhance further the educators desire to use it. Accordingly, it can be hypothesised that PLAIC has a positive significant impact on the intention to use ChatGPT:

**H3.** PLAIC has positive significant impacts on IUCG.

### 3.3.4 Perceived educators’ competency (PEC)

PEC refers to the extent to which an educator believes that using ChatGPT will improve their knowledge competency, i.e. their ability to use technology. If educators believe that using ChatGPT will improve their PDC, i.e. improve their skills and knowledge with respect to the use of a new technology, it could be assumed that they are more likely to adopt and use it consistently. Moreover, improving PDC will have a reciprocal influence on the use of technology in general and chatbots, in particular, which is supposed to increase the perceived usefulness of the adoption and further enhance the educators’ desire to use the technology. Lu et al. (2019) confirmed a significant impact of the “need for competence” (i.e. the need to feel capable of effective
performance, participation and achieving goals) on the perceived ease of use, perceived usefulness and intention to use a technology. Therefore, this study assumes that educators who believe that using ChatGPT could enhance their knowledge competency are more likely to have the intention to use it. Therefore, it can be hypothesised that:

**H4.** PEC has positive significant impacts on IUCG.

### 3.3.5 Innovative behaviour towards technological agility (IBTTA).

Innovativeness, in non-technical terms, is how open a person is to new ideas and innovations and how likely they are to adopt new technologies early. According to Agarwal and Prasad (1998), personal innovativeness is characterised by an individual’s willingness and enthusiasm to experiment with a new innovation. Users who possess a higher degree of personal innovativeness tend to have a greater intrinsic motivation towards adopting new technology (Dabhokar and Bagozzi, 2002). This logic is supported by research as the innovative behaviour is confirmed to have an impact on the adoption of an innovation (Ramos-de-Luna et al., 2016; Schmidthuber et al., 2020). In this study, IBTTA refers to the characteristics of educators, indicating their degree of willingness to experiment with the cutting-edge chatbot technology. Specifically, educators who are more willing to adopt new technologies and open to change are more likely to have a greater intention to use ChatGPT as a teaching aid. IBTTA is thus hypothesised to have a positive and significant impact on the intention to use ChatGPT:

**H5.** IBTTA has positive significant impacts on IUCG.

### 3.3.6 Perceived students’ engagement (PSE).

A student who feels excited about learning new things and is motivated to do well in class would be considered to have high perceived engagement. Technically, PSE is characterised by the extent to which students exhibit attentiveness, inquisitiveness, enthusiasm, positivity and dedication during the process of learning or receiving instruction (Andama, 2020). This encompasses the level of drive they possess to gain knowledge and advance in their academic pursuits. Highly engaged students are more likely to benefit from the learning activities and to have a positive attitude towards using new technology. Moreover, their teachers are more likely to seek out and adopt new technologies and resources to further improve student engagement. According to Zhang et al. (2017), students who were highly engaged in online learning were more likely to use and benefit from technology tools. Educational technology is thus linked to students’ engagement (Bond et al., 2020). Therefore, faculty members who perceive that ChatGPT can enhance students’ engagement tend to be more motivated and interested in the technology, which could lead to a greater willingness to use it. It can then be hypothesised that:

**H6.** PSE has positive significant impacts on IUCG.

### 3.3.7 ChatGPT resistance (CGR).

Samuelson and Zeckhauser (1988) asserted that SQB encompasses three distinct descriptive elements: psychological commitment, cognitive misperceptions and rational decision-making. Their research findings solidified the notion that SQB acts as a form of resistance within external systems. In a similar vein, Polites and Karahanna (2012) contended that users, when displaying inertia, develop a strong attachment to and persist in using an existing system, even in the presence of superior alternatives or incentives for change.

Technology resistance is subsequently defined as an individual’s reluctance or refusal to adopt new technologies. This could be due to a variety of factors, such as fear of the unknown. In the context of this study, ChatGPT resistance (CGR) is the resistance exhibited by educators towards the innovation due to the possibility of altering the current state of
contentment or conflicting with their beliefs. According to Ajzen (1991), attitudes, subjective norms and perceived behavioural control are the key factors that influence an individual’s intention to adopt a new technology. If educators have a negative attitude towards ChatGPT due to their resistance to change, their intention to use it would be decreased. Moreover, educators who are uncertain about how ChatGPT could influence teaching and learning practices may be hesitant to use it. Oreg (2003) confirmed that fear of the unknown is a significant predictor of resistance to change. In addition, the educators may resist due to incongruity with their beliefs, which according to Pajares (1992) have a significant role over teachers’ decision-making. Educators who believe that traditional methods of teaching are more effective than technology-based approaches may be resistant to using ChatGPT, leading to a negative impact on their intention to use it. Accordingly, this study assumes that CGR negatively affects the educators’ intentions to use ChatGPT:

\[ H7. \text{CGR has negative significant impacts on IUCG.} \]

3.3.8 Perceived unfair evaluation of students (PUES). Perceived unfairness refers to the belief that an evaluation is biased by whatsoever means. In this context, PUES refers to educators’ belief about unfair, imprecise, imbalanced or discriminating assessment of students if they produce ChatGPT-based assignments. Khalil and Er, (2023) confirmed that chatbots could provide students with a simple way to generate scholarly essays on demand, inside the class and remotely. Instructors may thus believe that using AI bots may not reflect the students’ true ability or effort or may produce work that is too advanced or sophisticated for the students’ level of knowledge or understanding. They may also believe that chatbots might undermine their ability to accurately assess students’ learning outcomes or to provide any meaningful feedback. In addition, there may be concerns about potential plagiarism by the students, which is typically challenging to detect (Akgun and Greenhow, 2022; Mhlanga, 2023). Instructors’ belief in any of these concerns might lead to a resistance towards using the technology. Accordingly, this study expects positive significant impacts of PUES on the resistance and hypothesises that:

\[ H8. \text{PUES has positive significant impacts on CGR.} \]

