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Exploring key factors influencing the adoption of Generative AI in computing education: A study of Saudi Arabian universities

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Abstract

Generative Artificial Intelligence (GenAI) is rapidly transforming computer science education. This paper aims to explore the factors potentially influencing computer science instructors' and students' behavioural intentions to adopt GenAI tools in Saudi Arabia. This study employs a two-phase research design to examine and validate the factors influencing GenAI adoption among educators and students in Saudi universities. The study used a mixed method methodology. Data were collected by semi-structured interviews on students and instructors' perspectives and behavioural intentions on the use of GenAI tools in learning or teaching. A sample of seven instructors, based in Saudi Arabia, formed the sample for the study and they expressed satisfaction with their use of AI. The results were examined in relation to secondary literature. The findings proposed seven factors that influence GenAI adoption: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, AI Self-Efficacy, AI Trust, and Perceived Risk. These were all found to be important when it came to the teachers' adoption of GenAI. The paper proposes a framework encompassing all UTAUT factors, in addition to AI Self-Efficacy, AI Trust, and Perceived Risk, to encourage computer science teachers and students to embrace GenAI technologies in Saudi Arabian universities.

Keywords: Computer science instructors, Computer science, GenAI tools, Generative AI, Higher education.

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Contents

Contribution of this paper to the literature
The study proposes a framework to examine the important factors that affect the adoption of GenAI in the field of computer teaching and learning in Saudi Arabia universities and to test the validity of the framework by conducting semi-structured interviews.

1. Introduction

The rapid developments in Artificial Intelligence (AI) have made a marked impact on most areas of society and leading to profound changes. With the introduction of Generative AI (GenAI), a set of AI algorithms that utilise existing data, such as text, audio, or images, to generate new content (Mittal, Sai, Chamola, & Sangwan, 2024), a new phase of technological development has emerged. Such advancements offer a unique opportunity to transform tertiary computer education by enhancing assessments, progress prediction, tutoring, and self-learning (Bahroun, Anane, Ahmed, & Zacca, 2023). Within the computing education community, there is enthusiasm regarding GenAI models (Tran, Li, Rama, Angelikas, & MacNeil, 2023). These models have substantial potential to improve instructional strategies and enhance learning outcomes through the personalisation of educational content and exercises that correspond to the needs, progress, and learning experiences of students (Deriba, Sanusi, Campbell, & Oyelere, 2024). Although GenAI offers many advantages, it may lead to dependency and diminished critical thinking abilities (Konecki, Konecki, & Biškupić, 2023) as well as increase the risks of plagiarism and compromise academic integrity (Chaudhry, Sarwary, El Refae, & Chabchoub, 2023). For computing students and developers, AI-driven programming tools can assist developers through various means, including completion of code, translation of source code into pseudo-code, predicting API sequences, and helping in debugging. There are several Generative AI models known for their code output, these include CodeParrot1, StarCoder[2] by HuggingFace and ServiceNow (Li et al., 2023), Copilot by Microsoft [3], Gemini by Google[4] and Codex by OpenAI[5].

To examine the factors influencing the adoption of Generative AI in education, many studies have drawn on established technology adoption frameworks, including the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003) and the Technology Acceptance Model (TAM) (Davis, 1989). Various studies have also examined students' acceptance levels of GenAI technology in educational settings (Budhathoki, Zirar, Njoya, & Timsina, 2024; Habibi et al., 2023; Supianto et al., 2024), whereas other research has focused on educators' adoption of GenAI for teaching and assessments (Khlaif et al., 2024). Furthermore, many researchers have extended the current frameworks to include more factors, such as anxiety, as in Budhathoki et al. (2024) trust, perceived risk and moral obligation in Lai, Cheung, Chan, and Law (2024), and digital skills and human-ChatGPT interaction in (Masoomi et al., 2024). Our study examines the main determinants influencing the adoption of GenAI in computer science education within the context of Saudi Arabia. Previous research has investigated the incorporation of GenAI in Saudi higher education (Al-Zahrani & Alasmari, 2024; Alammari, 2024; Aldossary, Aljindi, & Alamri, 2024; Alotaibi & Alshehri, 2023; Faisal, 2024; Sobaih, Elshaer, & Hasanein, 2024). This study proposes a theoretical framework to examine the factors influencing computer science teachers and students to embrace GenAI technologies in Saudi Arabian universities.

Our study adopts a two-phase research design to examine and validate the factors influencing GenAI adoption among educators and students in Saudi universities. Seven factors were proposed for examination to assess their significance and better understand the perspectives of computer science and e-learning instructors: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), AI Self-Efficacy (AISE), AI Trust, and Perceived Risk (PR). PE, EE, and SI are consistently identified as key predictors of users' behavioural intention to adopt Generative AI tools (Elshaer, Hasanein, & Sobaih, 2024; Khlaif et al., 2024; Poudel & Bastakoti, 2024; Sobaih et al., 2024), whereas FC is reported as an important predictor in fewer studies, such as Poudel and Bastakoti (2024). In addition, trust has emerged as an important determinant of Generative AI adoption, reflecting users' confidence in the reliability of AI systems (Albayati, 2024; Jo, 2025; Rana, Siddiqee, Sakib, & Ahamed, 2024). Similarly, AI self-efficacy, defined as users' confidence in their ability to effectively use AI tools and technologies to accomplish specific tasks, has been shown to positively influence ChatGPT adoption (Tailor & Tailor, 2025). Conversely, perceived risk, reflecting concerns about possible negative outcomes of AI use, has been found to negatively affect intentions for ChatGPT adoption (Lai et al., 2024).

The proposed framework was evaluated by conducting semi-structured interviews with seven experienced and knowledgeable respondents, mainly from the perspectives of computer science and e-learning instructors. Subsequently, we analyzed the results and examined the importance of each of the seven proposed factors. This study aims to achieve the following objectives.

- Investigate the multifaceted impact of GenAI integration within the context of higher education by conducting a comprehensive review to identify the key literature relating to the current state of GenAI and its intersection with computer science education and programming courses, the gaps in this area, and to gain an understanding of frameworks and factors that are proposed in this field.
- Propose a theoretical framework to investigate the factors influencing the adoption of GenAI tools among computer science students and instructors in Saudi Arabian universities.

The remainder of this paper is organized as follows. Section 2 reviews the related literature on the integration of Generative Artificial Intelligence in Saudi Arabian education and its applications in computing education. Section 3 describes the research methodology, including the research design, the proposed theoretical framework, participant selection, data collection procedures, and data analysis methods. Section 4 presents the results and analysis, including findings from expert interviews, participants' demographic information, and factor analysis results. Finally, Section 5 examines the implications of the results, while Section 6 summarizes the main contributions, limitations, and proposes future research.

[1]https://huggingface.co/codeparrot
[2]https://huggingface.co/blog/starcoder
[3]https://copilot.microsoft.com/
[4]https://gemini.google.com/
[5]https://openai.com/index/introducing-codex/

2. Related Work

In recent years many international studies have examined the adoption of AI in education in general, although few focus on Generative AI in computing education, particularly within the context of Saudi Arabia, which is a serious gap in the academic literature. In this section, the focus is on research concerning the adoption of AI in Saudi Arabian higher education and the influence of GenAI on computing education.

