



From Automation to Engagement: Teaching Academics' Future Plans for AI in Higher Education

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Abstract

Generative Artificial Intelligence (GenAI) is increasingly being used within higher education to enhance curriculum design, automate academic tasks, and personalise learning. Despite this, little is known about teaching academics' attitudes, intentions and behaviours and, in turn, how they use and plan to use GenAI in practice. This qualitative study explored teaching academic staff attitudes, intentions and behaviours regarding their use and future use of GenAI. Data was collected via five open-ended questions focusing on current teaching practices. The Theory of Planned Behaviour informed the analytical process. Academic staff were drawn from 20 different disciplines across 24 countries. Six main themes were identified: Efficiency and Automation, Ethics and Authenticity, Quality, Customised Learning, Institutional Policy–Practice and Sociocultural Implications. Overall, there was a dichotomy in responses. Participants noted that while GenAI could streamline teaching and enhance resource quality, it might also increase short-term workload and reduce the role of human judgement, risking unreliable outputs. They also highlighted limited institutional policies, strategies, and training. These attitudes have implications for updating policies, practical strategies, and meaningful training in higher education institutions.

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Practitioner Notes

1. Close the policy and training gap. Teaching academics expressed a wide range of views on GenAI, from enthusiastic and optimistic to cautious and resistant.
2. Use GenAI technologies to extend teaching capacity. Teaching academics use GenAI to automate tasks and personalise learning and enhance teaching effectiveness.
3. Build in ethical safeguards and quality assurance. Teaching academics worry that GenAI's focus on efficiency might undermine ethical considerations, devalue human educators and threaten academic jobs.
4. Develop a practical differentiated strategy with a concrete policy. Diverse and conflicting intentions highlight the need for stronger policies and practical strategies.

Keywords

generative artificial intelligence, teaching practices, behaviours, staff attitudes

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Introduction

The integration of Generative AI (GenAI) into higher education is accelerating and reshaping teaching, learning, and assessment practices (Samala et al., 2025). GenAI, a branch of Artificial Intelligence powered by large language models and trained on vast datasets, offers benefits over comparable technologies (Ronge et al., 2025), including the mimicking of creative human endeavour by generating novel output, rather than merely replicating or integrating existing output. GenAI can also respond dynamically to users, adapt flexibly to accommodate diverse tasks or requirements, and can integrate data from multiple modalities, such as text and videos (Sengar et al., 2024). With these features, GenAI tools are rapidly accelerating the digital transformation of learning within higher education, reshaping how knowledge is delivered and assessed. As Nikolic et al. (2024) highlighted, these technologies are not only enhancing learning and teaching but redefining the future of education.

This rapid adoption of GenAI has also raised many challenges, such as the possibility that GenAI output may promulgate existing biases or the concern that many extant policies or pedagogies may be obsolete (Albadarin et al., 2024; An et al., 2025; Nguyen, 2025). To assist the higher education sector in navigating these challenges, the Tertiary Education Quality and Standards Agency (TEQSA) in Australia developed resources and guidelines for how institutions can maintain academic integrity, reform assessments, and support students as GenAI proliferates (TEQSA, 2024). These materials are designed to help academics and graduates develop the capacity to utilise GenAI technology responsibly. Similarly, the UK Department for Education & Open Innovation Team (2024) and the European Union, amongst other OECD countries, have developed policies that encourage universities to embed GenAI capability development into their curricula rather than treat this skill as optional or distinct from other competencies. These policies and practices are vital according to research, as students and their teaching academics are often unaware of the economic, social, ethical, and environmental implications of GenAI in learning and teaching (Kangwa et al., 2025).

Although policy development has progressed, there is still limited research into how teaching academics are using GenAI in practice: the integration of these tools into curricula, upholding integrity standards, and the redesign of assessments (Cacho, 2024). To address this shortfall, this study explores the attitudes, intentions, and behaviours of teaching academics and their future intentions and beliefs surrounding the usage of GenAI technologies in teaching. This paper is structured around two research questions. It begins by outlining the key literature and the study's use of the TPB framework and qualitative design. Findings are organised around key themes emerging from that data, with discussions drawing inferences informed by TPB.

RQ1. What are the perceptions, attitudes, and beliefs of teaching academics on how GenAI will shape future teaching and learning and how do they plan to use GenAI in their teaching?

RQ 2. What contradictions or tensions do teaching academics experience as they plan to use Generative AI in their teaching in the future?

Although existing studies have explored current attitudes and uses of GenAI, they rarely examine future intentions or the implications for policy, training, workload and academic culture. Several systematic literature reviews have explored the benefits and risks of GenAI in education as well

as the barriers to implementation (Cong-Lem et al., 2025; Nguyen, 2025). Interestingly, teaching academics who perceive GenAI tools as useful, trustworthy, and embraced by peers are more inclined to utilise these technologies (Nikolic et al., 2024; Shata & Hartley, 2025). A key innovation of the present study is that it explicitly analyses the tensions and contradictions between beliefs, intentions, and anticipated practices, situated against evolving institutional policies and examined across a multi-country sample. Understanding academics' perspectives is essential for designing effective policies and professional development initiatives that align with real-world practices and expectations.

This study contributes to the growing body of literature on GenAI in higher education by providing insights into the beliefs, intentions, and perceived challenges of teaching academics across 24 countries. By amplifying their voices, the research informs institutional strategies, policy development, and capacity-building efforts to ensure responsible and effective integration of GenAI into teaching and learning. Ultimately, these findings will help universities move beyond reactive measures toward proactive, evidence-based approaches that support both educators and students in a rapidly evolving digital landscape.

Literature

Current use and attitudes of GenAI in university teaching

The release of ChatGPT in 2022 was a pivotal moment in the evolution of educational technology, igniting a rapid change in higher education (Robert & Muscanell, 2023). Since this moment, many organisations have developed and applied GenAI tools to reshape learning and teaching across universities worldwide (e.g., Hughes et al., 2025; TEQSA, 2024). GenAI tools are increasingly being used to support innovation and curriculum design, automate routine academic tasks, and personalise learning experiences (He et al., 2025; Hughes et al., 2025; Miron et al., 2025; Weng et al., 2024).

