Knowledge enablers and barriers in generative AI adoption: educator perspectives from higher education

Intesar Almugren, Issac K. Varghese, Shivani Agarwal, Attila Kurucz, Domenico Fontana and Mario Nobis

(Information about the authors can be found at the end of this article.)

Abstract

Purpose – *Generative artificial intelligence (GenAI) is transforming management practices, enabling the free flow of knowledge and enhancing learning ecosystems from which education branches. While it brings many opportunities, it also causes some problems. Those problems are serious but small in scale. This study aims to examine how management educators perceive, use and adapt GenAI tools for their instructional and evaluative activities.*

Design/methodology/approach – *To gather data, the researchers did 40 interviews with faculty members from different universities. The researchers used a range of theories in their study. Specifically, they used Gioia's approach along with the knowledge management theory, unified theory of acceptance and use of technology 2, the diffusion of innovations social cognitive theory, as well as the theory of activities.*

Findings – *Results paint a storyline. Some educators view GenAI as a game-changer and are finding ways to enhance student interaction while reducing the time spent creating learning materials. They highlight issues such as policies, ethics, over-reliance and threats to academic integrity. In essence, teachers are far from passive adopters. They also negotiate on mechanisms and approaches that are context-sensitive, assessing costs, benefits and the risks involved.*

Practical implications – *To support the responsible use of GenAI, regulatory frameworks, adequate training protocols and effective monitoring systems are necessary. This research shows how a teacher's voice can help higher education institutions to use AI to better effect without losing their standards and values.*

Originality/value – *The research incorporates ideas from multiple frameworks that help clarify the enablers and constraints of GenAI adoption. This helps both researchers and practitioners in the field.*

Keywords *Generative AI adoption, Knowledge management, Higher education, Educator perspectives, Knowledge sharing and pedagogical innovation*

Paper type *Research paper*

Received 12 September 2025
Revised 10 November 2025
13 February 2026
Accepted 26 March 2026

Funding: Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2026R429), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

1. Introduction

Education is approaching a turning point in the use of generative artificial intelligence (GenAI). It is now clear that it can change teaching practice, policy and the government's direction of post-secondary learning. They do not follow established methods of teaching, assessing and generating content in the area (Gupta *et al.*, 2024; Liu *et al.*, 2024; An *et al.*, 2025). Tools powered by large language models can help boost creativity, create content faster and boost students' interest. People are now getting more worried that the use of AI can harm integrity. Such concerns need to be addressed when deploying GenAI.

Institutions of higher education (HEIs) face growing challenges in policy, pedagogy and implementation as new AI tools are introduced in colleges. Although these technologies offer support for grading and problem-solving, faculty express concerns regarding academic rigour, fairness, policy alignment and the potential reduction of personalised instruction. As a result, many educators feel uneasy about the situation (Venkatesh *et al.*, 2012; Rogers, 2003). Because GenAI can generate and destabilise, it can offer teachers a framework by which they can think through whether – and how – they can include it in their repertoire (Cenfetelli, 2004).

The study attempts to apply a more extensive model that draws on a combination of theories, namely, knowledge management (KM) theory (Nonaka and Takeuchi, 1995; Drucker, 1999), unified theory of acceptance and use of technology 2 (UTAUT2) (Venkatesh *et al.*, 2012), diffusion of innovations (DOI) (Rogers, 2003) and social cognitive theory (Bandura, 1986). This framework broadens the view of how teachers sense, respond to and steer the rising tide of GenAI as it becomes embedded in the fabric of their daily practice.

This study is grounded in KM, which helps to understand how knowledge is taken up in practice, and UTAUT2, which explains how people form their intention to use technology. These two models act as the main tools for analysing educator attitudes and decision-making. Other important frameworks – DOI (which examines the dynamics of social contagion and communication channels), social cognitive theory (which emphasises the role of self-efficacy and learning by observation) and activity theory (which examines interactions within institutions and communities) – serve as guiding principles for GenAI adoption.

This investigation addresses the following broad research question (*RQ*):

> *RQ*. How do teachers feel and assess the pedagogical, strategic and pragmatic implications of adopting GenAI in their teaching practice, and what theoretical frameworks best account for these feelings?

Most earlier works investigated the use of GenAI from the students' perspective. This research focuses on educators' attitudes, habits, policy concerns, training requirements, policy development practices, inducements and interpersonal pressures – as the *locus* of understanding and directing the responsible and purposeful implementation. This study explores how teachers perceive, respond to and navigate the growing footprint of generative AI in their professional practice through the lens of angles.

This research is intended to support various stakeholders in higher education, including administrators, policymakers, instructional designers, department heads, faculty and students, in their efforts to understand how these technologies are being integrated into the curriculum.

GenAI has great potential to unleash creativity, but its use should not go against the ethical values of higher education as well as the academic goals of education (Ramesh *et al.*, 2021; An *et al.*, 2025).

AI is beginning to affect the traditional processes and domain of higher education. The introduction of new language models, including ChatGPT, CoPilot, Midjourney and DALL·E, changes the method of delivering and creating knowledge (Leong *et al.*, 2025; An *et al.*, 2025; Porsdam Mann, 2024). Education must generate policies, pedagogies, training and regulations which can meet this change. This study, which examines the friction or resistance of many theories, is supported by a large design. Cosmic theories are closely linked to the nature of the event. It makes us understand how teachers live react and respond to and fight against the explosion of AI across classroom practices, institutional settings and the policy environment around it. Previous research on GenAI either looked at students or focused on the details of the tools. Contemporary research does the opposite. The focus put on teacher perspectives takes first place. These perspectives include teachers' habits, motivations, policy issues, training needs, interpersonal stresses and even policy-development activities. These perspectives are the key drivers interpreting and steering the positive deployment of GenAI in higher education (Venkatesh *et al.*, 2012; Rogers, 2003). Increasingly, policymakers are recognising that without the buy-in and familiarity of teachers, even the best innovations in education will be underused and misused, yielding outcomes that generate resistance rather than change.

This study is significant since its policy ramifications are substantial for the several stakeholders in higher learning; administrators, policymakers, instructional designers, department chairs, instructors and even the students themselves, who together decide how to best embed these innovations into curricula to maximize their educational return, while also keeping in mind the ethical principles and intellectual intent on which higher learning rests (Ramesh *et al.*, 2021; An *et al.*, 2025). This also shows the need to increasingly structure initiatives to facilitate technology transfer and company collaboration, with the aim of accelerating the application of research outputs, including those arising from academic engagement (Romano *et al.*, 2014).

Overall, this study contributes to a holistic view of the human dimension of the growing role of GenAI in academia and the need for a purposeful approach to policy, training, pedagogy and oversight that maintains the intellectual and ethical standards of higher education. Pursuing this path is neither easy nor definite with outcomes. Moreover, the process is certainly a delicate balancing act and a constant negotiation of opportunity and risk, innovation and tradition, policy and practice. The study claims technology does not predict events that cannot be foreseen. People carry out through their judgement, routines, policy structures and collaborative processes.

2. Theoretical underpinning

Everyone has witnessed the tremendous abilities of GenAI, where it creates human-like text, images, audio, video and code and even fully fledged music through massive ingests of vast data sets (Leong *et al.*, 2025; Jeon *et al.*, 2025; Porsdam Mann, 2024). Among the intelligent “behaviour” mentioned previously, which includes machine learning (ML) and expert system, the text was produced based on conditions executing a continuous script, unlike the learning of patterns beyond input to produce original output, which is contextual and also far more imaginative. The change has a powerful effect on education as the educational enterprise centres around teaching practice, knowledge transfer and the formation of thought. The educational enterprise involves teaching practice, knowledge transfer and formation of thought. Any change in the educational enterprise has a powerful effect on education. In integrating ChatGPT, DALL·E, Midjourney, CoPilot and other such tools into daily lives, it is not just an advancement of existing technical systems but a transformation of the teacher role, the design of the courses and institutional policies (Ramesh *et al.*, 2021; Rejeb *et al.*, 2024; An *et al.*, 2025). Changing the approach makes it easier to develop personalised, flexible and creative learning experiences. However, this shift creates a mixed bag of policy and competency challenges (Nguyen, 2025; Gupta *et al.*, 2024; Fischer *et al.*, 2024). Business management is at a crucial juncture in higher education.

Deeper human understanding is formed through mentoring, case-based learning, group projects and reflections. When someone resists the given feedback, they are likely aware that even a soft tool can shape, shift or hasten the job, but never replace human judgement. Students’ exposure to learning helps them overcome barriers to innovation and become more innovative. (Venkatesh *et al.*, 2012; Rogers, 2003). GenAI can help teachers spend more time interacting, thinking creatively and analysing in more depth. It can also reduce the burden on teachers when it comes to grading, drafting syllabus and taking on duties (Cenfetelli, 2004). There are various issues related to policies and ethics which are being raised regularly by educators in their thinking and in policy discussions, which include honesty, fairness, privacy of data, bias in algorithms and increasing dependence on them.

2.1 Knowledge management theory

At a more theoretical–conceptual level, the study uses KM theory, which examines the processes of obtaining, creating, storing, sharing and using knowledge to improve decision-making and performance (Nonaka and Takeuchi, 1995; Drucker, 1999). In other words, knowledge can help gain a competitive edge and use resources more effectively. The knowledge-based hypothesis of the firm acknowledges that knowledge is an important resource which enables the development of innovative new products and better quality performance (Belkahla and Triki, 2011; Zack, 1999). In the higher education context, it points to the need to consciously create, share and train on the knowledge and practices of GenAI, as well as the risks, policies, classroom use and implications.

2.2 Unified theory of acceptance and use of technology 2

The UTAUT2 provides a framework for disentangling the forces that drive individuals to use technology, especially when adoption is voluntary and consumer-focused (Venkatesh *et al.*, 2012). The technology acceptance model (TAM) is based on the TRA. While TRA basically determines a person's intention to perform a certain action or behaviour that can be guided by one's perception, TAM is much more specific, which outlines the acceptance of a particular technology. They show the pros and cons educators associate with GenAI tools as they become entrenched in instruction and practice. Students can get extra help for grading, guiding and engaging. Training and ongoing support are essential as per effort expectancy (Gonzalez-Tamayo *et al.*, 2024). It appears that the teacher is authenticating and validating the use of the tools. The satisfaction and pleasure professors felt while using the tools also point to motivation. At once, the practices that steer routines and the practices in place shape whether new technology slips into those routines. The factors that will shape the adoption and use of GenAI in education will become clear in combination with the ideas. What this shows is that the technology's possibilities require policies, training, incentives and personal support.

2.3 Diffusion of innovations theory

Rogers' concept of the DOI explains how new ideas diffuse through a system, in this case, the higher education world, over time (Rogers, 2003). The model outlines a kind of ladder that people climb, starting with a moment of awareness, then growing their knowledge, working to persuade a moment of decision, the actual rollout and ending with a final confirmation. The shape of that ladder is influenced by a combination of factors, including the characteristics of the innovation, the chatter in the networks, the norms of the academic community and the incentives that lead people to accept or, conversely, reject the innovation.

