



Mind the gap: capability, policy and uncertainty in the adoption of generative AI within post-compulsory education

Paul Lees, Naomi Davis-Crane & Chris Taylor

To cite this article: Paul Lees, Naomi Davis-Crane & Chris Taylor (07 Oct 2026): Mind the gap: capability, policy and uncertainty in the adoption of generative AI within post-compulsory education, Research in Post-Compulsory Education, DOI: [10.1080/13596748.2026.2739104](https://doi.org/10.1080/13596748.2026.2739104)

To link to this article: <https://doi.org/10.1080/13596748.2026.2739104>



© 2026 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.



Published online: 07 Oct 2026.



Submit your article to this journal [↗](#)



View related articles [↗](#)



View Crossmark data [↗](#)

Mind the gap: capability, policy and uncertainty in the adoption of generative AI within post-compulsory education

Paul Lees , Naomi Davis-Crane  and Chris Taylor 

Liverpool John Moores University, Liverpool, UK

ABSTRACT

This qualitative, interpretivist study explores perceptions of Generative AI (GenAI) adoption among academic staff and Level 7 senior leader apprentices within a UK business school. Drawing on semi-structured interviews with sixteen participants, inductive thematic analysis revealed three interrelated themes: engagement under uncertainty, the capability gap, and the policy gap. Findings indicate that whilst participants recognise the potential utility associated with embracing GenAI, adoption is constrained by ethical sensitivity, limited application literacy, and the opacity of governance frameworks across the tripartite apprenticeship relationship. This study contributes to emergent debates on AI literacy and technological acceptance by surfacing how uncertainty is socially and structurally produced, offering practical recommendations for education providers seeking to embed GenAI both effectively and ethically.

ARTICLE HISTORY

Received 17 April 2026
Accepted 27 August 2026

KEYWORDS

AI literacy; degree apprenticeships; generative AI; higher education; leadership and management education; technology adoption

Introduction

Generative artificial intelligence tools (GenAI), such as ChatGPT, Microsoft Co-pilot, and Google Gemini have simultaneously invigorated, inspired, disturbed and challenged academics in higher education institutions globally. Such challenges require adaptation of delivery approach, curriculum content, and assessment design amongst a wealth of other changes and questions about the implications for the nature of teaching roles, ethics, governance, data protection, and cybersecurity. GenAI has touched, or will touch, every dimension of higher education, including apprenticeship programmes and as AI continues to evolve, we will see increasingly innovative, bespoke, and effective uses across the sector. Whilst higher education must necessarily explore the synthesis of GenAI across its functions, it is also germane to consider barriers to this integration.

The impetus for this study arose from a set of practical challenges the authors faced as educators within the Level 7 apprenticeship space. Chief

CONTACT Paul Lees  p.lees@ljmu.ac.uk

© 2026 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.
This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. The terms on which this article has been published allow the posting of the Accepted Manuscript in a repository by the author(s) or with their consent.

among these was a lack of real insight into learners' own experience of using GenAI: how they were engaging with it, what they found valuable or difficult, and what they needed in order to use it well. This limited the evidence available to inform decisions concerning curriculum content, learning activities and programme-level guidance. Where training and guidance existed, it tended to be pitched at a general level, oriented around the broad capabilities of GenAI or the risks of improper use, rather than grounded in learners' own experience, roles or organisational contexts.

A second, related challenge concerned the teaching environment. The prominence of misconduct concerns complicated efforts to create learning environments in which apprentices could experiment, disclose uncertainty, and develop confidence. A third challenge concerned divergence. In our experience, learners and staff alike varied enormously in their existing confidence and capability with GenAI, and this variation made it harder still to judge what support or guidance was needed, since no single starting point could be assumed for either group. This was further complicated by the diversity of the roles and settings our learners worked in. Level 7 apprentices work in a wide range of organisations including the NHS, local government, and large private organisations, and each context has its own norms, constraints, and experience of GenAI, making it extremely difficult to offer anything that felt genuinely aligned with organisational requirements.

Generative AI in professional education

According to the Higher Education Policy Institute (HEPI), GenAI has swiftly moved from an experimental technology towards a routine feature within UK higher education. In a 2025 survey, 92% of students reported using a GenAI tool whilst 88% disclosed usage in relation to assessment. Alarmingly, within the same piece of research, only 36% of students reported that they had received institutional training, strongly suggesting adoption outpaces HE pedagogical and policy responses (Freeman 2025). Consequently, the debate has widened beyond academic misconduct and moved towards AI literacy, equitable access, and assessment validity. From the degree apprenticeship perspective, learners can face dual uncertainty; how to use GenAI effectively in the workplace, and how to incorporate it into their academic practice.

Central to apprenticeships in England is the principle that through combining structured learning and paid employment the individual can develop the necessary knowledge, skills, and behaviours to be fully competent in their role. A distinctive feature of apprenticeships is the tripartite relationship between the apprentice, their employer, and the training provider; each of whom fulfils specific and complementary roles

in relation to learning. Whilst the training provider is responsible for the formal delivery of teaching, the employer is required to provide opportunities to develop and demonstrate competencies in the workplace and ensure the availability of protected learning time. The apprentice is responsible for engaging with the learning and evidencing their knowledge, skills, and behaviours. This three-way relationship helps ensure that the apprentice is supported in achieving the occupational standard, and that academic and workplace learning are aligned (HM Government 2026).

The Level 7 Senior Leader Apprenticeship was first delivered in 2018 and targeted at individuals with senior management responsibilities across sectors. Between 2018 and 2025 the apprenticeship standard was subject to several amendments, today comprising 20 knowledge, 21 skill, and 5 behavioural standards (Skills England 2026b). In the context of this research, the training provider was the business school of a large university in north-west England wherein the delivery of Level 7 and equivalent qualifications to professional audiences comprises a notable proportion of postgraduate provision.

Like many institutions, for the business school in question, the Level 7 Senior Leader Apprenticeship represented a significant number of learners over its lifespan and helped catalyse industry-university partnerships in leadership development; its demise lying in the government decision to place tight limits on the availability of Level 7 apprenticeship funding which precluded the majority of prospective candidates drawing upon the levy to finance their studies (Skills England 2026a). The present research retains its relevance to other higher education-industry partnerships that emphasise experiential leadership development.

The Senior Leader Apprenticeship therefore provides a particularly revealing environment in which to investigate GenAI adoption, because apprentices must reconcile academic-integrity requirements with workplace expectations, professional accountability, and organisation-specific restrictions on information and technology use. Taken together, these conditions make degree apprenticeship provision a distinctive site of GenAI adoption, in which capability and governance are shaped not by a single institution but through the interaction of the university, employer, and apprentice.

The present study represents exploration of the nature of GenAI adoption amongst educators and learners involved in the Level 7 Senior Leader Apprenticeship at a UK business school. Whilst the Level 7 Apprenticeship is likely to perish due to changes in funding arrangements, we argue that the results presented here are applicable to other leadership and management programmes delivered by UK institutions, particularly those including simultaneous study and industry employment, and where employers are closely involved in the education process.