Despite the perceived benefits of GenAI, academics, education specialists, and education leaders all raise concerns about the potential risks (Barnes & Hutson, 2024; Maxwell et al., 2025). To illustrate, teaching academics often express the concern that GenAI might circumvent effort and thus impede student learning as well as promote cheating or misuse (Arowosegbe et al., 2024; Bolívar-Cruz & Verano-Tacoronte, 2025). These ambivalent attitudes towards GenAI were exemplified in an analysis of academic tweets about #ChatGPT, in which mentions of trust and joy, but also fear and anger, were prevalent (Gonda & Park, 2025).

These studies, however, primarily focus on perceptions and attitudes towards the current, rather than future uses of GenAI in higher education teaching. Existing studies tend not to examine how GenAI might reshape future teaching and learning, or its implications for policy, training, workload, culture, and integrity. Despite the burgeoning use of AI by students and teaching academics, universities often rely on piecemeal guidelines or ad-hoc workshops to manage GenAI technology/practices, leaving academic teachers to navigate these challenges with little formal support (An et al., 2025; Kangwa et al., 2025; Nguyen, 2025). Policies and training, therefore, risk being ineffective by not reflecting teaching academics' views and practices around GenAI in teaching.

Theory of Planned Behaviour

The Theory of Planned Behaviour (TPB) (Ajzen, 1991; Bosnjak et al., 2020) guided the questions and interpretations of this study. This theory has often been applied in education and, for example, utilised to predict student behaviour in online courses (Wang et al., 2020) and mobile learning (Cheon et al., 2012), as well as understand teaching practices in assessment and classroom management (Knauder & Koschmieder, 2019). The essence of this theory is that rational considerations, rather than unconscious impulses, tend to guide actions (Ajzen & Fishbein, 2005). Specifically, according to this theory, the attitudes of individuals towards a practice, such as the application of GenAI, the degree to which individuals perceive this practice as embraced by peers, and their capacity to apply this practice affects intentions to implement this practice. These intentions then guide subsequent actions (Baig & Yadegaridehkordi, 2025).

Unsurprisingly, to a large extent, the attitudes of individuals towards a practice, that is, whether they perceive this act favourably or unfavourably, will tend to shape their intentions and behaviours. Several considerations shape these attitudes. First, individuals tend to experience favourable or positive attitudes to practices or behaviours that tend to generate desired outcomes (Blazar & Kraft, 2017). Second, individuals tend to experience favourable or positive attitudes to practices that have been conditioned to elicit pleasant emotions. Teaching academics who assume that GenAI is beneficial or enjoy GenAI will thus embed these technologies into their teaching (Chiu et al., 2023).

In addition to attitudes, subjective norms, or the predicted attitudes or behaviours of colleagues, friends, or family, can also shape intentions and actions (Ajzen, 1985, 1991). For example, teaching academics who believe that peers, such as other educators, often utilise or embrace GenAI may be more inclined to adopt these technologies. Schultz et al. (2007) demonstrated that descriptive norms, defined as the actual behaviour of peers, are more likely than injunctive norms, defined as peers' perceived attitudes towards these behaviours, to shape individuals' intentions.

Besides attitudes and social norms, the capacity of individuals to execute some act, called perceived behavioural control, also influences these intentions. Perceived behavioural control entails two facets: the degree to which individuals feel they have developed the capability to perform the behaviour, analogous to self-efficacy (Basileo et al., 2024), and the extent to which the circumstances, such as resources or time, enable rather than hinder the behaviour (Kraft et al., 2005). Accordingly, teaching academics who feel competent to use GenAI and feel the institution facilitates the use of GenAI should be more inclined to utilise these technologies (Knauder & Koschmieder, 2019). Consistent with these premises, teaching academics who express positive attitudes towards GenAI, believe that peers utilise GenAI, and feel able to use GenAI effectively, are indeed more inclined to utilise this technology in the classroom (Wang et al., 2025). Nevertheless, as research on TPB has demonstrated, the intentions of individuals to perform some act, such as adopt GenAI, will not invariably translate into action.

Method

Research design

This study adopts a qualitative, exploratory design (Young & Diem, 2023) to examine teaching academics' beliefs, intentions, and anticipated future practices concerning Generative AI (GenAI) in higher education, using the Theory of Planned Behaviour (TPB) as the guiding conceptual lens.

TPB posits that attitude, subjective norms, and perceived behavioural control jointly shape intention, which, under sufficient control conditions, predicts behaviour. The framework is widely used to study technology-related adoption decisions and interpret qualitative findings in educational contexts (Ajzen, 1991; Ajzen, 2020; Fishbein & Ajzen, 2010). Although TPB research is often quantitative, it has also been successfully operationalised in qualitative studies of university teaching, demonstrating the approach's methodological coherence for qualitative designs (Renzi & Klobas, 2008). Hagger and Hamilton's (2025) study adopted TPB when focusing on the intention–behaviour gap, supporting its relevance for studying emergent technologies like GenAI that are not yet fully institutionalised.

Here the term 'sufficient control conditions' warrants unpacking. Ajzen's stipulation is that intention predicts behaviour only where the act is largely volitional, that is, where actors hold the requisite capability, resources and opportunity, such that perceived control corresponds to actual control. In the present domain these conditions are largely institutional rather than personal, such as policy clarity, tool access and licensing, IT infrastructure, training provision, and discretionary time, and are themselves subject to rapid changes and often absent as institutions struggle to keep pace with technological change. Where control is low, intention is a weak predictor of subsequent behaviour, thus limiting the inferential reach of the TPB. This is a limitation we will return to in our section on limitations and future research. TPB is accordingly deployed here as a set of sensitising concepts (Blumer, 1954; Bowen, 2006) for organising expressed beliefs, norms and control perceptions, as opposed to a predictive model.

The qualitative responses were drawn from five open-ended questions. The TPB informed the wording and focus of the questions, designed to elicit beliefs (attitude), social influences (subjective norms), and control perceptions (perceived behavioural control) that underpin intentions toward GenAI use. Table 1 outlines the questions, why they were asked and the connection to the TPB.

Table 1

Questions that participants were asked.