3.3.9 Perceived fraudulent use of ChatGPT (PFUC). Perceived fraudulent use is the belief that someone is using a system or resource for fraudulent purposes. PFUC refers to the perception among educators that ChatGPT could potentially be used to retrieve improper, illegal, unethical or inappropriate content that could negatively influence students’ overall performance or ethics. This perception could lead educators to be hesitant to use the tool in the educational context. Fraudulent use of ChatGPT is a current research topic and several studies have provided evidence to support the argument (AlAfnan et al., 2023; Mhlanga, 2023; Sok and Heng, 2023). Ray (2023) argued that the existing capabilities of GPT-3 raise the concerns about its probable misuse. Kasneci et al. (2023) warned about the risks of unethical deployment that could lead to loss of integrity. It could then be assumed that educators who perceive ChatGPT as a potential tool for fraudulent use may be more resistant to adopt it. In conclusion, this study expects positive significant impacts of PFUC on CGR and hypothesises that:

\[ H9. \text{PFUC has positive significant impacts on CGR.} \]

3.3.10 Perceived students’ overreliance (PSO). PSO refers to the belief that students are relying too much on a specific technology to complete their tasks. This can include using technology to find answers to questions, complete assignments or writing essays.
Technically, PSO refers to the educators’ belief that the overdependence of the students on chatbots might imply killing their interest in the traditional sources of learning, including books, and consequently impairing their logical reasoning, critical thinking and intellectual development. Sok and Heng, (2023) warned about the overreliance on AI, as students who are habitual of preparing their assignments at the last minute, for example, may be benefited from the convenience of using chatbots to prepare their work without developing any skills targeted by the assignments. ChatGPT have been claimed to be harmful for the students problem-solving and critical thinking skills (Kasneci et al., 2023; Mhlanga, 2023; Shiri, 2023). It is then intuitive to assume that educators who recognise the negative impact of the overreliance on ChatGPT may be more likely to resist it and instead tend to recommend other sources of information to engage the students more in critical thinking and problem-solving activities. Thus, it is rational to expect that PSO can lead to an increase in the educators’ CGR. Hence, this study hypothesises that:

**H10.** PSO has positive significant impacts on CGR.

3.3.11 **Perceived bias/inaccuracies (PBI).** PBI refers to the belief that a particular source of information is biased or inaccurate. This can be due to a number of factors, such as the source’s political or ideological leanings, the way that the information is presented or fed into the system or even malfunctioning technology. In this study, PBI refers to the degree to which an educator perceives that the object produced by a student is biased, inaccurate or does not conform to the correct values or standards. This assessment can arguably influence the educators’ perception of the quality of the content produced by any technology and hence their intention to use it. Several studies have explored the impact of bias and inaccuracies in NLP models, including ChatGPT, and thus recommended a continuous human supervision to deal with the challenge (AlAfnan et al., 2023; Kasneci et al., 2023; Ray, 2023; Sok and Heng, 2023). In March 2023, Bing chat, based on the same model of ChatGPT, in its answer to our question about its limitations says: “The responses I generate are not always accurate or complete, and users should always verify information before relying on it”. Same conclusion is confirmed by Mhlanga (2023) who argued that a main challenge of ChatGPT is the potential bias in its output that needs continuous human monitoring. Other studies highlighted the presence of systemic biases in popular chatbots data sets, which can lead to inaccurate model predictions (Bender and Friedman, 2018; Thomas McCoy et al., 2020). Accordingly, this study assumes positive significant impacts of PBI on CGR.

**H11.** PBI has positive significant impacts on CGR.

### 3.4 Proposed model of the study

As detailed in Section 2.4, this study examines the factors that either facilitate or impede the adoption of the chatbots innovative technology in education. To establish its foundation, the study draws upon the UTAUT and SQB theories. Subsequent to this, the interview protocol is designed to specifically address both the drivers and barriers, incorporating a structured set of questions alongside follow-up inquiries. The aim is to comprehensively explore the factors influencing the acceptance and resistance towards this innovation. The outcomes of these interviews, outlined above, unveil distinct themes categorised into two groups: enablers and inhibitors. The enablers that positively impact educators’ inclination to embrace ChatGPT comprise:

- Perceived effort expectancy;
- educators’ autonomous motivation;
• perceived learners’ AIC;
• perceived educators’ competency;
• Educators’ innovative behaviour towards technological agility; and
• perceived students’ engagement.

On the other hand, inhibitors, which contribute to educators’ reluctance to adopt the technology, encompass:
• perceived unfair evaluation of students;
• perceived fraudulent use of ChatGPT;
• perceived students’ overreliance; and
• Perceived Bias/Inaccuracies.

Based on the aforementioned findings, this study proposes a comprehensive model that encompasses both facilitators and inhibitors. The study anticipates significant direct impacts of facilitators on educators’ intentions to use ChatGPT. Notably, two components from the UTAUT model, namely, social influence and facilitating conditions, are omitted from the proposed model. Respondents did not provide substantial arguments regarding the significance or relevance of these components to chatbot adoption in an educational context. For example, regarding facilitating conditions, any computer with internet connection is more than enough for the chatbots usage.