Comparing apprentices and academic staff enables GenAI adoption to be examined from two interdependent positions. Academic staff encounter the technology through pedagogy, assessment, academic integrity, and institutional accountability, whereas apprentices encounter it simultaneously through academic study, professional practice, and organisational responsibility. The comparison therefore illuminates how uncertainty, capability, and governance operate across, rather than solely within, the two sides of the educational relationship.

This paper progresses with a review of the literature related to opportunities and risks presented by GenAI in this context, incorporating influences upon adoption and barriers to acceptance. Followed by a description of the research conducted and an analysis of the findings, which is subsequently reflected upon in light of theory and used to inform recommendations for providers of leadership and management development programmes within post-compulsory education.

Literature review

Generative AI as an opportunity

GenAI offers (at least in part) a potential solution to some of the most enduring challenges in higher education concerning the need to engage students via personalised learning experiences, which is not practically achievable given the size of many of the programmes run by universities today. GenAI enables deeper analysis of learning needs at scale, the ability to adapt materials to engage individuals, and opportunities to identify and address gaps in knowledge (Rahiman and Kodikal 2023). In addition to offering the potential to facilitate planning and resource management via predictive analytics in areas such as marketing, enrolment management, and student risk identification. Thereby enabling targeted intervention and strategy development (Al-Abdullatif 2024), an imperative when working with learners balancing full-time work in senior positions with the demands of postgraduate level study.

From the perspective of academic staff, GenAI presents the potential to automate less valuable and/or routine tasks to allow greater capacity for higher order cognition and value enhancing activities (Alam and Mohanty 2022). Postgraduate leadership and management learners typically derive from a broad swathe of role and organisational backgrounds, creating challenges in designing applicable, engaging, authentic, and equally challenging assessments across a mixed cohort. GenAI presents potential opportunities in this respect as part of creative approaches to assessment design. In addition to enabling educators to take more data-led approaches to delivery

via the ability to synthesise and appraise large datasets, and conduct predictive analytics (Habibi et al. 2023).

From a learner perspective, the potential to receive a more personalised learning experience is a prominent benefit of GenAI (Bond et al. 2024), including via customised learning materials which facilitate student autonomy (Bearman, Ryan, and Ajjawi 2023; Buchanan et al. 2021). In apprenticeships there also exists the additional potential to generate learning materials specific to the student's employer. The ease with which this may be achieved at scale being particularly advantageous in cohorts of learners from multiple organisational and/or role contexts. GenAI tools further enable learners to achieve greater depths of immersive engagement with the learning content, including via interactive bespoke dynamic applications, which may be used to catalyse individual and group learning as required (Ruiz-Rojas, Salvador-Ullauri, and Acosta-Vargas 2024). Given the diverse range of background, skills, and roles within leadership and management programmes, this flexibility, utility, and adaptability therefore present significant advantages to learners and educators in terms of delivering high impact, and good quality learning opportunities.

Integrating GenAI into higher education programmes is integral to equipping learners with the knowledge and skills needed to thrive and progress in employment (Ruiz-Rojas, Salvador-Ullauri, and Acosta-Vargas 2024). We argue that this obligation is particularly potent in respect of leadership and management education, given that learners on these programmes will potentially be leading, or involved in, the development of AI-enabled working within their own organisations. However, it is also necessary to consider the risks and challenges associated with its use.

Generative AI as a risk and challenge

A broad range of challenges exist in relation to the integration of GenAI into higher education. Including a disconnect between existing and new systems (Ouyang, Zheng, and Jiao 2022) and the requirement for ethical education and oversight (Grunhut, Wyatt, and Marques 2021).

At an institutional level there is a requirement for significant and ongoing investment in technology and training to maintain currency as GenAI systems develop (Alotaibi and Alshehri 2023). Investment which may be jeopardised by financial constraints or an absence of coherency in strategic planning in respect of AI. Whilst across the education sector there remain concerns as to the use of GenAI to produce assessment content which is not the student's own, thereby subverting the education process and devaluing the awarded qualifications (Times Higher Education 2026). Andić (2025) highlights the potential for GenAI to catalyse a situation in which learners use GenAI to misrepresent their engagement in learning via algorithm,

rather than student, generated content thereby creating an illusion of competence.

Concerns exist as to the potential for GenAI to negatively impact upon learners' critical thinking skills and their development. GenAI tools have been identified as effective in supporting the development of lower-level cognitive skills, however their utility in aiding the development of critical thinking abilities is much less clear cut (Essien, Chukwukelu, and Essien 2021), necessitating educators to take a careful, considered, and creative approach to embedding GenAI into programmes. Critical thinking is a fundamental skill for leaders and consequently one which forms a key element of leadership and management education. Consequently, the introduction of GenAI requires educators to develop knowledge and skills relating to the wide variety of systems available and their functionality, whilst also critically reflecting upon their potential use in academic programmes.

Additional challenges faced by students in this context include differentiating ethical conduct from unethical use, over-reliance on GenAI output, plagiarism, referencing, and understanding the capabilities and limitations of both specific tools and the wider technology (Andić 2025). Further supporting the need for a strategic, comprehensive, resourced and holistic approach to its introduction at the institutional, faculty, school, and programme levels, whilst also addressing the range of ethical concerns associated with its use. The absence of which, we propose, creates a climate of uncertainty that in turn presents a cognitive barrier to adoption.

The question of ethics

GenAI is associated with a host of general ethical issues, such as its environmental impact (Chouksey et al. 2026) and the use of forced labour in supply chains which feed technology production (Williams, Miceli, and Gebru 2022), in addition to specific ethical concerns relating its application in higher education.

GenAI has both the potential to create, magnify, and perpetuate the existence of a range of biases (Zhang et al. 2023). For example, GenAI is further associated with concerns that its use may support confirmation type biases and limit opportunities to address preconceptions and stereotypes (Essien, Chukwukelu, and Essien 2021); skills which are essential for senior leaders to cultivate. This risk is potentially exacerbated where systems are trained upon biased data, provide high level overviews which ignore complexity and nuance, and encourage sole reliance upon the generated content as opposed to seeking further perspectives (Essien, Chukwukelu, and Essien 2021).

Inequity of access to GenAI tools may exacerbate achievement gaps between learners from different socio-economic backgrounds (George

and Sevak 2026). For example, free-to-use GenAI systems may lack the most up to date information, technical sophistication, accuracy, or capacity for repeated use compared to paid-for versions. Placing those with the means to pay at an advantage and, we argue, necessitating that higher education providers promoting GenAI use on their programmes ensure the provision of high-quality tooling for all learners and staff, to include consideration of barriers to its subsequent adoption.