Question	RQ addresses	Why the question was chosen
Q1. How might GenAI affect 'the future of' academic teaching in a higher education college, university, or institution?	RQ 1 (vision of the future)	Opens the conversation to establish the predicted trajectory of teaching with GenAI (Attitude, behavioural beliefs about outcomes)
Q2. What are your future plans regarding GenAI in your teaching?	RQ 1 (specific plans)	Directly targets intended practices and adoption of GenAI (Intention, linked to attitude, norms, and control)

Q3. How might current infrastructure, resources, workload and culture in your institution, support or hinder the use of GenAI in your teaching?	RQ 1 & RQ 2	Explores the practices of institutions that may enable or impede the use of GenAI and reveals potential tensions or contradictions (Perceived behavioural control, subjective norms)
Q4. What are the features of GenAI that you feel could assist your teaching?	RQ 1	Clarifies perceived usefulness and the concrete affordances academics value (Perceived behavioural control, subjective norms)
Q5. If you are resistant to adopting GenAI in your teaching, can you explain your reservations?	RQ 2	Invites reflections on discomfort, ethical qualms, or contradictions between ideals and actions (Attitude—negative valence; perceived barriers/control beliefs)

Derived from the qualitative responses of academic staff from 24 countries, we examine what teaching academics believe GenAI can offer, the plans they are formulating, the support they believe they need, and the reasons that some individuals may resist GenAI technology. To do this, we analysed the qualitative responses of individuals to an online questionnaire using Qualtrics.

Table 2

Participant and discipline information

Category	Subcategory	Count	Percentage
Gender	Males	189	36%
	Female	329	63%
	Non-binary/Third gender	4	1%
	Prefer not to say	2	0.38%

Age Group	20-29 years	176	34%
	30-39 years	165	31%
	40-49 years	103	20%
	50-59 years	58	11%
	60–69 years	17	3%
	70+ years	5	1%
Teaching Experience	5 years or less	315	60%
	6–10 years	108	21%
	11–20 years	65	12%
	20+ years	36	7%
Top Disciplines	Education	73	14%
	Language, Communication & Culture	58	11%
	Medical and Health Sciences	33	6%
	Commerce, Management, Tourism & Services	36	7%
	Engineering	29	6%
	Information and Computer Sciences	28	5%
	Biological Sciences	26	5%
	Mathematical Sciences	26	5%
	Other(e.g., Psychology, Sociology)	46	9%
		150	29%
Countries	South Africa	58	11%
	United Kingdom	35	7%
	Australia	280	53%
	Others (21 countries)		

Participants were teaching academics working in higher education institutions (e.g., colleges, universities, or institutes). The academics were selected on the basis that they had taught within the previous five years. This was important because GenAI has only recently entered the higher education space. Demographic data were collected on their location, age, gender, teaching

experience and discipline (see Table 2). Responses were gathered from teaching academics across 20 different disciplines and 24 countries, offering insight into diverse perspectives (i.e., gender, age, experience and discipline). These findings contribute to a larger study focused on the modifiable characteristics of teaching academics that influence their likelihood of using GenAI in higher education. Response rates were: Q1, n = 431; Q2, n = 495; Q3, n = 472; Q4, n = 419; and Q5, n = 411.

Data collection

For data collection we utilised two approaches to recruit academics who had been teaching for the past five years in a university or college. First, the authors utilised various channels, such as emails or newsletters, to contact their professional networks and elicit a snowball sample. Second, the researchers utilised an online platform, Prolific, to invite additional teaching academics across the globe. Ethics approval was granted for this cross-national study, from the Human Research Ethics Committee of the university, approval number (H2024/145).

A focus group was initially used to facilitate discussion on the proposed questions for inclusion in the online questionnaire, ensuring consistency and relevance. This process involved expert face validity and utilised the expertise of five independent teaching academics who provided feedback on the relevance of these questions (Hardesty & Bearden, 2004). The researchers utilised this feedback to refine and to clarify the five questions.

Data analysis

Five of the authors contributed to the analysis, with one researcher drawing ideas together for consensus. These researchers applied Braun and Clarke's (2006, 2019) six-phase thematic analysis (familiarisation; generating initial codes; generating themes; reviewing themes; defining and naming themes; producing the report), applying an inductive, reflexive approach to coding within a question-driven structure, consistent with an interpretivist epistemology that treats analysis as an active, situated interpretive process rather than a search for pre-existing categories. The research questions themselves provided the scaffolding for analysis, while coding and theme development remained open to unanticipated patterns in participants' responses.