The inhibitors are consolidated into a collective influence, anticipated to collectively heighten resistance towards the innovation in question. Furthermore, it is expected that this resistance factor will negatively affect educators’ intentions to use ChatGPT. The study also deliberately omits consideration of cost-related factors, such as transition cost and uncertainty cost, as discussed by SQB theory, owing to the reasonable and affordable nature of chatbots adoption. Proposed model of the study is shown in Figure 4.

4. Study 2: empirical testing of the proposed model
This research uses a mixed-method approach, which is considered more suitable when studying a phenomenon with incomplete existing research (French, 2017). This is particularly relevant to chatbots, for which research on their acceptance is still in its early

![Proposed model](Figure 4)

Source: Created by the authors
stages. Initially, interviews were conducted to gauge educators’ opinions about this phenomenon and to explore the key determinants influencing their intention to use ChatGPT. Subsequently, the study proposed a conceptual model, as depicted in Figure 4.

In the second phase, a survey was administered to test and validate the proposed model. The study utilised partial least squares-structural equation modelling (PLS-SEM) method to assess the psychometric properties of the measurement instrument and to test the hypothesised relationships of the model. Data analysis was conducted using SmartPLS 4.0 and SPSS 23.

4.1 Instrument development
For development of the scales, this study adopted measurement items of eight constructs found in prior relevant research within the domains of AI and information systems. In addition, four new constructs were introduced specifically for this study. Table 2 summaries these constructs and Appendix provides detailed information about their measurement items.

The eight constructs, adopted from the literature and slightly modified for the context of this study, include PEEE, EAM, PLAIC, PEC, IBTTA, PSE, CGR and IUCG. Furthermore, this study introduced four new constructs, each with specific item scales designed for them: PUES, PFUC, PSO and PBI. To ensure the validity of the newly designed items, they were reviewed by experts in the field of information systems. Four researchers, from different universities, shared their feedback and the scales were subsequently revised based on their input. For pre-testing of the scales, a group of experienced respondents was invited to complete the survey. The respondents showed their satisfaction with the survey in terms of its content, length, relevance and order.

For further validation, an exploratory factor analysis (EFA) was conducted following the completion of the final survey. The Kaiser-Meyer-Olkin value yielded a result of 0.908, indicating a reasonably adequate sample. Subsequently, the extraction column was examined in “Communalities” table where all values were higher than 0.3. In the “Total Variance Explained” table, the cumulative percentage reached 68.94%, surpassing the recommended threshold of 60%. In the “Pattern Matrix” table, the average loading for each construct exceeded 0.7. As a result, the outcomes of EFA affirm the sufficiency and adequacy of the scales.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Abb.</th>
<th>No. of items</th>
<th>References</th>
</tr>
</thead>
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<td>Perceived Educators’ Effort Expectancy</td>
<td>PEEE</td>
<td>4</td>
<td>Sun et al. (2014)</td>
</tr>
<tr>
<td>Educators’ Autonomous Motivation</td>
<td>EAM</td>
<td>4</td>
<td>Mullan et al. (1997)</td>
</tr>
<tr>
<td>Perceived Learners’ AI Competency</td>
<td>PLAIC</td>
<td>5</td>
<td>Huang (2021)</td>
</tr>
<tr>
<td>Perceived Educators’ Competency</td>
<td>PEC</td>
<td>5</td>
<td>Huang (2021)</td>
</tr>
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<td>Zeybek (2016)</td>
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<td>Perceived Bias/Inaccuracies</td>
<td>PBI</td>
<td>4</td>
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</table>

Table 2. Proposed model constructs, abbreviations, number of items and references

Source: Created by the authors
4.2 Sample
For model validation, data samples were gathered from universities in Pakistan using a survey method. Pakistan is home to 244 recognised public and private universities, all of which are endorsed by the Higher Education Commission. These universities collectively employ over 50,000 faculty members. The participants in this study were faculty members who actively employed ChatGPT for academic purposes. They were identified through an initial screening question at the outset of the survey questionnaire.

The research uses the PLS-SEM method to analyse the model. PLS-SEM is preferred over covariance-based SEM (CB-SEM) for complex models with numerous constructs that do not rely on the assumption of parametric data (Hair et al., 2017; Urbach and Ahlemann, 2010). This holds true for our model.

Selecting an appropriate sample size is crucial when using the PLS-SEM method. According to Hair et al. (2017), the sample size should be at least 10 times the highest number of paths leading to any latent variable in the PLS-SEM model. In our model, the maximum number of paths to a construct is 7. In addition, Stevens (2002) recommends 15 responses per predictor construct for least squares multiple regression. Considering the 12 variables in our model, a minimum of 180 cases is necessary. Furthermore, a power analysis using G*Power based on Cohen (1992) recommendations yielded a sample size of 178.

The survey ultimately garnered 269 responses. After rigorous data screening, 26 cases were excluded due to significant missing data, leaving 243 valid cases for model testing. This sample size exceeds the minimum requirements, ensuring robust statistical analysis despite the varying population of ChatGPT users and adopters in Pakistani universities.

Regarding university selection, the researchers employed a stratified sampling technique, selecting two public universities from each province based on the highest faculty member count. The survey was carried out across eight public universities situated in four provinces of Pakistan: Quaid-e-Azam University, University of the Punjab, University of Karachi, NED University of Engineering and Technology, University of Peshawar, University of Engineering and Technology Peshawar, University of Balochistan and Balochistan University of Engineering and Technology. Data collection occurred from February 2023 to March 2023 and involved a combination of in-person and digital methods.

