Developing a multilevel framework for AI integration in technical and engineering higher education: insights from bibliometric analysis and ethnographic research

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Abstract

Purpose – The rapid integration of artificial intelligence (AI) in technical and engineering higher education presents both unprecedented opportunities and significant challenges. This study investigates how disciplinary characteristics, cultural contexts and institutional readiness influence AI implementation success in higher education.

Design/methodology/approach – This study analyzes AI integration in higher education through a dual methodological approach combining systematic literature review and ethnographic observations across

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different institutes and then proposes a multilevel integration framework that addresses implementation challenges across institutional, departmental and course-specific levels.

Findings – The study identifies three distinct approaches to AI integration in assessment: AI-inclusive assessment design, case study-based resistance strategies and hybrid examination models. The bibliometric analysis reveals ChatGPT as the dominant focus in current AI education research. The analysis identifies critical dialectical tensions that shape the integration of AI within higher education assessment practices – namely, the Authenticity–Innovation Paradox (balancing authentic assessment with AI-driven innovation), the Competency–Augmentation Dilemma (preserving core skills amid AI support) and the Scale–Customization Conflict (reconciling scalable models with personalized learning needs). The findings suggest that effective AI integration necessitates a shift from isolated individual innovations to coordinated, institution-wide strategies, conceptualized as "structured flexibility frameworks," while acknowledging significant regional and cultural variations in implementation approaches worldwide.

Originality/value – This study makes several significant contributions to AI integration in technical and engineering higher education. First, it develops a comprehensive multilevel framework that links institutional strategy, departmental approaches and classroom practices, addressing the complex dynamics of AI implementation. Through ethnographic observations across multiple Australian universities, the study provides empirical evidence of successful adaptation strategies, documenting real-world outcomes. Finally, the research establishes a theoretical foundation for understanding how disciplinary and cultural factors influence AI implementation success, providing insights into why certain approaches succeed or fail in different educational contexts. This work advances both theoretical understanding and practical strategies for AI integration in diverse higher education settings.

Keywords Artificial intelligence (AI) integration, Higher education, ChatGPT, Post-COVID education, Assessment design, Institutional adaptation, Students, Higher education, Assessment and e-assessment

Paper type Research paper

1. Introduction

The integration of artificial intelligence (AI) in technical and engineering disciplines presents both transformative technological capabilities and complex pedagogical challenges, particularly in domains requiring hands-on competencies and practical problem-solving skills. The post-COVID era has witnessed a dramatic transformation in educational delivery methods, coinciding with the rapid emergence of AI tools such as ChatGPT. These developments have raised fundamental questions about the evolving role of AI and how engineering education should adapt to this new reality while maintaining educational quality and professional standards (Li *et al.*, 2024; Stöhr *et al.*, 2024).

Recent studies indicate that while AI technologies offer innovative solutions for personalized learning and educational support, they challenge traditional academic practices and assessment methods, particularly in technical disciplines where hands-on skills and core competencies are crucial (Groothuijsen *et al.*, 2024; Mustapha *et al.*, 2024). This duality underscores the urgency of identifying strategies that harness AI's potential while safeguarding essential learning outcomes. A pressing concern emerging from recent research is the decline in student attendance and engagement in face-to-face classes, partly due to the increased accessibility of AI tools and partly to post-COVID behavioral shifts (Bozkurt, 2024; Gouveia *et al.*, 2023). Equally troubling is the improper use of AI in assessment tasks, which can supplant human thinking and impede the development of essential skills. These trends are particularly concerning in engineering education, where physical presence and hands-on experience are often crucial for developing practical skills and professional competencies (Pham *et al.*, 2023b).

The complexity of this issue is underscored by research indicating that while a significant number of engineering students perceive AI tools as beneficial for learning when used appropriately, faculty members express substantial concerns about impaired collaborative learning and the potential erosion of practical skill development (Groothuijsen *et al.*, 2024). This divergence underscores the need for a pedagogical framework that reconciles student enthusiasm for AI-enhanced learning with educators' concerns about attendance, collaborative engagement and hands-on skill development, ensuring that AI integration fosters both innovation and essential professional competencies (Strzelecki and ElArabawy, 2024). The post-COVID digital transformation has accelerated these challenges, creating varying levels of digital readiness across institutions and disciplines (Abbasnejad *et al.*, 2024; Taghizadeh *et al.*, 2024). Research indicates the necessity of training and resources to integrate AI tools effectively (Caccavale *et al.*, 2024); however, engineering disciplines show different readiness approaches to AI integration (Pham *et al.*, 2023b). Such disparities highlight the need for context-specific strategies that address both institutional gaps and discipline-specific requirements.

The complexities surrounding AI integration in technical and engineering education extend beyond technical considerations, highlighting systemic and pedagogical challenges that demand immediate attention. As institutions grapple with this evolving landscape, several critical challenges have emerged:

- adapting teaching and assessment methods while maintaining technical competencies;
- addressing disparities in digital readiness across institutions and disciplines;
- navigating cultural and contextual factors in AI implementation; and
- supporting faculties in developing effective AI-enhanced teaching methodologies.

While existing research has examined various aspects of AI integration in higher education (Marengo *et al.*, 2024), significant gaps remain in understanding how different engineering and technical disciplines can effectively incorporate AI tools while maintaining educational quality. Current literature largely focuses on either broad institutional policy (Camacho-Zuñiga, 2024; Camacho-Zuñiga *et al.*, 2024) or specific technical applications (He *et al.*, 2024), with limited attention to how disciplinary characteristics and cultural contexts influence implementation success. Furthermore, while studies have investigated individual aspects of AI implementation (Bravo and Cruz-Bohorquez, 2024; Knoth *et al.*, 2024), there is limited research synthesizing these findings into cohesive strategies that account for the complex interplay between technical, cultural and institutional factors. This gap calls for an integrated approach that synthesizes theoretical, practical and contextual insights.