Using the innovation diffusion model in the field of higher education and AI makes several traits come to the forefront. These traits will largely shape its diffusion. One of the main reasons GenAI is taking hold is the perception of its benefits – the ability to ignite creativity, streamline grading, personalise learning and foster student engagement – all being a forceful nudge to include it in courses. Match existing practices and teaching objectives. Innovations that fit within existing instructor workflows are more likely to be adopted. The collective influence of opinion leaders, department chairs and policymakers, within colleges and universities can be. Based on their views and judgements, they either remove the hurdles from the path of ideas or put up obstacles. Amidst various networks of organisations, forms of networks of knowledge emerge that facilitate feedback and assessment among teachers to ensure that the social dimension is aligned with any possible shifting instruction behaviour (Almuaqel, 2024). According to Rogers' diffusion model, the characteristics of the innovation and the channels through which it travels must be considered. It captures how GenAI integrates into academies' rhythms as well as its institutional scaffolding.

2.4 Social cognitive theory

Social cognitive theory or SCT, was developed by Bandura (1986). SCT explains the interrelation between human action and effectiveness. It helps in understanding the growth of attitude and judgement of the instructors in using GenAI in higher education. One of the main ideas in social cognitive theory is self-efficacy, the belief in one's ability to successfully perform a task. This is directly related to teachers' eventual adoption of GenAI in their teaching. Teachers must be confident enough to use these tools effectively to improve their teaching delivery, to make a new curriculum or to do routine things like evaluation and attendance. They're also become more confident in using GenAI thanks to seeing their peers use it successfully, their own trial-and-error experiences with GenAI tools and their institution's training and resources.

SCT illustrates how teachers can observe their peers using GenAI productively, as well as the power of vicarious reinforcement when they see colleagues rewarded or recognised for their innovative use. It will increase the enthusiasm for mastering and embracing these technologies. Also, self-regulatory processes that help teachers set goals, monitor their work and reflect on it contribute to the ultimate, incidental and sustainable adoption of GenAI in higher education. That means they do not just go through the motions. Instead, they choose and adapt these materials so they fit their teaching goals, subject area and students. Also, SCT highlights that the environment, which is the interplay of social, structural, policy and cultural matters, shapes educators' attitudes towards technology and its eventual implementation. The presence of administrative support mechanisms, the development of a community of practice, the formulation of a policy agenda, the holding of training seminars and the provision of technical support (Srivastava *et al.*, 2024) can create an environment in which educators feel nurtured and supported in their work.

To conclude, reciprocal determinism is at the heart of SCT, which argues that personal, behavioural and environmental factors determine one another in an ongoing, dynamic process. This is the case in higher education, where technology, people, teaching and policy change together. As a result, using GenAI in higher education will ultimately not make sense when considered in isolation; rather, it needs to be understood in an overall model that incorporates all the different interdependent elements.

This research will examine the organisational mechanisms for the generation, sharing and use of knowledge about GenAI in universities. It aids in the better understanding of literature regarding technology and KM. The research identifies various knowledge enablers and inhibitors that hinder the use of GenAI. Knowledge enablers are the features or processes within an organisation, such as transparent policies, collaborative routines and active communities of practice, that help employees create, share and assimilate new knowledge about GenAI technology. They increase the absorptive capacity and learning for effective adoption. Knowledge barriers are anything that hinders knowledge flows, slows diffusion or creates resistance to GenAI. It can be an ambiguous policy or regulation, a lack of training, ethical uncertainties and more. They block the systematisation of new knowledge needed for sustainable integration.

3. Background literature

3.1 Generative artificial intelligence in higher education: evolution and impact

The time of GenAI is a remarkable time in the evolution of machine intelligence. According to Leong *et al.* (2025), GenAI takes the functionality of AI to the next level by generating new text, images, audio, video and intricate designs, to name a few. GenAI is a unique subfield of AI. The content generated is human-like in different modalities. This is in stark contrast to traditional AI. Traditional AI is a deterministic system. There is a need to understand what is happening now to sustainably implement GenAI in education. In order for this to happen, we should look through the history of AI. Every stage of AI has given rise to ample opportunities and challenges. It affected the mentality of professors in a similar manner (Trindade *et al.*, 2025). The different stages of AI – from basic rule-based systems, to adaptive intelligent tutoring, and subsequently GenAI – have influenced education practices in higher education and institutional flows of knowledge. Knowledge governance is greatly impacted by generative activities. In addition, requires new routines, formal policies and peer communities to mediate knowledge creation, sharing and validation.

AI has created knowledge challenges for the education sector and also created opportunities for managing knowledge in education. During the first "foundational" phase, expert systems and early computer-assisted instructions (CAIs) became available. It presented rigid yet structured pathways to pass on knowledge, giving rise to lasting disputes over automation and the role of teachers. In the next step, called the machine-learning and adaptive phase, personalisation and feedback benefits increased through ML and adaptive algorithms.

The ongoing "deep learning and generative" phase, which was initiated by deep learning, large language models and powerful GenAI tools such as ChatGPT and DALL-E, will change knowledge creation, flow and governance at the level of fundamentals. Institutions today must grapple not only with new pedagogical possibilities but also with more acute questions around academic integrity, relatedness and absorptive capacity–central issues in contemporary knowledge governance. There is a high potential for student dependency and decreased critical thinking, where students may use AI as a shortcut, skipping a genuine engagement with complex material and interfering with their learning of problem-solving and reasoning skills (Liu *et al.*, 2024).

3.1.1 Phase 1: Foundational artificial intelligence and early educational tools (1950s–1980s). The scholars have proposed many definitions for the term AI since its inception. One of the first definitions was proposed by Turing in the mid-20th century. Turing authored the seminal "Turing Test" (1950), where he studied high-level programming and machine intelligence. The first uses of AI were software programmes such as ELIZA (Weizenbaum, 1966), an natural language processing (NLP) conversation programme that emulates a human-like conversation. Despite being simple, ELIZA demonstrated that human–computer interaction was possible and brought forth visions of AI within the educational environment.

By this time, the efforts of behavioural psychologists had a significant impact on instructional design. Skinner's opinion about programmed instruction (Skinner, 1958) and Benjamin Bloom's mastery learning model (Bloom, 1968) influenced instructional design. The emerging capabilities of computing appeared to be a natural fit with the theories which favour individualised, self-directed learning, immediate feedback and sequential acquisition of knowledge. As a result, CAI systems, such as programmed logic for automated teaching operations (PLATO) at the University of Illinois (Bitzer, 1976) and time-shared, interactive, computer-controlled information television (TICCIT) (Bunderson, 1973; Merrill, 1975), were created. Helpful for primary and secondary school students, these computer-assisted learning systems were designed to deliver individualised tuition that allowed students to learn and get feedback immediately. Between 1975 and 2010, the development of intelligent tutoring systems (ITS) began. The cognitive tutor was one example developed in this period (Anderson *et al.*, 1995). In general, these systems focused on domain expertise modelling. These systems also provided customised feedback for the performance of students.

These innovations influenced teaching methods significantly. They brought innovation in the form of highly personalised and self-paced learning, allowing students to move through material at their own preferred speed, lessening some pressure of coming up to pace with the class. The CAI system offers instant feedback, which was a big step forward over more traditional methods. In other words, students were able to rectify mistakes immediately and build on correct answers to encourage mastery learning. Early research showed that students enjoyed going to the machines, and studies in the USA showed that students learned faster with machines. For underprivileged students, it was noted how useful the one-on-one attention that machines could provide proved to be beneficial (Suppes, 1966).

This was not without problems, however, and the attitude of teachers was complex. These systems required the use of large mainframe computers. An initial obstacle was the excessive cost and availability of the mainframe computers (Luehrmann, 1980). The systems were inflexible because they were rule-based and could not adapt to the variety of student responses and deviations from learning paths. Their usefulness for enhancing deep learning and critical thinking was usually variable as they stressed rote learning and procedural knowledge (Papert, 1980). Even though an early ITS was much smarter than the forest straight-A students, it could not show a human tutor's empathy, sympathy or emotional intelligence quotient. Teachers often resist the use of technology as they are not much aware of it and also fear that they will lose their job. They also oppose using technology as it brings a change in the old process of teaching (Cuban, 1986). Some teachers met film projectors and even calculators with initial resistance years ago, as seen in the ancient opposition to educational technology (Tyack and Cuban, 1995).

3.1.2 Phase 2: Machine learning and adaptive systems (1990s–2010s). The start of the new millennium witnessed a phenomenal upsurge in AI with respect to ML and NLP. During this period, more sophisticated algorithms were developed which could spot patterns and analyse data. In due course, “Adaptive AI” made its way to education. Two major ones are knowledge tracing (Corbett and R Anderson, 1995), where a student's knowledge state changes during learning and the system adapts according to the changed knowledge state.

Larger learning management systems (LMS) such as Blackboard and Moodle are becoming more widely used in higher education and are incorporating AI. With this, a digital delivery was somehow made more dynamic, along with the adaptive test and the basic adaptive learning pathways. The rapid growth of the internet also allowed for the emergence of MOOCs from Coursera and edX in the early 2010s (Wei and Taecharungroj, 2022). While in their early versions, MOOCs were not based on AI, they leveraged the internet's scalability and offered large data sets that would later be used for AI development, unintentionally stimulating demand for automated feedback and mass assessment tools (Bonk *et al.*, 2015). AI applications were used for data analysis and research support too. The first applications were for text mining and bibliographic management, as well as quantitative data analysis (Leong *et al.*, 2025).

At this stage, formal school and post-school education were marked by a greater ability for adaptive learning at scale and personalisation. AI is now better able to detect learning gaps in real-time with real-time interventions and customised exercises designed to benefit individual students (Baker and Rossi, 2013; Hosen *et al.*, 2023). It provided evidence-based insights for curriculum improvement that helped teachers identify the areas of studies where students struggled the most and to refine as well as improve their teaching on the basis of evidence. According to Kaplan and Haenlein (2016), MOOCs have been able to level the playing field by granting access to quality education worldwide, despite their high dropout rates. AI has begun automating some bureaucratic tasks, like automatically grading multiple-choice questions and sorting basic data, which has helped free up some of the instructors' time.

There were new challenges, and teacher perceptions were still diverse. The “digital divide” continues to be an issue, as it cannot be assumed that stable internet and personal computing hardware will be available to all (Warschauer, 2004). Most earlier systems were marred by interoperability problems, which, in turn, made for difficult integration of various AI elements and learning platforms. Use of ML models in clinical practice further reiterated the need for quality labelled data for training the ML model, a logistics challenge for most institutions. These gaps in educator digital literacy continued to persist and efforts were made to avoid full adoption of the tools provided. Scepticism about the internet and even Wikipedia persisted earlier (Koller *et al.,* 2019). Some adaptive learning systems were criticised for creating “adaptive loops of death”, where students become stuck in cycles of constant remediation without leaving the loops (Koedinger *et al.*, 2006). Moreover, even advanced ITS systems were unable to replicate social and emotional interactions as well as humans. Above all, during this time, there was a major data privacy issue where learning platforms started to collect a lot of student data. The ownership, protection and ethical usage now became important questions (Macfadyen and Dawson, 2012). Teachers did not feel ready to deal with these new technical and ethical challenges.