In the physical approach, researchers directly engaged with potential respondents (faculty members), explaining the study’s purpose and requesting voluntary participation. All participants provided informed consent, ensuring clarity for addressing queries. For digital data collection, platforms like Facebook Messenger, WhatsApp and email were used. Participants received a survey link along with a comprehensive letter and consent form outlining the voluntary nature of participation and privacy safeguards. Only those who agreed and provided consent took part in the study.

To ensure fairness and minimise potential biases, a two-step sampling approach was used. The first step involved using stratified sampling to select universities, whereas the second step used convenience sampling to choose faculty members. The research methodology emphasised transparency, reduced biases and maintained participant anonymity. The demographic characteristics of the participants are illustrated in Table 3.

4.3 Data analysis and discussion of results
PLS-SEM method is used to test the relationships proposed in the model. Initially, EFA results confirmed the adequacy of the scales as presented above. Second, Harman’s single-factor test was employed to assess the presence of common method bias (CMB) in the data. The single factor extracted 30.5%, which is significantly lower than 50%. This indicates
that CMB does not exist in the observed data. In the following sections, we will conduct a measurement model analysis followed by an assessment of the structural model.

4.4 Measurement model analysis

The measurement model was evaluated using reliability and validity tests, recommended by Hair et al. (2017). Internal consistency reliability was assessed using Cronbach’s alpha (>0.6). In addition, CR > 0.7 and indicators’ reliability (>0.7) were examined. The results of these tests, presented in Table 4 (Columns 2, 3 and 4) indicate that all measures meet the criteria for reliability, except PLAIC3, whose outer loading was found to be lower than 0.7. Consequently, PLIAC3 was removed from the structural model analysis. Convergent validity was assessed using the average variance extracted (AVE). As shown in Table 4 (Column 5), all the AVE values are greater than 0.5, indicating the validity of the scales. Fornell–Lacker’s criterion and Heterotrait-Monotrait ratio (HTMT) are used to assess discriminant validity. The square root of the AVE for each construct, i.e. the diagonal elements in Table 5, exceeds the correlations between the construct and the other constructs, suggesting that the discriminant validity has been established. Similarly, Table 6 presents the results of the HTMT analysis, wherein the HTMT ratios between any two variables are less than 0.9, indicating the establishment of the discriminant validity (Henseler et al., 2015).

4.5 Structural model analysis

To evaluate the structural model, we used a bootstrapping procedure with 5000 bootstrap samples, in addition to default settings. The significance of the hypothesised relationships was assessed using the corresponding p-values and t-values, as illustrated in Table 7. Figure 5 displays the path coefficients and corresponding p-values, obtained from the bootstrapping procedure.

The empirical results indicate that 10 hypothesised relationships in the model are statistically significant at a significance level of p < 0.05, with only one hypothesis not being supported. Specifically, six factors exhibit positive and significant impacts on the educators’ intention to use ChatGPT, whereas one factor, namely, CGR, negatively influences the intention to use it. In addition, three factors were found to have positive and significant
<table>
<thead>
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<th>Construct</th>
<th>Cronbach’s alpha</th>
<th>Composite reliability</th>
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**Source:** Created by the authors
Table 5.
Fornell–Lacker’s criterion

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<tr>
<td>CGR</td>
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</tr>
<tr>
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<td></td>
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</tr>
<tr>
<td>IBTTA</td>
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<td>PBI</td>
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<tr>
<td>PEC</td>
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<td>0.362</td>
<td>0.376</td>
<td>0.611</td>
<td>−0.250</td>
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<td>0.621</td>
<td>−0.226</td>
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<td>−0.205</td>
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<td>PSE</td>
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<td>0.315</td>
<td>0.593</td>
<td>−0.281</td>
<td>0.437</td>
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<td>−0.175</td>
<td>0.343</td>
<td>0.809</td>
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<tr>
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<td>−0.565</td>
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<td>0.477</td>
<td>−0.309</td>
<td>−0.261</td>
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<td>0.840</td>
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</table>

Source: Created by the authors

Table 6.
Heterotrait-Monotrait ratio (HTMT)

<table>
<thead>
<tr>
<th>Constructs</th>
<th>CGR</th>
<th>EAM</th>
<th>IBTTA</th>
<th>IUCG</th>
<th>PBI</th>
<th>PEC</th>
<th>PEEE</th>
<th>PFUS</th>
<th>PLIAC</th>
<th>PSE</th>
<th>PSO</th>
<th>PUES</th>
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</tr>
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</tr>
<tr>
<td>IUCG</td>
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<tr>
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<tr>
<td>PEEE</td>
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<td>0.075</td>
<td>0.345</td>
<td>0.210</td>
<td>0.144</td>
<td>0.280</td>
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<tr>
<td>PFUC</td>
<td>0.392</td>
<td>0.353</td>
<td>0.407</td>
<td>0.681</td>
<td>0.255</td>
<td>0.484</td>
<td>0.602</td>
<td>0.232</td>
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<tr>
<td>PLIAC</td>
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<td>0.434</td>
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<td>0.650</td>
<td>0.346</td>
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<td>−0.218</td>
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<td>0.514</td>
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<td>7.297</td>
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<td></td>
<td>0.064</td>
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<td>0.064</td>
<td>3.374</td>
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<tr>
<td></td>
<td>0.150</td>
<td>0.053</td>
<td>2.817</td>
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</table>