2.1 The Integration of GenAI into Saudi Arabia's Higher Education

Saudi Arabia is interested in integrating GenAI into its universities and higher education system. However, few studies have focused on the impact of GenAI on higher education. Al-Zahrani and Alasmari (2024) presented a study to evaluate AIs impact on higher education in Saudi Arabia, which is crucial for the KSA economy and the goals of Vision 2030. This quantitative research analyses data gathered from a survey involving 1113 respondents. The study found that AI has great potential for personalised learning, administration, and students independent learning and self-efficacy, but it noted ethical challenges such as privacy and biases, highlighting the need for transparency. Participants believed AI could significantly impact tertiary education, such as enabling lifelong learning, whilst also being able to enhance learning, improve student experiences, and thus engagement. Moreover, the authors highlighted the need for robust and practical ethical guidelines, developed through industry and academic partnerships, to ensure responsible AI use. Evaluation methods are required to assess AI's role in education (Al-Zahrani & Alasmari, 2024). A mixed-method study by Alammari (2024) was conducted to investigate the application of GenAI in Saudi Arabian higher education. Data were gathered from 125 faculty members to assess their knowledge and comprehension of GenAI, covering aspects such as readiness, performance, and other uses. The participants agreed that, if applied appropriately, technology offers numerous advantages, such as enhanced academic performance. The participants believed that it played a role in enhancing their professional growth. However, there were concerns about students becoming too dependent on it, and issues related to plagiarism were highlighted. Based on the interview data, personalised learning emerged as a key advantage of GenAI. Conversely, some identified challenges include diminished critical thinking and potential disruptions to the teacher-student relationship. The research emphasised the need to identify and establish ethical frameworks to address problems such as plagiarism and unethical practices among students. The study also urges the integration of traditional and AI-based teaching methods, recommends longitudinal research to examine its effects, and highlights the importance of considering diverse stakeholder views for responsible GenAI use.

A comprehensive review was undertaken by Faisal (2024) to examine the potential benefits of integrating ChatGPT into the Saudi Arabia university sector. There is an emphasis on how it can improve teaching, learning, and students' experience. Meanwhile, a variety of concerns were highlighted, one of which is the overreliance that could reduce learners critical thinking and problem-solving ability if it is seen as a replacement for orthodox teaching methods. The author argues that research on students' opinions concerning ChatGPT in higher education is required to evaluate its potential benefits and challenges. There is also a need to acknowledge the factors that determine its adoption, such as utility, ease of use, and reliability, to guide higher education integration strategies (Faisal, 2024).

A study by Sobaih et al. (2024) investigated Saudi higher education students' acceptance and usage of ChatGPT in their learning. It utilised the UTAUT framework through the categories of performance, effort, and social influence. The study found that there is a need for faculty and administrative assistance to make better use of ChatGPT to improve educational outcomes. On the other hand, Alotaibi and Alshehri (2023) explored how universities in the kingdom use AI-learning to help students. The study stated that King Abdulaziz University (KAU) and Al Qasim University had progressed greatly in the field. The results highlight the necessity to effectively integrate AI into higher education to enhance learning outcomes and student experiences, in order to train students to effectively use AI. There are challenges, though, associated with the new technology, which include students being competent in the use of AI and enabling teachers to have the necessary skills and technical knowledge in the use of AI in their teaching and faculty duties.

Another study conducted in Saudi Arabia by Aldossary et al. (2024) examined undergraduate students' perspectives on the role of GenAI in their education. Its goal was to investigate the link between students' perceptions of AI and their different scientific subjects. The current study specifically used a descriptive quantitative methodology to collect data through structured questionnaires from 1390 students at 15 Saudi Arabian universities. The main conclusion of the study was that students will accept and positively view using GenAI tools in their learning. The study recommends enhancing GenAI usage in education by using it to help students develop key skills such as programming skills, innovation, and problem-solving in computer science, which are essential in their future careers. This can enhance the English reading and speaking abilities of individuals whose native language is not English. Moreover, it has the potential to enhance the diagnostic and reasoning abilities of medical students. In general, in a range of fields, it also promotes collaborative learning among students (Aldossary et al., 2024). These studies provide data on the adoption and implementation of GenAI in the University sector in Saudi Arabia. However, to the best of the researcher's understanding, this is the first study to propose a conceptual framework for investigating the reasons that persuade computer science educators and students in adopting GenAI technologies.

2.2. GenAI in Computing Education

Many studies have examined how Generative AI tools influence students' coding education. Hou et al. (2024) focused on the effects of GenAI on help-seeking behaviours among students of computer science, while Chan and Hu (2023) analysed students' perceptions of GenAI, including current and potential benefits and challenges within higher education. Furthermore, the overall impact of GenAI tools on students' learning in areas such as coding and this was evaluated by Yilmaz and Yilmaz (2023). Other research has focused on instructors' understanding, perceptions, and the factors that affect their adoption of the application of GenAI in tertiary educational settings. Ghimire, Pather, and Edwards (2024) showed how it is possible to integrate these tools into computer science teaching. Additionally, Zastudil, Rogalska, Kapp, Vaughn, and MacNeil (2023) provided an analysis of both students' and instructors' perspectives, providing clear insights into how these specific tools have begun to be utilised in computing education in recent years.

GenAI enhances computing education by providing personalised learning through targeted exercises and coding suggestions Michel-Villarreal, Vilalta-Perdomo, Salinas-Navarro, Thierry-Aguilera, and Gerardou (2023) while exposing students to diverse coding strategies that foster creative problem-solving (Zviel-Girshin, 2024). These tools offer real-time feedback with error explanations and debugging guidance through platforms such as GitHub Copilot. These help generate adaptable sample solutions (Deriba et al., 2024) and translate natural language prompts into functional code (Zviel-Girshin, 2024). GenAI assistants (e.g., ChatGPT, Codex, GitHub, Copilot) outperform students on complex computing tasks while evading plagiarism detection (Deriba et al., 2024; Wang, Diaz, Brown, & Chen, 2023). They bridge skill gaps for novice programmers by generating code, explanations, and exercises at varying difficulty levels (Deriba et al., 2024; Zviel-Girshin, 2024) while providing real-time error correction and project support (Deriba et al., 2024). Comparatively, GenAI supports instructors by automating tasks (i.e., grading, exercise generation) and tracking student progress (Deriba et al., 2024; Zastudil et al., 2023). It potentially improves teaching materials by identifying learning gaps (Deriba et al., 2024) and adapts content to diverse learning styles by providing numerous forms of instructional content. AI also assists in code quality analysis, freeing instructors for higher-level evaluations (Yu & Guo, 2023). Nevertheless, the application of GenAI in coding should be approached with caution due to the risks of bias, misinformation, and harmful content (Mahaini, 2024). GenAI can produce factually inaccurate outputs, requiring constant and systematic verification (Rajendran, 2023). Educators face challenges in assessing true student understanding and ensuring critical evaluation of AI outputs (Zastudil et al., 2023). Meanwhile, ethical issues, including plagiarism, copyright, and overreliance that hinder critical thinking, must be addressed (Yu & Guo, 2023). The aforementioned studies have highlighted the importance of updating teaching strategies, tests, and learning to integrate GenAI in the curriculum. Practical recommendations included the development of ethical guidelines alongside enhanced training for both students and faculty to ensure that the advantages of AI are leveraged to improve learner outcomes. Recent research predominantly focuses on assessing GenAI tools' functionalities, often overlooking their potential long-term implications and issues. Given the rising prevalence of these tools within computer science education, it is imperative that educators understand their potential impact on students' learning. This gap demonstrates the need for a more comprehensive examination of GenAI's multifaceted influence on programming curricula.

3. Research Design and Methodology

3.1. Overview of Research Design

The current study adopted a mixed-methods approach to examine and validate the factors influencing the adoption of Generative AI (GenAI) tools among computer science instructors and students in Saudi universities.

In the first phase, a conceptual model was developed through an extensive review of the literature, particularly studies employing the Unified Theory of Acceptance and Use of Technology framework. Additional constructs were incorporated based on prior research on AI and technology adoption, including AI self-efficacy, perceived risk, and trust. The second phase involved a qualitative study aimed at gathering in-depth insights from experts in e-learning and computer science education regarding the key factors affecting the adoption of GenAI tools. The qualitative findings were integrated with the existing literature to provide preliminary validation of the proposed research model. To further strengthen the theoretical propositions, semi-structured online interviews were conducted using an exploratory approach to assess the significance of the identified factors for GenAI adoption among computer science instructors in Saudi universities. All participants provided their informed consent prior to participation and were informed that their involvement was entirely voluntary. Each participant received the following statement.

