A systematic literature review of attitudes, intentions and behaviours of teaching academics pertaining to AI and generative AI (GenAI) in higher education: An analysis of GenAI adoption using the UTAUT framework

Sasha Nikolic
University of Wollongong

Isabelle Wentworth
Australian Catholic University

Lynn Sheridan
University of Wollongong

Simon Moss
University of Wollongong

Elisabeth Duursma
Western Sydney University

Rachel A. Jones
University of Wollongong

Montserrat Ros
University of Wollongong

Rebekkah Middleton
University of Wollongong

The rapid advancement of artificial intelligence (AI) has outpaced existing research and regulatory frameworks in higher education, leading to varied institutional responses. Although some educators and institutions have embraced AI and generative AI (GenAI), other individuals remain cautious. This systematic literature review explored teaching academics' attitudes, perceptions and intentions towards AI and GenAI, identifying perceived benefits and obstacles. Utilising the unified theory of acceptance and use of technology framework, this study reveals positive attitudes towards AI's efficiency and teaching enhancement, but also significant concerns about academic integrity, accuracy, reliability, skill development and the need for comprehensive training and policies. These findings underscore the necessity for institutional support to navigate the integration of AI and GenAI in tertiary education.

Implications for practice or policy:
- Attitudes towards AI and GenAI integration are diverse with educators recognising benefits but raising ethical and practical concerns. These concerns indicate a need for a more comprehensive understanding and dialogue within academic communities.
- Academics' intentions to use these technologies are contingent upon the development of robust ethical guidelines and supportive institutional policies.
- Institutional support and training shape behaviours. The scarcity of formal training, systematic guidelines and policy frameworks currently limits effective integration.

Keywords: ChatGPT, generative AI (GenAI), policy development, technology adoption, technology integration, unified theory of acceptance and use of technology (UTAUT)

Introduction

The term artificial intelligence (AI) is not new, proposed in 1955 by McCarthy (McCarthy et al., 2006). Since McCarthy's original definition of AI as "a machine that deals with a certain problem in a manner of human intelligence", the definition has evolved and changed over time, with many interpretations now available (Gaber et al., 2023, p. 476). However, not until 2016 did interest in the application of this technology in education escalate (Adamopoulou & Moussiades, 2020). In a short period of time, the proliferation of AI capabilities within the higher education space had outpaced the research and regulatory frameworks necessary to understand and guide AI use (Miao et al., 2021). The pace of change was further underscored by the November 2022 launch of ChatGPT-3.5 (Nikolic et al., 2024). This evolutionary leap demonstrated that generative artificial intelligence (GenAI) could surpass traditional AI limitations, creating new content and driving unprecedented adoption rates (Nikolic, Daniel et al., 2023). Although GenAI is a form of AI, it is the generative capability that made the mainstream academic community take notice. Hence, this study transcends traditional reviews by comparing the traditional aspects of AI usage (referred to throughout as AI) with the generative aspects (referred to throughout as GenAI).

Before the rise of GenAI, higher education institutions were already grappling with AI adoption. Some encouraged its use, while others were cautious, maintaining conservative stances on new technology (O'Dea & O'Dea, 2023). Generally, there was little guidance on AI, leaving teaching academics to navigate its use with limited institutional support or training (Alnasib, 2023). In this study, "teaching academic" simply refers to someone who teaches students in higher education.

In early 2023, the term GenAI, through ChatGPT-3.5, became prominent for everyone working in higher education, partly because of the capacity of this tool to pass certain assessments, including exams, without significant intervention. Consequently, educators feared the prospect of widespread cheating (Nikolic, Daniel et al., 2023). This raised concerns about academic integrity, leading some institutions to ban GenAI (Tlili et al., 2023). Despite initial fears, a review by Crompton and Burke (2023) highlighted a diversity of perceptions, with many academics seeing potential in the technology to transform teaching and learning.

During the last 12 months, GenAI has evolved to be capable of passing a greater range and standard of assessments. Simultaneously, the community has been developing knowledge on how to integrate GenAI to enhance learning opportunities (Nikolic et al., 2024). This capability includes integrating GenAI into teaching and learning processes to empower learners and lecturers (Pham et al., 2023) and using this technology to develop course plans (Okulu & Muslu, 2024). At the moment, users are experimenting with various practices, and not all approaches are meeting expectations, but the potential is clearly identified (Ahmed et al., 2024).

The benefits of AI and GenAI vary across disciplines. In science, technology, mathematics and engineering, GenAI aids in understanding complex calculations and streamlining research tasks (Nikolic et al., 2024). In the humanities, AI enables advanced text analysis and interpretation (Gefen et al., 2021). GenAI has made notable strides in healthcare, improving diagnostics and patient care, particularly in medical imaging (Cervantes et al., 2024). Language education has benefited from GenAI's capabilities in translation and resource creation, transforming traditional language teaching (Law, 2024).

Looking ahead, educators must guide students not only to use AI but also to critically understand its capabilities (Lodge et al., 2023). For instance, the University of Sydney has approved a two-lane assessment approach for 2025, requiring faculty to adapt its assessment methods (Bridgeman & Liu, 2024). Since the release of ChatGPT, attitudes towards GenAI have evolved significantly, but the current state of adoption and integration is not yet fully understood, making it difficult to shape effective policies.

The development of institutional support for AI and GenAI in teaching pedagogy should be informed by the voices of the teaching academics because these scholars are currently navigating the complexities of under-regulated AI in the learning and teaching landscape (Tlili et al., 2023). Currently, understanding and consensus on the attitudes, intentions and behaviours of teaching academics around AI and GenAI integration in higher education teaching and learning are limited. Furthermore, studies have not clarified whether academics recognise the potential differences between AI and GenAI in utility and applicability. This shortfall hinders policy and practice development.