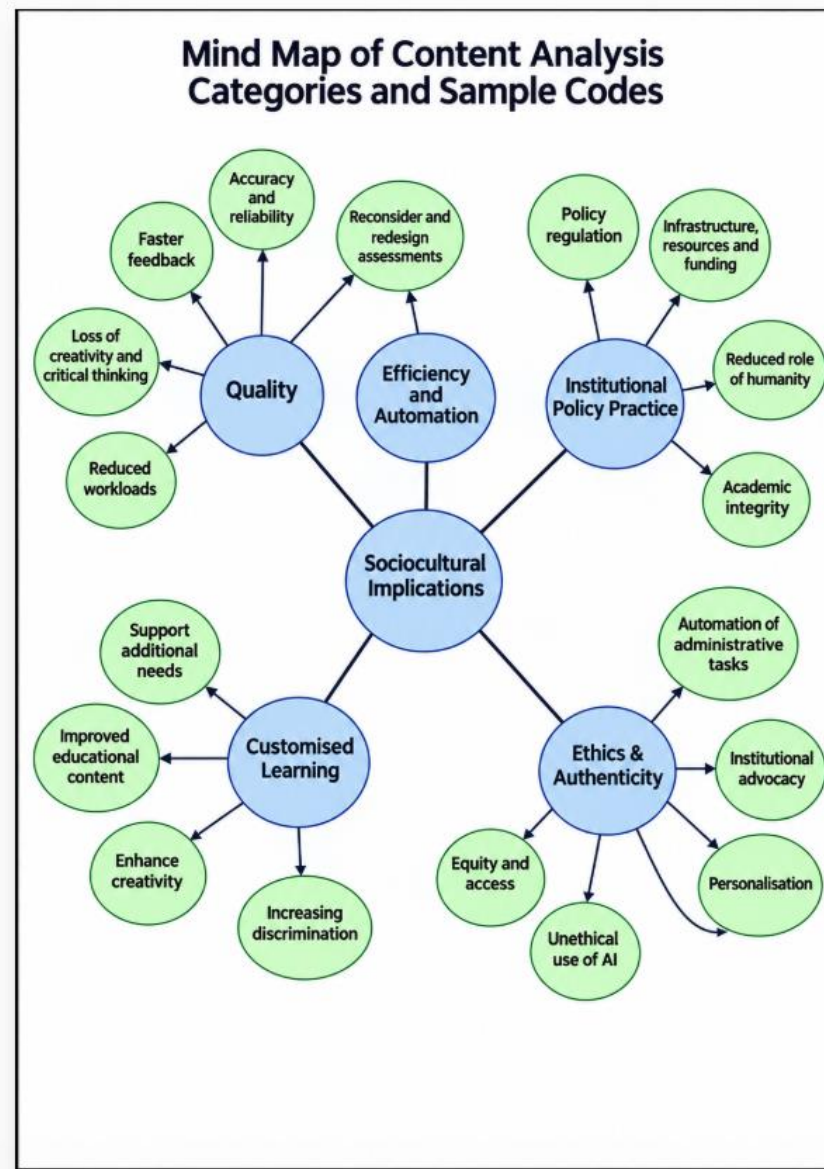
Interpretivism is most suited to exploring teaching academics' attitudes, intentions, and beliefs about GenAI because these constructs are subjective, context-dependent, and shaped by institutional norms and personal experiences. This approach values multiple perspectives, rather than seeking universal truths, and aims to understand the meanings participants ascribe to GenAI within their professional practice (Willis et al., 2007). It is particularly suited to qualitative research where the goal is to understand how individual teaching academics make meaning of their experiences (Matta, 2022).

In the context of analysing short-answer questions, this approach allowed the researchers to explore the nuanced, subjective interpretations teaching academics bring to their responses, rather than relying solely on response rates. Following familiarisation, five researchers independently coded responses to each question using short descriptive labels. One researcher (Author 1) then collated and clustered overlapping codes into candidate themes, which were iteratively reviewed, refined, and named through team discussion until consensus was reached across all researchers. Reflexivity was supported through regular team meetings in which coders

discussed and made explicit their disciplinary assumptions and interpretive decisions, consistent with Braun and Clarke's (2019) view of coding as an active, researcher-shaped process.

Figure 1

Summary of codes and categories generated from Content Analysis



Codes and categories generated from this content analysis are shown in Figure 1. The team of researchers then convened to agree on the titles and definitions of these categories. Table 3 presents the number of responses to each question that corresponded to each category.

To validate the categories, one researcher assigned each answer, or parts of an answer, to one of the categories. This procedure enabled the researchers both to refine the categories and to estimate the frequency with which each category was represented. Counting the frequency of the coded response themes can enhance transparency and provide a clearer sense of patterns without compromising interpretive depth (Maxwell, 2010). This approach uncovered six

categories: Efficiency and automation; Ethics and authenticity; Quality; Customised learning; Institutional policy–practice; and Sociocultural implications.

To refine the thematic analysis, salient excerpts were selected to exemplify each category and to examine relationships and tensions across categories. One researcher conducted the initial coding, after which the research team engaged in multiple analytic meetings to iteratively refine code definitions and resolve discrepancies. This process of investigator triangulation followed a structured, team-based validation approach, emphasising reflexive dialogue and consensus building, in alignment with the principles of triangulation outlined in Carter et al. (2014). The refined codes were then reduced into six overarching categories representing higher-order themes. The analysis ultimately identified six distinct yet interrelated categories.

Results

The first theme that emerged was related to efficiency and automation (n=737 comments – Table 3). This theme centred on the prospect that GenAI could expedite many teaching activities and reduce the long-term demands of academic teaching. Yet, as many participants noted, to accommodate the changes that GenAI may engender, there is also the potential to raise workload and job demands, at least temporarily.

The efficiencies that GenAI may afford could also enable inappropriate behaviour. Indeed, the second theme focused on ethics and authenticity (n=326 comments). For example, GenAI may enable teachers to circumvent academic rules or perpetrate other unethical behaviours.

The third theme centred on the concept of quality, rather than efficiency, in teaching (n=424 comments). GenAI might improve the quality of teaching materials and teaching methods, enabling teaching academics to integrate more extensive knowledge, information, and wisdom into their content. Yet, a reliance on GenAI might also diminish the role of human judgement and experience, generating materials that may be misleading or unreliable.

Despite these concerns, the fourth theme underscored the possibility that GenAI could personalise (customised learning) and thus improve learning (n=197 comments). That is, if GenAI were deployed effectively, students might receive information that is tailored to their unique needs, preferences, or interests, enhancing both engagement and learning.

Presumably, the degree to which GenAI can be utilised effectively and ethically depends on the policies and strategies of institutions. Accordingly, the fifth theme related to institutional policy and practices (n=305 comments). Some participants felt that higher education institutions had not introduced useful policies, training, infrastructure, resources, or funding to enable teaching academics to apply GenAI ethically and effectively. A minority of respondents, in contrast, believed their institutions had responded proactively to facilitate the effective use of GenAI in teaching and learning.

As the final theme underscored, GenAI does not only affect the learning and experience of students but generates many other sociocultural implications as well (n=217 comments). For example, the rapid decline of some jobs, in the aftermath of GenAI, could devastate many communities. Furthermore, GenAI may also shape the nature of work, such as eroding the human connection in education.