Ethical and other governance frameworks established to manage the use of GenAI should therefore be founded upon principles of fairness, transparency, and accountability. In the apprenticeship context therefore requiring at a minimum tripartite agreement between the learner, employer, and provider. Whilst GenAI systems themselves must be transparent and auditable, so the processes by which outputs are derived may be understood by those using them (George and Sevak 2026). Other significant ethical concerns arising in respect of GenAI include those relating to data privacy and security, particularly where systems are analysing and learning from sensitive personal data. In addition to introducing questions relating to data and intellectual property ownership (George and Sevak 2026). Finally, GenAI has considerably broadened the opportunities for academic misconduct across the education sector, resulting in considerable debate as to its role in education.

Ethical deployment of GenAI therefore requires transparency and equity in the development of the underlying algorithms, coupled with critical awareness on the part of users to understand, reflect upon, and mitigate enduring biases and ethical concerns. Further, we contend that it is necessary for institutions to invest in ethical training for staff and learners to reduce the potential for fear of ethical misconduct to have a negative impact upon acceptance.

Enabling acceptance

The effective deployment of GenAI in higher education institutions will be highly contingent upon the willingness of educators to adopt it. This willingness in turn catalysing their development of the necessary AI literacy and synthesis of this with pedagogic expertise to deliver considered ethical and engaging learner experiences.

The technology acceptance model (TAM) (Davis, Bagozzi, and Warshaw 1989) suggests that perceptions of usefulness and the ease of use are principal determinants in the decision whether to adopt a technology. Other research suggests that attributes of innovative technologies which influence their adoption include:

- (1) The perceived relative advantage the new system will provide compared to existing or similar systems (Ntemana and Olatokun 2012).
- (2) The extent to which the user regards the technology as compatible with their values (Bennett and Bennett 2003).
- (3) The perceived degree of complexity associated with using the new system (Ntemana and Olatokun 2012). As GenAI ease of use augments self-efficacy and trust in the technology, serving to increase engagement and reporting of a positive user experience (Baek and Kim 2023; Shahzad, Xu, and Asif 2024).
- (4) The degree to which the user is able to test and experiment with the new technology prior to adoption (Bennett and Bennett 2003).
- (5) Perceived trustworthiness of the technology. User trust in the accuracy, usefulness, and reliability of GenAI content has a substantial influence upon adoption. In contrast, decreased engagement may occur where trust is marred by poor quality outputs (Polyportis 2024).
- (6) And the extent to which the individual is able to access and observe the new technology (Ntemana and Olatokun 2012).

Previous research has further highlighted that openness to new technologies is higher amongst educators with elevated levels of engagement (Scherer, Siddiq, and Tondeur 2019). Which in turn is consistent with greater resilience, flexibility, and adaptability when it comes to digital innovation (Antonietti, Cattaneo, and Amenduni 2022). Whilst from a learner perspective, Ray (2023) recognises that learners who feel confident in using technology likely perceived themselves as having greater confidence in their ability to use GenAI. A potential challenge therefore emerges for leadership and management educators working with mid- to later-career learners who often profess to having limited digital skills. Placing a responsibility, we propose, on business schools to be taking a holistic approach to leadership and management education, which reflects the complex array of knowledge, skills, and behaviours required in industry today. Further, GenAI acceptance will be catalysed via applications which are bespoke to the educational context, secure, dependable, and easy to use (Shahzad, Xu, and Asif 2024). These features being particularly pertinent for educators working with time-poor senior leaders.

AI literacy is therefore central to enabling learners and educators to comprehend and work confidently with the technology, negating the potential for skills gaps to hinder effective use. AI literacy is embodied in the individual's ability to understand its potential utility in different contexts. Including any benefits, dis-benefits and ethical implications, and having the knowledge, skills, and awareness to select the most appropriate tools for the

task at hand. AI literacy increases willingness to engage with the technology via increasing familiarity and trust, and reducing perceived complexity (Al-Abdullatif 2024).

The effective implementation of GenAI across an institution is therefore conditional upon investment in the associated infrastructure, coupled with coherent schemes, policies, and processes to support educator and learner awareness, knowledge and skills development. The absence of which, we propose, results in uncertainty that serves to hinder adoption of the technology.

The extant literature explains several factors relevant to GenAI adoption, including perceived usefulness, ease of use, trust, opportunities for experimentation, and concerns about academic misconduct. However, two aspects remain comparatively underexplored. First, limited attention has been given to the first-hand experiences of senior professionals who combine post-graduate study with full-time employment, or to academic staff navigating GenAI within professional education. Second, existing models provide limited insight into how adoption is shaped by divergent organisational and sectoral conditions. Addressing these gaps provides the rationale for the present comparative study.

Materials and methods

The aim of this qualitative, comparative study is to contribute to existing research and knowledge related to the perceptions of both academic staff and Level 7 apprentices from an executive education programme, on the purpose and utility of generative artificial intelligence within the sphere of higher education and into the workplace beyond.

Our study employed a qualitative research design, underpinned by an interpretivist paradigm to explore participants' perceptions and lived experiences regarding the utility of GenAI. A qualitative approach was deemed most appropriate as it enables exploration of complex phenomena through the lens of participants' lived experiences and related subjective interpretations (Creswell and Poth 2018). The interpretivist framework aligns with the study's aim to understand how individuals construct meaning around AI utility within their individualised specific contexts, acknowledging that reality is a socially constructed phenomenon and consequently multiple perspectives exist and contain inherent value (Saunders, Lewis, and Thornhill 2019).

Participant recruitment and sample

The study comprised sixteen participants recruited through purposive sampling, divided into two distinct cohorts: eight staff members and

Table 1. Participant coding and demographics.

Code	Role/Position	Sector/Organisation type
Academic Staff		
S1 – S8	Senior lecturer	Higher education (Business School)
Level 7 Degree Apprentices		
A1	Manager	Higher education
A2	Senior clinical manager	Healthcare
A3	Senior clinical manager	Healthcare
A4	Senior clinical manager	Healthcare
A5	Senior policy manager	Government services
A6	Operations manager	Manufacturing
A7	Chief executive	Third sector
A8	Senior researcher	Healthcare

eight Level 7 apprentices. The sampling strategy was adopted to ensure representation from key stakeholder groups who interact with AI technologies in different capacities within the business school context for academic teaching, learning, scholarly activity, and research. Purposive sampling was chosen as it allows for the deliberate selection of participants who possess relevant knowledge and experience related to the research phenomenon (Patton 2015). Staff participants were all current employees with experience or exposure to AI technologies in their professional practice and learner participants were current students or recent graduates who have encountered AI tools on their academic journey and have a professional curiosity in workplace application. This dualistic cohort approach enables comparative analysis between two different user groups, providing a comprehensive understanding of AI utility across various roles and perspectives. All academic participants are at senior lecturer (SL) level within the business school, and all apprentice participants are working in senior roles within public, private, or third sector organisations (see Table 1).