This study seeks to address these gaps by answering three research questions:

RQ1. How are engineering schools adapting their teaching and assessment practices to integrate AI tools while maintaining core competencies, and what role do institutional digital readiness and infrastructure play in this adaptation?

RQ2. What patterns emerge in the implementation of AI integration across different in technical and engineering disciplines, and how do these patterns reflect institutional and cultural contexts?

RQ3. How do educational practices evolve in response to AI integration, and what dynamics emerge between traditional teaching methods and AI-enhanced approaches?

To address these questions, we use a dual-methodological approach that integrates a systematic literature review (SLR) with ethnographic observations across various technical and engineering higher education courses. This approach enables us to integrate theoretical insights with practical implementation experiences, offering a comprehensive understanding of the challenges and opportunities associated with AI integration (Peuker, 2024). Although the systematic review component can yield extensive standalone insights, our principal objective is to synthesize these findings with ethnographic observations to construct a practical, multilevel framework for AI integration.

To this end, this study makes several significant contributions to AI integration in higher education. Firstly, we develop a comprehensive multilevel framework that bridges institutional strategy with practical implementation, addressing the complex interplay between macro-level institutional policies, meso-level departmental approaches and microlevel classroom practices. Next, through detailed ethnographic observations across multiple Australian universities, we provide empirical evidence of successful adaptation strategies, documenting real-world implementations and their outcomes. Finally, we establish a theoretical foundation for understanding how disciplinary and cultural factors influence AI implementation success, explaining why certain approaches succeed or fail in different educational contexts.

The remainder of this paper is organized as follows: Section 2 presents our dual methodology; SLR and ethnography. Section 3 presents the findings from both methodologies, followed by a discussion of their integration in Section 4. Section 5 provides a theory-driven analysis of the findings, which forms the basis for the development of a multilevel framework for AI integration in higher education. Section 6 discusses theoretical and practical implications, limitations and future directions. Finally, Section 7 concludes the paper by summarizing key findings, discussing their implications and offering recommendations for future research and practice.

2. Methodology

This study uses a dual methodological approach that combines SLR with ethnographic observations drawn from first-hand teaching experiences across different technical and engineering courses at three Australian universities. This methodological integration leverages what Li *et al.* (2024) term a "theoretical-practical synthesis in educational technology research," enabling a comprehensive understanding of current research trajectories while offering contextual insights into practical implementation challenges and opportunities. SLR is a method for summarizing and presenting comprehensive overviews of both current and historical knowledge, drawn from an established body of literature (Aromataris and Pearson, 2014). It provides a rigorous and transparent approach to synthesizing scientific evidence in response to a specific research question. By aiming to include all relevant published studies and appraising their quality and findings, SLRs ensure both comprehensiveness and reproducibility (Lame, 2019). In this study, the SLR establishes a strong theoretical and empirical foundation by identifying the reported benefits, challenges and best practices of applying AI in education.

Ethnography, defined as "the study of social interactions, behaviors and perceptions that occur within groups, teams, organisations and communities" (Reeves *et al.*, 2008, p. 337), complements the SLR by providing in-depth, contextual insights. Ethnographic research, despite its considerable time investment, offers researchers direct access to data that is often difficult to obtain through alternative methods, allowing for a deeper understanding of real-world practices and behaviors (Murchison, 2010). In this study, ethnographic observations illuminate how AI applications in education are experienced in practice – highlighting adaptations, nuanced interactions and emergent innovations not yet widely reflected in the published literature.

2.1 Systematic literature review

2.1.1 Data collection. The SLR review, conducted using the Scopus database, focused exclusively on publications from 2023 to November 2024 to capture the transformative period marked by the increased adoption and integration of AI in education. This period has seen significant growth in AI adoption across higher education institutions, particularly following the release of ChatGPT in November 2022. Several studies, including those by Falebita and Kok (2024), Helmiatin *et al.* (2024) and Baidoo-Anu and Ansah (2023), provide empirical evidence of this significant rise in AI adoption during the 2023–2024 period, highlighting its integration into teaching, learning and administrative processes across universities.

Furthermore, a comprehensive search was conducted using systematically constructed search strings, incorporating key terms such as “Higher Education” AND (“Artificial Intelligence” OR “AI” OR “ChatGPT” OR “Claude”) AND (“Engineering” OR “Engineering Education” OR “Technical Education”) AND (“Learning” OR “Teaching”), to capture a broad yet relevant spectrum of literature across technical and engineering educational domains. This search initially yielded 534 potential papers, which were identified through the Scopus database. Through systematic application of the following inclusion and exclusion criteria – including peer-reviewed status, tertiary education focus and direct relevance to AI integration – the selection was refined to 85 papers that formed the core analysis base. Figure 1 illustrates the refinement steps of the SLR in accordance with the PRISMA guidelines (Moher *et al.*, 2015). Figure 2 presents the distribution of preliminary