Accordingly, researchers need to understand the impact of teaching pedagogy in higher education. Therefore, this systematic review explored the following research questions:

- RQ1. What are teaching academics' general attitudes, perceptions or intentions towards AI and GenAI?
- RQ2. What are teaching academics' perceived benefits and obstacles in the use of AI and GenAI?
- RQ3. What are the determinants of the adoption or intention to adopt AI and GenAI in teaching?
- RQ4. How do these attitudes and behavioural intentions shape the acceptance and use of GenAI, as defined by the unified theory of acceptance and use of technology (UTUAT) framework?

This systematic review addresses these questions, contributing to scholarly literature by offering a comprehensive overview and synthesis of global studies.

Background literature

AI and GenAI – definitions and differences

GenAI, a form of machine learning, is trained on vast data sets across various modalities, allowing it to create original content in response to user inputs (Sætra, 2023). Unlike traditional AI, which classifies or predicts based on existing data, GenAI produces new data – such as text, images and music – demonstrating adaptability and creativity. ChatGPT, a large language model developed by OpenAI, is currently the most popular GenAI, specialising in natural language processing and generating text that resembles human language (Nikolic et al., 2024). Other prominent large language models include Google's Gemini, Meta's LLaMA and Anthropic's Claude (Nikolic et al., 2024).

AI's role in education is polarising, with attitudes ranging from individuals who believe that AI is the faster, stronger, better classroom tool that will optimise learning and accelerate the progress of civilisation (Adıgüzel et al., 2023) to concerns that it may diminish intellectual disciplines and reduce human intelligence (Editorial Desk, 2024). Some critics highlight ethical concerns, such as AI perpetuating social bias (Khan, 2023), fostering educational inequality (Bulathwela et al., 2024) and raising privacy concerns (Berendt et al., 2020). Logistical challenges relate to maintaining academic integrity and ensuring research accuracy (Bin-Nashwan et al., 2023; Fiialka et al., 2023).

Theoretical frameworks offer a structured approach to explaining and predicting user acceptance and adoption of new technologies or innovations (Taherdoost et al., 2024). Frameworks such UTAUT, the technology acceptance model (TAM), the theory of planned behaviour (TPB) and the value-based adoption model (VBAM) incorporate key psychological and behavioural determinants of behaviour, including perceived usefulness, social influence and perceived ease of use (Taherdoost et al., 2024). These models are designed to understand and predict whether individuals will accept and use new technologies. Such predictive capabilities are crucial and directly informed the formulation of RQ3 and RQ4.

To explore the determinants of these changes, Ivanov et al. (2024) found that the variables from TPB – such as perceived behavioural control, attitudes and subjective norms – shape intentions to use and adopt generative AI. Sharma et al. (2024), using TAM, identified significant relationships between AI self-efficacy, behavioural intentions and organisational support in Indian universities. Additionally, Rahiman and

Kodikal (2024) observed that awareness of the technology, perceived risk and performance expectancy positively relate to AI adoption, with attitude acting as a mediating variable.

The wide range of attitudes towards AI influences its integration into higher education pedagogy (Wang et al., 2021). Although initial research has begun to assess academics' views, further evaluation and synthesis are required to fully understand these perspectives and their implications for policy and practice in higher education (Knight et al., 2023). This is crucial for ensuring AI's success in education, a challenge faced by many other technology-enhanced learning initiatives (Gregory et al., 2016).

AI and GenAI in higher education

The capacity for AI application in university teaching is wide and varied, offering opportunities for increased efficiency and differentiated instruction (Seo et al., 2021). For example, AI programmes can deliver interactive lessons and practice exercises while monitoring student performance as well as providing targeted, real-time feedback and personalised interventions (Miao et al., 2021; Hwang et al., 2020; Pham et al., 2023). AI teaching assistants can operate like human teaching assistants: answering students' questions in online discussion forums, responding to emails or assessing exams (J. Kim et al., 2020). In addition, learning analytics relying on AI can help instructors track student performance by analysing their clickstream data (Fong et al., 2019; Roll & Winne, 2015). All of these capabilities, in theory, enable academic staff to outsource the mundane tasks of teaching and student tracking, thus granting these individuals more time for, for example, course content and lecture planning.

However, more sophisticated, abstract and conceptual tasks are also sometimes outsourced to AI: lecturers discuss using large language models to help write lecture scripts and lesson plans, generate syllabi and create recommended reading lists. Similarly, image-generating AI can create presentation slides (Abd-alrazaq et al., 2023). Other AI tools can score students' written responses and predict outcomes from complex, multilayered datasets. Essentially, AI is fast becoming part of the fabric of education (Matthews & Volpe, 2023, p. 82).

Beyond replacing or improving existing educational practices or systems, AI could also transform pedagogy in a more fundamental sense. As the job market for which universities prepare students changes, the learning objectives shaping pedagogy will shift (Hutson & Ceballos, 2023). Institutions must educate students on the ethical and effective use of AI. These changes will be widely but unevenly felt across disciplines and industries. The new teaching methods, challenges and learning outcomes that AI poses warrant a deliberate and coordinated strategy by university educators, yet academics have reported that extant policy guidelines and training do not provide adequate support (Chun, 2023; Miao et al., 2021).

Method

The following review followed the preferred reporting items for systematic reviews (PRISMA) guidelines (Page et al., 2021) to explore generative AI and teaching academics' pedagogy in higher education, specifically their attitudes and behaviours towards generative AI. Studies included in the review were peer-reviewed primary research published in English between 2018 and 2023 and reported attitudes, behaviours and intentions of university teaching academics pertaining to AI and GenAI. Because of the rapid expansion of generative AI in higher education, we felt that 5 years was an important period to capture current and relevant empirical literature. All disciplines, full conference papers, dissertations and theses were included. Grey literature and opinion pieces were excluded from the search. Studies that focused on AI and research policy documents on AI, theoretical discussions and AI tools or papers marketing AI products were excluded as well. Table 1 outlines the inclusion and exclusion criteria applied in the search.