Data collection

Semi-structured interviews were employed as the primary data collection method. This approach was selected due to its flexibility in allowing researchers to explore predetermined themes whilst remaining responsive to emerging topics (Braun and Clarke 2013). Semi-structured interviews provided the optimal balance between structure and flexibility, enabling consistent coverage of key research questions while permitting deeper exploration of participant lived experiences and perspectives (Kvale and Brinkmann 2009).

The interview process and content were developed based on existing literature incorporating open-ended questions designed to elicit rich, detailed responses around participants' experience, perceptions, and attitudes. Interviews were conducted individually, using video conferencing, lasting approximately 45 minutes each. Identical questions were asked of

both sets, with questions provided in advance in order to promote richer, deeper responses. All interviews were recorded with participant consent and subsequently transcribed verbatim to ensure accuracy in data analysis (Poland 1995).

Data analysis

Data analysis followed Braun and Clarke's (2006) six-phase inductive thematic analysis framework, which the researchers felt particularly suited this exploratory research seeking to identify patterns and themes emerging from participant accounts without predetermined theoretical assumptions. This bottom-up approach allows themes to emerge from the data rather than being imposed by existing theoretical frameworks (Boyatzis 1998).

The analytical process comprised familiarisation, systematic coding of the dataset, collating codes, eliciting initial potential themes, final analysis, and selection. NVivo 14 software was utilised to facilitate the organisation, coding, and analysis of data. NVivo's functionality supports systematic data management while maintaining the interpretive flexibility essential to qualitative research (Bazeley and Jackson 2013). The software enabled efficient coding, theme development, and the maintenance of an audit trail throughout the analytical process, although to enhance the credibility and trustworthiness of findings, several strategies were employed consistent with Lincoln and Guba's (1985) criteria for qualitative research quality. Member checking was conducted by sharing preliminary findings with participants to verify accuracy of interpretations (Birt et al. 2016). Additionally, peer debriefing sessions were held with research colleagues to challenge assumptions and discuss emerging themes, thereby reducing potential for researcher bias (see reflexivity below) (Spall 1998).

The integration of the Gioia method with inductive thematic analysis offered us a robust framework for qualitative inquiry (see Figure A1. appendix). The Gioia method emphasises systematic data structuring through first-order concepts, second-order themes and aggregate dimensions, which enhances transparency and theoretical development (Gioia, Corley, and Hamilton 2013). Inductive thematic analysis, on the other hand, provides flexibility in identifying patterns and themes directly from the data without imposing preconceived categories (Braun and Clarke 2006).

Using these approaches together allows researchers to maintain the richness of participants' voices while progressively abstracting insights into higher-order theoretical constructs. This combination strengthens methodological rigour by ensuring both data-driven theme generation and structured conceptualisation, making it particularly suitable for exploratory studies aiming to build grounded theory or conceptual frameworks.

Ethical considerations

The study adhered to all ethical principles in accordance with the university's research ethics framework and received institutional ethical approval prior to data collection. Informed consent was obtained from all participants, who were provided with comprehensive information about the study's purpose, procedures, potential risks, and their rights as participants (British Educational Research Association 2024). Participants were assured of their right to withdraw from the study at any time without consequence.

Data confidentiality and anonymity were maintained throughout the research process. All identifying information was removed from transcripts, and participants were assigned alphanumeric identifiers. Data was stored securely in password-protected files accessible only to the research team, in compliance with data protection regulations (General Data Protection Regulation, 2018).

Reflexivity

Acknowledging the researcher's role in the interpretive process, reflexive practices were maintained throughout the study. Regular reflection on potential biases, assumptions, and positionality was documented in research memos to enhance transparency and acknowledge the constructed nature of knowledge production in qualitative research (Finlay 2002).

The next section outlines the findings from the inductive thematic analysis of the interview data. Themes are reported at an analytical level and are deliberately focussed on patterns of meaning across the participant contributions rather than detailed individual narratives. In line with the interpretivist nature of the research, findings aim to elucidate how academic staff and degree apprentices make sense of generative artificial intelligence within respective educational and professional organisational contexts.

Results

This section presents the findings from the thematic analysis of interviews with eight academics and eight Level 7 degree apprentices. Three interrelated themes were identified: engagement under uncertainty, the capability gap, and the policy gap. Taken together, the three themes articulate how both participant groups navigate generative artificial intelligence in conditions of limited or invisible guidance, unequal capability, and elevated ethical sensitivity.

Theme one: engagement under uncertainty

A major, defining feature of the dataset is that both staff and apprentices are in varying degrees engaging with generative AI within conditions of persistent uncertainty. S3 admits openly that they *'don't fully trust it'*, a sentiment that resonated with many. This uncertainty transcended conceptualisation as a mere barrier to engagement; rather, the participants frequently described cautious, selective, or experimental usage underpinned by concerns relating to ethics, authenticity, quality (or lack thereof), data security, and potential professional consequences.

Whilst many concerns were distributed across both groups, the actual orientation of concern differed markedly. That is to say academic staff tended towards an emphasis on integrity, misconduct, and institutional liability, as S5 notes in reference to academic misconduct panels (AMP) *'this year there's so many more coming through . . . there's always calls for people, for the AI panel'*. Institutional data reveals that the first incidence of a GenAI related AMP occurred in May 2023, but the staff member is right when reporting increasing volume. Several described encountering AI primarily (and in some cases initially) through academic misconduct processes as opposed to andragogical experimentation. This resulting in defensive framing, conceptualising AI as something that learners needed to be protected or rescued from. This is clearly expressed by S4 and S6 who respectively perceived *'a nervousness around . . . introducing something to our students . . . that is then going to get them into trouble'* and *'they don't want to fall foul of academic misconduct'*. By contrast, apprentices were more likely to frame concerns around authenticity, legitimacy, and professional identity, particularly manifesting in organisational contexts where AI-generated outputs were perceived through the lens of devaluing or obscuring professional expertise. A7 reflects *'I want to be an authentic person, and I really don't like the idea of someone else's piece of technology writing something that I'm then going to pass off as my own'*. This is further supported by A6 when they existentially question the ownership and authenticity of generative AI outputs *'that's not me . . . I don't know where I begin and that ends'*.

Importantly, these concerns reflected reasoned judgement as opposed to abject fear. Apprentices questioned the reality of legitimately substituting weeks of human labour with AI-generated material, whilst academic staff disclosed apprehension over promoting experimentation without boundary setting, their fear being that learners could be at risk from accusations of misconduct. Shared fears around data security (particularly within public sector and highly regulated contexts) manifested as hard constraints which rendered some usage redundant regardless of individual preference. For S2, this manifested as a series of questions *'Where does it go? Who uses it? How is it interpreted somewhere else? If something is free, then you are usually the*

one being consumed. A1 focusses on their own context with the statement *I've got a lot of sensitive data, really none of that which I could put into this*.