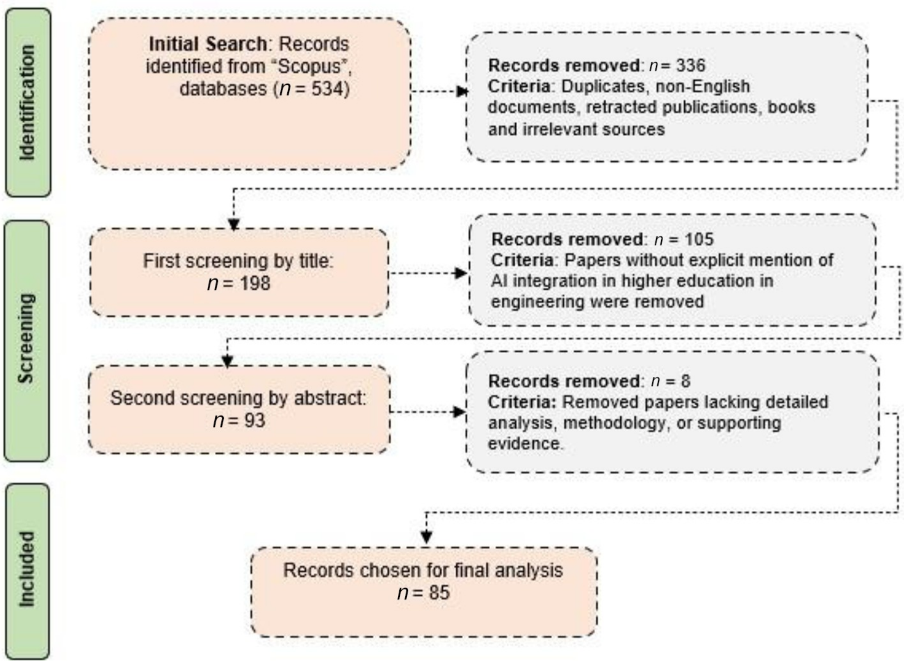

Figure 1. SLR Refinement process following PRISMA guideline
Source: Authors’ own work; adapted from Moher *et al.* (2015)

and refined search results, revealing that the majority of publications in this context are conference proceedings and journal articles, followed by book chapters and books.

2.1.2 Inclusion/exclusion criteria. The inclusion criteria emphasized peer-reviewed articles that addressed AI integration in higher education, particularly in in technical and engineering disciplines. Exclusion criteria eliminated non-peer-reviewed materials, irrelevant educational contexts and studies lacking empirical evidence. This meticulous selection ensures that conducted analysis captures the most relevant and credible insights.

Inclusion Criteria:

- publications from 2023 to November 2024;
- peer-reviewed journal articles and conference papers;
- English language publications;
- studies explicitly addressing AI integration in higher education;
- focus on technical/engineering disciplines; and
- papers with empirical evidence or substantial theoretical analysis.

Exclusion Criteria:

- non-peer-reviewed publications and grey literature;
- books and book chapters;
- retracted publications;
- duplicated records;
- papers without a specific focus on educational implementation;
- studies focused solely on technical aspects without educational context;
- publications addressing only pre-tertiary education;

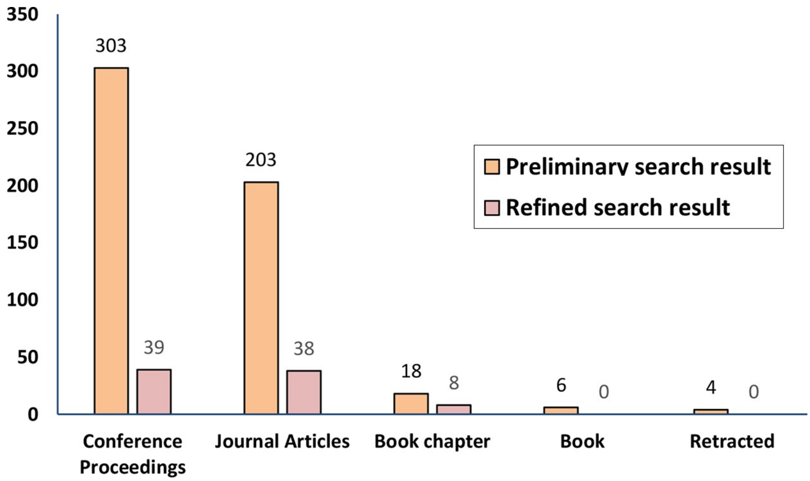

Figure 2. Preliminary and refined search result types and distributions
Source: Authors' own work

- opinion pieces and commentaries without supporting evidence;
- white papers and industry reports; and
- works lacking a clear methodology or research framework.

2.1.3 Data analysis. Our SLR incorporated bibliometric analysis as a key analytical component. Through systematic application of inclusion and exclusion criteria – including peer-reviewed status, tertiary education focus and direct relevance to AI integration – the selection was refined to 85 papers that formed the core analysis base. The analytical process extended beyond traditional narrative review by applying bibliometric analysis using VOSviewer software, enabling the identification of key research clusters and thematic relationships. This approach, following methodological principles established by Bozkurt (2024) and Li *et al.* (2024), revealed four distinct research clusters representing different aspects of AI integration in engineering education. The bibliometric analysis particularly highlighted the interconnections between technical implementation, pedagogical approaches and institutional responses, providing a robust framework for understanding the current research landscape.

2.1.4 Reliability and validity. To ensure reliability and validity, all papers were independently reviewed by the first two researchers using a standardized evaluation protocol. Any discrepancies in the assessment were resolved through discussion until a consensus was reached. The validity of the analysis was further strengthened through triangulation, which involved the use of multiple data sources and methods. Specifically, in addition to the SLR, ethnographic observations were conducted across various higher education courses in technical and engineering disciplines. This combination of data sources, along with diverse participants in the ethnographic research, provided a comprehensive perspective and enhanced the robustness of our findings. Triangulation in this manner allowed us to cross-validate results and ensure the reliability of the conclusions drawn from both the literature review and the ethnographic data.

2.2 Ethnography

The second methodological component comprises ethnographic observations drawn from our direct teaching experiences across six technical and engineering courses in construction engineering and management, mechanical engineering and electrical engineering at three Australian universities during 2023–2024. This period coincided with the rapid adoption of AI tools in higher education, providing a unique opportunity to observe and analyze the transformation of teaching and learning practices in real time. The ethnographic approach focused on first-hand experiences in course delivery, assessment design and student engagement within the context of increasing AI integration. Ethnographic approaches are especially valuable when seeking to understand “what really happens” in organizational settings, making it ideal for examining how AI tools are actually being integrated into teaching practice rather than just how they are reported to be used (Oswald and Dainty, 2020).