Table 1
Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
• Last 5 years • Higher education/university • Teaching focus • Empirical research • All disciplines • Full conference papers • Dissertations and theses • Refereed journal articles	• Papers older than 2018 • Policy documents • Theoretical research • Papers that focus on AI tools only, with no teaching and learning attitudes, behaviours and intentions • Marketing, promotional or procedural materials related to AI • Publications not in English

Search strategy

Searches were completed in databases that included higher education and AI studies and offered advanced search features useful in narrowing our search focus. The databases consisted ofProQuest Education, Scopus, Web of Science and Education Research Complete. These databases are frequently utilised in the education field and include studies that report on different aspects of AI. These databases also span most disciplines – relevant to this study given the broad focus of higher education and GenAI. Additionally, these databases offered advanced search features that enabled our search terms to be used. Within each database, we searched for relevant studies, using the selection criteria and keywords that appear in Table 2. All of us researchers assisted in the development and approval of the search criteria.

Table 2
Keywords used in searches

University	Artificial intelligence	Academics	Pedagogy	Attitudes	Behaviours
Higher education	Generative AI	Faculty	Instruction	Outlook	Integration
Tertiary education	ChatGPT	Teaching staff	Curriculum*	Approach*	Use
Undergraduate education		Teaching academic*	Teach*	Intention*	
			Assessment	Perception*	

The search strings included [university OR tertiary OR "higher education" AND ai OR "artificial intelligence" OR ChatGPT AND attitudes OR perceptions OR intentions OR thoughts OR feelings OR beliefs AND pedagogy OR "teaching strategies" OR behaviour OR use] and made extensive use of “*” to include related terms. The process flow is shown in Figure 1.