Table 3*Number of responses for categories 1–6, across Questions 1–5*

Categories	Q1 (n=431)	Q2 (n=495)	Q3 (n=472)	Q4 (n=419)	Q5 (n=411)	Total
1. Efficiency and Automation (+/-)	168	215	121	195	38	737
2. Ethics & Authenticity	92	49	97	7	81	326
3. Quality (+/-)	73	78	67	108	98	424
4. Customised learning	56	61	3	74	3	197
5. Institutional policy-practice	66	29	196	0	14	305
6. Sociocultural implications	84	5	88	1	39	217
Total	539	437	572	385	273	

Question key:

Q1 = 1. Affect 'the future of' academic teaching (n=431)

Q2 = 2. Future plans in your teaching (n=495)

Q3 = 3. Infrastructure, resources, workload and culture in HE, support or hinder the use of GenAI in your teaching (n=472)

Q4 = 4. Features that assist your teaching (n=419)

Q5 = 5. Resistant to adopting GenAI in your teaching (n=411)

Respondents' beliefs, attitudes, and intentions towards the likely proliferation of GenAI in higher institutions (Q1) offered insights into how GenAI may affect their role in the future, the practices of institutions that could shape this role, as well as the benefits and risks of these technologies, as described below.

In the following sections, participant quotations are identified by the specific question and respondent number. For example, Q1,141 refers to respondent 141's response to Question 1.

Efficiency and automation

Many participants recognised the possibility that GenAI could expedite tasks that demand limited judgement or expertise. To illustrate, GenAI could expeditiously generate assessment tasks, marking rubrics, lecture plans, case studies, and illustrative examples, as other researchers have underscored (Cong-Lem et al., 2025).

Accordingly, GenAI may enable teaching academics to devote their time and efforts to more productive and useful activities: "GenAI has the potential to free up educators' time to focus on

more meaningful interactions with students” (Q1,141). For example, teaching academics could strive to enhance the degree to which their materials engage students. In this vein, one respondent said, “I would like to use AI to streamline and automate processes to give me more time for other tasks. I will also be using it to help me develop interesting and engaging teaching materials” (Q2,278). Similarly, teaching academics could adjust their materials to suit the individual needs of specific classes or students: “AI-driven tools could automate routine tasks like grading, allowing instructors to focus more on interactive and personalised teaching methods” (Q1,311).

Teaching academics also referred to other benefits of the time that GenAI may conserve; these benefits extend beyond the classroom. To illustrate, GenAI might diminish the extent to which work responsibilities impinge on family responsibilities or personal interests: “(GenAI) would stop me working out of hours and longer hours than normal; it would give me some of my life back” (Q4,364).

Besides time, the use of GenAI might also conserve other resources and thus diminish costs or waste. For example, as one respondent noted, “There is now less paperwork which is a good thing” (Q2,278). This insight, however, may overlook the pronounced levels of energy that GenAI tends to consume, or the initial time cost to the academic of upskilling.

Some respondents, however, were dubious about the degree to which GenAI may improve efficiency and enhance productivity. To illustrate, a few participants assumed that entrenched practices and beliefs may limit the extent to which GenAI will change teaching behaviours: “Fear and uncertainty have led many to cling to familiar systems and processes, despite their known inefficiencies and ineffectiveness”(Q3,191). Similarly, the elevated workloads of teaching academics may, at least in the foreseeable future, limit their capacity to integrate these technologies into their practices due to significant adoption cost: “The high workload and time constraints faced by faculty members make it difficult to dedicate time to learning and integrating new technologies”(Q3,91). Teaching academics may even need to dedicate significant ongoing time to learning about the latest updates and applications of GenAI, potentially amplifying their workload.

Ethics and authenticity

As many participants recognised, the efficiency of GenAI can also generate or exacerbate a range of ethical concerns, ranging from the tendency of students to become dependent on AI to issues around data privacy and equity. As one respondent wrote, “Reliance on AI raises concerns about data privacy, academic integrity, and the need for educators to maintain critical thinking and ethical standards” (Q1,128). Yet, research indicates that many individuals, including students, are unaware of these ethical implications (Nikolic et al., 2024).

Many of these ethical concerns are centred on the perceived role of higher education. Students invest heavily into their studies, anticipating they will receive teaching and guidance from experts. If these experts, the teaching academics, depend excessively on GenAI to prepare materials and to deliver feedback, students may not feel they have received the wisdom or personalised guidance they expected. As one respondent stated, “(GenAI) lacks authenticity. Students are paying for my knowledge; they should get my knowledge” (Q4,364). Similarly, another participant

felt that “I do not believe that it is ethical; it borders on plagiarism, in terms of having something else do your work for you - this is not something that sits comfortably with me” (Q1,137).

This reliance on GenAI in lieu of human wisdom might not only disadvantage students but could reduce the engagement of teaching academics. Teaching academics felt that excessive use of GenAI may limit the degree to which they utilise their judgement, ingenuity, critical thinking, and creativity in their work, compromising personal engagement, professional satisfaction, and academic standards as well as diminishing a sense of authenticity at work. As one respondent reflected, “I feel using GenAI will somehow alienate me from my work as everything will just be created for me. In a way it makes people lazy to think and honestly lacks authenticity” (Q1,190).

Like teaching academics, the students themselves may depend unduly on GenAI, limiting the degree to which they grapple with challenging concepts and thus impeding their learning, development, and growth. One participant commented,

It is incredibly common to receive work from students that is clearly not of their creation. I see my university turning away from this technology because it has not (and I believe, will not) be suitable to promoting student growth. It's a great tool but it's so easy to abuse, I worry for young learners (Q3,206).

The prospect that students may use GenAI excessively and perpetrate academic misconduct not only impedes student learning but can also foster an adversarial relationship between students and educators, as manifested in the statement, “It is going to be an arms race between faculty and students on who can master it more quickly” (Q1,352). This adversarial relationship, coupled with undue reliance on GenAI, may preclude the personal connections and mentorship between students and teaching academics that is central to learning and development. As one respondent highlighted, this role of educators is “not something that can be easily replaced. It requires the expertise of staff who ‘know’ the students that we teach in class. This is what makes the learning experience unique for students” (Q3,206).

The possibility that teaching academics but not students could utilise GenAI freely could also exacerbate this adversarial relationship. That is, in some institutions, educators were encouraged to use GenAI to expedite their work, whereas students were discouraged, and sometimes prohibited, from utilising these technologies. One participant expressed this concern explicitly:

I don't see a strong case for using it and I think it would set a questionable example for students – if we use it to do our job yet it's a punishable offence for them to use it in their assessments (Q3,304).