2.2.1 Data collection and analysis. The ethnographic component of this study is grounded in intensive participant observation across six distinct engineering and technical courses. Unlike typical single-site ethnographic studies in educational research, this multi-sited approach – spanning three universities and multiple disciplines – facilitates both depth and breadth of insight. By engaging directly in course design, delivery and assessment, we were able to observe and participate in the evolving pedagogical dynamics shaped by AI integration. Systematic data collection methods included detailed field notes, reflective teaching journals and ongoing documentation of course implementation strategies, allowing for consistent comparison across contexts. This form of embedded observation, as emphasized by Oswald and Dainty (2020), enhances the validity of ethnographic findings through cross-contextual pattern recognition and comparative analysis.

Our participant role enabled close tracking of real-time shifts in classroom interaction, assessment strategies and student engagement. This approach aligns with what Strzelecki and ElArabawy (Strzelecki and ElArabawy, 2024) describe as "contextual implementation analysis," providing granular insights into how institutional strategies and disciplinary cultures influence adoption of AI. Through this lens, we identified three recurring models of AI integration across the observed settings:

(1) AI-Inclusive assessment design – where AI tools are embedded as part of assessment tasks to enhance learning authenticity and technological literacy.

(2) Case study-based resistance strategy – where educators restrict AI use and instead use rich case-based tasks to preserve traditional competencies.

(3) Hybrid examination approaches – combining AI-regulated coursework with proctored examinations to balance innovation and integrity.

The ethnographic data were subjected to a rigorous thematic analysis, following Braun and Clarke's (2006) six-phase framework. The process began with familiarization through repeated reading of observational accounts and reflective narratives, enabling immersion in the contextual nuances of each case. Initial open coding was conducted inductively, allowing codes to emerge organically from the data without imposing preexisting theoretical constructs. These codes were then refined and clustered into axial categories representing emergent patterns in AI integration across teaching practices, assessment design and student engagement. Next, themes were developed iteratively through constant comparison, allowing for the identification of both intra-institutional particularities and cross-institutional consistencies. Particular attention was paid to identifying tensions between innovation and pedagogical integrity, as well as variations in disciplinary responses to AI integration. Memos and analytical notes supported the process of theory-building by capturing reflections on meaning, contradictions and contextual influences throughout the analysis. The analysis was further validated through triangulation across the multi-sited data corpus, which will be discussed in the following section, enabling robust pattern recognition and enhancing interpretive credibility. This analytic strategy ensured that the findings were not only grounded in the empirical realities of teaching practice but also capable of informing a scalable and context-sensitive implementation framework for AI in higher education.

2.2.2 Reliability and validity. The reliability of the ethnographic approach was ensured through regular cross-checking of observations within the research team, adherence to consistent documentation protocols and the intentional search for disconfirming evidence to challenge emerging patterns. Validity was enhanced by triangulating findings across a multi-sited data corpus – enabling robust pattern recognition across diverse teaching contexts and disciplines. Furthermore, member checking with faculty colleagues, who were not directly involved in the research, provided external validation of the interpretations, ensuring the credibility of the findings.

3. Findings from systematic literature review and ethnographic research methods

This section is structured into two parts. The first part presents and analyzes the findings from the SLR from multiple perspectives. The second part examines ethnographic data through various analytical lenses to identify the patterns and themes that emerged from the field research.

3.1 Systematic literature review findings

Drawing on secondary data derived from the SLR, this section provides a comprehensive, multi-perspective analysis of AI integration in technical and engineering education. The results are presented under two complementary lenses – bibliometric and thematic – and are examined in the subsequent subsections.

3.1.1 Bibliometric analysis. 3.1.1.1 Bibliometric metrics overview. The bibliometric analysis conducted on 85 papers revealed significant patterns in AI integration research through term frequency and relevance measures. Table 1 presents the most significant terms and their bibliometric indicators, showing that "ChatGPT" emerged as the most frequently occurring term (74 occurrences, relevance score 1.2861), followed by "higher education" (53 occurrences, 0.73) and "artificial intelligence" (38 occurrences, 0.5219). Notably, technical terms like "LLM" showed high relevance despite lower occurrences (12 occurrences, 4.737), indicating their significant impact in the discourse.

The highest relevance scores were observed in technical terminology, with "large language model" (3.7942) and "LLM" (4.737) leading, followed by institutional terms like "higher education institution" (1.2778) and educational practice terms such as "engineering

Table 1. VOSviewer-derived key terms and relevance scores in ai education literature

ID	Term	Occurrences	Relevance score
1	AI tool	22	0.4493
2	Artificial intelligence	38	0.5219
3	Assessment	19	0.6795
4	Benefit	17	0.8807
5	Challenge	29	0.6567
6	Chatbot	25	0.6264
7	ChatGPT	74	1.2861
8	Concern	22	0.6836
9	Course	21	0.8823
10	Development	26	0.404
11	Educator	22	0.4625
12	Engineering	29	0.8817
13	Engineering education	16	1.0579
14	Generative AI	19	0.5786
15	Higher education	53	0.73
16	Higher education institution	10	1.2778
17	Impact	20	0.6407
18	Implication	17	0.5034
19	Integration	15	0.4926
20	Large language model	16	3.7942
21	Learning	31	0.4513
22	Limitation	15	1.2291
23	LLM	12	4.737
24	Opportunity	17	0.7784
25	Perception	19	0.8085
26	Teaching	20	0.9415
27	University	24	0.5643

Source(s): Authors' own work

education" (1.0579). Implementation-related terms showed moderate but consistent relevance, with "teaching" scoring 0.9415 across 20 occurrences.