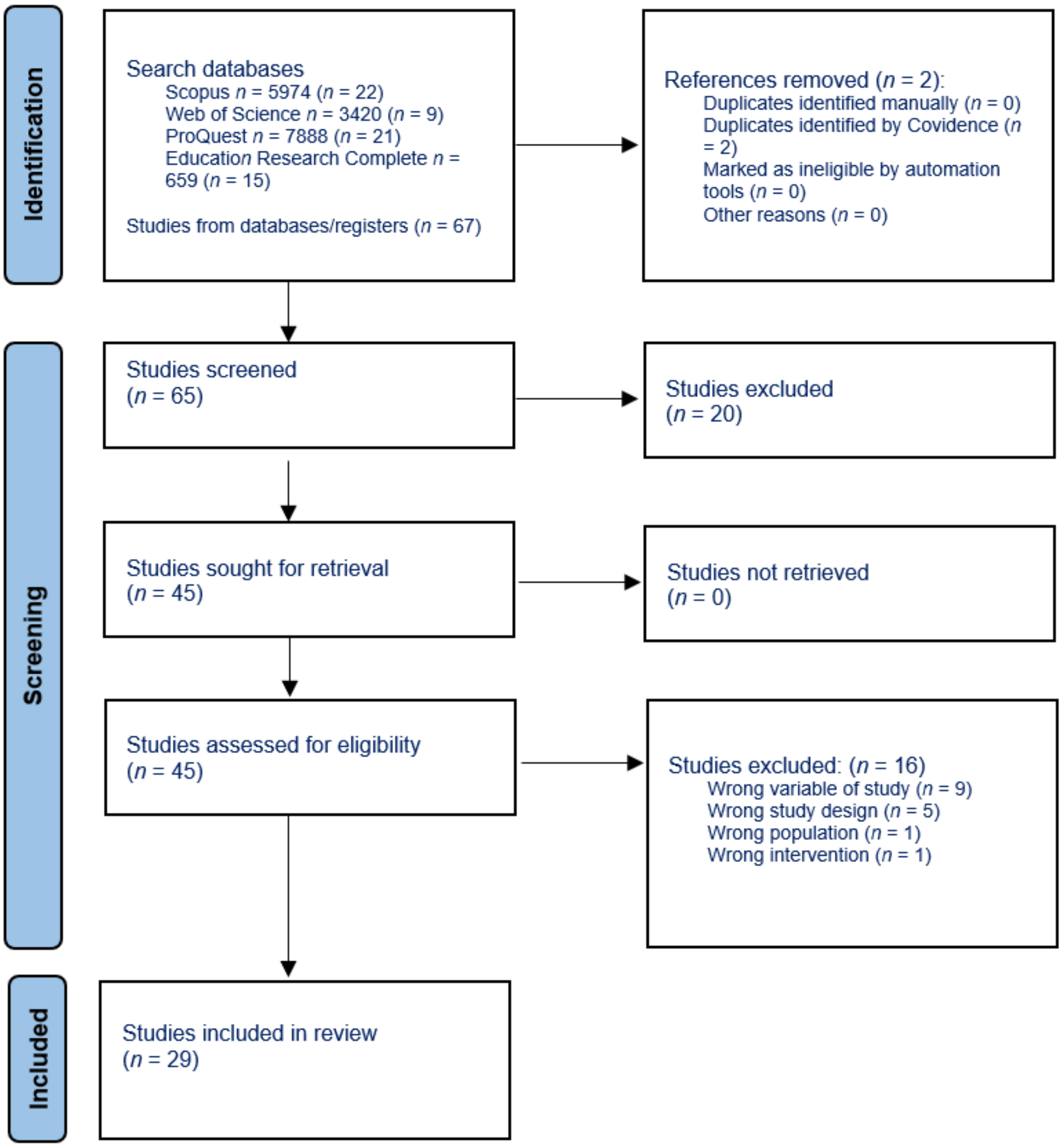

Figure 1. PRISMA flowchart

Screening process

The search was completed in July 2023 and yielded 659 results from Education Research Complete; 3,420 from Web of Science; 5,974 from Scopus; and 7,888 from ProQuest Education. One of us completed the initial title, keywords and abstract screening. A total of 67 papers from the four databases were then imported into Covidence and two duplicates were removed. Two of us then subjected the abstracts to secondary screening. The full papers were then uploaded into Covidence. Full-text screening, using the inclusion and exclusion criteria, of 45 studies was completed. In response to each discrepancy, the two of us discussed the paper until a consensus was achieved. A total of 29 studies from the 46 studies were ultimately included in the review. Six of us then contributed to the data extraction. A data extraction table was developed in Covidence and consisted of title; date of study; country in which the study was conducted; faculty; aim of study; the phenomenon being studied; study design; methods of data collection used in the study; theoretical framework used; population description; total number of participants; study limitations; results; and other points of interest. Data extraction was confirmed by two of us, using a final total of 29 empirical papers published between 2018 and 2023, across a range of disciplines and regions.

Analysis

Once all of us completed the data extraction and checked for consistency, an Excel spreadsheet containing all the data extracted was downloaded. From the data extraction, a summary table was developed, with coded details on the 29 studies, including an executive summary (see Appendix A, https://doi.org/10.7910/DVN/FOYRCD). The research questions were investigated in a systematic manner. The first research question used the coded data to provide an overview of the general attitudes, perceptions and intentions towards AI and GenAI collectively. The second research question used coded data to explore the perceived benefits and obstacles of AI and GenAI separately. The purpose of this second research question was to determine whether perceptions remained constant under the umbrella of traditional AI or whether the evolution of GenAI ignited a shift. The third research question used coding to consider the determinants of behavioural intention towards or adoption of AI. This research question was explored to determine the framework of analysis required to answer and position the final research question. From the selected frameworks undertaken on traditional AI, the UTAUT was chosen as best fitting to help provide insights into how users could evolve to accept and use GenAI. This research question would help clarify the attitudes and behavioural intentions towards AI acceptance (Ahmad et al., 2023). The codes were then used to construct a summary of the UTAUT analysis against the four core constructs (see Appendix D, https://doi.org/10.7910/DVN/FOYRCD). We identified the UTAUT constructs as follows (Venkatesh et al., 2003):

- **Performance expectancy:** How users expect a system to aid in achieving gains in job performance. For each of the 10 studies, an analysis was undertaken on how staff expected GenAI to enhance or affect their academic or professional performance.
- **Effort expectancy:** The ease of using the technology. For each of the 10 studies, an analysis was undertaken to determine the perceived ease of use of GenAI.
- **Social influence:** The extent to which users perceive that other individuals in the community believe AI is useful. For each of the 10 studies, an analysis was undertaken to extract any discussions or findings related to peer influence, institutional endorsements, or cultural expectations.
- **Facilitating conditions:** The organisational and technical infrastructures to support the use of AI. For each of the 10 studies, an analysis was undertaken to identify any references to institutional support, availability of resources and external conditions that facilitate or hinder the adoption and use of AI technologies.

Limitations

Several limitations of this review should be considered. The rapid pace of technological innovation means that, since the review was conducted, many new studies have likely emerged. The existing research is also highly heterogeneous, making future reviews necessary to track evolving attitudes and behaviours of teaching academics towards AI.

Although grey literature and opinion pieces were excluded to avoid unvalidated conclusions or personal biases, these sources might offer valuable insights into recent trends. However, the focus of this review was strictly on teaching academics' attitudes, intentions and perceptions regarding GenAI, not on individual opinions or policy documents. Our thorough search strategy, aligned with the PRISMA statement, helped minimise potential biases.

Results and discussion

Overview

A total of 29 studies were included in the review and are outlined in Appendix A (https://doi.org/10.7910/DVN/FOYRCD). All were written in English and published between 2019 and 2023. A total of 19 studies revolved around traditional AI, and 10 studies revolved around GenAI. Some of the studies were difficult to categorise based on the provided information (e.g., Ahmad 2023; Alhwaiti 2023). Studies that did not mention GenAI or technologies such as ChatGPT were classified as traditional AI. The participants from each study were sampled from a range of international regions: six studies were undertaken in Saudi Arabia; two studies were undertaken in the United States, Turkey, Romania, Jordan, and China; and one study each was undertaken in Nigeria, Cyprus, Oman, Spain, Hong Kong, Ukraine, India, Indonesia, Australia, Canada, Sweden, Estonia and Bulgaria. The aggregated sample comprised 4,341 participants, all of whom were teaching university academics. The participants were from a range of disciplines within both the humanities and science, technology, mathematics and engineering fields. Most commonly, the participants worked in the faculties of medicine, language teaching and education (*n* = 5, *n* = 5 and *n* = 3 studies, respectively), whereas the remainder were from social science, engineering, information technology, business, agriculture, finance, economics and technology, physics and computer science. Most studies (*n* = 20) used cross-sectional surveys and self-report questionnaires. A total of seven papers used semi-structured interviews, and two used essays or long-form written responses as qualitative data.

The studied phenomena included the determinants of AI acceptance in university teaching (*n* = 7), behaviour towards and use of AI in university teaching (*n* = 10), attitudes and perceptions of AI in university teaching (*n* = 22) and the level of current institutional support of AI adoption in university teaching (*n* = 6).