Table 7.
Summary of the path coefficients, t-values and p-values

<table>
<thead>
<tr>
<th>Hyp. #</th>
<th>Path</th>
<th>Path coefficient (β)</th>
<th>Standard deviation</th>
<th>t-values</th>
<th>p-values</th>
<th>Sig. level</th>
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</thead>
<tbody>
<tr>
<td>H1</td>
<td>PEEE → IUCG</td>
<td>0.187</td>
<td>0.060</td>
<td>3.121</td>
<td>0.002</td>
<td>***</td>
</tr>
<tr>
<td>H2</td>
<td>EAM → IUCG</td>
<td>0.088</td>
<td>0.043</td>
<td>2.068</td>
<td>0.039</td>
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<td>H3</td>
<td>PLIAC → IUCG</td>
<td>0.214</td>
<td>0.053</td>
<td>4.037</td>
<td>0.000</td>
<td>***</td>
</tr>
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<td>H4</td>
<td>PEC → IUCG</td>
<td>0.198</td>
<td>0.046</td>
<td>4.275</td>
<td>0.000</td>
<td>***</td>
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<tr>
<td>H5</td>
<td>IBTTA → IUCG</td>
<td>0.170</td>
<td>0.043</td>
<td>3.915</td>
<td>0.000</td>
<td>***</td>
</tr>
<tr>
<td>H6</td>
<td>PSE → IUCG</td>
<td>0.155</td>
<td>0.057</td>
<td>2.702</td>
<td>0.007</td>
<td>***</td>
</tr>
<tr>
<td>H7</td>
<td>CGR → IUCG</td>
<td>−0.218</td>
<td>0.042</td>
<td>5.161</td>
<td>0.000</td>
<td>***</td>
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<tr>
<td>H8</td>
<td>PUES → CGR</td>
<td>0.514</td>
<td>0.070</td>
<td>7.297</td>
<td>0.000</td>
<td>***</td>
</tr>
<tr>
<td>H9</td>
<td>PFUC → CGR</td>
<td>0.064</td>
<td>0.057</td>
<td>1.122</td>
<td>0.262</td>
<td>NS</td>
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<tr>
<td>H10</td>
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<td>0.064</td>
<td>3.374</td>
<td>0.001</td>
<td>***</td>
</tr>
<tr>
<td>H11</td>
<td>PBI → CGR</td>
<td>0.150</td>
<td>0.053</td>
<td>2.817</td>
<td>0.005</td>
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</tr>
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</table>

Note: *p < 0.1; **p < 0.05; ***p < 0.01; NS = not significant

Source: Created by the authors
effects on “ChatGPT Resistance”, whereas significant impacts of one factor, “Perceived Fraudulent Use of ChatGPT”, on CGR were not confirmed. Firstly, PEEE is found to have statistically significant positive effects on IUCG ($\beta$: 0.187, $p < 0.002$, $t = 3.121$), providing empirical support for hypothesis $H1$. The empirical findings also confirmed a significant effect of EAM on IUCG, as proposed in $H2$ ($\beta$: 0.088, $p < 0.039$, $t = 2.068$). The impacts of PLIAC on IUCG were found to be significant ($\beta$: 0.214, $p < 0.000$, $t = 4.037$), supporting $H3$. The outcomes also revealed a significant relationship between PEC and IUCG ($\beta$: 0.198, $p < 0.000$, $t = 4.275$), providing empirical support for $H4$. IBTTA was found to have a significant influence on IUCG ($\beta$: 0.170, $p < 0.000$, $t = 3.915$), confirming $H5$. Finally, the results ($\beta$: 0.155, $p < 0.007$, $t = 2.702$) provided empirical support for $H6$ by demonstrating the significant relationship between PSE and IUCG. In addition, our analysis results also supported the negative impact of CGR on IUCG, as hypothesised in $H7$ ($\beta$: $-0.218$, $p < 0.000$, $t = 5.161$).

Regarding the four inhibitor factors that may increase resistance to using ChatGPT, the findings confirmed significant positive effects of PUES, PSO and PBI on CGR, supporting $H8$ ($\beta$: 0.514, $p < 0.000$, $t = 7.297$), $H10$ ($\beta$: 0.215, $p < 0.001$, $t = 3.374$) and $H11$ ($\beta$: 0.150, $p < 0.005$, $t = 2.817$), respectively. However, $H9$, which proposed a significant relationship between PFUC and CGR, was rejected ($\beta$: 0.064, $p < 0.262$, $t = 1.122$), indicating that the effects of “fraudulent use of ChatGPT” on “ChatGPT Resistance” are not prominent.

In summary, the empirical test results confirmed the proposed model, demonstrating that six key factors: PEEE, EAM, PLIAC, PEC, IBTTA and PSE, enable educators’ intention to use ChatGPT, while the resistance factor inhibits their intention. Furthermore, the resistance
ITSE

is enhanced by three factors: PUES, PSO and PBI. The final model of the study has an $R^2$ value of 0.721, indicating a 72.1% descriptive capacity of the model in explaining educators’ intention to use ChatGPT.

5. Discussion

The present study examined the factors influencing educators’ intention to use chatbots, especially ChatGPT, as AI-based assistants to support educators and learners in their teaching-learning activities. A mixed-method approach was adopted, incorporating theoretical foundations from the UTAUT and SQB frameworks, along with insights gathered from in-depth interviews with 17 educators. The study has developed a conceptual model aimed at elucidating the factors that either facilitate or impede educators’ intentions to use ChatGPT for academic purposes. A survey method was used to test the framework and the SEM technique was used to analyse the data.