"By continuing with the survey, you consent to the use of your responses for research and product development purposes. If you have any concerns, feedback, or questions, please contact a member of the research team". Additional details are provided in Appendix A1.

3.2. The Proposed Theoretical Framework for the Adoption of Generative AI in Computing Education

In addition to the core UTAUT constructs, it was essential to incorporate additional factors identified in the literature on AI and technology adoption, namely AI self-efficacy, perceived risk, and trust. Figure 1 illustrates the proposed research framework.

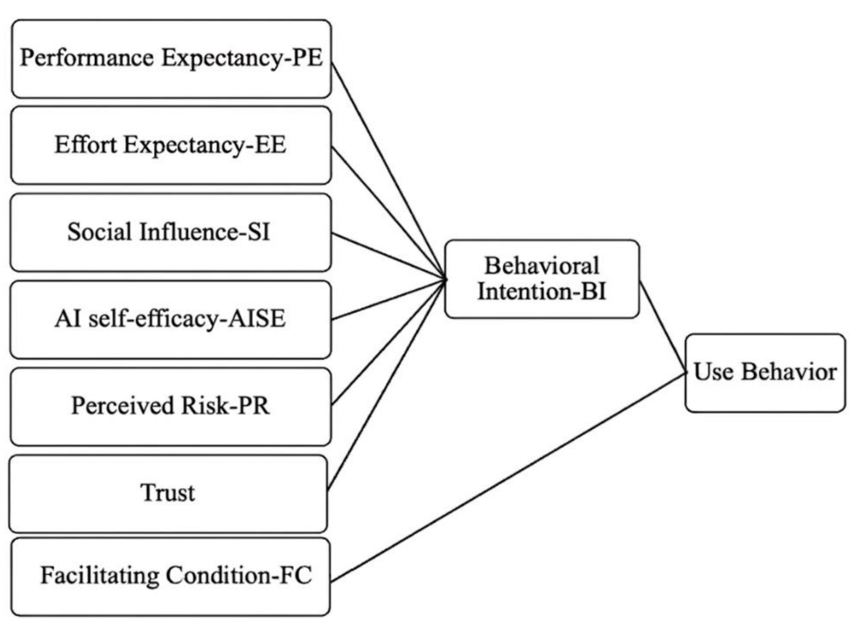

Figure 1. The proposed framework.

Venkatesh et al. (2003) identified four primary direct determinants within their UTAUT model for predicting user behavioural intention and acceptance of use. These factors are theorised to play substantial roles, as indicated below.

Performance Expectancy (PE), defined by Venkatesh et al. (2003) as: "...the degree to which an individual believes that using the system will help him or her to attain gains in job performance". The authors explained that the PE construct relates to 5 constructs from five previous models, which are: Perceived usefulness (TAM/TAM2 – C-TAM-TPB), extrinsic motivation (MM), job-fit (MPCU), relative advantage (IDT), and outcome expectation (SCT). The authors concluded that the PE construct was the strongest predictor of the users' behavioural intentions within the previous individual models. In the current study, PE refers to the degree to which computer science students and instructors in Saudi universities believe that using Generative AI tools will help them to attain better teaching and learning performance. Many prior studies have identified PE as a significant predictor of user behavioural intention to adopt Generative AI tools, such as Almahri, Bell, and Merhi (2020); Elshaer et al. (2024); Rajendran (2023); Poudel and Bastakoti (2024); Sobaih et al. (2024); Strzelecki (2024) and Yu and Guo (2023). However, the significance level of this relationship may vary depending on the context and type of AI application.

Effort Expectancy (EE), defined by Venkatesh et al. (2003) as: "...the degree of ease associated with the use of the system". The authors explained that the EE construct integrates 3 constructs from 3 previous models, which are: Perceived ease of use (TAM/TAM2), complexity (MPCU), and ease of use (IDT). In this study, EE refers to the degree of ease associated with using and adopting Generative AI tools. Consistent with prior studies, EE was identified as a strong predictor of user behavioural intention to adopt emerging technologies, including Generative AI (Elshaer et al., 2024; Khlaif et al., 2024; Poudel & Bastakoti, 2024; Sobaih et al., 2024).

Social Influence (SI), defined by Venkatesh et al. (2003) as: "... the degree to which an individual perceives that important others believe he or she should use the new system". The authors explained that the SI construct integrates 3 constructs from 4 previous models, which are: Subjective Norm (TRA, TAM2, TPB/DTPB and C-TAM-TPB), social factors - MPCU, and image-IDT. In this study, SI refers to the degree of the impact of others in believing users should use or adopt generative AI tools. Many scholars have identified SI as a strong predictor of user behavioural intention to adopt Generative AI tools, including (Elshaer et al., 2024; Khlaif et al., 2024; Poudel & Bastakoti, 2024; Sobaih et al., 2024).

Facilitating Conditions, defined by Venkatesh et al. (2003) as: "...the degree to which an individual believes that an organisational and technical infrastructure exists to support use of the system". The authors explained that the FC construct relates to three constructs that were used in the four previous models. The three constructs are the perceived behavioural control (TPB/DTPB, C-TAM-TPB), facilitating conditions (MPCU), and compatibility (IDT). In this study, FC refers to the existence of organizational and information technology infrastructure to support the implementation of generative AI tools. In comparison with PE, EE, and SI, few prior studies have identified FC as an important predictor of user behavioural intention to adopt Generative AI tools, including (Poudel & Bastakoti, 2024).

Self-efficacy is defined by Venkatesh et al. (2003) as "judgment of one's ability to use technology (e.g., computer) to accomplish a particular job or task". Therefore, this construct relates to the confidence of the individual in their ability to use a particular technology. In this study, AI self-efficacy, AISE, refers to the judgment of users' (i.e., CS instructors) ability to apply AI tools and technologies (such as generative AI tools) to accomplish a particular task. AISE has been shown to positively influence ChatGPT adoption (Tailor & Tailor, 2025).

Trust is generally defined as an individual's belief that a technology or system is reliable and capable of performing as expected while safeguarding the user's interests (Falcone & Castelfranchi, 2001; Roy, Dewit, & Aubert, 2001), as cited in Albayati (2024). AI trust in this study refers to the degree of confidence that users (students and instructors) have in the reliability, effectiveness, and integrity of the generative AI tools.

Perceived Risk (PR) is defined as "individuals' perception about the uncertainty and seriousness of consequences associated with a behavior" ((Bauer, 1967) as cited in Lai et al. (2024)). In this study, PR is relevant when users encounter situations with uncertain outcomes or where there is a risk of negative consequences from their decisions. PR is found to affect behavioral intention (Lai et al., 2024).

3.3. Participants and Sampling

The study adopted an exploratory qualitative approach using semi-structured interviews. Data collection continued until sufficient depth of insights was reached. The primary aim of this phase was to identify the significant factors influencing adoption of GenAI tools by computer science instructors and students at universities. This exploratory phase provided indicative validity for the factors included in the proposed study framework.

Participants were selected based on their relevant expertise and experience in e-learning and computer science education. Consequently, a total of seven participants who met the inclusion criteria, including faculty members who have experience in computer science, participated in the study. Notably, four out of seven participants previously used GAI tools in their courses. Table 1 presents a summary of the participants' demographic information.

Table 1. Participants demographic information.