3.1.3 Phase 3: Deep learning and generative artificial intelligence revolution (2010s–present). This phase, which began sometime around the early 2010s, is characterised by the incredible boom of deep neural networks and, more recently, the GenAI boom. This period has been brought along by the major advances in hardware, particularly the use of graphic processor units (Nvidia, 2007), allowing for quick training of deep learning models. The concept of processing sequential data at a certain time has already been in the literature for neural network architectures such as recurrent neural networks (Elman, 1990) and long short-term memory (Hochreiter and Schmidhuber, 1997). Nonetheless, the introduction of transformer architectures marked a turning point for GenAI (Vaswani *et al.*, 2017).

Because of these architectural advances, strong LLMs like the GPT-2 (Radford *et al.*, 2019), GPT-3 and especially ChatGPT are available (OpenAI, 2022). These LLMs can create text that is very similar to human writing for different purposes. While GenAI for multimodal content has gained traction, with DALL·E (Ramesh *et al.*, 2021) and Midjourney’s ability to create high-quality images from text prompts. Today’s AI-powered assistants and autonomous agents are developing increasingly more sophisticated reasoning and task execution capabilities (Porsdam Mann, 2024). The pedagogical impact of GenAI is unprecedented. It offers higher levels of personalisation and adaptive feedback that unlock new opportunities for individualised learning that were not achievable before. GenAI can provide tailored explanations, offer gentle pushback on open-ended tasks and even act as a conversational tutor. Most importantly, GenAI automates critical content creation and administrative tasks for teachers. Teachers can easily create lecture notes and formulate varied quiz questions, and even formulate case studies and communicate now. This allows them enough time for more value-added work like mentoring and sophisticated pedagogical planning. New possibilities have arisen in inquiry-based learning and creative exploration, in which students may use GenAI as a tool for brainstorming, researching or creating. Curriculum development can now be data-driven and highly accurate, as AI can study large quantities of student behaviour to discover learning trends and areas for improvement. GenAI also enhances accessibility and equity by offering various output types (e.g. text-to-speech and text-to-picture) and, potentially, the opportunity to break the language barrier or to provide accommodations for students with needs. (Al-Emran *et al.*, 2025).

The educators always had a digital mindset, recognised the limitations of Web 2.0 technology and learnt from the past. It can produce text that is so smooth that any reader may struggle to spot mistakes and accept it as human writing. As a result, questions may arise regarding the effectiveness of AI detection tools, simultaneously raising broader existential concerns about authorship and evaluation over time. There are many data privacy and security threats that are also serious. Teachers readiness is a real issue, as educators feel overwhelmed by the unfolding pace of technologies and perceive insufficient directives from their institutions on their use. Since this can lead to bias, there are also ethical issues that may arise. Models can reinforce and amplify the bias in their training data. Institutions and solo educators encounter great hurdles arising from the sheer product landscape and cost-related challenges affecting commercial GenAI tools (Jeon *et al.*, 2025). Finally, educators often resist changes related to teaching methods because they are already adjusted to the existing system. To bring educators on board with the AI-enabled learning process, it is necessary to conduct mindset shifts and instill professional development. Scholars have different views on GenAI and these various views are depicted in a debate whether GenAI is an equaliser or an amplifier of disparities, whether it helps meritocracy or only a few learned scholars (Jeon *et al.*, 2025), as shown in Figure 1 depicted below.

Table 1 provides an overview of the evolution of AI in education, identifying the key technologies characterising each stage, along with their pedagogical implications, associated challenges and corresponding teacher attitudes.

4. Methodology

The qualitative research design of this study is based on Gioia's methodology (Gioia *et al.*, 2013). The aim is to offer a quality, contextually rich glimpse of educators' experiences and responses to the increasing incorporation of GenAI into their practices, policy frameworks and pedagogies. This focus aligns with this study's multi-theoretical design and the intricate, multilevel reality of technology adoption in higher education (Cenfetelli, 2004; Rogers, 2003).

4.1 Participant selection and inclusion criteria

Participants who varied in academic rank, discipline and type of institution have been selected for this study. The selection criteria for the participants of this research were based on the following: (a) teaching experience in higher education of not less than three years. (b) Currently used in management or related disciplines. (c) Experimented with or willingness to use GenAI tools in teaching or assessment or curriculum design. The study has excluded faculty members who had no prior experience or interest in GenAI functions to ensure the study remained relevant.

4.2 Sample size and diversity

Forty faculty members from 16 universities, namely, public, private and autonomous, covering diverse geographical region of India, participated. The sample was made up of

Figure 1 Categories of AI ethics discourse (Jeon *et al.*, 2025)

Table 1 Evolution of AI

Phase	*Period*	*Key AI technologies/ concepts*	*Impact on education and pedagogy*	*Associated challenges and educator perceptions*
Phase 1: Foundational AI and early educational tools	1950s – 1980s	Alan Turing's foundational concepts, ELIZA (early NLP), computer-assisted instruction (CAI) (e.g. PLATO and TICCIT), rule-based intelligent tutoring systems (ITS) (e.g. cognitive tutor) and the influence of Skinner and Bloom	Introduction of automated, individualised instruction; self-paced learning; immediate feedback; focus on mastery learning; positive student attitudes and learning rates, especially for disadvantaged students	High costs and limited access to bulky technology; system inflexibility (rule-based, limited adaptability); mixed effectiveness for deeper learning; ITS lacked human nuance/emotional touch; initial educator reluctance and unpreparedness; historical resistance to new tech (e.g. calculators)
Phase 2: Machine learning and adaptive systems	1990s – 2010s	Advancements in machine learning (ML) and natural language processing (NLP); "adaptive AI" (e.g. knowledge tracing); integration into learning management systems (LMS); rise of massive open online courses (MOOCs) (e.g. Coursera and edX); AI for data analysis and research support	Enhanced personalisation and adaptive learning at scale; faster identification of learning gaps; data-driven insights for curriculum optimisation; increased accessibility of quality education; and streamlined administrative tasks	Digital divide persistence; interoperability issues and need for high-quality data; educator digital literacy gaps and resistance (e.g. internet and Wikipedia); "adaptive loops of death" in early systems; ITS still lacked social/emotional engagement; and general feeling of unpreparedness among educators; emerging data privacy concerns
Phase 3: Deep learning and GenAI revolution	2010s – Present	Deep neural networks; large language models (LLMs) (e.g. GPT-2, GPT-4 and ChatGPT); GenAI for multimodal content (e.g. DALL·E and Midjourney); and AI-powered assistants and autonomous agents	Unprecedented levels of personalisation and adaptive feedback; significant automation of teacher content creation and administrative tasks; new opportunities for inquiry-based learning and creative exploration; data-driven curriculum evolution; and enhanced accessibility and equity potential	Paramount academic integrity and plagiarism concerns (flawed AI detection); heightened data privacy and security risks; risk of student over-reliance and critical thinking erosion; widespread educator unpreparedness and lack of institutional guidance; algorithmic bias and ethical dilemmas; overwhelming product landscape and cost barriers; and resistance to fundamental pedagogical shifts

assistant, associate and full professors within the discipline of management and business analytics and technology management. Since no new codes or categories emerged in the 36th interview, data saturation was reached, but 4 more interviews were conducted to confirm saturation.

4.3 Reflexivity

The researchers are academic and professional management educators with personal backgrounds and experiences in digital pedagogy, which may have affected their interpretation of faculty experiences. Thus, a reflexive statement was added. To limit bias, memos have been written with reflections. Prior peer debriefings have been carried out. The coding decisions have been revisited during the analysis to ensure interpretive rigour.

4.4 Ethical approval and data privacy

According to ethical rules, the participants were provided with an information sheet describing aim of study and that it is voluntary. Moreover, it guaranteed them the confidentiality of the information collected. Before taking part in the study, all participants signed an informed consent form. To facilitate the protection of participants' identities, personal and institutional identifiers were replaced with pseudonyms or false names. Only the research team could access the password-protected folders containing all the transcripts and audios.

4.5 Informed consent and confidentiality

The participants were clearly informed that the responses would only be used for academic research purposes and that they can withdraw at any point without pretence. The manuscript's quotations have been altered or encoded, making it impossible to trace back to individuals or institutions.

4.6 Method used

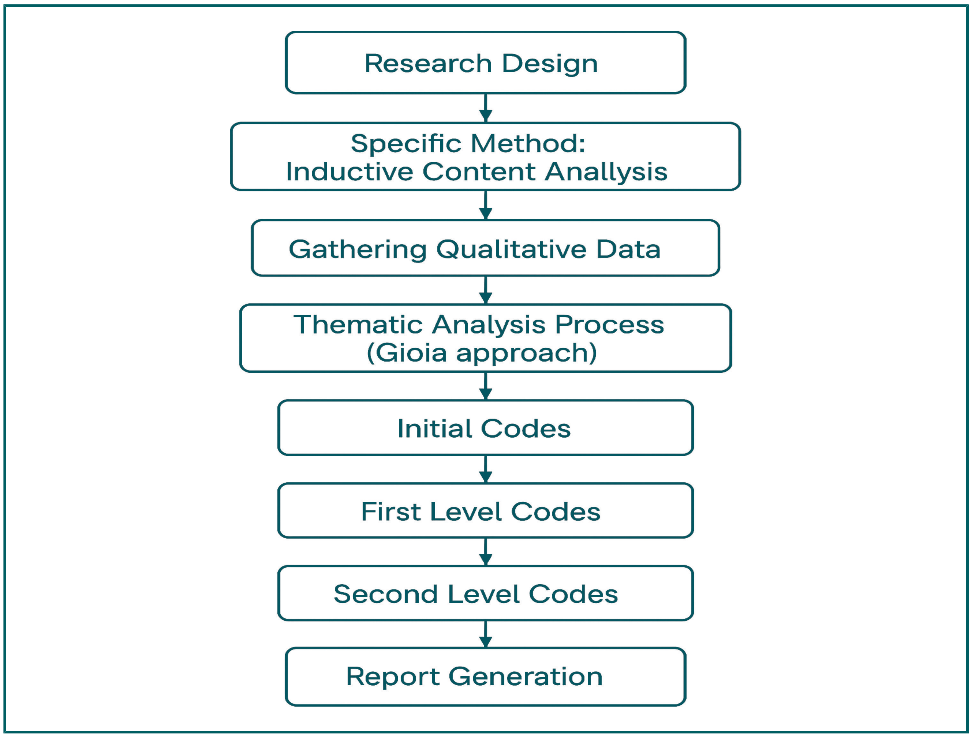
Educators are the study's stakeholders, and this research will investigate their views. The rationale for choosing a qualitative design is to probe deeply and gain rich, contextual and process views from the most directly involved. The study focuses on subjective experience, policy conflicts, motivational frames and colleagues' interpersonal pressures and habits, which together shape how professors introduce GenAI into their teaching, rather than relying on quantitative questionnaires that yield broad generalisations. The qualitative method is most appropriate when investigating a phenomenon whose hows and whys are not well understood and in which the context is an important mediator of the ultimate outcome (Gioia *et al.*, 2013). Furthermore, the conjoint use of activity theory and Gioia's grounded theory helps in valuing, firstly, the social organisation of the workplace system in which the teacher is situated and, secondly, their interpretive procedures. There are interactions between subjects, mediating artefacts, community, routine, division of labour, regime policy and the ultimate outcome, as per the activity theory. This helps in understanding what cannot be done by strict statistical mechanisms (Leont'ev, 1978; Vygotsky and Cole, 1978).