In addition to this disparity between teachers and students, disparities across students were also recognised, raising concerns of equitable access to technology. Some respondents were concerned that only a portion of students will be able to leverage the benefits of GenAI, compromising equity: “The digital divide among students, with varying access to technology at home, could lead to unequal learning opportunities” (Q3,91). Yet, other participants felt that GenAI may broaden educational inclusivity.

Quality of teaching and learning materials: reliability, accuracy and bias

In addition to the ethical implications of GenAI, participants also raised concerns about the possibility that such technologies could impair the 'quality of teaching and learning', with concerns regarding the reliability, accuracy and bias of GenAI output, used in developing teaching materials and content. To illustrate, respondents were often concerned that GenAI could generate material that is biased or inaccurate for several reasons. First, the data that inform the neural networks may not be representative of broader society and thus may skew the models. Second, because no authority or measure can verify the accuracy of AI output continually, the frequency of plausible but factually incorrect or unsupported outputs, called hallucinations, is typically unknown, impeding trust in these tools: "AI also has its own limitations in terms of accuracy and so that also reduces its trustworthiness" (Q3,279). Accordingly, higher education students need to be apprised of the frequency and nature of these hallucinations (Alimardani, 2025).

Nevertheless, respondents conceded that such concerns may subside over time. Recent advances, such as larger datasets, more parameters, and comparisons between multiple models, diminish the incidence of hallucinations. These improvements could address some of the hesitations of teaching academics: "I will only start to incorporate it as it becomes more reliable (Q4,290).

In addition to biases and inaccuracies, respondents also alluded to other limitations in GenAI that could impair the quality of teaching materials. For example, participants indicated that AI content may not produce the creativity or nuance that human experts can generate.

In contrast to these concerns, teaching academics also broached the possibility that GenAI could enhance teaching quality. For example, GenAI may enable teaching academics to collate and to integrate more diverse knowledge and insights into their classrooms. Similarly, GenAI may enable students to explore a topic they learned in more detail. That is, students can interact and probe a GenAI tool, seeking explanations and examples to deepen their understanding: "Virtual assistants can ... provide additional explanations" (Q4,37).

Personalised learning

Despite some divergent opinions about whether GenAI will tend to enhance or impair teaching quality, most of the teaching academics recognised that such technologies could enhance their capacity to accommodate the needs and preferences of particular students, a benefit that past reviews have corroborated (Tillmanns et al., 2025). For example, as participants revealed, teaching academics can utilise GenAI to tailor their materials to the progress or knowledge of their students. These tools would impart knowledge or information that students can understand but do not know already. As one respondent wrote "This technology could also facilitate the development of adaptive learning platforms that adjust to students' progress in real-time" (Q4, 200). GenAI tools may consider performance on assessments or other information to customise these materials: "Using AI to analyse learning outcomes and student interactions, educators can create more effective and responsive curricula that cater to the needs of diverse student populations" (Q3,157).

In addition to catering to the progress or knowledge of students, GenAI tools can also accommodate the learning styles or preferences of students. That is, GenAI may generate

materials that are consistent with the format, style, or other features that students prefer, promoting engagement, persistence, and learning. Thus, GenAI can “support diverse learning styles, enhancing engagement and comprehension” (Q2,157). Likewise, GenAI may generate materials that utilise the strengths or overcome the limitations of students: “Creates personalised study plans based on students’ strengths, weaknesses, and progress” (Q2,237).

In addition to imparting knowledge, GenAI can deliver feedback, at any time, in response to the tasks or assignments that students complete, fostering engagement and interaction. To illustrate, according to one participant, “GenAI can significantly enhance teaching by ... providing instant and detailed feedback, and creating engaging, interactive learning tools.” (Q2,354).

Institutional policy and practice

Higher education institutions can introduce a range of policies and provisions to amplify the benefits of GenAI, such as personalised learning, and mitigate some of the risks and costs (Baig & Yadegaridehkordi, 2025). Nevertheless, respondents often expressed concerns regarding whether institutions were succeeding in this role.

First, many respondents felt their institutions had not introduced cohesive and unambiguous policies around which GenAI practices are encouraged or permitted. That is, existing policies often seem hazy or uninformative rather than definitive and tangible: “Many new position statements, policies, procedures, and guidelines lack clarity or decisiveness” (Q3,191). Alternatively, some policies may seem ad hoc rather than integrated into a cohesive and meaningful framework:

There is no coherent policy on the use of GenAI in my institution currently.... The development of a policy will clarify what I am able to implement. There needs to be a group that will look at and address questions on this issue (Q3,299).

In response to this uncertainty, teaching academics experiment with a range of GenAI practices, unsure whether their approaches are endorsed or effective: “Many lecturers currently play it by ear” (Q3, 299). To override this uncertainty, teaching academics may establish unofficial coalitions or communities of practice to explore how they can apply GenAI appropriately: “There are a few beacons of hope in my institution who are willing to embrace GenAI and try something new. These are the people with whom I am aligning myself” (Q3,191).

Second, in addition to a dearth of helpful policies, many respondents also felt the institution had not equipped teaching academics with the computers, software platforms, and other IT infrastructure they need to apply GenAI effectively, such as powerful computers or adequate storage:

Universities with robust IT infrastructure and access to high-performance computing resources are better positioned to support the computational demands of GenAI applications. This includes access to powerful GPUs or TPUs for training models, and sufficient storage for large datasets. ... Institutions lacking such infrastructure may struggle with slow processing speeds, insufficient storage, or high costs associated with upgrading to support GenAI application (Q3,283).

These shortfalls were often ascribed to limited availability of funding, exacerbated by the financial pressures that many of these institutions were experiencing. This limited funding can explain not

only limitations in IT infrastructure but also inadequate technical support to assist GenAI implementation: “Availability of funding for purchasing software licenses, accessing cloud services... and hiring technical support staff can facilitate the integration of GenAI into teaching” (Q3,283).

Inadequate training opportunities on GenAI may have magnified the impact of this scarcity in technical support. Consequently, as several respondents underscored, teaching academics often do not feel they are granted the opportunities they need to learn how to apply GenAI proficiently in their classroom as well as how to manage risks, such as data privacy:

We are currently running around without guidance on this subject. ... I have received some minimal training to this point, but the continued cuts in professional development and travel makes it less likely that I can get the training I need or the time to be able to think about how I might use it. I am not confident in the higher education framework as it exists now to effectively manage a response to GenAI and to be able to help individual faculty members manage and learn how to use it (Q3,472).