Theme one therefore highlights a pattern of tense engagement; potential was realised, but caution was shaped by overarching uncertainties related to ethics, professionalism, and context. The findings within this theme reflect the proposition advanced within the literature section in as much as uncertainty functions as both a cognitive and affective barrier to adoption rather than a straightforward lack of awareness.

Theme two: the capability gap

Our second prominent finding relates to a clear gap between conceptual awareness and the individual ability to operationalise potential in practice. Across both participant groups, respondents demonstrated the ability to identify highly specific, highly role-aligned applications of generative AI whilst paradoxically 'confessing' to limited engagement and/or making self-effacing disclosures related to lack of skill. A7 sees the potential value of AI usage to their role in a small third sector organisation but admits they are *'clueless ... I've no idea what you can, or you can't do'* but alludes to imagined *'huge efficiencies'*.

This so-called awareness to application gap highlighted above was particularly in evidence among the apprentices, several of whom described detailed, applied scenarios which could automate analytical, reporting, or communication tasks, yet described their understanding as 'basic' or as disclosed above, 'clueless'. Rather than underlining ignorance, these disclosures appeared to reflect uncertainty around how to effectively act in a safe, ethical way. Similarly, a pattern was identified amongst academic staff, some of whom recognised support for andragogical or efficiency gains whilst expressing uncertainty around prompt generation, issues of verification, and an overriding concern of appropriate usage.

Without exception, the awareness to application gap was consistently linked to a paucity of meaningful training. Generic AI literacy was universally viewed as insufficient. A4 called for utility tailored to their job role *'maybe half a dozen really common things that we do that you could have very specific guidance about'*. Both sets of participants highlighted the need for contextualised, role-specific support. In particular, apprentices called for examples based on the realities of their contexts, constraints, and responsibilities. A3 called for training to be *'quite bespoke'* and reflective of their client needs and geographical location. S1 mirrored this sentiment when calling for the deployment of differentiated support rather than *'one size fits all'*. In the absence of such support, informal peer learning, experimentation, and self-directed exploration were the only means to fill the gap left by the absence of structured interventions. S4 proposed deployment of 'AI

buddies', whereby more competent users could coach and mentor neophytes, a feeling echoed by S8 who, in order to meet their own learning preference, required *'hands on demonstration sessions'*.

This theme extends existing discussion of AI literacy by putting forward the argument that the key barrier to adoption is not around awareness but rather relates to a lack of application literacy. That is to say, a scarcity in the ability to shift a conceptual understanding into situated practice. In absence of this competency, for many, AI remains high risk in spite of perceived value.

Theme three: the policy gap

Our final theme, and the strongest structural finding in the dataset, pertains to the absence of policy, guidance, and organisational stewardship regarding AI usage. Apprentices in particular voiced frustration on two fronts as they were searching for organisational clarity whilst at the same time attempting to navigate opacity within university guidelines. *'What's the policy? What are we allowed to do?'* questions A5 in relation to these two points. A8 appears to suggest that within organisations there is perceived disparity *'whether individual departments are doing anything with AI is not common knowledge'*. For A2, there was irritation around the perception that *'we always put that on our values and missions that we're innovative but ... we're not, we just wait'*.

This left learners in a confused space with lack of clarity around what was permitted, encouraged, discouraged, or prohibited. We conceptualise this as an accountability vacuum. Responsibility for development in relation to generative AI appeared diffuse across the tripartite apprenticeship model. Universities focussed on preventing misconduct, employers were on a continuum somewhere between restriction and silence, and academic staff appeared uncertain around whether or not AI competency development was actually under their purview. Unsurprisingly, engagement with generative AI therefore was reliant upon the motivated individual rather than coordinated strategy.

Further compounding this gap was time pressure, resource limitation, and restrictions relating to specific sectors. From a public sector perspective, data protection and risk aversion imposed strict limits on experimentation and uptake, whilst academic staff described self-development in relation to AI as *'a bit of an indulgence'* (S2) rather than a workload priority.

Collectively, there is a real sense that the policy gap does not merely pertain to a lack of documentation but surfaces a deeper, more concerning structural issue: AI engagement is occurring in the absence of leadership, defined accountability, and aligned expectations across all stakeholders. A2 laments *'we always seem to play catch up because the people that are at the*

head are so scared . . . they want it tried and tested, maybe in the private sector before it ever comes across to us’.

Within the next section, we situate the findings within the broader literature of generative AI adoption, technological acceptance, and overall AI literacy. Specifically, we examine and consider how uncertainty, capability gaps, and policy absence intersect and shape engagement amongst academic staff and degree apprentices and considers the implications of these patterns for leadership and management education. Through an interpretive lens, the discussion highlights both the theoretical contribution and practical significance of findings.

Discussion

This study set out to explore perceptions of generative AI amongst academic staff and Level 7 apprentices within a business school context. The findings contribute to the rapidly expanding literature around AI adoption in higher education by uniquely highlighting how uncertainty, capability, and policy interact to shape engagement amongst both educators and senior professional learners.

Engagement, uncertainty, and technological acceptance

The pervasive uncertainty identified within theme one aligns with established models of technological adoption. The Technology Acceptance Model (Davis, Bagozzi, and Warshaw 1989) emphasises perceived utility alongside ease of use as key determinants of adoption; however, this study suggests that perceived risk plays an equally influential role in educational and professional contexts. Concerns around but not limited to misconduct, authenticity, data governance, and job displacement appear to overshadow willingness even when usefulness is clearly acknowledged.

Importantly the data appears to complicate simplistic staff/student binaries often present in AI debates. Both participant groups expressed professional and ethical concern, albeit oriented towards different risk factors. The apprentice perspective emphasises authenticity and identity which aligns with the literature on ethical usage and deep learning (Andić 2025), whilst academic staff concerns reflect institutional accountability and assessment integrity discourse (Bearman, Ryan, and Ajjawi 2023). These findings strongly suggest that incertitude is institutionally and socially generated rather than being individually manifested.

Reconceptualising the capability gap

Theme two enriches existing discussions of AI literacy (Al-Abdullatif 2024) through a demonstration that awareness in isolation does not result in assimilation. Participants operated within the realm of conceptual understanding. In essence they were able to ‘imagine’ AI application without the confidence or specific skill to implement. This element supports the view that AI literacy needs to be understood as multi-factorial, incorporating not only the knowledge associated with AI capability, but the skills required to apply, evaluate, and verify output.

The espoused preference for bespoke, context-derived training resonates with studies that champion the value of contextual compatibility in adoption decisions (Bennett and Bennett 2003). It appears that for leadership and management learners in particular, generic demonstrations hold limited inherent value unless orientated towards role demand and organisational parameters. In absence of alignment, engagement will remain tentative due to persistent uncertainty.