Participant #	Country	University Name	Major
P-1	Australia	University of Adelaide	E-learning
P-2	Saudi Arabia	King Saud University	Computer Science
P-3	Saudi Arabia	Shaqra University	Software Engineering
P-4	Saudi Arabia	Saudi Electronic University	Information Technology
P-5	Saudi Arabia	Saudi Electronic University	Computer Science
P-6	Saudi Arabia	University of Jeddah	Computer Science
P-7	United Kingdom	University of Strathclyde	Information Technology

3.4. Data Collection and Interview Instrument

Data collection involved the use of semi-structured interviews to evaluate the extended UTAUT model. This data collection tool was used to investigate the factors influencing the adoption of generative AI in computer science education in Saudi universities. Every interview commenced with a collection of demographic and background information. This included age, gender, university, academic specialisation, and experience level in using generative AI in teaching. Protocols for the interview were developed by the researcher based on the extended constructs of the Unified Theory of Acceptance and Use of Technology framework. These constructs, which have been widely used in academic research, include the following: Performance Expectancy, Effort Expectancy, Social Influence, AI Self-Efficacy, Perceived Risk, Trust, and Facilitating Conditions. The constructs were operationalized and developed into open-ended interview questions. These questions aimed to capture the participants' opinions and views on the proposed model. This strategy ensured a comprehensive account of all the theoretical dimensions that was still flexible and allowed for elaboration and follow-ups. The relationship between the extended UTAUT constructs and each of the relevant interview questions is presented in Appendix A2. A pilot study was conducted to ensure the feasibility of the study, and this was carried out by a member of the faculty of the Saudi Electronic University. The faculty members met the inclusion criteria. The pilot study ensured that the interview questions could capture the required information. Feedback from the pilot study allowed for minor changes to the questions and their language so that they could more effectively capture the intended construct. The interviews were conducted online, which took place between May and July 2025. Each interview lasted approximately 30-45 minutes. The study received ethical approval from the Research Ethics Committee at the Saudi Electronic University, reference number [SEUREC-4654]. Appendix A3 illustrates Research Ethical Approval. Participants' concern regarding their privacy meant that the interviews were not audio recorded but were recorded in writing at the time of the interviews. The data were kept confidential, and participants' identities were anonymised. All the data were securely stored and only used for the stated research purposes.

3.5. Data Analysis

The data analysis employed a thematic analysis approach to examine participants' perspectives regarding their experiences with the study framework. An initial understanding was derived through a reviewing and reflective process by interpreting findings with a review of previous literature and introspective consideration of personal insights. In this study, the data analytical process consisted of three stages. First, organizing and structuring the data. Second, creating a coding schema to obtain the critical content within the interviewee transcripts, followed by applying this coding scheme to each identified participant comment. Third, developing themes to investigate the frequency and patterns within the results. This stage involved an iterative comparative analysis, whereby individual data were contrasted with other data elements and forms to determine similarities, differences, and data correlations.

The analysis provided both explicit and implicit findings from the interview data. The process of data coding ensured the thorough analysis of the interviews, which was an iterative procedure concentrated on establishing internal consistency and generating data links to the framework's components. Each interview provided valuable insights into the identified factors, clarifying how these elements are perceived in practical, real-world contexts. Generally, the resulting themes provide a clear understanding of the significance of the factors that have been added to the UTAUT model. Also, the results provided the opportunities and challenges involved in integrating GenAI tools into the teaching and learning processes.

4. Results and Analysis

4.1. Expert Interviews Analysis and Findings

This section presents the results of the email interviews conducted, with the interview analysis examining the perception of experts towards applying GenAI in computer science education. The findings of the interviews illustrated the relevant significant factors and correlations regarding using GenAI in computer science education. The participants responded to the interview questions concerning factors proposed in the study framework and their perception of the opportunities and challenges associated with integrating GenAI tools into teaching and learning processes.

To further explore the experience and future expectations of using GenAI tools, participants were asked to share their thoughts and intentions for future use. Among the four participants who applied GenAI tools in their courses, they expressed satisfaction (P-1, P-4, P-6, and P-7). Participants gave an Excellent (5) and a Good (4) rating for their overall experience with using GenAI tools in their teaching course. All participants (P-1, P-4, P-6, and P-7) also confirmed they intend to keep using GenAI tools in their teaching. A subsequent query inquired about the tools that participants use. P-1 listed several tools: ChatGPT, Claude, Copilot, Getimg.ai, 11Elevenlabs.io, and Udio beta. Where P-4 and P-6 each listed one tool: P-4 mentioned Gemini, while P-6 noted ChatGPT. P-7 listed multiple tools: ChatGPT, NapkinAI, LLMnote, and Grok.

4.2. Qualitative Findings

This section presents the empirical validation of the seven factors identified in the literature review, which constitute the proposed framework constructs influencing users' behavioural intentions to adopt generative AI tools. After discussing each factor using open-ended questions, participants were asked to rate each factor on a 5-point Likert scale from their perspective to assess its significance. The subsequent subsections present the findings for each factor and its sub-themes based on participant responses.

The factors are presented in the following order.

Performance Expectancy - PE, Effort Expectancy - EE, Social Influence - SI, Facilitating Conditions - FC, AI Self-Efficacy - AISE, Trust, and Perceived Risk -PR.

4.2.1. Performance Expectancy – PE

PE indicates the perceived usefulness and impact of GAI tools on instructors' performance. Overall, the qualitative findings indicate that PE has emerged as one of the strongest predictors that influence computer science instructors' intentions to adopt generative AI tools in computing education. The findings were consistent with prior studies that showed that PE was one of the strongest predictors (Elshaer et al., 2024; Poudel & Bastakoti, 2024).

Generally, seven participants highlighted the importance of this factor. Participants shared similar views, drawing on their teaching experiences, and believed that GenAI tools could improve their teaching. Participants (P-3, P-4, P-5, and P-6) emphasised the role of the tools in creating content for their courses, including assignments, quizzes, etc.; for example, P-5 stated that *"They can help with creating course materials, assignments, and exams; also, they can be utilised for grading as well"*. P-1 and P-7 highlighted that this is very relevant to computer science and is crucial for student involvement and diverse uses, such as brainstorming the course structure.

Five of the seven participants agreed that the tools enhance their teaching effectiveness, while two disagreed and stayed neutral. Participants P-1, P-3, P-4, P-5, and P-6 concurred that GenAI tools improve the CS course teaching. P-1 mentioned that "GenAI tools such as ChatGPT can provide tailored explanations and code examples, allowing students to learn at their own pace and revisit difficult concepts as needed". While he added that for the instructor, *"GenAI can be used to generate interactive exercises, quizzes, or real-world problem scenarios that enhance active learning and student interest"*. Meanwhile, P-7 disagreed that the tools make teaching CS courses more effective, adding, *"We cannot test the effectiveness of the tool; however, I experienced that we can make lectures engaging, especially with illustrations"*.

Regarding the role of GAI tools in enhancing productivity and instructors' academic performance, participants gave varied responses. P-1, P-3, and P-6 agreed that this saves their time, while P-4 and P-5 stated that it is valuable to create content. In contrast, P-7 emphasised that this tool has limited usage: "It helped me tackle the blank screen problem. GenAI helps with initiating a thought process; beyond that, *they are just tools without "cognition"*.

This finding suggested that performance expectancy plays a key role in computer science instructors' intention to adopt GAI tools.

4.2.2. Effort Expectancy – EE

EE indicates the ease of use relevant to computer science instructors' adoption of generative AI tools. Overall, the qualitative results show that EE positively influences computer science instructors' willingness to adopt generative AI tools in education. These findings align with previous research where EE was a key predictor (Elshaer et al., 2024; Poudel & Bastakoti, 2024; Rajendran, 2023; Sobaih et al., 2024; Yu & Guo, 2023). Typically, five participants emphasised the significance of this factor, while one was neutral; P-6 stated, *"I am not sure how such tools can enhance the teaching process itself"*. However, all six participants agreed, with P-5 noting that *"they can make the teaching process easier as instructors can use them to create course materials, such as PowerPoint slides, allowing them to focus more on preparing for lectures"*.