RQ1: Attitudes, perceptions or intentions towards AI and GenAI

Addressing RQ1, “What are teaching academics’ general attitudes, perceptions or intentions towards AI and GenAI?”, this review uncovered 29 studies. Most of these studies revealed somewhat or largely favourable attitudes towards the adoption of AI or GenAI in teaching (e.g., Alnasib, 2023; Barrett & Pack, 2023; Firat, 2023; Guo & Wang, 2023; Kiryakova & Angelova, 2023; Livberber & Ayvaz. 2023; Mangera et al., 2023; Pisica et al., 2023; Ruiz-Rojas et al., 2023). Sassis et al. (2021) demonstrated that almost 80% of medical academics surveyed felt that AI should be embedded in the curriculum, and Wood et al. (2021) showed that medical academics were more likely to report positive attitudes to the use of AI in medical teaching. Oluwadiya et al. (2023) revealed the median score on a measure of these attitudes was 6.8 out of 10. Participants also expressed favourable attitudes to specific AI applications, including the use of robots, guided by AI, in the education system of Indian universities (Roy et al., 2022).

Some of the research has explored the beliefs that underpin these attitudes. For instance, as Al-Ruwaili (2023) revealed, participants tend to appreciate the efficiency of these AI tools but express concerns that AI may diminish social interactions among students. Leoste et al. (2021) reported that participants depicted AI as convenient and were thus confident that teaching staff would adopt these tools in the future. Furthermore, McGrath et al. (2023) showed that participants felt that AI might diminish inequalities in the level of support that students receive. Firat (2023) revealed some academics felt that GenAI might transform the role of educational institutions and the learning methods that teachers adopt.

Attitudes to GenAI in teaching may depend on the degree to which academics are cognisant or aware of the various uses and applications of these tools. Past research suggests that participants tend to be familiar with, or at least believe they are familiar with, AI tools (e.g., Abouammoh et al., 2023; Wood et al., 2021). Nevertheless, this familiarity with AI tools in teaching is not uniform: both McGrath et al. (2023) and Gaber et al. (2023) reported moderate levels of awareness about GenAI.

Notwithstanding this variation in familiarity with AI tools, many teaching academics reported the intention to utilise generative AI in the future (Ahmad et al., 2023; Roy et al., 2022). To illustrate, in one study, academics reported a high intention to use generative AI in teaching – with a mean of 4.07 on a 5-point scale (Alnasib, 2023). For example, some academics planned to use GenAI to personalise advice and instructions to students more effectively (Seo et al., 2021).

RQ2: Perceived benefits and obstacles in the use of AI and GenAI

The first research question found that attitudes towards AI and GenAI were favourable collectively. To explore the source of these attitudes, the second research question sought to determine "What are teaching academics' perceived benefits and obstacles in the use of AI and GenAI?". The analysis compared traditional AI and GenAI. Appendix B (https://doi.org/10.7910/DVN/FOYRCD) outlines the key benefits of AI that were identified, and Appendix C (https://doi.org/10.7910/DVN/FOYRCD) outlines the key obstacles.

When analysing the benefits, some common themes surfaced. Both traditional AI and GenAI offer significant benefits in enhancing efficiency and facilitating teaching and learning processes. These benefits can be categorised as improving efficiency, enhancing teaching and learning and supporting teaching and learning.

The key differences between AI and GenAI revolved around how the technology could support teaching and learning. Traditional AI studies concentrated more on systemic and administrative activities, such as decision-making and inquiries. For example, participants valued the capacity of traditional AI to streamline administrative tasks. Numerous studies (e.g., Alnasib, 2023; Gaber et al., 2022) highlight the effectiveness of these traditional AI tools in automating routine tasks, granting educators the time to focus more on teaching and interacting with students.

In contrast, GenAI studies focused more on generative qualities such as the generation of ideas, assessment and learning materials. For example, Livberber and Ayvaz (2023) as well as Barrett and Pack (2023) discuss the capacity of GenAI to generate ideas and help with writing, including the ability to remove foreign language barriers. When writing research reports, ChatGPT was perceived as useful for generating ideas when experiencing writer's block, finding topics for academic articles, arranging the arguments and content cohesively and editing the final draft (Livberber & Ayvaz, 2023).

Besides facilitating writing, GenAI was also used to generate syllabi and prepare assignments and tests (Fiialka et al., 2023). The study by Kiryakova and Angelova (2023) found that 49% of university professors regarded GenAI as beneficial for creating learning scenarios, learning materials and presentations for lectures and exercises. However, attitudes towards such benefits were dependent on how the tools were implemented. For example, Barrett and Pack (2023) recognised that whether a student is already competent in the required skill determines the perceived benefit of GenAI. Generally, both students and teachers perceived GenAI as more "acceptable in the early stages of the writing process (i.e., brainstorming and outlining) than in later stages" (p. 17).

Differences between the attitudes towards traditional AI and attitudes towards GenAI can be ascribed to the generative nature of GenAI. Specifically, GenAI displays solutions that transcend the trained boundaries of traditional AI, increasing the likelihood of hallucinations or false answers. Yet, despite these concerns about hallucinations, across regions and disciplines, cautious optimism was prevalent. These technologies were perceived as opportunities to enhance learning, despite the likely hurdles to acceptance and integration across higher education.

The key and most consistent benefit outlined in both AI and GenAI studies is related to customisation or personalisation. Customisation can include personalised learning experiences and assessment feedback. This feature enables universities to deliver personalised attention to students at scale (Popescu et al., 2023), meet the specific needs of each student and facilitate the academic progress and comprehensive development of these students (Ruiz-Rojas, 2023). One of the best examples of this benefit was summed up by one student: "The AI won't judge me. The AI is not thinking like, wow, what an idiot." (Seo et al., 2021, p. 11). This level of comfort affords many different applications, such as enabling students to practise speaking skills using authentic language (Kohnke et al., 2023).