The research was designed using the GEM framework – gather, elaborate and model – and a data analysis was performed using grounded theory guidelines, and the Gioia coding process was used. The three-step procedure is chosen for its methodological rigour and theoretical richness. The entire method followed in this study is illustrated in Figure 2.

4.7 Data collection

Data was collected from 40 management educators from various institutions of higher learning in the country. It was done to get the maximum variation with respect to experience, discipline, policy-setting and institutional policy-setting. The researchers collected data from both government and private institutions and from research institutions and teaching institutions located in various places for comparison. This sampling procedure is a conventional procedure in qualitative research (Gioia *et al.*, 2013), which maximally varied to get an in-depth understanding of the phenomenon. The interview guides were designed to elicit rich narratives, policy-focused challenges, reflections and routines related to applying GenAI in higher education. Participants were invited to talk about their innovations, the policy-related challenges that they face, their teaching routines and the assumptions that they may have of the future direction of their area of expertise in the face of GenAI. This study has used some open-ended questions to widen the feedback and thoughts of the participants. This helped gather detailed data on their routines and the

Figure 2 Diagram representing the methodology used



policy issues that concerned them. It created depth and texture for the theoretical framework. A coding framework was established in advance to support subsequent analysis of the findings. Key phrases and constructs related to the studied phenomenon emerged during the open coding process.

4.8 Data validity and analysis

The data were studied based on Gioia's protocol, which consists of three coding stages, namely open, axial and selective. This offers a grounded view of the phenomenon which is being studied (Gioia *et al.*, 2013). The transcripts have been considered using open coding that took out first-order constructs – basically raw or semantic data – about policy battles, routines, incentives, training gaps and interpersonal pressures that we collated to adopt GenAI in higher education. The process of axial coding yielded numerous first-order codes, which were later grouped into a shade- or cluster-like category. Pedagogical enhancements, governance for ethical and reflective use of AI, prompt engineering practices, contextual encounters and reflections. During this stage, selective coding was applied, which makes it possible to synthesise the clusters and to explain the linkages, mechanisms and processes that link the clusters together in a more effective way to form an integrated and holistic whole.

The following techniques were adopted to ensure rigorous data collection and analysis and thus strengthen the credibility, transferability, dependability and confirmability (Guba and Lincoln, 1994) of the research findings. The initial interpretations were shared with the participants through member checks. The audit trails have been kept for coding, data transformation and analytics decisions. Analytic triangulation helped in applying different theoretical lenses (activity theory, SCT and DOI) alongside the raw data, resulting in a rich and credible understanding of the phenomenon. Using different theories strengthens the experiment and yields better conclusions.

5. Discussion

The data were analysed according to the methodology established by Gioia, which consists of open coding, axial coding and selective coding (Gioia *et al.*, 2013). The method emphasises the importance of effective theory building in a study. The transcripts have been thoroughly analysed using open coding. Secondly, the first-order constructs were removed. These basically refer to raw or semantic data. For example, first-order constructs about the policy struggle and practices have been removed. During axial coding, numerous first-order codes emerged, which were then organised into groupings of specific shades or clusters, e.g. enhancing teaching skills through the ethical use of AI, good practices for aids, contexts and effects. Later on, selective coding was used to find the main connections, mechanisms and processes between these clusters to understand the phenomenon being studied systematically (Figure 3).

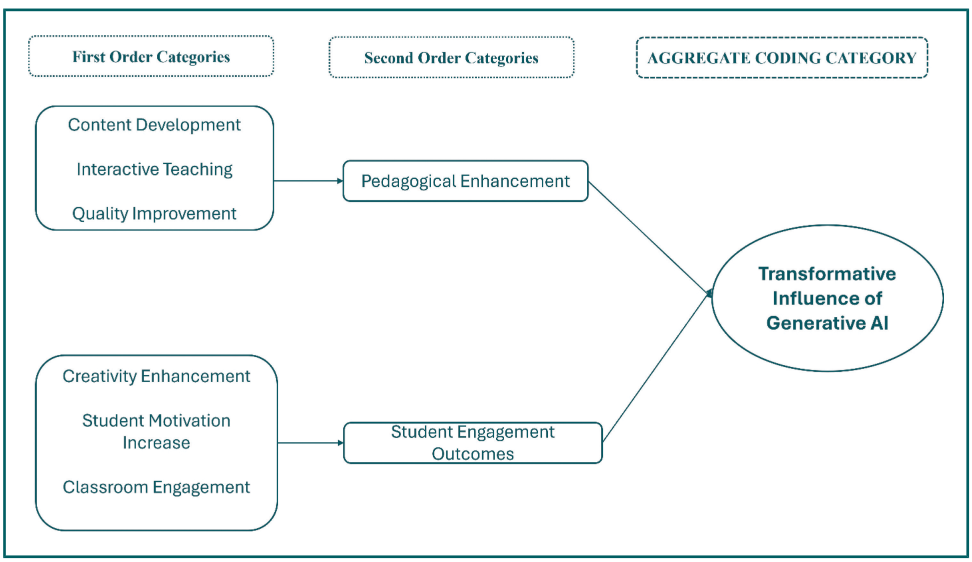
It is essential to ensure that the research results can be credible, transferable, dependable and confirmable (Guba and Lincoln, 1994). In this respect, several measures will be undertaken to ensure the validity of data collection and analysis. Using diverse theories strengthened the study, which improved the experiment results. Each category was further deconstructed into sub-themes representing the continuum of acceptance, support mechanisms and perceived obstacles to practical use. The pointers are underpinned by anonymised quotes below to provide a grounded understanding of GenAI's prevailing and changing view among institutions providing management education.

5.1 Transformative influence of generative artificial intelligence (knowledge infrastructure evolution)

5.1.1 Pedagogical enhancement. 5.1.1.1 Content development (knowledge creation). Publishing knowledge objects and their creation and engagement are done faster by GenAI. For instance, if a user were to instruct GenAI regarding a scholarly paper, GenAI would generate an abstract of the paper, the questions that are usually asked in a class and a tutorial video. This shows a new way of creating knowledge:

> I used for content development: I was given a topic for each session, but had to create the content within each topic by myself (R-2).

Figure 3 Transformative influence of GenAI



GenAI refers to a knowledge artefact as it externalises the tacit pedagogical knowledge of an educator and makes it explicit that could be readily reused, applied and adapted by others, including the educator.

5.1.1.2 Interactive teaching (knowledge application). With GenAI, users are able to apply knowledge through adapted resources such as simplified explanation and interactive practice activities. Adaptive resources use input from learners to adjust the complexity of the content. Thus, keeping learners involved through personalised learning modules enables teachers to use their pedagogical expertise on a large scale:

> In a literature course, an AI tool can assess students' writing, feedback, and quiz scores to recommend specific readings, practice exercises, or writing prompts tailored to their current level (R-25).

These practices show how a type of knowledge, stored by the educator as pedagogy, is attracted to a site and deployed through the mediation of AI and its interfaces, reasonably open to different types.

5.1.1.3 Quality improvement (knowledge sharing in teams). AI tools for collaboration can facilitate knowledge sharing and the division of labour. This enhances the quality of educational work. Moreover, GenAI enhances the content's quality by incorporating and synthesising various sources of knowledge. Consequently, it facilitates the learning process:

> Students who have used AI-powered tools to collaborate on group projects… helped them communicate effectively and divide the work fairly (R-21).

This is indicative of KM principles of distributed knowledge creation, where GenAI mediates the knowledge flows between team members and individual contributions into collective knowledge products.

5.1.2 Student engagement outcomes. 5.1.2.1 Creativity enhancement (Knowledge conversion: Tacit → Explicit). GenAI acts as a trigger for tacit-to-explicit conversion. Students find GenAI an indispensable source of brainstorming new ideas and visualising projects. As a result, students generate new ideas on subjects and participate:

> I integrated generative AI into creative thinking, a content topic in Business management (R-10).

5.1.2.2 Student motivation increase (knowledge personalisation). GenAI improves participation by providing personal knowledge through the learning platform that adapts the course complexity to individual needs. GenAI makes learning fun through gamification, quizzes and interactive challenges:

> This level of interactivity significantly increased their motivation, as it allowed them to 'play' with concepts in a way that felt much more engaging than traditional textbook methods (R-9).

5.1.2.3 Classroom engagement (knowledge co-creation). GenAI helps both teachers and students build knowledge together, with its capabilities to help in the design of new courses or interactive discussions:

> Students can engage with AI-driven tools more actively, exploring content or receiving personalised feedback (R-25).

This represents an emerging knowledge ecosystem where GenAI mediates reciprocal knowledge flows between educators, students and institutional resources. The overall dimension of transformative impact is enabled through the pedagogical improvement and student engagement outcomes identified by teachers. The themes addressing the benefits included AI-enabled content creation, incorporation of interactivity in teaching formats and improvement of quality in teaching. As the results from UTAUT2 show, they obtained these benefits as teachers thought GenAI would enhance the efficiency of teaching (high performance expectancy) and hedonic motivation, which was achieved after the implementation of GenAI, as it evoked curiosity and satisfaction. Moreover, consistent with Rogers' DOI theory, the observability of effective GenAI enactments in instruction (including those showcased in faculty development workshops) raised peer interest and subsequent adoption.

5.2 Strategic guidance for generative artificial intelligence utilisation

5.2.1 Governance for ethical and reflective artificial intelligence use (knowledge governance). 5.2.1.1 Need for policy guidelines (knowledge codification and storage). Academic institutions must establish codified knowledge artefacts – well-articulated AI policies aligned with national guidelines – that formalise acceptable GenAI use and prevent misuse. These policies serve as institutional knowledge repositories that specify permitted applications, disclosure requirements and controls against *verbatim* AI replication. Most critically, they embed academic integrity norms by mandating paraphrasing, citation of AI contributions and critical engagement beyond raw AI outputs:

> We have a detailed AI use policy in force, and the tasks students need to do [...] they experienced differences in the AI-generated results compared to what was taught in class (R-36).

These policies function as explicit knowledge storage mechanisms that reduce ambiguity in GenAI knowledge application, enabling consistent institutional practice while safeguarding knowledge quality and authenticity.

5.2.1.2 Encourage critical thinking (knowledge validation processes). Policies around GenAI are changing how we assess knowledge. Teachers should instruct pupils to analyse content created by AI before using it. The students must also modify it and justify their modifications. Teachers grade the process, modifying the knowledge, not the final output. Students are required to justify their amendments and acknowledge the problems associated with AI:

> They can use AI to generate exciting levels that are good for critical thinking (R-13).