3.1.1.2 Network structure and clustering. The VOSviewer network visualization of keyword co-occurrence (Figure 3) reveals a complex interconnected structure organized around four distinct clusters. The four identified clusters – institutional impact, implementation dynamics, technical foundations and educational practice – will be examined in detail in the next section. Interestingly, ChatGPT emerges as the central node with the highest betweenness and degree centrality scores, indicating its dominant position within the academic discourse on AI in engineering and technical education. This centrality suggests that ChatGPT has not only captured substantial research interest but has also become the most studied and referenced AI tool in this context. Its prominence reflects its role as a conceptual anchor point, frequently cited by scholars when discussing broader themes of AI integration in engineering and technical education. Moreover, its central position underscores its function as a unifying element across diverse scholarly conversations and educational applications.

3.1.1.3 Cluster analysis. Institutional impact cluster (Red) primary nodes include "higher education" (53 occurrences, 0.73), "integration" (15 occurrences, 0.4926) and "impact" (20 occurrences, 0.6407). This cluster shows dense internal connections and strong links to implementation nodes, reflecting the institutional dimensions of AI integration. The

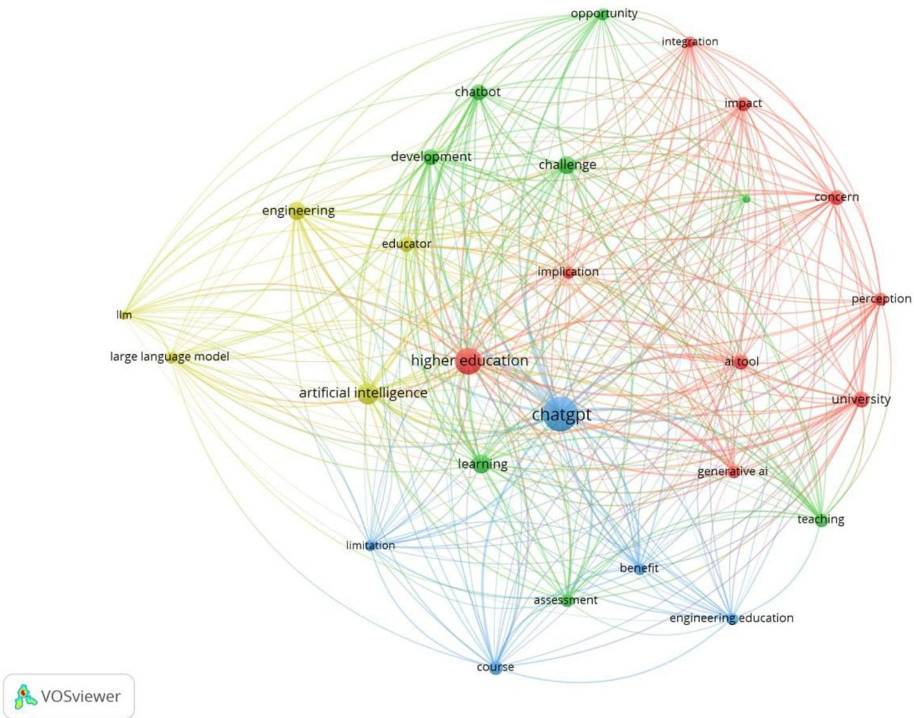

Figure 3. VOSviewer network visualization of keyword co-occurrence
Source: Authors' own work

high occurrence of "higher education institution" (10 occurrences, 1.2778) despite lower frequency indicates its structural importance in the discourse.

Implementation dynamics cluster (Green) characterized by terms like "opportunity" (17 occurrences, 0.7784), "development" (26 occurrences, 0.404) and "chatbot" (25 occurrences, 0.6264). The educator node (22 occurrences, 0.4625) within this cluster highlights the critical role of faculty in implementation. Strong connections to both technical and educational clusters suggest their bridging function in practical applications.

Technical foundations cluster (Yellow) dominated by technical terminology including "engineering" (29 occurrences, 0.8817), "LLM" (12 occurrences, 4.737) and "artificial intelligence" (38 occurrences, 0.5219). The high relevance scores of technical terms, particularly "large language model" (3.7942), indicate their fundamental importance despite lower occurrence frequencies.

Educational practice cluster (Blue) features terms like "course" (21 occurrences, 0.8823), "assessment" (19 occurrences, 0.6795) and "engineering education" (16 occurrences, 1.0579). This cluster shows balanced connections to both benefits (17 occurrences, 0.8807) and limitations (15 occurrences, 1.2291), indicating comprehensive consideration of AI's educational impact.

The interconnections between clusters reveal groupings of research themes that inform this study's subsequent analysis of the literature. These relationships suggest three primary areas of focus: institutional adaptation strategies, implementation approaches and educational practice evolution, which were explored in detail through the conducted SLR findings.

3.1.2 Thematic analysis. 3.1.2.1 Institutional impact and policy developments. *Pedagogical Adaptation and Course Redesign*: The transformation of engineering pedagogy in response to AI integration reveals complex patterns of both innovation and resistance. For example, Groothuijsen *et al.* (2024) conducted a detailed study at the Eindhoven University of Technology, documenting how programming education is being adapted to incorporate AI tools. While their research demonstrates positive outcomes in using AI for error checking and debugging, it also reveals critical tensions between innovation and traditional skill development. Notably, while students showed improved debugging capabilities with AI assistance, questions emerged about their ability to develop fundamental programming intuition.

Digital readiness and infrastructure: The effective integration of AI in higher education depends not only on the availability of digital tools but also on an institution's overall readiness – encompassing technological capacity, IT support systems, staff digital literacy and leadership commitment to innovation. The level of digital infrastructure directly shapes the feasibility, scope and sustainability of AI-enhanced teaching and learning practices. Camacho-Zuñiga (2024) highlights how institutions with different levels of resources have adapted their AI integration strategies. Their research reveals that while some programs could rapidly implement comprehensive AI solutions, others needed to develop more resource-efficient approaches based on their existing digital infrastructure. Pham *et al.* (2023b) identified a complex relationship between digital infrastructure and implementation success, noting that while robust digital platforms facilitate integration, they alone do not guarantee effective implementation. Their research revealed that universities with established digital learning platforms experienced "infrastructure-implementation gaps" – where technical capability outpaced pedagogical readiness.