Regarding EE, participants were asked if they agreed that their interactions with students using GenAI tools would be clearer and more understandable. Responses were fairly split between agreement and neutrality. P-1, P-2, P-5, and P-6 were neutral, with P-5 noting, "generally, I think the generated data of GenAI needs to be evaluated by instructors." P-3, P-4, and P-7 agreed that these tools could enhance clarity. P-3, who strongly agreed, explained that *"GenAI tools can break down complex concepts into simpler language, helping instructors explain ideas more clearly to students with different levels of understanding"*. GenAI responses provide consistent, well-structured information for all students. Additionally, students can ask follow-up questions in real-time, creating a continuous clarification process that deepens understanding. The tools can also deliver answers via text and diagrams.

Therefore, the findings suggested that effort expectancy plays a key role in computer science instructors' intention to adopt GAI tools.

4.2.3. Social Influence – SI

SI indicates the influence of others and motivations for adopting generative AI tools among computer science instructors. Overall, the qualitative results indicate that SI may not affect computer science instructors' willingness to adopt generative AI tools in education. These findings are inconsistent with earlier research, in which SI was identified as a crucial predictor (Elshaer et al., 2024; Poudel & Bastakoti, 2024; Rajendran, 2023; Yu & Guo, 2023).

Generally, only three participants considered it significant, with two participants remaining neutral and another two viewing it as not significant. Most participants confirmed that their colleagues are already using these tools. The participants listed several reasons for utilizing GenAI tools, some of which include.

- Personal interest (P4, P-5, and P-7).
- Saving time (P-1, and P-3).
- Research and proofreading (P-1, and P-3).
- Gaining beneficial capabilities (P-6).

Responses regarding the role of the SI on instructors' decisions were nearly evenly split between agreement and disagreement, with one participant remaining neutral. P-1, P-4, and P-7 disagreed, believing that SI does not influence their decisions, with P-4 emphasising, *"it is the value, not SI"*. Conversely, P-2, P-3, and P-5 agreed, with P-3 highlighting the impact of SI, saying, *"as I've heard from my colleagues, GenAI tools can be used for summarising articles, grading assignments, and many other features that encourage individuals to use them"*.

Therefore, the findings suggested that social influence may not play a key role in computer science instructors' intention to adopt GenAI tools.

4.2.4. Facilitating Conditions – FC

FC indicates the availability of IT infrastructure and support for instructors to adopt generative AI tools. Overall, the qualitative results indicate that FC positively affects computer science instructors' willingness to adopt generative AI tools in education. These findings are inconsistent with earlier research, where FC was identified as a significant predictor (Poudel & Bastakoti, 2024). Generally, seven participants highlighted the importance of this factor.

Regarding FC, participants were asked whether they received support from their university in adopting or using GenAI tools. Indeed, five participants received some support. For example, P-6 commented that *"my university provided policies for using Generative AI tools"*. While two participants did not receive any support relating to AI tools from their university.

In addition, participants were asked whether they had attended training workshops on using the technologies required to operate GenAI tools. Only three participants attended seminars and workshops on technologies used in GenAI tools. P-1 stated that *"I received lots of online seminars and workshops. Also, I have designed a couple of courses regarding ethical AI use for students and staff"*.

Therefore, based on the significance rating of FC's construct, FC likely plays an important role in instructors' intentions to adopt generative AI tools.

4.2.5. AI Self-Efficacy – AISE

AISE reflects instructors' perceived ability and confidence in employing GAI tools to support their teaching and professional activities. The findings showed that there is a strong agreement on the significant role of AISE as a factor that influencing instructors' willingness to use GAI tools (Almahri et al., 2020). Participants linked their confidence in using GAI tools with their ability to integrate these GAI tools effectively into their teaching and work activities.

Relating to AISE, participants were asked about their confidence in using GenAI tools effectively in their role as a computer science instructor. Indeed, five participants felt confident of using AI tools effectively in their role, while two participants remaining neutral. According to P-7, *"I explored GenAI out of curiosity, learned about its tools and then use them in my teaching"*. The finding showed that instructors with higher levels of AISE are more likely to experiment with emerging technologies and innovative instructional methods.

In addition, participants were asked whether they think that AI self-efficacy can enhance the students' learning experience. Six participants agreed that AISE can improve the learning experience of students. According to P-6, *"GenAI tools can provide personalised content to the students which can be useful for them and provide them good experience"*. Also, P-7 commented that *"AISE is mother of all actions we take. If we do not have AISE, we will not perform an action"*. Participants viewed AISE as a basic requirement for successful GAI tool adoption. The findings confirmed that educators who have strong AI-related competencies are better equipped to provide guidance on the use of GenAI in teaching and learning activities.

4.2.6. AI Trust

AI Trust represents users' confidence in using GenAI tools and their reliability, which will influence their adoption and use of these tools. The findings show that AI Trust appeared as a multidimensional factor that affects the level of user confidence and their behavioral intentions to use GenAI tools in teaching and learning. These findings are aligned with previous studies that considered AI trust as a key predictor of user behavioral intention toward the adoption of GenAI tools (Jo, 2025; Rana et al., 2024). Overall, participants agreed on the importance of this factor.

Relating to AI Trust, participants were asked if they agreed that GenAI tools are effective and secure to use in teaching and learning courses. Five participants were neutral, while the remaining two participants agreed and disagreed. P-7 disagreed with this statement as they do not believe that GenAI tools are secure to use in teaching and learning roles. P-7 stated that *"these tools are still being developed, so still not foolproof and need more research"*. On the other hand, P-1 agreed with this statement and believed that GenAI tools can be effective and secure to be used in their roles. P-2, P-3, P-4, P-5, and P-6 were neutral regarding this point. According to P-5, *"security is a big concern in AI generally, so the output of GenAI tools needs to be evaluated"*. Additionally, P-6 stated that *"as any other information resources, GenAI tools should be checked in terms of accuracy, correctness and reliability"*.

Also, participants were asked if they agreed that the output and results of GenAI tools are honest. Interestingly, responses were almost evenly divided between agreement and neutral, with one participant remaining in disagreement. P-3, P-5, and P-6 were neutral about this statement, as they do not believe that the results of GenAI tools can always be reliable and accurate. While P-1, P-2, and P-4 agreed with the statement. But P-7 disagreed and stated that *"GenAI tools do not think. They simply predict what word will come next based on their training, so often they fabricate the text. So, it is not a case of honesty but reliability"*.

Participants viewed GenAI content as a valuable resource for supporting teaching and learning activities. Nevertheless, they emphasized the importance of reviewing and validating GenAI information before using it in educational context. This finding suggests that participants have trust in AI depending on its uses and the situation.

4.2.7. Perceived Risk (PR)

PR reflects users' perceptions about the potential risks and negative impacts associated with using GenAI tools. The findings showed that PR was identified as a significant factor that shapes participants' attitudes toward the adoption of GenAI in computing education (Lai et al., 2024). Participants highlighted several concerns relating to using GenAI, including student overreliance on these tools, academic integrity, privacy, and data security issues.

Relating to PR, participants were asked whether they could determine issues, such as plagiarism, associated with the GenAI tool usage by students. Participants shared various answers that were quite similar based on their experiences of detecting GenAI issues in students' work. For example, P-1 mentioned tools that can be used on the university system to support detecting any plagiarism in student work and stated that *"we have AI detection tools embedded in the learning management system; however, it's almost completely unreliable"*.

Participants highlighted the challenges related to detecting inappropriate uses of GenAI. Since educational organisations have increasingly employed AI-detection and plagiarism-detection tools, several participants revealed concerns about the accuracy, reliability, and effectiveness of these systems. This finding reflects a broader challenge that will be faced by educational organisations when ensuring appropriate accountability and regulation of the use of GenAI in academic contexts.

Also, participants were asked whether they could be disappointed if they found out that students used GenAI tools to complete their assessment. The main concern among participants was the students misuse of GenAI tools during assessments and coursework during assessments. Particularly, they expressed that the dependence on GenAI-responses could reduce the students' development of essential competencies, such as critical thinking, problem-solving, and analytical skills. For example, P-2, P-3, P-4, P-5 and P-6 expressed frustration that students have not made any effort and depend completely on GenAI to do their assignments, and this will affect their skills negatively. P-3 commented that *"the goal of the assignments is to improve students' critical and analytical thinking, so when they use GenAI tools without making multiple attempts to answer the questions themselves, it can negatively affect their thinking skills"*.