5.2.2 Capacity building for artificial intelligence-enhanced pedagogy (knowledge infrastructure development)

5.2.2.1 Curriculum integration (institutional knowledge expertise). AI-driven pedagogical experts who have a good mix of technical and education competencies are human knowledge enablers. Every higher educational institution has to build them as knowledge guardians. This will allow them to determine the parameters for meaningful integration of curriculum to tap the potential of AI. The faculty is also given responsible use. Also, we must check for embedding creativity, criticality and problem-solving:

> It is essential to maintain human oversight to ensure accuracy, fairness, and relevance. I learned this lesson using AI-powered grading tools (R-8).

5.2.2.2 Faculty training (knowledge transfer and communities of practice). Knowledge transfer infrastructure – workshops, training centres, peer learning communities – is essential for building faculty AI competency. These mechanisms develop shared communities of practice where educators co-create AI-enhanced teaching resources, codifying effective practices into reusable knowledge assets:

> One faculty member I know participated in a workshop first and then co-created AI-generated quizzes and discussion prompts for a business ethics course. This initial exploration made them feel more confident about... (R-11).

Training programmes represent systematic knowledge dissemination, converting individual trial-and-error learning into institutional best practice repositories that enhance collective organisational intelligence. Many educators expressed the need for strategic guidance on governance for ethical and reflective AI use and capacity building in spite of the enthusiasm. Study participants indicate that unclear policy is an institutional deficit and a source of anxiety. One of the parties replied that they are guessing what is ethical or acceptable without formal guidance, which is the assessment of AI-assisted tasks of students. Similarly, within the UTAUT2 framework's facilitating conditions construct – schools without adequate support systems diminished teachers' confidence to mainstream GenAI tools. These interrelated dimensions are synthesised in Figure 4, which presents the proposed strategic guidance framework for GenAI utilisation.

5.3 Prompt engineering and optimisation practices (emerging knowledge management routines)

5.3.1 Clarity in output expectations (knowledge specification processes). 5.3.1.1 Instructional clarity (prompt as knowledge blueprint). In simple terms, prompt clarity is a knowledge specification structure that allows for clear communication. In addition, it does this by removing all vagueness from the query. In a nutshell, it helps clear out all your thoughts and expectations on the output. It helps ensure that GenAI produces outputs that are pedagogically sound:

> To get the best responses from GenAI, prompts should be clear, specific, and structured to encourage critical thinking, analysis, and originality rather than just providing direct answers (R-25).

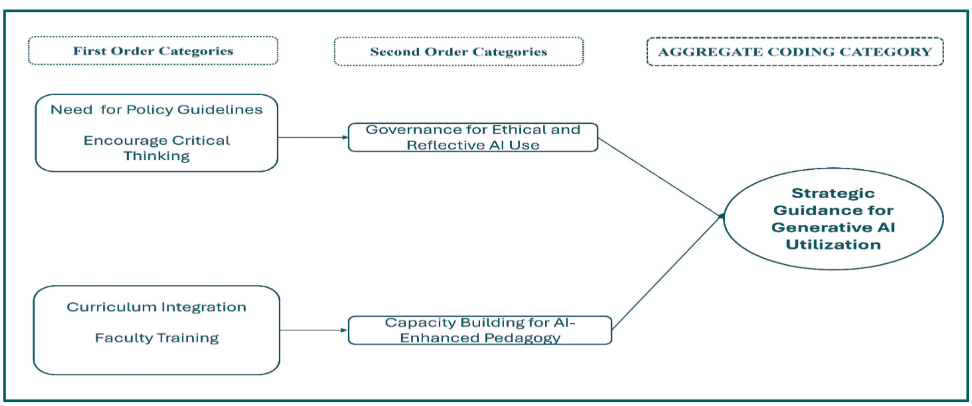
Prompts serve as explicit knowledge directives that govern the knowledge conversion process from raw computational capacity to pedagogically validated outputs.

5.3.1.2 Specifying output (knowledge format codification). The output specification entails a type of technical construction for expressing knowledge requirements in a specific format, such as discussion questions, case studies, evaluation rubrics and business analysis. The requirement specification leaves no ambiguity whatsoever in the task:

> Develop a business plan for a startup in [Industry], including market research, financial projections, and marketing strategies. Justify your decisions and provide supporting data (R-14).

These prompts create standardised knowledge artefacts that can be stored, shared and adapted across courses, building institutional knowledge repositories of AI-enhanced teaching materials.

Figure 4 Strategic guidance for GenAI utilisation



5.3.2 Intentional and contextualised assessment (contextual knowledge application).
5.3.2.1 Purpose-driven prompts (pedagogical knowledge alignment). Purpose-driven prompting aligns AI outputs with specific learning objectives, generating assessment-aligned knowledge products that directly support teaching goals. This represents sophisticated knowledge application engineering:

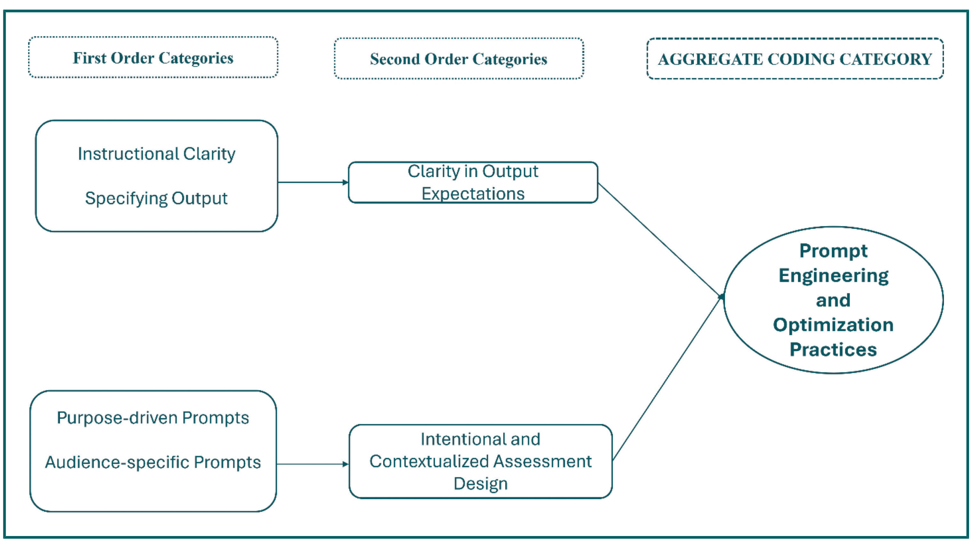
> Create a case study scenario where a multinational corporation faces a major ethical dilemma involving its supply chain. Provide background information, details about the dilemma, and questions prompting students to explore ethical frameworks and decision-making processes (R-9).

5.3.2.2 Audience-specific prompts (knowledge personalisation routines). Audience-specific prompting tailors knowledge delivery to learner characteristics, ensuring cognitive accessibility and relevance. This represents advanced knowledge customisation practices:

> What good grammar games will interest beginner ESL students? (R-29).

Audience-aware prompts demonstrate adaptive knowledge delivery systems, dynamically reconfiguring institutional knowledge for diverse learner needs. Teachers' increasing proficiency in prompt engineering was an especially emergent and new aspect. The instructional clarity, purpose-driven prompts and audience-specific prompting sub-themes represent a cognitive shift in how faculty interact with AI tools beyond passive use as active engineers of learning outcomes. Members provided many illustrations of sharpening prompts to get specific outputs. For instance, one teacher said, "How I ask determines how AI answers. I have learned over time to pose prompts in a way that corresponds with Bloom's taxonomy for critical thinking". "This is consistent with UTAUT2's Effort Expectancy—while there were initial learning curves, effort decreased as faculty became more competent—and Performance Expectancy, in that improved prompts corresponded to more relevant, higher-quality outputs. Prompt engineering also alleviated the complexity perceived in the DOI theory, demystifying GenAI and rendering it more accessible to larger faculty groups". Figure 5 presents the framework for prompt engineering and optimisation practices, conceptualised as emerging KM routines that enable effective GenAI utilisation in pedagogical contexts. These practices reflect a shift from passive AI usage to intentional knowledge design and application.

Figure 5 Prompt engineering and optimisation practices



5.4 Contextual encounters and reflections on artificial intelligence use (knowledge risk governance)

5.4.1 Governance of artificial intelligence in education (knowledge policy codification). 5.4.1.1 Artificial intelligence usage guidelines and policy (explicit knowledge rules). Faculty demand codified knowledge governance through clear AI usage policies that specify disclosure requirements, position AI as an assistive knowledge tool (not substitute) and establish boundaries around coding/origination tasks where AI limitations are pronounced:

> Provider clear guidelines on when it is appropriate to use it (R-1).

The rules governing the movement of knowledge and preventing the misappropriation of knowledge between human knowledge and AI-generated knowledge can also be called institutional knowledge rules.

5.4.1.2 Detection and regulation (knowledge quality assurance). Educators use a mixture of Turnitin checks, plagiarism thresholds and higher-order questioning to differentiate between actual student knowledge and AI-generated artefacts.

More and more people are becoming aware of the risks of knowledge contamination and the need for the application:

> I have been using the Turnitin app to detect if my learners' work is not AI-generated and if it was truly their work and thinking (R-5).
>
> It is important to understand how students use GenAI for assessments to discourage copied responses but encourage students to use AI for assistance and research (R-33).

5.4.2 Pedagogical adaptation for artificial intelligence integration (knowledge application redesign). 5.4.2.1 Assessment adaptation to artificial intelligence (knowledge authentication strategies). Faculty can redesign assessments to aid knowledge authentication through open-ended, analytical, project-based tasks that require human knowledge synthesis beyond AI capabilities. Process-oriented evaluation (drafts and reflections) verifies genuine knowledge work:

> I have introduced project-based evaluations that require students to work on real-world problems, using GenAI as a tool to support their work. This approach helps to assess students' ability to apply AI-generated insights in a practical context (R-8).

5.4.2.2 Leveraging artificial intelligence as a learning tool (scaffolded knowledge development). AI serves as a knowledge scaffold through personalised explanation, rapid breakdown of concept, quiz generation, making the work of faculty hassle-free. They can subsequently focus on knowledge interactions of higher value:

> We try to become more creative with our scenarios, typically reframing real-life case studies instead of using typical business problems. This ensures students are thinking critically and actively trying to find solutions to the problem (R-37).

5.4.3 AI-facilitated higher-order learning (knowledge refinement processes). 5.4.3.1 Design for critical thinking and higher-order skills (knowledge critique development). Students should evaluate knowledge as assessments undergo change. As an illustration, students may be required to evaluate, combine and enhance the output of AI:

> I focus on evaluating students' abilities to analyse, synthesise, evaluate, and create. I design assessments that require students to apply their knowledge and skills to real-world problems or scenarios. This makes it harder for students to rely solely on AI-generated content. I now emphasise the students' process of completing an assignment, not just the final product (R-21).