The findings suggest that several factors play key enabling roles in shaping educators’ intention to use ChatGPT. These factors include perceived educators’ effort expectancy (PEEE), EAM, PLAIC, perceived educators’ competency (PEC), IBTTA and PSE.

PEEE and PEC emerged as significant predictors of the educators’ intention to use ChatGPT. Firstly, educators who perceive a minimal effort requirement of using ChatGPT are more likely to adopt it. Similarly, educators with a perception that using ChatGPT is essential for enhancing their knowledge competency are more attracted to its adoption. These results comply with the literature that confirmed a significant impact of both of EE (Davis, 1989) and need for competence (Lu et al., 2019) on the intention to use a technology.

EAM and IBTTA were also confirmed as key determinants of educators’ intentions. Educators who believe that ChatGPT will encourage their students to engage in learning activities autonomously and with enjoyment are more likely to perceive it as a useful and valuable tool. Moreover, educators who are more open to change and willing to experiment with new technologies are more likely to adopt ChatGPT. Consequently, innovative, adaptable and intrinsically motivated educators have a higher chance of recognising the potential benefits of chatbots and, therefore, are more willing to invest time and effort in effectively learning and using them. These findings are in line with previous research that has consistently demonstrated the strong predictive power of intrinsic motivation (Davis, 1989) and personal innovativeness (Dabholkar and Bagozzi, 2002) in technology adoption.

PSE and PLAIC were also proven to be critical and significant factors influencing the intention to use chatbots. These findings reveal that educators who believe that allowing ChatGPT can enhance the students’ attention, curiosity, interest, passion and AIC are more likely to be motivated to use it. These findings suggest that educators who see the potential benefits of using ChatGPT for their students, particularly in terms of developing their AI skills that are essential in today’s world, are more likely to use it. These results support the previous research that directly links educational technology to students’ benefit (Bond et al., 2020).

CGR, on the other hand, emerged as a significant barrier to educators’ intention to use ChatGPT. This study assumes that CGR is a composite construct that encompasses four factors: PSO, PUES, PBI and PFUC. Among these factors, three were confirmed to have significant impacts on CGR, namely, PSO, PUES and PBI.

Firstly, educators who perceive chances and are aware of implications of students’ overreliance on ChatGPT may be reluctant to use it. This finding implies that these educators would prefer their students to engage more with traditional sources of knowledge rather than with easier or faster methods that could impede the development of their skills in searching for and acquiring knowledge. PUES and PBI were also found to be significant
predictors of CGR. More specifically, educators who perceive risks of unfair evaluation or the chances of biased or inaccurate contents may be less likely to adopt the technology.

Interestingly, the construct of PFUS was found to have no significant impact on CGR. This finding suggests that educators are not particularly concerned about the possibility of cheating using chatbots. As presented above, educators are more concerned with unfair evaluation, as if they presume that students will inevitably use the technology. It is also perhaps due to their belief that cheating and plagiarism have always been possibilities and chatbots are just additional tools rather than an original method. It is also possible that they believe that there will be systems, processes and resources in place to identify fraud if chatbots are officially approved.

5.1 Theoretical implications

This study builds upon previous research to enhance the understanding of chatbot usage in the realm of education. It validates a two-factor model that incorporates both enablers and inhibitors in a single framework. While the enablers are derived from the UTAUT framework, the inhibitors draw inspiration from the SQB perspective. By postulating the impact of these factors on educators’ intentions, it elucidates which factor constructions serve as enablers and how incumbent constructions act as inhibitors to the adoption of a novel system. Identifying pathways for enabler and inhibitor constructions, along with theorising their impacts on user intentions to use ChatGPT, constitutes a significant contribution. This dual perspective provides a valuable set of theoretical explanations that can be further leveraged to identify similar constructions and relationships in other contexts.

The study introduces six new constructs within the technology adoption context. Two constructs, PLAIC and PEC, are adapted from previous work (Huang, 2021), with contextual modifications. The remaining four constructs represent novel contributions to the literature: PSO on ChatGPT, PUES, PBI and PFUC. The study also devises a set of scales to facilitate the measurement of these four newly proposed constructs.

Moreover, the research findings extend the existing body of literature on the theoretical models of technology acceptance. Specifically, the determinants of educators’ intention to use ChatGPT align with and supplement well-established theories such as UTAUT (Venkatesh et al., 2003), TAM (Davis, 1989), self-determination theory (SDT) (Deci and Ryan, 1985), social cognitive theory (SCT) (Bandura and McClelland, 1977) and theory of planned behaviour (TPB) (Fishbein and Ajzen, 1975). Firstly, autonomous motivation emerges as a pivotal determinant of educators’ intentions, aligning with SDT, which posits that individuals are more inclined to engage in behaviour when they perceive autonomy. Secondly, a tendency towards innovation proves instrumental in adoption intentions, underscoring the TPB notion that individuals are more likely to engage with technology if they hold a positive attitude towards it. In addition, perceived EE emerges as a significant factor in chatbot adoption intentions, in accordance with the UTAUT model. Similarly, the determinant of PSE, which suggests that educators are more motivated to use ChatGPT if they perceive it as effective in enhancing students’ engagement, resonates with TAM, where perceived usefulness is a recognised factor influencing technology acceptance. Finally, the study highlights the importance of perceived learners’ AIC as a determinant of educators’ intentions to use ChatGPT, echoing SCT, which posits that people’s behaviour is shaped by their perception of the behaviour of others and the consequences of that behaviour.