Because of limitations in technical assistance and Gen AI training, respondents felt that some older individuals, individuals often assigned to positions of power and influence, may be especially reluctant or unable to learn about these technologies:

No one in positions of power knows anything about AI, they are completely befuddled and overwhelmed, and then the generation gap is simply too vast to overcome—can you really imagine my 68-year-old director, who struggles to use a phone, accepting tutoring and guidance from a young person with AI expertise? (Q3,472).

Accordingly, if staff in positions of power and influence do not embrace GenAI sufficiently, a culture will evolve in which traditional practices may be preferred over innovation: “A culture that values innovation and continuous improvement in teaching methods can facilitate the integration of GenAI, however in many cases a more traditional or rigid academic culture has been resisting these changes” (Q3,232). This culture may stifle collaborative efforts to optimise the utility of GenAI applications, impeding the utility of these technologies: “Some faculty members may be resistant to adopting GenAI, which could hinder collaborative efforts to integrate these technologies across the institution” (Q3,42).

As a manifestation of this emphasis on tradition rather than innovation, discourse about GenAI is often dominated by concerns around academic integrity rather than discussions about future opportunities, a tendency that past research has uncovered as well (Coates et al., 2025). As one concerned respondent noted, “We have a good support system, but most resources in this area go to academic integrity issues” (Q3,472).

Sociocultural implications

Yet, as participants revealed, the resistance of many teaching academics to GenAI cannot be ascribed only to limited familiarity or training with these technologies. Instead, this resistance can partly be attributed to concerns about the impact of GenAI on sociocultural values.

Specifically, several respondents suggested that, because GenAI can expedite or automate many tasks, higher education institutions might orient their attention more to efficiency than depth of

learning. These institutions, including their leaders, staff, and students, may gradually attach less value to skills that demand significant contemplation, effort, time, and patience.

I do worry however that some of the cognitive processes involved in doing traditional research (reading/writing vs experiments) is diminished when we allow AI to do the work for us. I also think it makes us less patient as people (Q1,280).

For example, students might not learn topics from multiple perspectives and may thus overlook the inter-relationships, similarities, and contradictions across diverse concepts. These students may not appreciate the nuances of these topics, compromising critical thinking, creativity, and other skills that are vital to personal development, workplace productivity, and society more generally (Nikolic et al., 2024; Kangwa et al., 2025). As one respondent proposed, “I feel it leads to intellectual stagnation both on the parts of educators and students” (Q2,378).

As the importance that institutions attach to deep learning subsides, the perceived value of human teachers may dissipate as well (e.g., Chan & Tsi, 2024). Teaching academics may, in future, be supplanted with GenAI and other technologies, culminating in a decline in jobs and teaching expertise. As one respondent warned: “Universities will use it as an excuse to lay off academics and professors as it becomes more advanced. Budgets are tight, and any way to save money will be embraced” (Q1,384). Similarly, according to another respondent,

I could be cautious about the long-term implications of integrating GenAI into higher education, such as the potential for it to replace certain teaching roles or reduce the need for human instructors. This could lead to a loss of jobs and a devaluation of the teaching profession (Q1,61).

This decline in teaching jobs would not only elicit significant stress in teaching academics but impair the educational quality of institutions. Nevertheless, because of the neoliberal values that pervade many institutions globally, the financial benefits of GenAI will overshadow these concerns about quality: “I do believe it is ultimately, like social media etc, being forced on education by a capitalist mindset - it is not really necessary- it plays to humanity's weaknesses” (Q5,374).

Discussion

The findings indicated that teaching academics’ future plans regarding the adoption of GenAI in higher education depend not only on individual intentions and beliefs, but also on institutional preparedness, personal orientations, and perceptions of feasibility. This corresponds with the Future of Work framework presented by Renkema & Tursunbayeva (2024), which identified that the impacts of AI usage on teaching academics depend on both individual and higher-level factors. The influence of norms (e.g., higher education expectations or discipline teaching practices) and perceived behavioural control (e.g., confidence in using new GenAI tools or having adequate resources) on behaviour highlights how contextual and capability factors shape educators’ practices. Many participants were attuned to the favourable outcomes that GenAI could provide, a key determinant of adoption (Honig et al., 2025).

In response to (Q2) on teaching academics’ experiences and plans to use Generative AI in the future, contradictions or tensions emerged between opposing perspectives. For example, in terms of efficiency and automation, GenAI was seen as being useful for streamlining tasks and diminishing the time or effort that individuals dedicate to teaching or learning activities. This is in alignment with Malik et al.’s (2025) qualitative survey of 12 teaching academics, which identified

beliefs regarding GenAI's ability to increase teaching productivity. However, other participants were concerned about whether they will be granted the time to embrace these changes, potentially impeding perceived behavioural control and thus hindering this adoption (Knauder & Koschmieder, 2019). Furthermore, tensions exist between ethics and authenticity: as individuals dedicate less time or effort to teaching activities, they are less likely to reflect upon their approaches carefully and may overlook the ethical implications of their choices. For example, GenAI may evaluate assignments and generate feedback expeditiously and effortlessly. However, because of this reliance on GenAI, the accuracy, and hence the fairness of these assessments and advice, might deteriorate through an over-reliance on AI.

Furthermore, contradictions emerged between personalised learning and ethics or authenticity with insights conflicting with one another. That is, GenAI can tailor the content to the learning styles and preferences of students, called personalised learning. However, because content accommodates the preferences of students, these individuals may not be exposed to diverse perspectives, beliefs, or attitudes. Instead, they may learn information that is biased rather than representative of broader society, potentially reinforcing existing prejudices and culminating in discrimination or cultural hegemony: "... incorrect information and/or bias towards certain viewpoints" (Q2,195). This aligns with the findings of Barnes & Hutson (2024), who warn of the complex biases that may be embedded in GenAI uses within higher education.