Policy, responsibility, and institutional readiness

The policy gap identified within theme three represents what we believe to be a significant contribution of this study. Whilst extant literature calls for governance frameworks (George and Sevak 2026), findings here suggest that policy absence functions less as a neutral gap and more as a de facto barrier that replicates uncertainty and inhibits development. In fact, the apprenticeship context amplifies this issue as the tripartite model necessitates a level of coordination between the university, the employer, and the learner. Concerningly, respondents describe each element as a conduit for responsibility displacement. Thus, in the absence of ownership, individual experimentation or ad hoc peer learning surface as default strategies that in turn reinforce inequity and variability.

These findings support the call for a holistic, institution-led approach to generative AI intervention. Such approaches must transcend misconduct prevention and move towards proactive capability development (Alotaibi and Alshehri 2023). In the absence of coordinated efforts, AI engagement is at risk of remaining uneven, fragmented, and dependent on individualised confidence rather than deliberate organisational intent.

Conclusions

In exploring the use of generative AI with learners and educators in the context of Level 7 apprenticeships delivered by a business school, the present research has illuminated the interaction between capability,

uncertainty, and policy in influencing adoption. Uncertainty and concerns relating to generative AI use may serve to eclipse the potential benefits. These factors being heightened by the (perceived) absence of relevant policy, guidance, and training. Which in turn derive from an absence of clear leadership or responsibility for their establishment.

As a result of this research, it is recommended that parties to the apprenticeship relationship work collectively to establish, implement, and maintain joint governance of the use of generative AI in teaching and learning. Including establishing responsibility for the development, dissemination, and upholding of policy and its alignment with wider institutional, sector and organisational frameworks. Whilst also creating fora for stakeholders to engage at all levels to address socially generated incertitude. For example, using action learning sets in teaching to address challenges, establishing peer-support networks, or using asynchronous discussion boards to share learning. Further, it is recommended that this tripartite approach is also applied to the development of training solutions tailored to the unique context as a means of supporting adoption. Enabling parties to contextualise and apply the learning to their specific circumstances. Collectively, these elements forming part of a holistic strategy aiming to address the multi-factorial uncertainty serving to impede AI adoption in its context.

Whilst this research may be limited by its comparatively small participant population drawn from a single institution it nevertheless provides a potential launch point for further enquiry into the establishment of governance and support mechanisms in executive education and apprenticeship contexts, including extending the research to encompass a wider range of academic and professional programmes, education levels and delivery formats. Particularly given the ongoing draw down of Level 7 apprenticeship teaching as funding provision reaches its end.

The present research is also limited by the absence of the employer voice as the third pillar of the tripartite apprenticeship arrangement and a critical one in terms of establishing programme requirements. Consequently, future research should endeavour to engage employers to understand their expectations of education providers in equipping apprentices with the knowledge and skills to implement and use AI technologies in the workplace. Potentially using action learning or other dialogic techniques to facilitate three-way co-creation of solutions.

Future research may also seek to explore the causal pathways by which limited guidance, unequal capability, and elevated ethical sensitivity serve to influence engagement with GenAI, including their implications for individual self-efficacy and autonomous motivation, and potential existence of mediating factors. Likewise, more specific research could be conducted in respect of each of the principal findings of this work. For example, exploring

means of generating and disseminating guidance in the executive education context, taking into account the specific needs of this group of learners. Possibly, incorporating AI-enabled tooling as a generation and delivery device in addressing the policy gap.

GenAI also offers potential research opportunities in addressing inequality of capability, as identified as the second prominent theme in this work. Including examining ways in which executive learners may develop their capability through continual progressive interaction with GenAI tooling that provides real-time feedback and coaching. In respect of uncertainty, particularly relating to ethical use, future research may consider in greater detail specific concerns with a view to understanding their antecedents and implications for AI adoption. Thereby facilitating the further development of policy and guidance to enable users to ethically, confidently, and securely use the technology in teaching, learning, and other aspects of their employment.

GenAI presents a wealth of opportunities in executive and apprenticeship education. However, realisation of these benefits is contingent upon adoption, which in turn requires user confidence. In contrast, pervasive uncertainty associated with gaps in policy, governance, and training may impede adoption, leading to inequality in capability and wider socially derived uncertainty. Consequently, this research calls for higher education providers, employers and learners to adopt strategic and collegiate approaches to embedding generative AI in professional education for the long term. Thus, enabling benefits realisation within an environment which places learners at the heart, fosters equity, and maintains high academic standards.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Paul Lees  <http://orcid.org/0000-0001-8951-4865>

Naomi Davis-Crane  <http://orcid.org/0009-0009-0956-7269>

Chris Taylor  <http://orcid.org/0000-0003-3814-9217>

Acknowledgments

The authors would like to thank the academic staff and degree apprentices who generously contributed their time and insights to this study. We are also grateful to colleagues within

the business school for informal peer discussion and critical reflection during the development of the research design and analysis. Their altruistic engagement supported the refinement of methodological and conceptual decisions throughout the research process.

Declaration statement

All three authors declare that there is no conflict of interest associated with this research. No financial or personal relationships influenced the design or execution of this study.

Ethical approval

University Ethics Approval Code: 24/LBS/040.

References

- Al-Abdullatif, A. M. 2024. "Modeling teachers' Acceptance of Generative Artificial Intelligence Use in Higher Education: The Role of AI Literacy, Intelligent TPACK, and Perceived Trust." *Education Sciences* 14 (11): 1209. <https://doi.org/10.3390/educsci14111209>.
- Alam, A., and A. Mohanty. 2022. "Foundation for the Future of Higher Education or 'Misplaced optimism'? Being Human in the Age of Artificial Intelligence." In *Innovations in Intelligence Computing and Communication*, Edited by Mrutyunjaya Panda, (eds.). 17–29. Cham, Switzerland: Springer International Publishing https://doi.org/10.1007/978-3-031-23233-6_2.
- Alotaibi, N. S., and A. H. Alshehri. 2023. "Prosper and Obstacles in Using Artificial Intelligence in Saudi Arabia Higher Education Institutions: The Potential of AI-Based Learning Outcomes." *Sustainability* 15 (13): 10723. <https://doi.org/10.3390/su151310723>.
- Andić, B. 2025. "Artificial Intelligence and Deepfake Learning in Higher Education." *Journal of Baltic Science Education* 24 (1): 4–6. <https://doi.org/10.33225/jbse/25.24.04>.
- Antonietti, C., A. Cattaneo, and F. Amenduni. 2022. "Can teachers' Digital Competence Influence Technology Acceptance in Vocational Education?" *Computers in Human Behavior* 132:107266. <https://doi.org/10.1016/j.chb.2022.107266>.
- Baek, T. H., and M. Kim. 2023. "Is ChatGPT Scary Good? How User Motivations Affect Creepiness and Trust in Generative Artificial Intelligence." *Telematics and Informatics* 83:102030. <https://doi.org/10.1016/j.tele.2023.102030>.
- Bazeley, P., and K. Jackson. 2013. *Qualitative Data Analysis with NVivo*. 2nd ed. London, United Kingdom: Sage Publications Ltd.
- Bearman, M., J. Ryan, and R. Ajjawi. 2023. "Discourses of Artificial Intelligence in Higher Education: A Critical Literature Review." *Higher Education* 86 (2): 369–385. <https://doi.org/10.1007/s10734-022-00937-2>.
- Bennett, J., and L. Bennett. 2003. "A Review of Factors That Influence the Diffusion of Innovation When Structuring a Faculty Training Program." *Internet and Higher Education* 6 (1): 53–63. [https://doi.org/10.1016/S1096-7516\(02\)00161-6](https://doi.org/10.1016/S1096-7516(02)00161-6).
- Birt, L., S. Scott, D. Cavers, C. Campbell, and F. Walter. 2016. "Member Checking: A Tool to Enhance Trustworthiness or Merely a Nod to Validation?" *Qualitative Health Research* 26 (13): 1802–1811. <https://doi.org/10.1177/1049732316654870>.
- Bond, M., H. Khosravi, M. de Laat, N. Bergdahl, V. Negrea, E. Oxley, P. Pham, S. W. Chong, and G. Siemens. 2024. "A Meta Systematic Review of Artificial Intelligence in Higher Education: A Call for Increased Ethics, Collaboration, and Rigour." *International Journal*