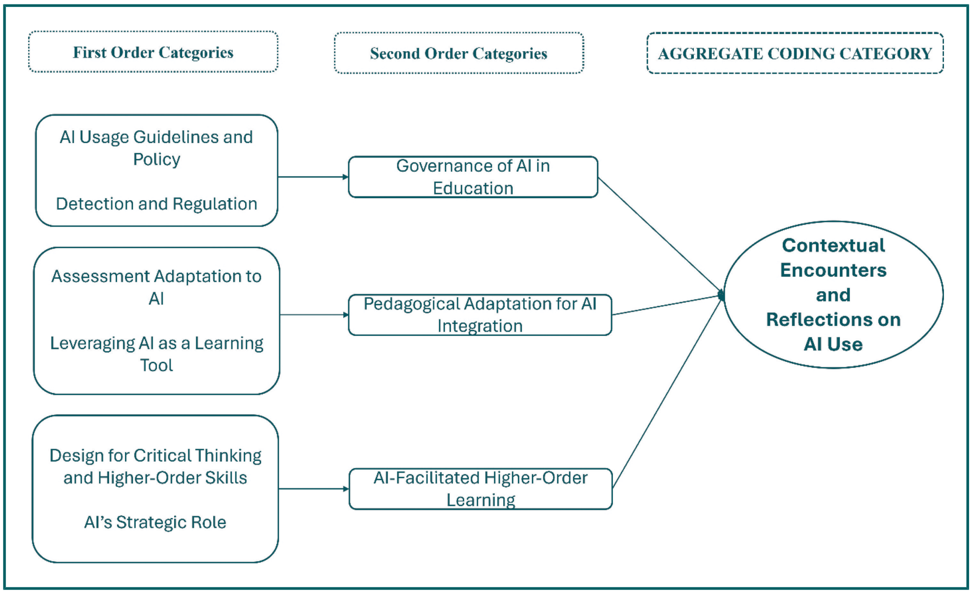
5.4.3.2 Artificial intelligence's strategic role (knowledge augmentation architecture). GenAI has become the strategic knowledge infrastructure for multiple professional organisations today, with the mundane workload being removed by them. It helps in automatically delivering routine knowledge work, such as content generation:

> GenAI has significantly impacted how educators provide personalised feedback and mentorship, making student interactions more efficient, targeted, and reflective. While AI can automate some aspects of feedback, it also allows for deeper engagement by freeing up time for higher-level discussions, individualised coaching, and critical thinking exercises (R-25).

The final dimension considers wider institutional and pedagogical tensions through contextual encounters. Assessment adaptation, AI usage guidelines, detection and regulation and higher-order learning design have highlighted undesirable scenarios including moral dilemmas, policy vacuum and academic dishonesty concerns.

One respondent depicted the challenge this way: "A student submitted a perfect essay but the things seem to be 'too perfect'. As we have an ill-defined policy, I didn't want to flag it". Their state of not answering makes their use uncomfortable and unpopular. Activity theory observations can take advantage of this space, where tensions between educational wishes and institutional norms come to light. Moreover, there was a widespread presence of negative outcome expectancies as stated by social cognitive theory. Teachers were concerned that unregulated use of GenAI could lead to surface learning or piracy. However, this theme also revealed hopeful signs. Some teachers decided to try integrating GenAI as a meta-cognitive and reflective tool. This allowed students to assess the AI output as a way of critiquing the content generated by a machine and developing critical thinking. These examples show creative ways of using AI technology in education. They are also an example of trialability, which offers the option of trying out a little bit first. These interrelated dynamics are synthesised in Figure 6, which conceptualises contextual encounters and reflective practices as central to knowledge risk governance in AI-enabled education.

Figure 6 Contextual encounters and reflections on AI use



6. Implications of the study

6.1 Theoretical implications

This study makes three primary KM contributions to technology adoption literature in higher education, demonstrating how GenAI functions as both a strategic knowledge resource and a disruptive knowledge governance challenge.

6.1.1 Integrated knowledge management-technology adoption framework. The research develops a novel layered KM framework that synthesises KM theory with UTAUT2, DOI, SCT and activity theory to explain GenAI adoption as a knowledge infrastructure transformation:

KM theory frames GenAI as an organisational knowledge capability that accelerates knowledge creation, sharing and application processes. UTAUT2's constructs (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation and habit) explain how individual educators recognise and assimilate this knowledge capability into practice. DOI demonstrates how observability (peer demonstrations), communication networks and social norms accelerate knowledge diffusion across institutional boundaries, while SCT's self-efficacy and vicarious learning mediate knowledge competency development. Activity theory reveals knowledge rule contradictions – between innovation aspirations and regulatory gaps – that paradoxically drive institutional knowledge evolution through tension resolution.

6.1.2 Knowledge management process reconfiguration by generative artificial intelligence. The findings map GenAI's specific impacts across core KM processes, extending Nonaka and Takeuchi's socialization, externalization, combination, internalization (SECI) model. The findings further demonstrate how GenAI reconfigures core KM processes, extending the logic of the SECI model by introducing AI-mediated knowledge transformations across the KM lifecycle. These transformations, along with their corresponding theoretical linkages, are summarised in Table 2.

GenAI simultaneously amplifies knowledge velocity (creation/application acceleration) while destabilising knowledge governance (authenticity and quality control), making KM architecture the critical determinant of adoption success.

6.1.3 Knowledge governance as adoption determinant. The study establishes knowledge governance capacity as the missing mediator between individual technology beliefs (UTAUT2) and institutional adoption outcomes. Specifically:

- Knowledge enablers (clear policies, training infrastructure and communities of practice) resolve activity theory tensions and amplify DOI diffusion.
- Knowledge barriers (policy ambiguity, capability gaps and validation uncertainty) create SCT negative expectancies and UTAUT2 facilitating condition deficits.
- Knowledge routines (prompt engineering and detection protocols) emerge as institutional best practices that reduce DOI complexity perceptions.

Table 2 KM process reconfiguration by GenAI

KM process	*GenAI impact*	*Theoretical linkage*
Knowledge creation	AI-mediated content generation	UTAUT2 performance expectancy
Knowledge codification	Prompt engineering → Templates	DOI complexity reduction
Knowledge sharing	Peer workshops → Observability	SCT vicarious learning
Knowledge application	Adaptive/personalised delivery	UTAUT2 effort expectancy
Knowledge governance	Policy gaps → Validation needs	Activity theory contradictions

[Figure 7](#)'s integrated data structure empirically demonstrates how these KM mechanisms operate across individual, social and systemic levels, providing a comprehensive adoption model superior to single-theory approaches.

6.1.4 Methodological knowledge management innovation. The Gioia methodology operationalises KM constructs at three levels:

1. First-order concepts → Raw knowledge practices (quotes)
2. Second-order themes → Knowledge processes (creation and governance)
3. Aggregate dimensions → Knowledge infrastructure transformation

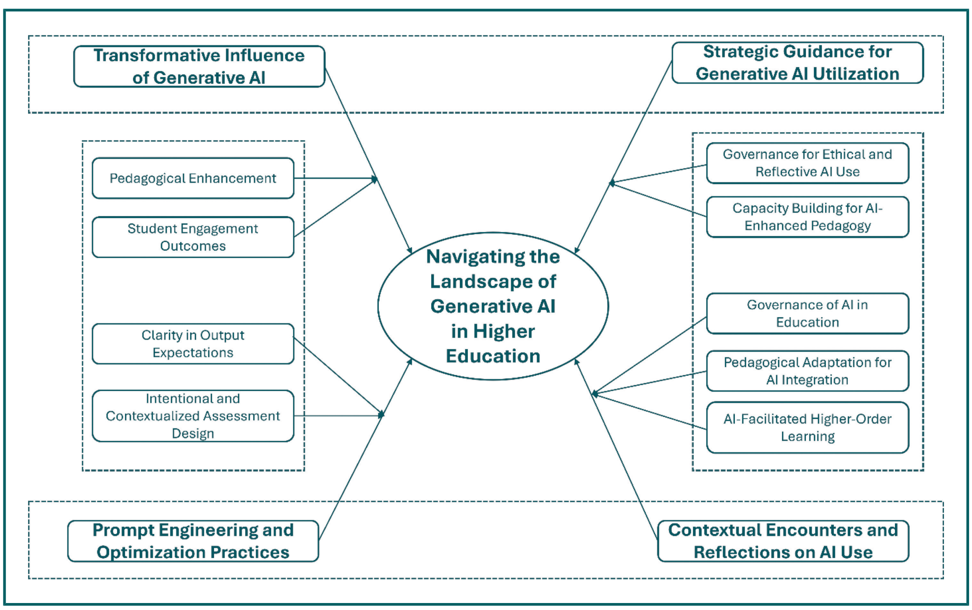
This multi-level KM mapping advances beyond traditional technology adoption studies by capturing how micro-level knowledge routines aggregate into macro-level institutional knowledge architectures. This work extends KM theory from corporate to academic knowledge ecosystems, demonstrating how GenAI creates dual knowledge governance challenges. The study links KM with established technology adoption theories, positioning knowledge governance as the integrative construct that explains why belief structures (UTAUT2) + social processes (DOI/SCT) + systemic tensions (activity theory) translate (or fail to translate) into sustained adoption. The integrated model (Figure 7) provides HEIs with a knowledge audit tool for assessing GenAI readiness across individual competencies, social diffusion mechanisms and institutional governance capacity.

6.2 Practical implications

This study provides HEIs with a knowledge governance roadmap for responsible GenAI integration, translating empirical findings into actionable KM infrastructure across policy, training and assessment domains.

6.2.1 Co-created knowledge governance policies. Policies must function as explicit knowledge repositories that codify acceptable GenAI practices while accommodating disciplinary variation.

Figure 7 Aggregate coding of factors affecting GenAI usage in HEI



Recommendations:

- *Faculty co-creation:* Develop discipline-specific AI guidelines through collaborative workshops, resolving activity theory contradictions between universal policies and subject-specific needs.
- *Knowledge architecture:* Policies should address internet protocol (IP)/data privacy (knowledge ownership), ethical use (knowledge quality) and pedagogical boundaries (knowledge substitution vs augmentation).
- *Iterative refinement:* Establish feedback loops for continuous policy evolution based on classroom learning.

6.2.2 Systematic knowledge transfer infrastructure. Prompt literacy and ethical AI competency represent strategic organisational capabilities requiring institutionalised knowledge transfer.

Training architecture:

- *Technical KM:* Prompt engineering mastery ("how I ask determines how AI answers");
- *Pedagogical KM:* AI-enhanced teaching design aligned with learning objectives;
- *Ethical KM:* Knowledge governance protocols for academic integrity; and
- *DOI activation:* Leader demonstrations leveraging observability to reduce adoption uncertainty.

Delivery mechanisms: Dedicated AI centres of excellence → Faculty learning communities → Peer mentoring networks.

6.2.3 Educator agency as knowledge engineers. Position faculty as active knowledge engineers rather than passive technology consumers, leveraging GenAI to amplify pedagogical expertise.

Curriculum imperative: Develop student meta-knowledge competencies:

- critical evaluation of AI-generated knowledge;
- knowledge attribution and citation standards; and
- strategic deployment of AI as a knowledge scaffold (not substitute).

6.2.4 Actionable knowledge management implementation toolkit. A template for policy development may help universities introduce GenAI in a gradual manner. The model should explain how one can use GenAI:

- Mandatory disclosure on the usage of AI tools.
- Institutions should articulate distinctions between acceptable AI-assisted work and plagiarism or other forms of academic misconduct.
- Incentivising the usage of AI to aid in creative support and not replace critical thinking.