Another concern associated with the adoption of GenAI is privacy risks. Participants were asked whether they agreed that using GenAI tools would put their privacy at risk? Interestingly, four participants agreed with this statement and believed that users' privacy is an important concern when using GenAI tools. According to P-1, *"there is no trust regarding what the AI tools do with your data"*. Meanwhile, two participants disagreed with this point, and they thought that they could control the type of data collected from the user and one participant remained neutral. Many participants demonstrated that they are unsure about how GenAI tools collect, store, process, and share user data. Because the lack of transparency, this raised concerns about the information security and confidentiality of GenAI tools in an educational context. These concerns indicate that privacy considerations present an important barrier to GAI tool adoption and thus might affect instructors' willingness to integrate these technologies.

4.3. Participant Perspectives- Adding or Removing any Factors

To further explore participants' perceptions of any contributories or barrier factors not mentioned in this study, participants were asked to share their thoughts and suggestions regarding adding any motivational or barrier factors that may affect the use of GenAI tools in teaching and learning. The participants offered various suggestions and recommendations that aimed to enhance the use of GenAI tools in these domains. Three participants suggested additional factors, such as training and promotion, and developing an institutional policy for using GenAI tools in education. Moreover, one participant stated the need for efficient infrastructure and a model that could be used as guidance in adopting GenAI tools in education that were targeted at the appropriate tiers of user behaviour.

5. Discussion

To the best of the researchers' knowledge, this is the first study that proposed a theoretical framework to examine the factors influencing computer science teachers and students to adopt GenAI technologies in Saudi Arabian universities. To develop the framework that aims to investigate the factors that could influence computer science instructors' and students' behavioural intentions to adopt GenAI tools, a literature review was conducted on the studies that applied the UTAUT model in e-learning, technology adoption in the education field, investigating students or instructors' perspectives on behavioural intentions to use GenAI tools in learning or teaching, as discussed earlier in Section 2. As a result. Seven factors were proposed to investigate their significance to gain insights into computer science and e-learning instructors' perspectives: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, AI Self-Efficacy, AI Trust, and Perceived Risk. Subsequently, an exploratory qualitative study was conducted, with the proposed framework evaluated by conducting semi-structured interviews with seven experienced and knowledgeable respondents, mainly from the perspectives of computer science and e-learning instructors. The results provide rich data and evidence supplied by the participants on the significance of each of the seven proposed factors. The results reveal that all proposed factors are significant from the instructors' perspectives (see Table 2).

The analysis of the primary data supports the current literature by underscoring the significance of various factors influencing the adoption of GenAI) tools in teaching and learning processes. The initial study framework has been validated through a combination of literature review and expert insight. This study presents preliminary insights. There is a need for additional investigation and empirical research. Future work will expand to develop a statistical framework for identifying the significance of factors from computer science instructor and student perspectives. This will involve a quantitative survey across multiple universities. The teachers expected GenAI to meet their expectations and these are based on the requirements of the students and providing them with a positive learning experience. The sample was somewhat risk-averse when it came to using GenAI, even though they are very aware of its potential to improve students' outcomes. What is clear is that acceptance of the technology was conditional and that teachers, if they saw risks to the quality of teaching, would withdraw their support for the technology. There are widespread concerns about GenAI. However, their attitudes to this technology varied from teacher to teacher and some were more willing than others to accept it. The implications of this for Universities in the KSA are that they need to address the concerns of individual educators to ensure its widespread adoption in computing education.

Table 2. Summary of the key insights regarding the factors and the themes related to each that collected from seven experts.

Main Factors/ Sub Themes	# of Agreement	# of Neutral	# of Disagreement
1- Performance Expectancy (PE)	7	0	0
Better teaching experience	7	0	0
Increase teaching effectiveness	5	1	1
Enhancing productivity and academic performance	7	0	0
2- Effort Expectancy (EE)	5	2	0
Making the teaching process easier?	6	1	0
Interaction with students when using GAI tools would be clearer and understandable	3	4	0
3- Social Influence (SI)	3	2	2
The reasons for using GAI tools	Responses Vary		
The social influence encourages you to employ GAI tools	3	1	3
4- Facilitating Condition (FC)	7	0	0
University Support for GAI Adoption	Responses Vary		
Training and Workshops for GAI Tool Operation	Responses Vary		
5- AI Self-Efficacy (AISE)	7	0	0
Confidence in Using GAI Tools as a Computer Science Instructor	5	2	0

AI Self-Efficacy and Improving Student Learning Experience	6	0	1
6- AI Trust	7	0	0
Effectiveness and Security of GAI Tools in Teaching and Learning	1	5	1
Perceived Honesty and Trustworthiness of GAI Tool Results	3	3	1
7- Perceived Risk (PR)	6	0	1
Detecting GAI-Related Issues (e.g., Plagiarism) in Student Work	Responses Vary		
Perceived Disappointment with Student GAI Misuse in Assessments	5	1	1
Privacy Concerns with using GAI Tools	4	1	2

6. Conclusions

The paper examines the factors that may impact the intentions of computer science instructors and students to adopt GenAI tools. A review was conducted of the current research on the viewpoints of both students and educators concerning the application of GenAI tools within educational environments and suggested a framework encompassing all the UTAUT factors, in addition to AI Self-Efficacy, AI Trust, and Perceived Risk to understand and support the adoption of GenAI in Saudi tertiary education settings. The findings indicate that all the suggested factors appear to be significant according to the instructors' viewpoints, but some are more important than others; for example, performance expectancy is more important than social factors. Future research work involves extending the results of the first qualitative phase by undertaking a second phase of quantitative data collection and analysis. This second phase will consist of distributing a structured questionnaire among both instructors and students. As a result, such findings can be used to develop and empirically verify the proposed framework.

References

Al-Zahrani, A. M., & Alasmari, T. M. (2024). Exploring the impact of artificial intelligence on higher education: The dynamics of ethical, social, and educational implications. *Humanities and Social Sciences Communications*, *11*(1), 912. https://doi.org/10.1057/s41599-024-03432-4

Alammari, A. (2024). Evaluating generative AI integration in Saudi Arabian education: A mixed-methods study. *PeerJ Computer Science*, *10*, e1879. https://doi.org/10.7717/peerj-cs.1879

Albayati, H. (2024). Investigating undergraduate students' perceptions and awareness of using ChatGPT as a regular assistance tool: A user acceptance perspective study. *Computers and Education: Artificial Intelligence*, *6*, 100203. https://doi.org/10.1016/j.caeai.2024.100203

Aldossary, A. S., Aljindi, A. A., & Alamri, J. M. (2024). The role of generative AI in education: Perceptions of Saudi students. *Contemporary Educational Technology*, *16*(4), ep536. https://doi.org/10.30935/cedtech/15496

Almahri, F. A. J., Bell, D., & Merhi, M. (2020). *Understanding student acceptance and use of chatbots in the United Kingdom universities: A structural equation modelling approach*. Paper presented at the 2020 6th International Conference on Information Management (ICIM).