When delving into the inhibitors, this research extends SQB theory by introducing CGR as an impacting factor, shedding light on why individuals may opt to stick with an existing system. It underscores that technology anxiety has subconscious roots, which can skew...
preferences towards maintaining SQB instead of embracing a newly introduced system. This addition broadens the SQB perspective and enhances our understanding of the dynamics at play in technology adoption.

5.2 Managerial implications
Chatbots have the potential to be a valuable tool for education systems. They can enhance students’ engagement by providing personalised learning experiences through tailored responses to each student’s needs and interests. Furthermore, they can also help students to stay motivated and learn more effectively. Moreover, they can be programmed to allow students to study at their own pace, as they are available 24/7 to answer questions and provide support. Chatbots can also collect data on student learning, track progress and identify areas of weakness.

On the other hand, chatbots can help to reduce educators’ workload by answering students’ questions, collecting materials, grading assignments and more. This can free up teachers to focus on other creative tasks, such as course planning, benchmarking and nurturing innovative students. They can also improve educators’ competency, leading to increased self-confidence and teaching capabilities.

In that respect, the findings of this study could provide policymakers and practitioners with valuable insights into the factors that influence educators’ adoption of conversational chatbots and leverage their full potential. Stakeholders should focus on addressing the enhancing factors and mitigating the resistance predictors identified in this study.

Firstly, the study suggests that EE is a key enabler, emphasising the importance of providing educators, especially those who are not tech-oriented, with adequate training and technical support to improve their chances of adoption. Secondly, the study recommends that educational institutions should promote innovation and cultivate a positive attitude towards technology among educators. This can be achieved by offering technology-related training and workshops and launching awareness programs by vendors. Thirdly, it is evident that autonomous motivation plays a crucial role in influencing intentions, highlighting the need to develop strategies to motivate educators towards autonomous behaviours. Recognition and rewards for those who adopt and use the technology can be effective in this regards. Fourthly, as educators expect chatbots to enhance their competency, practitioners should address the educational needs while developing new educational chatbot applications. Fostering a culture of innovation and experimentation can encourage educators to embrace the use of the technology, leading to the advancement of the field and better student preparation for the AI era. Finally, policymakers should consider incorporating features into educational chatbots that enhance students’ engagement and AIC. This can be achieved by incorporating AI-related materials in the applications and designing assignments to guide students while working on them. AIC is a valuable asset for students in today’s world and those who can understand and use AI will have an advantage.

On the other hand, practitioners should focus on mitigating the three identified concerns about the technology. Firstly, the findings highlight the need for a careful evaluation of any chatbot considered for use in education to ensure that it is free from bias and inaccuracies. In addition, it is important to establish new standards, mechanisms and tools that promote fair and transparent usage of chatbots, as well as reduce the presumed overreliance on them. For example, oral exams, discussions and presentations should be highly recommended as evaluation tools before allowing chatbots in education systems. AI plagiarism detectors, such as ChatZero and Turnitin, should be made available and enforced to detect any misuse. Such precautions can alleviate educators’ concerns and enhance their willingness to adopt the technology.
5.3 Limitations and future research

Although this study provides valuable insights into the factors that influence educators’ acceptance of ChatGPT, it is important to acknowledge that it still has several limitations. Firstly, the sample was limited to faculty members only, which restricts the generalisability of the findings. Exploring the perceptions and experiences of other stakeholders in education systems, such as, administrators, businesses, students and parents, would certainly add value. Secondly, this study focused on the usage of a single AI chatbot tool, ChatGPT, within a specific cultural and geographic context. This limitation may affect the applicability of the findings to other contexts. Therefore, future research should explore the acceptance of ChatGPT and other AI tools in different settings to gain a better understanding of the factors influencing their use and adoption. Thirdly, this study did not examine any moderating effects, such as education level and controlled motivation, which should be considered in future research as they are expected to provide further insights into the phenomenon. Fourthly, while the study identified several important determinants of educators’ intention to use ChatGPT, future research should investigate the actual use of ChatGPT in the classroom and its impact on teaching and learning outcomes. Finally, the study identified several factors that contributing to resistance in using ChatGPT, including concerns about unfair assessment, bias and inaccuracies in the tool. Future research could explore ways to address these concerns including the development of different standards for evaluation and assessment and improving the accuracy and reliability of the tools.

6. Conclusion

The present study offers a comprehensive exploration of the factors influencing educators’ intentions to use chatbots, especially ChatGPT, as AI-based assistants in educational settings. Through a mixed-method approach and the incorporation of established frameworks like UTAUT and SQB, this research has illuminated both the enablers and inhibitors of chatbot adoption among educators.

The findings highlight the significance of factors such as PEEE, EAM, PLAIC, PEC, IBTTA and PSE as key drivers in educators’ willingness to embrace chatbots. These factors emphasise the significance of educators’ views regarding ease of use, intrinsic motivation and the potential advantages of chatbots in improving student engagement and AI competence.

Conversely, CGR emerged as a significant barrier, with components like PSO, PUES and PBI, playing pivotal roles in educators’ reluctance to adopt chatbots. These findings emphasise the need for addressing concerns related to potential overreliance on chatbots, unfair evaluation and content inaccuracy.

The contributions of the study extend beyond the realm of education technology acceptance, enriching our understanding of the dynamics at play in the adoption of novel systems. It aligns with established theories like UTAUT, SDT, SCT and TPB, reinforcing the relevance of intrinsic motivation, innovation inclination, perceived EE and perceived usefulness in technology adoption.