This finding is further complicated by Caccavale *et al.* (2024) research, which identified significant variations in faculty digital readiness across disciplines, suggesting a critical misalignment between institutional technological capabilities and faculty preparedness. This misalignment manifests in what we might term “digital readiness stratification,” where different departments within the same institution show markedly different capabilities and attitudes toward AI integration.

Ethical Considerations and Academic Integrity: As AI tools become integrated into engineering education, concerns about responsible use and academic honesty are increasingly important. Schools must develop updated frameworks to address issues like authorship, originality and ethical AI use to preserve academic standards. He *et al.* (2024) analyze how institutions create guidelines for appropriate AI tool usage while ensuring students develop genuine engineering competencies. Their research reveals that schools are implementing policies that encourage responsible AI use while maintaining academic standards.

Cultural Dimensions and Institutional Response: Beyond technical deployment, the integration of AI in engineering education is deeply shaped by institutional norms and cultural values. The cultural impact of AI adoption in education manifests through multiple interconnected layers, each contributing to how AI tools are perceived, implemented and utilized within different educational contexts. A detailed examination of recent literature reveals several critical cultural dimensions:

- *Gender-Based Cultural Dynamics*: A particularly noteworthy cultural aspect emerges in the gender-based differences in AI tool adoption. The research by Stöhr *et al.* (2024) found that female students consistently expressed more reservations about AI’s role in learning and assessment compared to their male counterparts. This gender disparity reflects deeper cultural patterns in technology adoption and highlights the need for more inclusive approaches to AI integration. The study reveals that female students from humanities and medicine expressed significantly more concerns about AI’s impact on learning outcomes, suggesting that cultural factors intersect with gender and disciplinary backgrounds.
- *Institutional Cultural Variations*: The organizational culture within different institutions significantly influences AI adoption patterns. Caccavale *et al.* (2024) studied the Technical University of Denmark’s implementation of AI tools, revealing how institutional culture shapes both faculty and student responses to AI integration. They found that institutions with a strong tradition of innovation and technological advancement were more likely to embrace AI tools, while those with more traditional academic cultures showed greater resistance. This institutional cultural divide manifests in varying levels of support for AI integration, with some institutions actively promoting AI literacy while others maintain more cautious approaches.
- *Regional and National Cultural Influences*: Cross-cultural studies provide particularly rich insights into how national and regional cultures affect AI implementation. Strzelecki and ElArabawy (2024) comparative analysis between Polish and Egyptian universities revealed distinct cultural patterns in AI adoption. They found that cultural attitudes toward technology, educational traditions and societal norms significantly influenced how students and faculty approached AI tools. In some cultures, there was a stronger emphasis on collaborative learning using AI, while others focused more on individual achievement and viewed AI primarily as a personal learning tool.

- *Professional Cultural Context*: The profession's cultural norms and expectations also shape AI integration in education. Groothuijsen *et al.* (2024) observed that in programming education, there is a cultural tension between traditional coding practices and AI-assisted development. This reflects broader professional cultural debates about the role of automation and AI in engineering practice. The study found that students' attitudes toward AI tools were often influenced by their perception of professional engineering culture and future workplace expectations.
- *Global* applicability and regional variations: Research on AI integration in education highlights significant regional and cultural differences that impact implementation, adoption and pedagogical approaches. Strzelecki and ElArabawy's (2024) study comparing Polish and Egyptian universities showed that while performance expectancy predicted the intention to use ChatGPT in both countries, gender effects were stronger in Egypt, underscoring the influence of cultural context on technology adoption. Additionally, Wang and Wu (2023) examined critical thinking education in East Asia, revealing that Western tools and definitions often clash with Confucian values like "introspection," which can both facilitate and hinder critical thinking. This challenge parallels AI education, where frameworks prioritizing student autonomy may conflict with East Asian traditions valuing collective learning and authority. Moreover, resource disparities between developing and developed nations create distinct challenges for AI adoption. Camacho-Zuñiga (2024) argues that institutions in developing countries should prioritize human resources, followed by the integration of Generative AI in teaching, before investing in infrastructure for equitable access. Su *et al.* (2022) found that AI education strategies vary across the Asia-Pacific region. For example, China's approach leveraged its strength in large datasets and pioneering AI companies to pursue AI education with diverse technologies, including biotechnology, drone technology and immersive technology, whereas Japan emphasized data literacy and values-based AI education, with a significant focus on AI ethics and societal impacts. These regional differences illustrate how cultural values, technological infrastructure and local resources shape AI integration, emphasizing the necessity of adaptable frameworks that consider both global trends and specific regional needs.
- *Intercultural Communication and Collaboration*: The increasingly globalized landscape of higher education introduces complex intercultural dynamics that shape how AI tools are adopted and experienced. Li *et al.* (2024) discussed AI applications in language and technical communication can serve as both enablers and disruptors – facilitating cross-cultural understanding while simultaneously exposing differences in communication norms, pedagogical expectations and learning preferences across diverse educational settings. These dynamics underscore the need for culturally responsive AI integration strategies that acknowledge local educational values while enabling global collaboration.
- *Change Management Culture*: The culture of change management within institutions significantly affects AI integration success. Pham *et al.* (2023b) highlight how institutions with more adaptive and flexible organizational cultures were better positioned to implement AI tools effectively during the post-COVID digital transformation. They found that institutions with a culture of continuous improvement and innovation were more successful in integrating AI tools into their curriculum compared to those with more rigid organizational structures.