Alotaibi, N. S., & Alshehri, A. H. (2023). Prospers and obstacles in using artificial intelligence in Saudi Arabia higher education institutions—The potential of AI-based learning outcomes. *Sustainability*, *15*(13), 10723. https://doi.org/10.3390/su151310723

Bahroun, Z., Anane, C., Ahmed, V., & Zacca, A. (2023). Transforming education: A comprehensive review of generative artificial intelligence in educational settings through bibliometric and content analysis. *Sustainability*, *15*(17), 12983. https://doi.org/10.3390/su151712983

Budhathoki, T., Zirar, A., Njoya, E. T., & Timsina, A. (2024). ChatGPT adoption and anxiety: A cross-country analysis utilising the unified theory of acceptance and use of technology (UTAUT). *Studies in Higher Education*, *49*(5), 831-846. https://doi.org/10.1080/03075079.2024.2333937

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, *20*(1), 43. https://doi.org/10.1186/s41239-023-00411-8

Chaudhry, I. S., Sarwary, S. A. M., El Refae, G. A., & Chabchoub, H. (2023). Time to revisit existing student's performance evaluation approach in higher education sector in a new era of ChatGPT—A case study. *Cogent Education*, *10*(1), 2210461. https://doi.org/10.1080/2331186X.2023.2210461

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340. https://doi.org/10.2307/249008

Deriba, F. G., Sanusi, I. T., Campbell, O. O., & Oyelere, S. S. (2024). Computer programming education in the age of generative AI: Insights from empirical research. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4891302

Elshaer, I. A., Hasanein, A. M., & Sobaih, A. E. E. (2024). The moderating effects of gender and study discipline in the relationship between university students' acceptance and use of ChatGPT. *European Journal of Investigation in Health, Psychology and Education*, *14*(7), 1981-1995. https://doi.org/10.3390/ejihpe14070132

Faisal, E. (2024). Unlock the potential for Saudi Arabian higher education: A systematic review of the benefits of ChatGPT. *Frontiers in Education*, *9*, 1325601. https://doi.org/10.3389/feduc.2024.1325601

Falcone, R., & Castelfranchi, C. (2001). Social trust: A cognitive approach. In C. Castelfranchi & Y.-H. Tan (Eds.), *Trust and deception in virtual societies* (pp. 55–90). Dordrecht, Netherlands: Springer. https://doi.org/10.1007/978-94-017-3614-5_3

Ghimire, A., Pather, J., & Edwards, J. (2024). *Generative AI in education: A study of educators' awareness, sentiments, and influencing factors*. Paper presented at the 2024 IEEE Frontiers in Education Conference (FIE).

Habibi, A., Muhaimin, M., Danibao, B. K., Wibowo, Y. G., Wahyuni, S., & Octavia, A. (2023). ChatGPT in higher education learning: Acceptance and use. *Computers and Education: Artificial Intelligence*, *5*, 100190. https://doi.org/10.1016/j.caeai.2023.100190

Hou, I., Mettille, S., Man, O., Li, Z., Zastudil, C., & MacNeil, S. (2024). *The effects of generative AI on computing students' help-seeking preferences*. Paper presented at the Proceedings of the 26th Australasian Computing Education Conference (ACE '24).

Jo, H. (2025). Decoding the ChatGPT mystery: A comprehensive exploration of factors driving AI language model adoption. *Information Development*, *41*(3), 875-895. https://doi.org/10.1177/02666669231202764

Khlaif, Z. N., Ayyoub, A., Hamamra, B., Bensalem, E., Mitwally, M. A. A., Ayyoub, A., . . . Shadid, F. (2024). University teachers' views on the adoption and integration of generative AI tools for student assessment in higher education. *Education Sciences*, *14*(10), 1090. https://doi.org/10.3390/educsci14101090

Konecki, M., Konecki, M., & Biškupić, I. (2023). *Using artificial intelligence in higher education*. Paper presented at the Proceedings of the 15th International Conference on Computer Supported Education (CSEDU 2023).

Lai, C. Y., Cheung, K. Y., Chan, C. S., & Law, K. K. (2024). Integrating the adapted UTAUT model with moral obligation, trust and perceived risk to predict ChatGPT adoption for assessment support: A survey with students. *Computers and Education: Artificial Intelligence*, *6*, 100246. https://doi.org/10.1016/j.caeai.2024.100246

Li, R., Ben Allal, L., Zi, Y., Muennighoff, N., Kocetkov, D., Mou, C., . . . de Vries, H. (2023). StarCoder: May the source be with you! *arXiv preprint arXiv:2305.06161*. https://doi.org/10.48550/arXiv.2305.06161

Mahaini, D. (2024). Generative AI in computer science education: A study on academic performance. Bachelor's Thesis, University of Twente, Enschede, Netherlands.
Masoomi, H. A. S., Dharejo, N., Mahar, Z. A., Nazeer, M. I., Khoso, I. A., & Shah, A. (2024). Significant predictors influencing the adoption of ChatGPT usage in the academia in Sindh, Pakistan: Extension of UTAUT model. *Pegem Journal of Education and Instruction*, *14*(4), 135-145. https://doi.org/10.47750/pegegog.14.04.14
Michel-Villarreal, R., Vilalta-Perdomo, E., Salinas-Navarro, D. E., Thierry-Aguilera, R., & Gerardou, F. S. (2023). Challenges and opportunities of generative AI for higher education as explained by ChatGPT. *Education Sciences*, *13*(9), 856. https://doi.org/10.3390/educsci13090856
Mittal, U., Sai, S., Chamola, V., & Sangwan, D. (2024). A comprehensive review on generative AI for education. *IEEE Access*, *12*, 142733-142759. https://doi.org/10.1109/ACCESS.2024.3468368
Poudel, R. L., & Bastakoti, C. K. (2024). Impact of behavioural intention to use generative artificial intelligence on academic performance of students in higher education institutions. *Prithvi Journal of Research and Innovation*, *6*(1), 1-21. https://doi.org/10.3126/pjri.v6i1.72853
Rajendran, R. M. (2023). Importance of using generative AI in education: Dawn of a new era. *Journal of Science & Technology*, *4*(6), 35-44. https://doi.org/10.55662/JST.2023.4603
Rana, M. M., Siddiqee, M. S., Sakib, M. N., & Ahamed, M. R. (2024). Assessing AI adoption in developing country academia: A trust and privacy-augmented UTAUT framework. *Heliyon*, *10*(18), e37569. https://doi.org/10.1016/j.heliyon.2024.e37569
Roy, M. C., Dewit, O., & Aubert, B. A. (2001). The impact of interface usability on trust in Web retailers. *Internet Research*, *11*(5), 388-398. https://doi.org/10.1108/10662240110410165
Sobaih, A. E. E., Elshaer, I. A., & Hasanein, A. M. (2024). Examining students' acceptance and use of ChatGPT in Saudi Arabian higher education. *European Journal of Investigation in Health, Psychology and Education*, *14*(3), 709-721. https://doi.org/10.3390/ejihpe14030047
Strzelecki, A. (2024). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments*, *32*(9), 5142-5155. https://doi.org/10.1080/10494820.2023.2209881
Supianto, Widyaningrum, R., Wulandari, F., Zainudin, M., Athiyallah, A., & Rizqa, M. (2024). Exploring the factors affecting ChatGPT acceptance among university students. *Multidisciplinary Science Journal*, *6*(12), 2024273. https://doi.org/10.31893/multiscience.2024273
Tailor, R. K., & Tailor, D. (2025). Examining the role of anxiety and self-efficacy as psychological barriers to ChatGPT adoption in academic contexts. *Discover Artificial Intelligence*, *5*, 395. https://doi.org/10.1007/s44163-025-00701-2
Tran, A., Li, L., Rama, E., Angelikas, K., & MacNeil, S. (2023). *Using large language models to automatically identify programming concepts in code snippets*. Paper presented at the Proceedings of the 2023 ACM Conference on International Computing Education Research.
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540
Wang, T., Diaz, D. V., Brown, C., & Chen, Y. (2023). *Exploring the role of AI assistants in computer science education: Methods, implications, and instructor perspectives*. Paper presented at the 2023 IEEE Symposium on Visual Languages and Human-Centric Computing (VL/HCC).
Yilmaz, R., & Yilmaz, F. G. K. (2023). The effect of generative artificial intelligence (AI)-based tool use on students' computational thinking skills, programming self-efficacy and motivation. *Computers and Education: Artificial Intelligence*, *4*, 100147. https://doi.org/10.1016/j.caeai.2023.100147
Yu, H., & Guo, Y. (2023). Generative artificial intelligence empowers educational reform: Current status, issues, and prospects. *Frontiers in Education*, *8*, 1183162. https://doi.org/10.3389/feduc.2023.1183162
Zastudil, C., Rogalska, M., Kapp, C., Vaughn, J., & MacNeil, S. (2023). *Generative AI in computing education: Perspectives of students and instructors*. Paper presented at the 2023 IEEE Frontiers in Education Conference (FIE).
Zviel-Girshin, R. (2024). The good and bad of AI tools in novice programming education. *Education Sciences*, *14*(10), 1089. https://doi.org/10.3390/educsci14101089

Appendix A.