- of Educational Technology in Higher Education* 21 (1): 4. <https://doi.org/10.1186/s41239-023-00436-z>.
- Boyatzis, R. E. 1998. *Transforming Qualitative Information: Thematic Analysis and Code Development*. Thousand Oaks, CA: SAGE Publications.
- Braun, V., and V. Clarke. 2006. "Using Thematic Analysis in Psychology." *Qualitative Research in Psychology* 3 (2): 77–101. <https://doi.org/10.1191/1478088706qp063oa>.
- Braun, V., and V. Clarke. 2013. *Successful Qualitative Research: A Practical Guide for Beginners*. London, United Kingdom: Sage Publications Ltd.
- British Educational Research Association. 2024. *Ethical Guidelines for Educational Research*. 5th Edited by. British Educational Research Association. Accessed April 10, 2026. <https://www.bera.ac.uk/publication/ethical-guidelines-for-educational-research-fifth-edition-2024>.
- Buchanan, C., M. L. Howitt, R. Wilson, R. G. Booth, T. Risling, and M. Bamford. 2021. "Predicted Influences of Artificial Intelligence on Nursing Education: Scoping Review." *JMIR Nursing* 4 (1): e23933. <https://doi.org/10.2196/23933>.
- Chouksey, A., A. K. Rajan, V. Gurjar, R. Tiwari, and P. K. Mishra. 2026. "The Green Paradox: The Climate, Environmental, and Sustainability Implications of Artificial Intelligence." *Global Environmental Change Advances* 6:100029. <https://doi.org/10.1016/j.gecadv.2025.100029>.
- Creswell, J. W., and C. N. Poth. 2018. *Qualitative Inquiry and Research Design: Choosing Among Five Approaches*. 4th ed. Thousand Oaks, CA: Sage Publications Ltd.
- Davis, F. D., R. P. Bagozzi, and P. R. Warshaw. 1989. "User Acceptance of Computer Technology: A Comparison of Two Theoretical Models." *Management Science* 35 (8): 982–1003. <https://doi.org/10.1287/mnsc.35.8.982>.
- Essien, A., G. Chukwukelu, and V. Essien. 2021. "Opportunities and Challenges of Adopting Artificial Intelligence for Learning and Teaching in Higher Education." In *Fostering Communication and Learning with Underutilized Technologies in Higher Education*, Edited by Mohammed Banu Ali and Trevor Wood-Harper, (eds.). 67–78. Hershey, PA: IGI Global. <https://doi.org/10.4018/978-1-7998-4846-2.ch005>.
- European Union. 2018. *General Data Protection Regulation (GDPR)*. Brussels: European Union. Accessed July 21, 2026. <https://gdpr-info.eu/>.
- Finlay, L. 2002. "Negotiating the Swamp: The Opportunity and Challenge of Reflexivity in Research Practice." *Qualitative Research* 2 (2): 209–230. <https://doi.org/10.1177/146879410200200205>.
- Freeman, J. 2025. HEPI Policy Note 61: Student Generative AI Survey 2025. Oxford: Higher Education Policy Institute. <https://www.hepi.ac.uk/reports/student-generative-ai-survey-2025/>.
- George, B., and K. Y. Sevak. 2026. "Artificial Intelligence in Higher Education: Opportunities and Concerns." *Research and Practice in Technology Enhanced Learning* 21:19. <https://doi.org/10.58459/rptel.2026.21019>.
- Gioia, D. A., K. G. Corley, and A. L. Hamilton. 2013. "Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology." *Organizational Research Methods* 16 (1): 15–31. <https://doi.org/10.1177/1094428112452151>.
- Grunhut, J., A. T. Wyatt, and O. Marques. 2021. "Educating Future Physicians in Artificial Intelligence (AI): An Integrative Review and Proposed Changes." *Journal of Medical Education and Curricular Development* 8. <https://doi.org/10.1177/23821205211036836>.
- Habibi, A., M. Muhaimin, B. K. Danibao, Y. G. Wibowo, S. Wahyuni, and A. Octavia. 2023. "ChatGPT in Higher Education Learning: Acceptance and Use." *Computers and Education: Artificial Intelligence* 5:100190. <https://doi.org/10.1016/j.caeai.2023.100190>.