The analysis regarding obstacles could be categorised as ethical and privacy concerns, the detrimental impact on learning, implementation challenges, as well as limitations in resourcing and training. Again, many commonalities between traditional AI and GenAI studies were uncovered. However, with the shorter publication window for GenAI articles, some differences in focus were noted. Concerning ethics, most articles mentioned in some way the possible impact of GenAI on academic integrity. For example, Kiryakova and Angelova (2023) highlight that the potential to use GenAI unfairly and unethically is a significant concern among educators, educational institutions and society, potentially impeding uptake. These risks launched ChatGPT as a hot discussion topic in early 2023 (Nikolic, Daniel et al., 2023). Barrett and Pack (2023) claim that “submitting an essay written by ChatGPT without disclosure violates academic integrity, but students may not readily see a problem with it” (p. 2). Indeed, this tendency to not disclose the use of GenAI is becoming an increasing problem within research and extends beyond students (Nikolic et al., 2024).

If students decide to cheat and circumvent key learning activities, or if the GenAI is taught before foundational skills are entrenched, skill development may be impeded (Livberber & Ayvaz, 2023). Kiryakova and Angelova (2023) suggest that their findings align with concerns that “using ChatGPT to complete assignments will make learners lazy and may prevent the development of valuable skills such as critical thinking” (p. 15). To limit these concerns, educators must maintain their focus on ensuring the validity of assessments rather than becoming overly fixated on concerns about cheating (Dawson et al., 2024).

Besides these issues around cheating, concerns about the relevancy and inaccuracy, or hallucinations of GenAI, are other obstacles identified. These inaccuracies, however, may facilitate learning, because such errors enable critical thinking skills to be integrated into the learning experience (Fiialka et al., 2023). For example, some assignments could revolve around the task to identify hallucinations in the responses of AI tools.

The key solution for addressing many of the obstacles is through institutional support and training. This solution was identified in the traditional AI studies and continues to this day. A total of six studies investigated teaching faculty’s perceived level of institutional support and training surrounding the integration of AI into the teaching and learning process. Overwhelmingly, these studies found an inadequate level of institutional training and policy, and faculty frequently reported a low understanding or awareness of how AI was to be appropriately integrated into their teaching (Gaber et al., 2022; Leoste et al., 2021; Nagro, 2021; Wood et al., 2021). In each study, a majority of faculty members reported the need for additional institutional support.

Wood et al.'s (2021) survey of faculty from the United States of America found that participants had not acquired a basic understanding of AI tools. These participants were generally interested in further AI training conducted by the university. This interest was observed in GenAI studies as well, where Ruiz-Rojas (2023) stated that “educators must understand how to take full advantage of the capabilities of generative AI tools and how to integrate them into their teaching practices effectively” (p. 17). Supporting this perspective, Barrett and Pack (2023) found that participants wanted explicit guidelines and professional development on the integration of GenAI in the tertiary educational context. Key to such progression was ensuring “a strong emphasis on maintaining the essential human aspect” in education (Abouammoh et al. 2023, p. 13).

RQ3: Determinants of behavioural intention towards or adoption of AI

The third research question aimed to explore the determinants of adoption or behavioural intention to adopt AI and GenAI in teaching. Only 23% of the reviewed studies examined the adoption of AI in teaching practices among university faculty using theoretical models. None of the studies were related to GenAI, providing a research gap for further exploration. The AI-based studies used four different models: UTAUT, TAM, TPB and VBAM.

Three AI studies (Ahmad et al., 2023; Alhwaiti, 2023; Al-Riyami et al., 2023) invoked the UTAUT framework developed by Venkatesh et al. (2003). UTAUT posits three direct determinants of intention to use – performance expectancy, effort expectancy and social influence – as well as two direct determinants of usage behaviour – intention and facilitating conditions. In this context, constructs such as performance expectancy and effort expectancy are theoretical components of the UTAUT model, which act as determinants of behavioural intention and usage behaviour when operationalised and tested. UTAUT can explain approximately 70% of the variance in usage intention. All three studies found a significant positive relationship between the constructs of UTAUT and AI adoption. Al-Riyami et al.'s (2023) study of 275 faculty members in Oman found that all five constructs of the UTAUT model significantly affect the behavioural intention of AI adoption with different degrees of influence: performance expectancy (43%), facilitation condition (27%), effort expectancy (21.5%), social influence (15.4%) and attitude towards using the technology (15.4%). Ahmad et al.'s (2023) study of 250 Jordanian faculty members found significant correlations between the UTAUT constructs and AI adoption, but variability in the strengths of these correlations: performance expectancy (strong), effort expectancy (medium), social influence (medium), facilitating conditions (weak). Alhwaiti et al. (2023) used the updated UTAUT2 model, which also explores hedonic motivation, price value and habit. These additional constructs similarly serve as determinants of behavioural intention and usage behaviour within the extended framework. The study on 350 Saudi Arabian faculty members found a significant positive relationship between the constructs of the updated unified theory of acceptance and use of technology.

Two AI studies (Roy et al., 2022; Wang et al., 2021) applied TAM developed by Davis(1985) to explain how users learn to accept and use a technology. TAM posits that two factors – perceived usefulness and perceived ease of use – influence user attitudes toward using the technology, which in turn determine their behavioural intention to use this technology and, ultimately, their actual usage behaviour. Using TAM, Wang et al. (2021) found that endogenous constructs of anxiety, self-efficacy, attitude towards AI, perceived ease of use and perceived usefulness predicted 70.4% of teaching faculty's behavioural intention to use AI in their teaching, with self-efficacy and perceived ease of use demonstrating the highest effect. The relationship between self-efficacy and anxiety was negatively correlated, suggesting that increasing teachers' self-efficacy could decrease their anxiety around the use of AI-based tools in their teaching. The second study (Roy et al., 2022) not only used TAM but also explored TPB. Using the combined frameworks, Roy et al. examined perceived usefulness, perceived ease of use, discomfort, insecurity, trust, subjective norms and perceived behaviour control. They found high degrees of perceived usefulness, ease of use, trust, subjective norms and perceived behavioural control, and a high correlation of these factors with behavioural intention. Discomfort and insecurity were not significantly correlated with behavioural intention to use AI in teaching. Using a modified TAM, Gaber et al. (2023) found no statistically significant correlation between AI awareness and technology acceptance but a direct positive correlation between AI awareness and digital competence.