Integrated Generative AI Tools in Computer Science Education

* Required

Information Sheet

Purpose:
The study aims to examine and understand the impact of Generative AI (GenAI) tools on computer science education in Saudi Arabia, particularly focusing on programming courses for students and instructors in Saudi Arabian universities. The study propose a theoretical framework using the UTAUT model to investigate the factors influencing the adoption of GenAI tools among computer science students and instructors. The study seeks to address the multifaceted implications of GenAI tools integration in teaching and learning, including its benefits, challenges, and ethical considerations. We are conducting this survey to evaluate the proposed framework by gathering insights from experts in order to understand their perspectives and factors influencing the adoption of GenAI tools.
Survey Details:
The survey will take approximately 8-15 minutes to complete. You will be asked questions related to the key aspects of the study, focusing on the factors influencing the adoption of GenAI tools, as well as their impact on teaching and learning in computer science education.
Confidentiality:
All responses provided will be kept confidential and anonymous that will be used for research purposes only. No personally identifiable information will be collected.
Participation:
Participation in this survey is entirely voluntary. You may choose to exit the survey at any time.
Consent Form:
By continuing with the survey, you consent to the use of your responses for research and product development purposes. If you have any questions or concerns regarding the survey, please get in touch with one of our team.

Thank you for taking the time to share your insights. Your contribution is invaluable to us.

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Appendix A1. Integrated generative AI tools in computer science education.

Appendix A2. A comprehensive list of interview questions.

#	Factor	Interview questions
1	Performance Expectancy-PE, defined by Venkatesh et al. (2003) as: "…the degree to which an individual believes that using the system will help him or her to attain gains in job performance." In this study, PE refers to the degree to which computer science students and instructors in Saudi universities believe that using generative AI tools, will help them attain better teaching and learning performance.	1. Do you think applying (GAI) tools would enable computer science instructors to provide a better teaching experience in their course? (Yes – No) Kindly explain your opinion. 2. To what extent do you agree that employing (GAI) tools makes the teaching of a computer science course more effective? (5, 4, 3, 2, 1) In which way? 3. To what extent do you agree that using (GAI) tools would enhance your productivity and academic performance? (5, 4, 3, 2, 1) In which way? 4. How significant do you believe that PE is considered as a key factor in the model? (5, 4, 3, 2, 1)
2	Effort Expectancy, defined by Venkatesh et al. (2003) as: "…the degree of ease associated with the use of the system". In this study, EE refers to the degree of ease associated with using and adopting generative AI tools.	1. To what extent do you agree that applying (GAI) tools would make the teaching process easier? (5, 4, 3, 2, 1) In which way? 2. To what extent do you agree that your interaction with students when using (GAI) tools would be clearer and understandable? (5, 4, 3, 2, 1) In which way? 3. How significant do you believe that EE is considered as a key factor in the model? (5, 4, 3, 2, 1)
3	Social Influence, defined by Venkatesh et al. (2003)as: "… the degree to which an individual perceives that important others believe he or she should use the new system". In this study, SI refers to the degree of the significant impact of others in believing users should use or adopt generative AI tools.	1. What are your reasons for using (GAI) tools? (Ex: is it a personal interest, college dean, colleagues, etc.) 2. To what extent do you agree that the social influence encourages you to employ (GAI) tools? (5, 4, 3, 2, 1) In which way? 3. Have there been other colleagues who have used (GAI) tools in your department? (Yes – No) 4. How significant do you believe that SI is considered as a key factor in the model? (5, 4, 3, 2, 1)
4	Facilitating Conditions, defined by Venkatesh et al. (2003) as: "…the degree to which an individual believes that an organisational and technical infrastructure exists to support use of the system". In this study, FC refers to the existence of organisational and information technology infrastructure to support the implementation of generative AI tools.	1. Would you comment of the support received from the university management / IT support / E-learning Dept. to apply or adopt the (GAI) tools? 2. Have you received training/workshops to employ technologies required to operate the (GAI) tools? (Yes – No) If yes, kindly explain. 3. How significant do you believe that FC is considered as an important factor in the model? (5, 4, 3, 2, 1)
5	AI self-efficacy, according to Venkatesh et al. (2003) p.432), defines self-efficacy as "judgment of one's ability to use technology (e.g., computer) to accomplish a particular job or task". Therefore, this construct relates to the confidence of the individual in their ability to use a particular technology. In this study, AISE refers to the judgment of users' (instructors and faculty) ability to use AI tools and technologies (such as generative AI tools) to accomplish a particular task.	1. To what extent are you confident that you can use the (GAI) tools effectively in your role as a computer science instructor? (5, 4, 3, 2, 1) In which way? 2. Do you think AI self-efficacy could play a role in enhancing the students' learning experience? Kindly explain. How significant do you believe that AI self-efficacy is considered as an important factor in the model? (5, 4, 3, 2, 1)
6	AI Trust, according to Albayati (2024) and Lai et al. (2024), define trust "refers to the confidence users have in an AI-based learning system's capability to deliver dependable and effective services". The behavioral intention to adopt and use AI is significantly and positively influenced by trust. In this study, trust refers to the level of user confidence that affects the user's (students/instructors) behavioural intentions to use/adapt the generative AI tools.	1. To what extent do you believe that (GAI) tools are effective and secure for what you need to do in teaching and learning your courses? (5 – 4 – 3 – 2 – 1) scales. In which way? 2. To what extent do you believe that the results of (GAI) tools are honest? (5 – 4 – 3 – 2 – 1) scales. In which way? 3. To what extent do you believe that the (GAI) tools were made by trusted organisations? (5 – 4 – 3 – 2 – 1) scales.

#	Factor	Interview questions
		In which way? 4. How significant do you believe that Trust is considered as an important factor in the model? (5, 4, 3, 2, 1)
7	Perceived Risk (PR), according to Albayati (2024) and Lai et al. (2024), define PR as "how people view the potential uncertainty and severity of the outcomes linked to a specific action or behavior". PR of privacy and data security reduces users' satisfaction, which negatively affects their continued use intention. In the current study, PR is relevant when users encounter situations with uncertain outcomes or where there is a risk of negative consequences from making wrong or poor decisions.	1. To what extent are you able to find out the issues (such as, plagiarism) associated with the GAI tool usage by students? 2. To what extent would you be disappointed if you find out that students used (GAI) tools to complete their assessment, such as plagiarism, cheating, etc. (5 – 4 – 3 – 2 – 1) scales. In which way? 3. To what extent do you agree that using (GAI) tools would put your privacy at risk? (5 – 4 – 3 – 2 – 1) scales. In which way? 4. How significant do you believe that perceived risk is considered as an important factor in the model? (5, 4, 3, 2, 1)
8	Other (additional motivational/barriers factors) to employ (GAI) tools.	1. Are there any motivational factors related to using or employing (GAI) tools (for example, training, promotion, publication, grants, rewards, etc.)? 2. Are there any barrier factors related to employing the (GAI) tools? 3. Would you like to add any comments?

The contents of the table present the semi-structured questions that were administered to the participants (computer science instructors). The various asked in relation to every factor that influenced GenAI adoptions are presented.