- HM Government. 2026. "Roles and Responsibilities." *HM Government*. July 21, 2026. <https://www.apprenticeships.gov.uk/apprentices/roles-responsibilities>.
- Kvale, S., and S. Brinkmann. 2009. *InterViews: Learning the Craft of Qualitative Research Interviewing*. 2nd ed. Thousand Oaks, CA: Sage Publications Ltd.
- Lincoln, Y. S., and E. G. Guba. 1985. *Naturalistic Inquiry*. Newbury Park, CA: Sage Publications Ltd.
- Ntemana, T. J., and W. Olatokun. 2012. "Analyzing the Influence of Diffusion of Innovation Attributes on Lecturers' Attitude Towards Information and Communication Technologies." *Human Technology an Interdisciplinary Journal on Humans in ICT Environments* 8 (2): 179–197. <https://doi.org/10.17011/ht/urn.201211203034>.
- Ouyang, F., L. Zheng, and P. Jiao. 2022. "Artificial Intelligence in Online Higher Education: A Systematic Review of Empirical Research from 2011 to 2020." *Education and Information Technologies* 27 (6): 7893–7925. <https://doi.org/10.1007/s10639-022-10925-9>.
- Patton, M. Q. 2015. *Qualitative Research & Evaluation Methods: Integrating Theory and Practice*. Thousand Oaks, CA: Sage Publications Ltd.
- Poland, B. D. 1995. "Transcription Quality as an Aspect of Rigor in Qualitative Research." *Qualitative Inquiry* 1 (3): 290–310. <https://doi.org/10.1177/107780049500100302>.
- Polyportis, A. 2024. "A Longitudinal Study on Artificial Intelligence Adoption: Understanding the Drivers of ChatGPT Usage Behavior Change in Higher Education." *Frontiers in Artificial Intelligence* 6:1324398. <https://doi.org/10.3389/frai.2023.1324398>.
- Rahiman, H. U., and R. Kodikal. 2023. "Revolutionizing Education: Artificial Intelligence Empowered Learning in Higher Education." *Cogent Education* 11 (1). <https://doi.org/10.1080/2331186X.2023.2293431>.
- Ray, P. P. 2023. "ChatGPT: A Comprehensive Review on Background, Applications, Key Challenges, Bias, Ethics, Limitations and Future Scope." *Internet of Things and Cyber-Physical Systems* 3:121–154. <https://doi.org/10.1016/j.iotcps.2023.04.003>.
- Ruiz-Rojas, L., L. Salvador-Ullauri, and P. Acosta-Vargas. 2024. "Collaborative Working and Critical Thinking: Adoption of Generative Artificial Intelligence Tools in Higher Education." *Sustainability* 16 (13): 5367. <https://doi.org/10.3390/su16135367>.
- Saunders, M. N. K., P. Lewis, and A. Thornhill. 2019. *Research Methods for Business Students*. 8th ed. New York: Pearson.
- Scherer, R., F. Siddiq, and J. Tondeur. 2019. "The Technology Acceptance Model (TAM): A Meta-Analytic Structural Equation Modeling Approach to Explaining teachers' Adoption of Digital Technology in Education." *Computers and Education* 128:13–35. <https://doi.org/10.1016/j.compedu.2018.09.009>.
- Shahzad, M. F., S. Xu, and M. Asif. 2024. "Factors Affecting Generative Artificial Intelligence, Such as ChatGPT Use in Higher Education: An Application of Technology Acceptance Model." *British Educational Research Journal* 51 (2): 489–513. <https://doi.org/10.1002/berj.4084>.
- Skills England. 2026a. "Evidence on the Defunding of Level 7 Apprenticeships." *Skills England*.
- Skills England. 2026b. "Senior Leader." *Skills England*. July 21, 2026. <https://skillsengland.education.gov.uk/apprenticeships/st0480-v1-2>.
- Spall, S. 1998. "Peer Debriefing in Qualitative Research: Emerging Operational Models." *Qualitative Inquiry* 4 (2): 280–292. <https://doi.org/10.1177/107780049800400208>.
- Times Higher Education. 2026. "Is Mass Cheating the Inevitable Result of AI's Rise?" *Times Higher Education*. April 9. <https://www.timeshighereducation.com/depth/mass-cheating-inevitable-result-ais-rise>.

- Williams, A., M. Miceli, and T. Gebru. 2022. "The Exploited Labor Behind Artificial Intelligence." *Noema*. April 10, 2026. <https://www.noemamag.com/the-exploited-labor-behind-artificial-intelligence/>.
- Zhang, W., M. Cai, H. J. Lee, R. Evans, C. Zhu, and C. Ming. 2023. "AI in Medical Education: Global Situation, Effects and Challenges." *Education and Information Technologies* 29 (4): 4611–4633. <https://doi.org/10.1007/s10639-023-12009-8>.

Appendix

The Gioia method

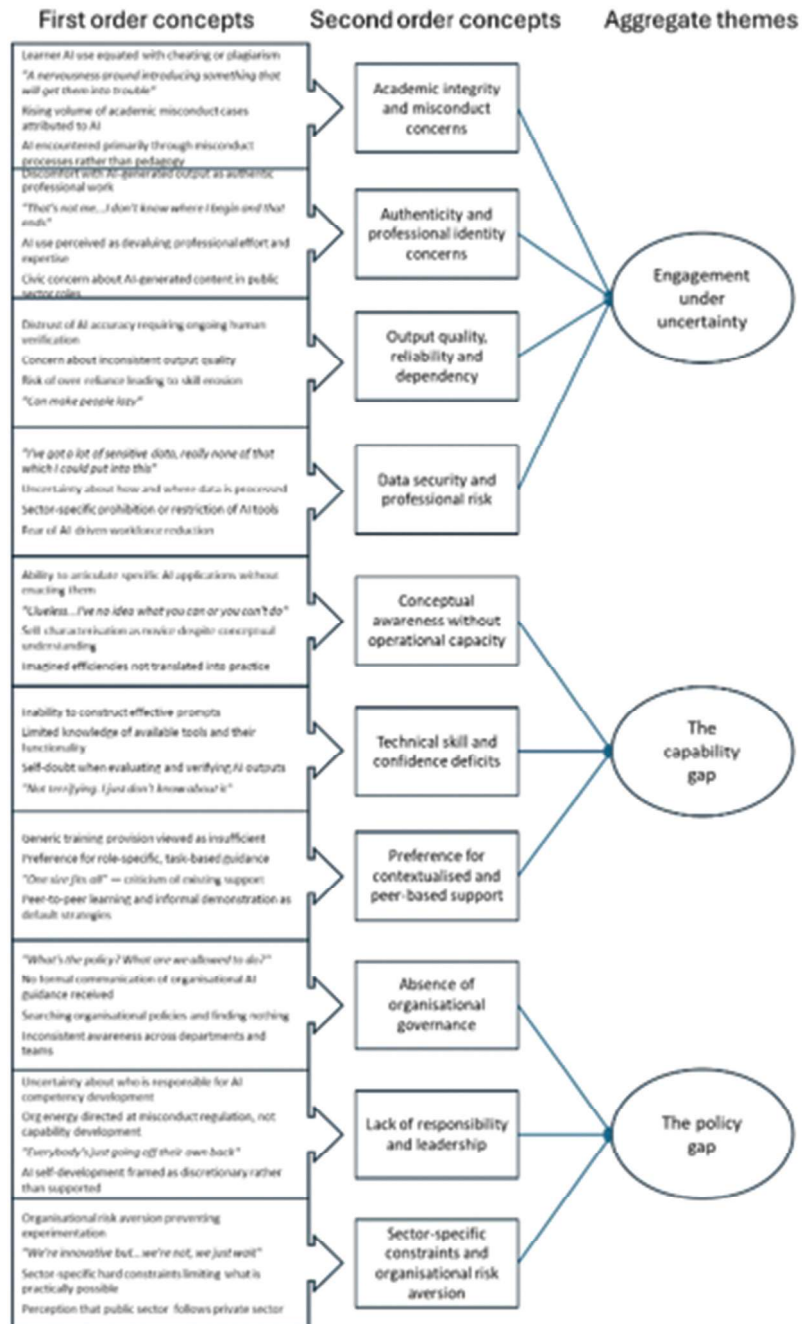


Figure A1. Concepts and aggregated themes.