The final model used VBAM developed by H.-W. Kim et al. (2007). This model extends TAM to explain technology adoption where the users are also consumers. Du and Gao (2021) found that, among 17 Chinese faculty members, perceived effectiveness and efficiency were the most influential factors affecting teachers to use AI-based applications whereas perceived time, flexibility and enjoyment were found to demonstrate intermediate effects on the adoption of AI.

RQ4: Attitudes and behavioural intentions that lead to the acceptance and use of GenAI: a UTAUT framework

The fourth and final research question was to determine how attitudes and behavioural intentions shape the acceptance and use of GenAI by considering a UTUAT framework. The UTAUT framework was selected because the insights uncovered for RQ3 revealed that this framework could explain approximately 70% of the variance in usage intention. As research had been conducted using UTAUT on traditional AI, but not GenAI, this research question addresses an identified gap. Appendix D (https://doi.org/10.7910/DVN/FOYRCD) provides a summary of the UTAUT analysis against the GenAI-based studies.

Performance expectancy: All studies consistently indicated that staff recognised the potential of GenAI to improve performance in academic settings. The prevalent attitude towards GenAI is largely positive, with expectations that such technology will transform educational and research practices by increasing productivity. Additionally, the behaviour towards integrating GenAI reflects a strong inclination to leverage GenAI for personalising educational practices and content, affording students with more tailored learning experiences and more effective information management, boosting student engagement and overall educational quality.

Effort expectancy: Collectively, all studies demonstrated a positive attitude and strong behavioural intention towards GenAI based on the perceived ease of use (effort expectancy). GenAI was deemed as user-friendly and able to streamline complex tasks such as generating exam questions, summarising information, analysing data, generating content and writing academic reports. Although educators found the basic functions of GenAI tools relatively straightforward, they acknowledged that more time and familiarity are required to fully harness this technology within teaching practices.

Social influence: All 10 studies revealed a complex scenario of mixed feelings among the academic community. Despite clear recognition of the potential benefits of GenAI as indicated via the performance and effort expectancies in enhancing educational opportunities, concerns persist about the impact of this technology on critical thinking, academic integrity and the potential to dehumanise learning. These concerns create a social influence environment where adoption is both encouraged and impeded based on varied perceptions from peers, institutions, and external opinions. This dichotomy suggests that, despite the potential for increased integration of GenAI, driven by positive peer influence and a trend towards digital transformation, significant fears remain that may impede full acceptance and integration.

Facilitating conditions: Collectively, the 10 studies highlight a significant gap in the facilitating conditions necessary for the effective adoption and integration of GenAI. Despite some extant technological infrastructure, formal training, systematic guidelines and comprehensive policy, frameworks are scarce – a shortfall given the unprecedented capability of GenAI to transform almost every aspect of education. To address these challenges, improve attitudes, promote behavioural intentions, as well as harness the full potential of GenAI, a concerted effort to establish clear policies, ethical guidelines and more accessible training resources is crucial.

In summary, attitudes and perceptions on the performance and effort towards GenAI are generally favourable. However, how social influence relates to facilitating conditions needs attention. A recent study by Jiang et al. (2024) explored perceptions of GenAI in 9733 tweets. The study corroborated similar conclusions, helping to validate the key findings of this paper. Institutions will need to place great effort in upgrading their systems, processes, policies and training to enable their staff and students to successfully adapt to a GenAI world.

Implications for policymakers and educators

The study's findings highlight several critical areas where AI and GenAI can influence policy decisions, curriculum development and teaching practices in higher education. Understanding these implications is essential for guiding the responsible integration of these technologies.

Policy decisions

Three key considerations revolved around the development of comprehensive AI/GenAI policies, regulation of AI-generated content and research and innovation. Policymakers need to create comprehensive frameworks that regulate the use of AI and GenAI in educational settings. These policies should address ethical use and ensure these technologies enhance learning without compromising academic integrity, equity or privacy. Although much attention is given to academic integrity factors, the emphasis cannot be placed on assessments alone and needs a holistic approach (Ellis & Murdoch, 2024). Care needs to be taken with such policies, as the sector's intense focus on rule adherence has shifted the emphasis to cheating, treating rule compliance as the ultimate goal (Dawson et al., 2024). These policies should be developed to manage the use of AI-generated content in academic work. This includes setting clear guidelines on when and how students and educators can use GenAI tools, ensuring transparency in usage. Central to making such decisions is supporting and funding research initiatives. Research that explores innovative uses of AI/GenAI in education is needed to ensure adoption in education is both effective and responsible.

Curriculum development

Curriculum transformation is essential to integrate AI/GenAI into education while emphasising human skills and adapting to evolving job markets. AI literacy should become a core component, ensuring students understand AI's usage, principles, limitations, and ethical concerns. As AI automates more learning processes, curricula should focus on skills that AI cannot easily replicate, such as strong evaluative judgment (Bearman et al., 2024) and incorporating psychomotor and affective skills (Nikolic, Grundy et al., 2023; Nikolic, Suesse et al., 2023). The rise of AI/GenAI is likely to reshape job market demands, making certain skills, like basic data analysis or coding, less valuable as AI performs these tasks more efficiently. However, three broad skills are expected to become scarcer and more valuable. First, strong evaluative judgement will be critical for ensuring the accuracy, validity and nuance of AI/GenAI outputs. Although many can use AI to analyse data, few will possess the expertise to detect flaws or biases in the results. Second, the ability to identify unique solutions will be essential, as AI-generated solutions may lack novelty and competitive value. Individuals who can overcome this limitation will stand out in the workforce. Finally, the capacity to use AI/GenAI efficiently will be important due to the financial and environmental costs associated with its use. Education institutions must adapt their graduate attributes, policies, and priorities to foster these crucial skills, preparing students for a future shaped by AI.