Moreover, this research underscores the immense potential of chatbots in education, not only in enhancing student engagement but also in alleviating educators’ workload and fostering their competency. It highlights the need for ongoing training, support and a culture of innovation within educational institutions to facilitate chatbot adoption.

To harness the benefits of chatbots in education fully, policymakers and practitioners should take into account the study’s recommendations. They should prioritise training and support for educators, encourage a positive attitude towards technology and recognise and
reward autonomous adoption behaviours. In addition, efforts should focus on ensuring chatbot fairness, accuracy and transparent usage while addressing concerns about potential overreliance. Evaluation mechanisms and tools must be in place to maintain the integrity of education systems.

References


ITSE


Menabrea, F.L. and Lovelace, K.A. (1843), Sketch of the Analytical Engine Invented by Charles Babbage Esq, Taylor and Francis.


Appendix. Measurement items
Perceived Educators’ Effort Expectancy adopted from Sun et al. (2014) and modified slightly according to the context of the study

- PEEE1: My interaction with the ChatGPT is clear and understandable.
- PEEE2: It is easy for me to become skilful at using the ChatGPT.
- PEEE3: I find the ChatGPT easy to use.
- PEEE4: Learning to operate the ChatGPT is easy for me.

Educators’ Autonomous Motivation adopted from Mullan et al. (1997) and modified slightly

- EAM1: I use/allow ChatGPT because it’s fun for my students
- EAM2: I enjoy my using/allowing ChatGPT
- EAM3: I find to use/allow ChatGPT a pleasurable activity
- EAM4: I get pleasure and satisfaction from using/allowing ChatGPT

Perceived Learners’ AI Competency adopted from Huang (2021) and modified slightly

- PLAI1: Acquiring AI knowledge is beneficial
- PLAI2: Knowledge of AI based tools is crucial in understanding AI
- PLAI3: AI has changed life and learning to a great extent
- PLAI4: Intelligent chatbots are useful in our life
- PLAI5: It is worthwhile to know how AI imitates the human intelligence
**Perceived Educators’ Competency adopted from Huang (2021) and modified slightly**

- PEC1: Using ChatGPT will make my logical thinking stronger
- PEC2: Using ChatGPT will make my abstract thinking is stronger
- PEC3: Using ChatGPT will make my critical thinking is stronger
- PEC4: Using ChatGPT will make me good at observing
- PEC5: Using ChatGPT will make me good at analysing

**Innovative Behaviour towards Technological Agility adopted from Zeybek (2016) and modified slightly**

- IBTTA1: If I heard about a new agile technology, I would look for ways to gain experience with it
- IBTTA2: Among my peers, I am usually the first to try out new agile technology
- IBTTA3: I like to experiment with agile technology

**Perceived Students’ Engagement adopted from Zainuddin et al. (2019) and modified slightly**

- PSE1: Using ChatGPT motivates the students to listen very carefully in the class activities
- PSE2: Using ChatGPT motivates the students to pay attention in the class
- PSE3: Using ChatGPT motivates the students to make a hard effort in the class
- PSE4: Using ChatGPT motivates the students to work hard in learning activities

**ChatGPT Resistance adopted from Leong et al. (2020) and modified slightly**

- CGR1: I fear of wasting my time using ChatGPT.
- CGR2: It is unlikely that I use ChatGPT in the near future.
- CGR3: ChatGPT is not suitable for me.
- CGR4: I do not need ChatGPT.

**Perceived Unfair Evaluation of Students: New items designed by this study**

- PUES1: Students’ assessment is unfair if students use ChatGPT
- PUES2: Students’ assessment is imprecise if students use ChatGPT
- PUES3: Students’ assessment is unjust if students use ChatGPT
- PUES4: Students’ assessment is imbalanced if students use ChatGPT
- PUES5: Students’ assessment is discriminating if students use ChatGPT

**Perceived Fraudulent Use of ChatGPT: New items designed by this study**

- PFUC1: Students use ChatGPT to retrieve improper content
- PFUC2: Students use ChatGPT to retrieve illegal content
- PFUC3: Students use ChatGPT to retrieve unethical content
- PFUC4: Students use ChatGPT to retrieve inappropriate content

**Perceived Students’ Overreliance: New items designed by this study**

- PSO1: Overreliance of students on ChatGPT decreases students’ interest in books.
- PSO2: Overreliance of students on ChatGPT decreases students’ interest in classroom.
- PSO3: Overreliance of students on ChatGPT decreases students’ interest in lectures.
- PSO4: Overreliance of students on ChatGPT impairs their logical reasoning.

**Perceived Bias/Inaccuracies: New items designed by this study**

- PBI1: Using ChatGPT, students produce biased objects
- PBI2: Using ChatGPT, students produce inaccurate objects
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- PBI3: Using ChatGPT, students produce objects that do not conform to standards
- PBI4: Using ChatGPT, students produce prejudiced objects

Intention to Use ChatGPT adopted from Kaur et al. (2020) and modified slightly

- IUCG1: I expect my use of ChatGPT to increase in the future.
- IUCG2: I intend to use ChatGPT in the future.
- IUCG3: If I have an opportunity, then I will use a ChatGPT.
- IUCG4: I will always try to use a ChatGPT.
- IUCG5: I plan to use ChatGPT frequently.

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Corresponding author
Imdadullah Hidayat-ur-Rehman can be contacted at: imdad7371@hotmail.com

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