Institutions are always learning and developing. They usually take a staged approach that starts with broad rules that ultimately add detail.

A toolkit to help educators evaluate and assess AI Tech can be developed. As summarised in Table 3, such a toolkit addresses ongoing concerns regarding the use of AI-generated content (e.g. essays) in student evaluations by providing structured guidance. The speculation continues about the possibility of using essays generated by ChatGPT in evaluations. The toolkit would include:

Table 3 Assessment redesign toolkit

Component	*Purpose*	*KM function*
AI-Resistant assignment design	Open-ended and process-oriented tasks	Knowledge authentication
AI-enhanced rubrics	Process + Product evaluation	Knowledge quality assurance
GenAI competency assessment	Meta-cognitive AI skills	Future-ready knowledge capacity
Formative feedback templates	AI + Human synthesis	Knowledge refinement protocols

- Guidelines on designing assignments that involve AI usage.
- The rubrics that can assess the ability to use AI, create and reason.
- Designing sample formative and summative assessments to assess students' GenAI skills.

Institutions may also provide a governance checklist outlining roles and responsibilities over the institutional activity system. As presented in Table 4, this knowledge roles matrix delineates stakeholder-specific responsibilities and associated accountability mechanisms, ensuring alignment between policy intent and implementation.

The significance of this research may have potential real-life effects on the higher education sector. According to the study's findings, policies should be crafted and implemented in consultation with faculty members. Authorities should not try to shut down or heavily regulate GenAI but collaborate with teachers to create flexible discipline-based guidelines on responsible use. The policy framework must take into account IP and data privacy, pedagogy, ethics and responsible use.

The research indicates that teachers need long-term, holistic professional development for effective teaching. Training should cover technical proficiency knowledge (effort expectancy), pedagogy, ethical standards and prompt engineering (how I ask influences how AI answers). In addition, the training may tap into the DOI's observability principle to showcase effective leader uses of GenAI to lessen uncertainty and resistance to the use of GenAI. Activity theory helps us collaborate to create policies and practices. Contradiction leads to the misalignment of parts of the activity system with each other, resulting in inconsistencies. When policies overlook subject-specific practices or rewards are contradictory to teachers' practice. Stakeholders must bring academic administrators, teachers, instructional designers and policymakers together into the same room so they can agree on where the contradictions are and turn them into a source of creativity. The strategy

Table 4 Institutional governance checklist [knowledge roles matrix]

Stakeholder	*Knowledge responsibilities*	*Accountability mechanisms*
Faculty	Policy implementation, prompt engineering and assessment redesign	Student learning outcomes
Programme leads	Compliance monitoring and faculty development coordination	Programme-level adoption rates
IT services	Secure AI infrastructure and equitable access	Technical reliability metrics
Quality assurance	Policy audits and impact assessment	Institutional effectiveness KPIs
Students	Policy compliance and feedback provision	Meta-knowledge competency

Note(s): KPI = Key performance indicator can help create a shared understanding through collaboration and purposeful, sustainable and continuous implementation of GenAI.

As the data of the present study shows, the teachers should consider themselves as engines of learning rather than mere users of technology. This study believes that if teachers are creative and use GenAI to enhance their teaching and help students learn better, that will optimise the impact. These teachers use GenAI to make learning easier and more enjoyable. In the end, students are what the process relies on, even though it never directly involves them. The curriculum should develop powerful critical and metacognitive capacities and the use of GenAI, so students do not overly rely on automated support but learn to deploy technology in a manner that automatically enhances their learning.

7. Conclusions

This study provides a comprehensive analysis of GenAI adoption in higher education through the lived experiences of 40 management educators, employing an integrated KM-centric framework. Synthesising KM theory with UTAUT2, DOI, SCT and activity theory, the research reveals GenAI as both a powerful knowledge accelerator and a profound knowledge governance challenge.

The results identify a mutually intertwined Web of motivational enablers and hindering obstacles that together define educators' intentions and practices. Enablers noted as significant are the possibility of profound pedagogical enhancement (e.g. better content construction, interactive instruction and quality improvement), higher student engagement outcomes (e.g. creativity promotion, student motivation and classroom participation) and the creation of advanced "Prompt Engineering Practices" enabling faculty to guide learning outcomes actively. In contrast, significant inhibiting factors arise from ubiquitous, systemic uncertainty in institutional policy, moral debates over academic integrity and intellectual honesty, student anxiety about dependence and concerns about justice and algorithmic prejudice. More importantly, the research illustrates that teachers neither embrace nor reject GenAI in a dichotomous manner.

This study strongly emphasises the critical necessity of purposeful policy frameworks, robust and continuous professional training, and thoughtfully designed pedagogy to ensure the responsible, ethical and effective utilisation of GenAI. By addressing these core aspects, institutions can successfully maintain the intellectual and ethical rigour that characterises higher education and chart this revolutionary period with vision and purpose.

7.1 Limitations and future research directions

This study presents rich insights into educators' attitudes and experiences with GenAI within higher education. However, it is essential to acknowledge its inherent limitations and propose future research directions. Although this research approach supplied rich, contextual and process-based observations on the "hows" and "whys" of GenAI adoption, its results cannot be statistically generalised to all fields, types of institutions or the overall population of educators in higher education worldwide. While giving depth, the emphasis on management education also restricts immediate transferability to areas with clear pedagogical expectations or ethical dimensions. The data collected are participants' self-reported attitudes, perceptions and experiences. Self-report data inherently carry the risk of social desirability bias or recall bias, in which responses may be influenced by what participants believe is expected or by their subjective memory. The present study is a snapshot. Due to the rapid and continuous development of GenAI technologies, applications and institutional responses, the challenges and opportunities may evolve. A cross-sectional approach cannot completely reflect these transient changes over time. Although an intentional strength in confronting the research question, the sole initial priority on educators tends to mean that student experience, understanding of GenAI's effects on learning, critical thinking or the risk of over-reliance are indirectly assumed through educator issues rather than definitively examined through empirical student data.

Future research would benefit markedly from a longitudinal qualitative design that tracks a cohort of courses or educators over time as policies evolve and as GenAI tools are adopted and integrated. Such longitudinal studies will help capture dynamic changes, contextual shifts and the unfolding of knowledge governance in real-time. This will offer rich insights beyond a static snapshot.

In the future, it would be particularly useful for research to take on a longitudinal qualitative design that follows a cohort of courses or educators over time as policies change and as GenAI tools are taken on and integrated. Over time, the studies will capture the movement of knowledge governance as well as dynamic context changes. This will offer rich insights beyond a static snapshot. For future research, it's recommended to conduct large-scale and quantitative surveys involving discursively diverse educators from different disciplines, types of institutions (e.g. research universities vs teaching universities vs community colleges) and different geographical locations. This would improve the generalisability of the results. Students' attitudes, experiences, behavioural intentions and actual usage patterns of GenAI tools require qualitative and quantitative research on a continued basis. This research study seeks to understand how GenAI affects students' learning processes, development of higher-order thinking skills, critical and creative thinking and tendencies of dependency and cheating from the perspective of students. Longitudinal studies would be very helpful given the dynamic nature of GenAI. Over time, longitudinal studies would allow evidence to track changing trends in GenAI adoption and sustained pedagogical impact, effectiveness of institutional policies and evolution of new faculty skills. Future research could create and test the results of interventions.

Research in different disciplines, both applied (because they offer insights into social and natural sciences and fine arts) and not, would reveal how diversity of disciplinary norms and epistemic cultures, evaluative practices and ethical issues shape the use and usefulness of GenAI tools. Teachers and students using GenAI should encourage research that can empirically measure its direct causal effect on specified learning outcomes, development of critical thinking capacities, problem-solving skills, as well as academic performance in various contexts. This may be done through quasi-experimental or experimental studies. As the accuracy of AI in essay writing comes under scrutiny, researchers need to evaluate the effectiveness, equity and ethics of AI detection tools in future work. Future studies can also explore methods that do not facilitate the use of GenAI for academic assessments and that help students learn for real. GenAI policies produced by different institutions will require systematic investigation to evaluate their actual effects and effectiveness on faculty behaviour, violations of student academic integrity and overall campus climate. This may involve looking at organisations with different policy positions to find best practices, and help understand how differences in policy influence uptake, ethical use and teaching outcomes. Studies of these kinds would provide regulators with a significant source of evidence to conduct their jobs. They can impose regulations that will allow innovation and yet defend academic standards. As a result, such studies can also help define which policy architectures best promote the responsible integration of GenAI and dissipate related risks.

References

Al-Emran, M., Al-Sharafi, M.A., Foroughi, B., Al-Qaysi, N., Mansoor, D., Beheshti, A. and Ali, N.A. (2025), "Evaluating the influence of generative AI on students' academic performance through the lenses of TPB and TTF using a hybrid SEM-ANN approach", *Education and Information Technologies*, Vol. 30 No. 12, pp. 1-31, doi: 10.1007/s10639-025-13485-w.

Almuaqel, I.A. (2024), "Managing knowledge to enable learning individuals with intellectual and developmental disabilities: the missing piece on knowledge management", *Journal of Knowledge Management*, Vol. 28 No. 10, pp. 2976-2996.

An, Y., Yu, J.H. and James, S. (2025), “Investigating the higher education institutions’ guidelines and policies regarding the use of generative AI in teaching, learning, research, and administration”, *International Journal of Educational Technology in Higher Education*, Vol. 22 No. 1, p. 10.

Anderson, J.R., Corbett, A.T., Koedinger, K.R. and Pelletier, R. (1995), “Cognitive tutors: lessons learned”, *Journal of the Learning Sciences*, Vol. 4 No. 2, pp. 167-207.

Baker, R.S. and Rossi, L.M. (2013), “Assessing the disengaged behaviors of learners”, *Design Recommendations for Intelligent Tutoring Systems*, Vol. 1, p. 153.

Bandura, A. (1986), “Social foundations of thought and action”, *Englewood Cliffs, NJ*, Vol. 1986 Nos 23-28, p. 2.

Belkahla, W. and Triki, A. (2011), “Customer knowledge enabled innovation capability: proposing a measurement scale”, *Journal of Knowledge Management*, Vol. 15 No. 4, pp. 648-674.

Bitzer, D. (1976), “The wide world of computer-based education”, In *Advances in Computers*, Vol. 15, Elsevier, pp. 239-283.

Bloom, B.S. (1968), “Learning for mastery. Instruction and curriculum. Regional education laboratory for the Carolinas and Virginia”, *Topical Papers and Reprints, Number 1. Evaluation Comment*, Vol. 1 No. 2, p. n2.

Bonk, C.J., Lee, M.M., Reeves, T.C. and Reynolds, T.H. (2015), *MOOCs and Open Education Around the World*, Routledge.

Bunderson, C.V. (1973), *The TICCIT Project: Design Strategy for Educational Innovation*, Institute for Computer Uses in Education, Division of Instructional Services, Brigham Young University.

Cenfetelli, R.T. (2004), “Inhibitors and enablers as dual factor concepts in technology usage”, *Journal of the Association for Information Systems*, Vol. 5 No. 11, p. 16.