Teaching practices

Three key areas of focus include enhancing pedagogical approaches, professional development for educators, and collaborative learning with AI/GenAI. While maintaining a human-centred approach to education, there is strong potential for educators to leverage AI/GenAI to enhance their pedagogical practices, such as personalising learning experiences, providing real-time feedback, and automating administrative tasks (Crompton & Burke, 2024). However, this is only possible by providing ongoing professional development for educators and providing the workload capacity that they can actually engage and implement. A starting point is to provide support for mitigating potential drawbacks, such as issues related to academic integrity. The pathway promotes joint learning experiences that combine human and technological intelligence to improve productivity and results (Mollick, 2024).

Conclusions

This systematic review has explored the attitudes, perceptions, and behavioural intentions towards AI and GenAI. While both terms are related, and the definitions of AI vary, this explicit separation provided a research platform to observe the implications associated with the generative ability of GenAI. For RQ1, it found that academics generally view AI and GenAI positively, acknowledging their potential benefits but also recognising challenges. For RQ2, although GenAI's ability to create new content offers opportunities, it also presents unique challenges. Many perceived benefits and obstacles overlap between AI and GenAI, but traditional AI has more system-specific considerations. RQ3 outlined the various theoretical frameworks used to analyse the attitude and behavioural intentions towards AI, and from this, UTAUT was chosen as the framework to analyse the GenAI studies to address RQ4. No UTAUT analysis has been undertaken in the literature for GenAI, addressing a gap in the literature. In terms of performance expectancy, most participants believed that using GenAI would help them perform better. These benefits could be classified as improving efficiency and enhancing and supporting teaching and learning. This performance is driven by the positive perception of its user-friendly and intuitive design. However, accuracy and reliability are key concerns due to GenAI's tendency to hallucinate. This creativity and resultant hallucination is a key distinguishing difference from traditional AI. This results in great uncertainty on how to integrate and accept GenAI into the classroom.

The mixed messaging between the benefits and obstacles of GenAI will indeed limit intentions to adopt it. These concerns are linked to the lack of formal training, clear guidelines and comprehensive policies. For example, these uncertainties have been demonstrated by the need for parliamentary inquiries into the use of GenAI in education in countries around the world, including Australia and Canada, as well as requests for information on how universities will ensure learning, such as the one initiated by the Tertiary Education Quality and Standards Agency in Australia (2024).

Although this study was undertaken early in the GenAI adoption cycle, it has provided insights into the similarities and differences between the attitudes, intentions and behaviours of teaching academics. The technology's benefits are acknowledged, but the obstacles outlined need attention before the wider academic community can become comfortable with its use. Social influence might be encouraged or hindered based on peer and institutional attitudes and training, and policy development is necessary to fully facilitate its use. Therefore, synthesising the findings from this study, the following recommendations offered for researchers, educators and institutions can assist in advancing the responsible use of AI in education:

Development of comprehensive training programmes: Institutions should develop robust training programmes for educators and administrators to enhance their understanding and effective use of AI and GenAI tools in education. These programmes should focus on the practical applications of these technologies in various teaching scenarios and address common challenges, such as accuracy, reliability, ethics, data privacy and assessment security.

Creation of institutional support structures: Institutions should establish dedicated AI support teams that can assist educators in integrating AI/GenAI technologies into their teaching practices. This could include providing resources, technical assistance and ongoing professional development opportunities. Scaffolding is not just for students but is also required for teaching staff.

Implementation of pilot programmes: Researchers and educators should collaborate to design and implement pilot programmes that experiment with different uses of AI and GenAI in the classroom. These programs can help identify best practices and potential pitfalls, providing valuable insights for broader implementation. An exemplar is the Australasian Artificial Intelligence in Engineering Education Centre (https://www.aaieec.org), a collaboration of engineering departments from 14 universities working together to pilot use cases and frameworks that allow flexibility in application. Multidisciplinary studies and approaches could lead to a more complete understanding.

Development of ethical guidelines and policies: Institutions should work with legal and ethical experts to develop comprehensive guidelines that govern the use of AI and GenAI in education. These guidelines should address issues such as data privacy, bias, and academic integrity, ensuring that AI/GenAI is used in a way that aligns with ethical standards.

Encouraging student engagement, critical thinking and capability beyond the machine: Educators should develop strategies to use AI and GenAI as tools to foster student engagement and critical thinking rather than as replacements for traditional learning methods. This also provides the opportunity to consider shifting learning priorities to focus on outcomes that are uniquely human, such as psychomotor or affective skills.

Author contributions

Sasha Nikolic: Investigation, Data analysis, Writing – original draft, Writing – review and editing; **Isabelle Wentworth:** Investigation, Data analysis, Writing – original draft, Writing – review and editing; **Lynn Sheridan**: Conceptualisation of study, Data collection and analysis, Writing – original draft, Writing – review and editing; **Simon Moss**: Investigation, Writing – original draft, Editing – review; **Elisabeth Duursma**: Conceptualisation of study, Writing – original draft, Writing – review and editing; **Rachel Jones**: Investigation, Writing – original draft; **Montse Ros:** Investigation, Writing – original draft; **Rebekah Middleton**: Investigation, Writing – original draft.

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Corresponding author: Sasha Nikolic, sasha@uow.edu.au

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