- *Cultural Resistance and Adaptation*: Research by Khatoon *et al.* (2024) reveals patterns of cultural resistance to AI integration, particularly among faculty members with long-standing traditional teaching methods. Their study identifies how cultural beliefs about the role of educators and the nature of learning influence attitudes toward AI adoption. This resistance often stems from deeply embedded cultural values about education and the teacher–student relationship.

3.1.2.2 Implementation dynamics and educational practice. The integration of AI tools in higher education encompasses several key operational areas, from how assessments are redesigned to how practical skills are developed and validated in the classroom which will be discussed below.

Assessment Strategy Evolution: The transformation of assessment practices reveals complex patterns that go beyond simple technological adaptation. Wilson and Nishomoto (2023) describe a shift from traditional code-correctness evaluation to assessing students' understanding and effort during in-person grading sessions. Their research demonstrates that students who actively participated in these modified assessment approaches performed significantly better on midterm exams, suggesting that new assessment methods can effectively validate learning while acknowledging AI tool usage. Research by Knoth *et al.* (2024) reveals the systematic integration of AI educational content, emphasizing that students need to develop skills in prompt and critical evaluation of AI-generated content. Their research shows that institutions are developing frameworks to teach students how to use AI tools effectively and ethically as part of their professional toolkit.

Professional Skills Development and Industry Alignment: The evolution of professional skill development reveals a sophisticated interplay between technological enhancement and core competency maintenance. Caccavale *et al.* (2024) research at the Technical University of Denmark identifies what we might term "competency-augmentation patterns." Their findings suggest that successful integration requires a delicate balance between leveraging AI capabilities and ensuring students develop fundamental professional judgment.

This balance is particularly evident in project-based learning environments, where institutions must navigate what we call the "tool-skill development continuum." The research shows that while AI tools can enhance problem-solving capabilities, they also risk creating what we termed "competency illusions" – situations where AI assistance masks gaps in fundamental understanding.

Laboratory and Practical Skills Integration: The maintenance of hands-on in technical and engineering skills remains crucial. Taghizadeh *et al.* (2013) and Pham *et al.* (2023a) document how engineering schools are redesigning laboratory-related assessments to combine AI-enhanced learning with practical skills development. Their studies demonstrate how institutions are creating hybrid learning environments that leverage AI for theoretical understanding while maintaining emphasis on physical laboratory work. Their research reveals that successful integration requires careful attention to what we term "experiential authenticity" – ensuring that AI enhancement does not diminish the crucial hands-on experience necessary for engineering competency.

Student Engagement Patterns: Research by Mohandas and Mentzer (2024) shows how student engagement with AI tools varies across disciplines and institutional contexts. Their findings indicate that students in more technically oriented programs tend to adopt AI tools more readily, while those in disciplines requiring more hands-on skills show more varied adoption patterns.

3.1.2.3 Quality assurance and implementation support. Institutions are increasingly developing mechanisms to verify student competencies within AI-enhanced learning environments. This includes rethinking assessment strategies, embedding AI-detection tools and enhancing formative evaluation processes to ensure the authenticity of student outcomes. In parallel, institutions are also establishing support systems – such as staff training initiatives, ethical implementation policies and adaptive learning frameworks – to uphold academic standards amid rapid technological change. These efforts form part of a broader institutional response, which will be further examined in the following sections on faculty development and support and monitoring and evaluation. *Mechanisms*. *Faculty Development and Support*: The transformation of faculty support systems reveals systemic challenges in institutional adaptation. Fuhrmann and Niemetz (2023) research highlights *that* faculty require substantial support in redesigning courses, pointing to a more fundamental challenge: the development of "AI-aware pedagogical frameworks" that maintain educational standards while embracing technological innovation. The findings reveal a pattern of "adaptive professional development" – where faculty support systems must continuously evolve to address emerging challenges. This pattern is particularly evident in the struggle of institutions to develop "integrated competency frameworks" that effectively combine traditional teaching expertise with modern technological demands.

Monitoring and Evaluation Mechanisms: An effective monitoring system is essential to track the effectiveness of AI integration. The multi-institutional study by Nikolic *et al.* (2023) identifies "evaluation evolution patterns" – ways in which assessment methods adapt to maintain academic rigor in an AI-enhanced environment. The research highlights the emergence of "dynamic verification frameworks"- approaches that acknowledge AI's presence while ensuring genuine understanding. This evolution in monitoring systems suggests a broader pattern of "adaptive quality assurance" – where institutions develop increasingly sophisticated methods to verify learning outcomes in AI-enhanced environments. *S*uccessful monitoring systems are shown to balance "verification flexibility" with "competency consistency" – maintaining rigorous standards while accommodating new modes of learning and demonstration of understanding.

These developments in quality assurance and faculty support reveal a broader pattern of institutional transformation, indicating that successful AI integration depends on "systemic adaptability"- the capacity for institutions to evolve their support structures while maintaining educational quality and professional standards.

3.2 Ethnographic findings

This section summarizes ethnographic findings, examining how participants' behaviors, interactions and cultural contexts intersect from different perspectives and investigating diverse strategies for integrating AI into higher education.

In terms of cultural context, the performed analysis reveals previously undocumented patterns in how cultural factors influence AI integration. Systematic variations in how diverse cultural contexts adapt AI tools, suggest the existence of "cultural technology adaptation matrices". This extends beyond the simple cultural differences noted by Strzelecki and ElArabawy (2024) to include complex patterns of adaptation and modification. The observations suggest that institutions undergo "cultural evolution cycles" as they integrate AI tools, developing new organizational cultures that blend traditional academic values with technological innovation.

Ethnographic observations conducted across universities revealed diverse strategies for integrating AI into higher education. These findings highlight evolving approaches to assessment design, faculty adaptations and student engagement shaped by institutional philosophies and practical challenges. Three core themes emerged from this study:

assessment models that balance AI with traditional competencies, implementation challenges and adaptations and individual innovation versus systematic implementation.