Similarly, the themes around personalised learning and sociocultural implications also generated some contradictory perspectives. Specifically, GenAI can personalise the experience of learning for students; that is, these technologies can tailor responses to the unique needs and distinct preferences of every student. Conversely, GenAI may depersonalise the experience of teaching for academics, with technologies diminishing the opportunity for teachers to utilise their own judgement and to convey personal insights and perspectives. Teaching academics may also feel emotionally disconnected from the classroom i.e., "the fear that [GenAI] may depersonalise the learning experience" (Q1,99).

Accordingly, as GenAI burgeons, teaching academics cannot as readily fulfil their traditional roles, such as demonstrating an understanding of the cultural dynamics and emotional intelligence necessary to establish social bonds and foster safe and trusting learning environments. As these roles subside, students may be less likely to learn effectively or develop the empathy or moral capabilities that are vital to a thriving society. As one participant wrote: "I just don't think [GenAI] should replace the human essence of content creation. It is important that a person remains at the heart of the teaching" (Q5,191). Participants felt that GenAI should support, rather than supplant, academics, thereby retaining the relational and human dimensions of education.

Finally, insights regarding institutional practices and teaching quality also contradicted each other. To prevent unethical or inappropriate use of GenAI, many institutions may impose strict restrictions on how this technology can be applied. Yet, these regulations may also discourage experimentation and limit the ingenuity or creativity of staff, stifling innovation and diminishing the quality of materials that academic teachers develop.

Even the responses that correspond to the same category were sometimes contradictory, as some teaching academics felt that GenAI may impede their capacity to utilise their judgement and experience to guide their teaching, alienating them from the work of teaching. In contrast, others felt that GenAI could offer insights or opportunities that may reinvigorate teaching academics,

enhancing the degree to which they feel absorbed in their work: "[GenAI] enables me to create a bond with my job" (Q5,103). This aligns with previous reviews which have emphasised that GenAI can both impede and enhance the quality of teaching practices and learning experiences (Cong-Lem et al., 2025).

Likewise, some of the responses that focused on sociocultural implications were also conflicting. While some participants felt that GenAI may supersede human teachers and jeopardise jobs, epitomised by comments like "I plan to use it to assess students but am resistive to using it too widely due to fears of future job security" (Q2,380), other participants expressed a divergent perspective. Specifically, as GenAI pervades higher education, leaders may become more attuned to the unique role that humans can offer. Institutions will thus value and retain academic teachers. Institutions may become more aware of the role and importance of human qualities, such as the capacity to establish trusting relationships between students and teachers.

In terms of environmental factors, as a result of limitations in institutional policies, infrastructure, training, and guidance, many teaching academics expressed reluctance to adopt GenAI in their teaching, consistent with findings from past research (An et al., 2025; Hughes et al., 2025). This highlights that limited perceived behavioural control hinders teaching academics' behavioural intention toward the use of GenAI (Basileo et al., 2024). Thus, institutions need to plan carefully to redress these shortfalls and to implement changes in GenAI approaches progressively, systemically, and cohesively.

Limitations and future research

A limitation of this study is that findings were drawn from short-answer responses. Future research should use in-depth interviews across specific disciplines to map longitudinal attitude changes as GenAI is more broadly adopted. In addition, future research should consider how institutional pressures may obscure links between intentions and behaviours, as many academic teaching decisions are shaped by forces beyond individual control. Influences such as accommodating managerial expectations and the availability of resources may also shape future engagement with GenAI and will need further exploration. The inclusion of students' perspectives would further clarify how institutional- and learner-level factors interact to influence teaching and learning practices.

Applying TPB to our present context requires some qualifications. Our present era, and specifically in the context of AI development, has been labelled as BANI (brittle, anxious, nonlinear, and incomprehensible, as coined by Jamais Cascio in 2020). This does not undermine the construct validity of TPB, since the theory does not assume a stable environment, and already specifies volatility as a boundary condition by acknowledging that intention predicts behaviour only insofar as it is under control. However, it does limit the generalisability over time of the findings: rapid tool and policy change shortens the life of the beliefs on which intentions are formed, and so findings that TPB can offer will have limited forward reach. Future studies will need to track these beliefs longitudinally, establishing which attitudes are tied to the capabilities of particular tools and therefore transient, and which are anchored in more durable features of academic work.

Conclusion

This study offers teaching academics an opportunity to voice their perspectives on their institutions' policies, approaches, and strategies around GenAI in teaching. Teaching academics expressed strong, nuanced, and conflicting opinions about the role of GenAI in the future of higher education teaching. These opinions are likely to shape future intentions (Blazar & Kraft, 2017). When teaching academics were prompted to convey their attitudes and beliefs around the role of GenAI in the future, they expressed a spectrum of perspectives, ranging from enthusiasm and optimism to caution and resistance. As evidence of enthusiasm and optimism, these teaching academics recognised the possibility that GenAI may not only expedite and automate teaching activities but also generate materials that integrate more diverse perspectives and provide personalisation that accommodates the unique needs and preferences of each student. As evidence of caution and resistance, respondents also expressed concern that an emphasis on efficiency might preclude ethical contemplation, a concern that may be exacerbated by ambiguous institutional policies or inadequate training. Teaching academics' capacity to apply GenAI in practice can affect their intentions to use it in teaching (Baig & Yadegaridehkordi, 2025). Similarly, reliance on GenAI to enhance efficiency might also trivialise the value of teachers, hinder student learning, and jeopardise the jobs of many academics.

Rather than positioning GenAI as something every academic is required to teach, a more practical implication is that educators may consider how these tools can inform their own teaching and assessment design. GenAI should be used selectively, integrated when it strengthens learning outcomes, rather than applied uniformly across all disciplines/subjects. This approach preserves human control while offering flexibility to align GenAI use with their disciplinary contexts and teaching priorities.

A focus on professional discretion and alignment with a teaching ethos is important for teaching academics' future use of GenAI, especially as many teaching academics reported limited institutional support and low behavioural control over GenAI use. Highlighting how GenAI can enhance and maintain the human element in teaching is important for career sustainability, teaching quality, and students' future readiness and may also help to build positive attitudes among teaching academics who value clarity and long-term direction.

The attitudes, social norms, and perceived behavioural control surrounding the use of GenAI in teaching and learning are multifaceted and ambivalent. These findings suggest that institutions seeking to encourage GenAI use will need to acknowledge and accommodate these complexities.

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