Corbett, A.T. and R Anderson, J. (1995), “Knowledge decomposition and subgoal reification in the ACT programming tutor”, in *Proceedings of AI-ED 95: 7th World Conference on Artificial Intelligence in Education*.

Cuban, L. (1986), *Teachers and Machines: The Classroom of Technology since 1920*, Teachers College Press.

Drucker, P.F. (1999), *Management Challenges for the 21st Century*, HarperCollins, New York.

Elman, J.L. (1990), “Finding structure in time”, *Cognitive Science*, Vol. 14 No. 2, pp. 179-211.

Fischer, I., Sweeney, S., Lucas, M. and Gupta, N. (2024), “Making sense of generative AI for assessments: contrasting student claims and assessor evaluations”, *The International Journal of Management Education*, Vol. 22 No. 3, p. 101081.

Gioia, D.A., Corley, K.G. and Hamilton, A.L. (2013), “Seeking qualitative rigor in inductive research: notes on the Gioia methodology”, *Organizational Research Methods*, Vol. 16 No. 1, pp. 15-31.

Gonzalez-Tamayo, L.A., Maheshwari, G., Bonomo-Odizzio, A. and Krauss-Delorme, C. (2024), “Successful business behaviour: an approach from the unified theory of acceptance and use of technology (UTAUT)”, *The International Journal of Management Education*, Vol. 22 No. 2, p. 100979.

Guba, E.G. and Lincoln, Y.S. (1994), “Competing paradigms in qualitative research”, *Handbook of Qualitative Research*, Vol. 2 Nos 163-194, p. 105.

Gupta, P., Mahajan, R., Badhera, U. and Kushwaha, P.S. (2024), “Integrating generative AI in management education: a mixed-methods study using social construction of technology theory”, *The International Journal of Management Education*, Vol. 22 No. 3, p. 101017.

Hochreiter, S. and Schmidhuber, J. (1997), “Long short-term memory”, *Neural Computation*, Vol. 9 No. 8, pp. 1735-1780.

Hosen, M., Ogbeibu, S., Lim, W.M., Ferraris, A., Munim, Z.H. and Chong, Y.L. (2023), “Knowledge sharing behavior among academics: insights from theory of planned behavior, perceived trust and organizational climate”, *Journal of Knowledge Management*, Vol. 27 No. 6, pp. 1740-1764.

Jeon, J., Kim, L. and Park, J. (2025), “The ethics of generative AI in social science research: a qualitative approach for institutionally grounded AI research ethics”, *Technology in Society*, Vol. 81, p. 102836.

Kaplan, A.M. and Haenlein, M. (2016), “Higher education and the digital revolution: about MOOCs, SPOCs, social media, and the cookie monster”, *Business Horizons*, Vol. 59 No. 4, pp. 441-450.

Koedinger, K.R., Corbett, A. and Sawyer, R.K. (2006), "Cognitive tutors: technology bringing learning sciences to the classroom", in *The Cambridge Handbook of the Learning Sciences*, Cambridge University Press, pp. 61-77.

Koller, V., Kopf, S. and Miglbauer, M. (2019), *Discourses of Brexit*, Routledge, London.

Leong, L.Y., Hew, T.S., Ooi, K.B., Tan, G.W.H. and Koohang, A. (2025), "Generative AI: current status and future directions", *Journal of Computer Information Systems*, pp. 1-34.

Leont'ev, A.N. (1978), *Activity, Consciousness, and Personality*, Prentice-Hall.

Liu, J., Wang, C., Liu, Z., Gao, M., Xu, Y., Chen, J. and Cheng, Y. (2024), "A bibliometric analysis of generative AI in education: current status and development", *Asia Pacific Journal of Education*, Vol. 44 No. 1, pp. 156-175.

Luehrmann, A. (1980), "Computer illiteracy-a national crisis and a solution for it", *Byte*, Vol. 5 No. 7, pp. 98-102.

Macfadyen, L.P. and Dawson, S. (2012), "Numbers are not enough. Why e-learning analytics failed to inform an institutional strategic plan", *Journal of Educational Technology & Society*, Vol. 15 No. 3, pp. 149-163.

Merrill, M.D. (1975), "Learner control: beyond aptitude-treatment interactions", *AV Communication Review*, Vol. 23 No. 2, pp. 217-226.

Nguyen, K.V. (2025), "The use of generative AI tools in higher education: ethical and pedagogical principles", *Journal of Academic Ethics*, Vol. 23 No. 3, pp. 1-21.

Nonaka, I. and Takeuchi, H. (1995), *The Knowledge-creating Company: How Japanese Companies Create the Dynamics of Innovation*, Oxford University Press, New York.

Nvidia, C. (2007), "Compute unified device architecture programming guide", available at: https://developer.download.nvidia.com/compute/cuda/1.0/NVIDIA_CUDA_Programming_Guide_1.0.pdf

Papert, S. (1980), "Personal computing and its impact on education", *The Computer in the School: Tutor, Tool, Tutee*, pp. 197-202.

Porsdam Mann, S. (2024), "Guidelines for ethical use and acknowledgement of large language models in academic writing", *Nature Machine Intelligence*, Vol. 6 No. 11, doi: 10.1038/s42256-024-00922-7.

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D. and Sutskever, I. (2019), "Language models are unsupervised multitask learners", *OpenAI Blog*, Vol. 1 No. 8, p. 9.

Ramesh, A., Pavlov, M., Goh, G., Gray, S., Voss, C., Radford, A., Chen, M. and Sutskever, I. (2021), Zero-shot text-to-image generation. *International Conference on Machine Learning*, *PMLR*, pp. 8821-8831.

Rejeb, A., Rejeb, K., Appolloni, A., Treiblmaier, H. and Iranmanesh, M. (2024), "Exploring the impact of ChatGPT on education: a web mining and machine learning approach", *The International Journal of Management Education*, Vol. 22 No. 1, p. 100932.

Rogers, E.M. (2003), *Diffusion of Innovations*, 5th ed., Free Press.

Romano, M., Del Giudice, M. and Nicotra, M. (2014), "Knowledge creation and exploitation in italian universities: the role of internal policies for patent activity", *Journal of Knowledge Management*, Vol. 18 No. 5, pp. 952-970.

Skinner, B.F. (1958), "Teaching machines: from the experimental study of learning come devices which arrange optimal conditions for self-instruction", *Science*, Vol. 128 No. 3330, pp. 969-977.

Srivastava, P., Sehgal, T., Jain, R., Kaur, P. and Luukela-Tandon, A. (2024), "Knowledge management during emergency remote teaching: an interpretative phenomenological analysis of the transition experiences of faculty members", *Journal of Knowledge Management*, Vol. 28 No. 11, pp. 78-105.

Suppes, P. (1966), "Models of data", In *Studies in Logic and the Foundations of Mathematics*, Vol. 44, Elsevier, pp. 252-261.

Trindade, M.A., Edirisinghe, G.S. and Luo, L. (2025), "Teaching mathematical concepts in management with generative artificial intelligence: the power of human oversight in AI-driven learning", *The International Journal of Management Education*, Vol. 23 No. 2, p. 101104.

Tyack, D. and Cuban, L. (1995), *Tinkering with Utopia: A Century of Public School Reform*, Harvard University Press, Cambridge, MA.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., A.N., Gomez, A.N., Kaiser, L. and Polosukhin, I. (2017), “Attention is all you need”, *Advances in Neural Information Processing Systems*, Vol. 30.

Venkatesh, V., Thong, J.Y. and Xu, X. (2012), “Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology”, *MIS Quarterly*, Vol. 36 No. 1, pp. 157-178.

Vygotsky, L.S. and Cole, M. (1978), *Mind in Society: Development of Higher Psychological Processes*, Harvard University Press.

Warschauer, M. (2004), *Technology and Social Inclusion: Rethinking the Digital Divide*, MIT Press.

Wei, X. and Taecharungroj, V. (2022), “How to improve learning experience in MOOCs an analysis of online reviews of business courses on Coursera”, *The International Journal of Management Education*, Vol. 20 No. 3, p. 100675.

Weizenbaum, J. (1966), “ELIZA—a computer program for the study of natural language communication between man and machine”, *Communications of the ACM*, Vol. 9 No. 1, pp. 36-45.

Zack, M.H. (1999), “Developing a knowledge strategy”, *California Management Review*, Vol. 41 No. 3, pp. 125-145.

Further reading

Bin-Nashwan, S.A., Sadallah, M. and Bouteraa, M. (2023), “Use of ChatGPT in academia: academic integrity hangs in the balance”, *Technology in Society*, Vol. 75, p. 102370.

Chen, J.J. and Lin, J.C. (2024), “Artificial intelligence as a double-edged sword: wielding the POWER principles to maximise its positive effects and minimise its negative effects”, *Contemporary Issues in Early Childhood*, Vol. 25 No. 1, pp. 146-153.

Jeon, J. and Lee, S. (2023), “Large language models in education: a focus on the complementary relationship between human teachers and ChatGPT”, *Education and Information Technologies*, Vol. 28 No. 12, pp. 15873-15892.

Leoni, L., Gueli, G., Ardolino, M., Panizzon, M. and Gupta, S. (2024), “AI-empowered KM processes for decision-making: empirical evidence from worldwide organisations”, *Journal of Knowledge Management*, Vol. 28 No. 11, pp. 320-347.

Rana, N.P., Chatterjee, S., Dwivedi, Y.K. and Akter, S. (2022), “Understanding dark side of artificial intelligence (AI) integrated business analytics: assessing firm’s operational inefficiency and competitiveness”, *European Journal of Information Systems*, Vol. 31 No. 3, pp. 364-387.

Rodriguez, C.O. (2012), “MOOCs and the AI-Stanford like courses: two successful and distinct course formats for massive open online courses”, *European Journal of Open, Distance and E-Learning*.

Turing, A.M. (2007), “Computing machinery and intelligence”, in *Parsing the Turing Test: Philosophical and Methodological Issues in the Quest for the Thinking Computer*, Springer Netherlands, Dordrecht, pp. 23-65.

Yan, L., Sha, L., Zhao, L., Li, Y., Martinez-Maldonado, R., Chen, G., Li, X., Jin, Y. and Gašević, D. (2024), “Practical and ethical challenges of large language models in education: a systematic scoping review”, *British Journal of Educational Technology*, Vol. 55 No. 1, pp. 90-112.

Author affiliations

Intesar Almugren is based at the Department of Teaching and Learning, College of Education and Human Development, Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

Issac K. Varghese is based at the Department of Strategy and General Management, T A Pai Management Institute, Manipal Academy of Higher Education, Manipal, India.

Shivani Agarwal is based at Institute of Management Studies (IMS) Ghaziabad, Ghaziabad, India.

Attila Kurucz is based at the Department of Corporate Leadership and Marketing, Kautz Gyula Faculty of Business and Economics, Śzechenyi István University, Györ, Hungary.

Domenico Fontana is based at the Department of Management and Economics, Pegaso Digital University, Napoli, Italy.

Mario Nobis is based at the Department of Economics and Statistics, University of Salerno, Salerno, Italy.

Corresponding author

Attila Kurucz can be contacted at: kurucz.attila@sze.hu