3.2.1 Ethnographic observations in higher education: assessment design. Throughout the conducted observational study across the three universities during 2023–2024, an interesting evolution was witnessed in how schools approached the AI revolution in education, particularly for assessments. The ethnographic investigation revealed three distinct approaches to managing AI integration, each reflecting different institutional philosophies and practical constraints.

AI-inclusive assessment design: In one university, the term "guided AI integration" was observed. one faculty members actively embraced AI tools as part of the learning process. Walking into a third-year engineering design class, students openly used ChatGPT and other AI tools while documenting their process. In one of the courses, students were required to maintain a "prompt diary" detailing their interactions with AI tools, including failed attempts and iterations. The assessment criteria explicitly included how well students could critically evaluate and refine AI-generated solutions. A civil engineering lecturer shared their experience:

> Initially, I was resistant to allowing AI tools, but then I realized we could transform this challenge into a learning opportunity. Now students don't just get answers; they learn to question and validate AI outputs.

This approach manifested in assignments where students would compare multiple AI-generated solutions, analyze discrepancies and justify their final design choices based on engineering principles.

Contextual insulation assessment strategy: This approach involves designing assessments that are deeply grounded in the specific learning environment and student experiences, thereby reducing opportunities for generic or AI-generated responses. Here, some faculty members developed highly localized, context-specific assessments that required deep integration of local knowledge and personal experience. In a construction engineering course where assignments were built around actual local infrastructure projects, specific geological and environmental conditions were incorporated into the region. One of the lecturers explained their rationale: "*We're not fighting against AI; we are simply making its generic responses less relevant.*" students in these courses needed to demonstrate understanding beyond what AI could provide, integrating their site visits, local building codes and specific institutional practices into their solutions. This approach was particularly evident in a geotechnical engineering unit where assessments incorporated recent local construction challenges and required students to reference specific site conditions they had observed during field trips. The questions were so deeply embedded in the local context that generic AI responses proved inadequate without substantial human interpretation and local knowledge.

Hybrid assessment design: The third pattern observed was a pragmatic hybrid approach. One engineering department particularly stood out in their implementation of this strategy. They maintained traditional closed-book examinations for testing fundamental concepts while incorporating AI-assisted components for practical applications. A fascinating example was in an engineering course where students faced a three-part assessment: an in-person written examination testing theoretical understanding, an AI-assisted design project and an ongoing portfolio assessment capturing both traditional and AI-enhanced work. During the observations, students appeared more engaged with this mixed approach, as it allowed them to demonstrate both their fundamental knowledge and their ability to leverage modern tools effectively. A lecturer shared:

> This approach lets us maintain rigorous testing of core concepts while acknowledging the reality of AI in professional practice. It is about finding the right balance.

3.2.2 Implementation challenges and adaptations. Throughout observations, it was noticed that each approach required significant adaptation over time. Faculty members regularly met to share experiences and refine their strategies. Several iterations of assessment designs were witnessed as educators learned from student responses and engagement patterns.

Student Responses: student reactions varied across these different approaches. In the AI-inclusive environment, students initially showed uncertainty about how to document their AI use but gradually developed sophisticated strategies for tool integration. Under the contextual insulation approach, some students initially expressed frustration at not being able to rely on AI tools but later reported deeper engagement with the material. The hybrid approach received positive student feedback, though some struggled with transitioning between AI-assisted and traditional assessment modes.

Faculty Development: A crucial observation was the need for ongoing faculty development. Each approach required distinct types of support and training. Regular workshops were organized where faculty members shared experiences, discussed challenges and refined their approaches based on collective learning.

Moving Forward: By the end of the observation period, it became clear that these approaches were not static but rather evolving frameworks that continued to be refined based on experience and feedback. Each institution was developing its own unique variation of these basic approaches, adapted to their specific context and needs.

3.2.3 Individual innovation versus systematic implementation. The conducted study identified a critical gap in current AI integration approaches: the reliance on individual unit coordinators and course lecturers for implementation strategies. While ethnographic observations demonstrate impressive innovation at the individual level, with educators developing sophisticated adaptation strategies, this *ad hoc* approach creates several challenges that the theoretical analysis helps illuminate.

Through the lens of Socio-Technical Systems theory, individual-led adaptation demonstrates admirable agility but often lacks the structural support necessary for sustainable implementation. As evidenced by Caccavale *et al.* (2024), this creates the term "implementation islands" – pockets of innovation that remain isolated within larger institutional contexts. This term refers to isolated, independent efforts or practices where individual unit coordinators innovate and implement changes without broader institutional coordination or integration.

The conducted ethnographic observations across different universities confirm this pattern, showing how successful strategies developed by individual educators often fail to scale or transfer effectively across departments.

The Cultural-Historical Activity theory framework helps explain why this individual-centric approach, while initially effective during rapid post-COVID adaptation, may not provide a sustainable long-term solution. Performed analysis reveals the term "structural-individual tension," where innovative individual practices struggle to integrate with broader institutional systems and policies. This tension manifests in several ways:

- inconsistent student experiences: different approaches across units create varying levels of AI integration, potentially disadvantaging some students while benefiting others;
- resource inefficiencies: individual educators independently developing similar solutions results in duplicated efforts and missed opportunities for resource sharing;

- quality variation: without systematic frameworks, the quality of AI integration varies significantly based on individual educator capability and motivation; and
- sustainability challenges: successful practices often remain tied to specific individuals, making them vulnerable to staff changes or departures.

4. Integration of systematic literature review and ethnographic findings

This section analyzes the synthesis of bibliometric, theoretical and ethnographic findings. Ethnographic observations across different courses provide a unique perspective for critically analyzing and extending the existing literature. The documented AI integration approach provides a nuanced understanding that complements the theoretical frameworks presented in current research. For instance, while Groothuijsen *et al.* (2024) document the broad patterns of AI adoption in programming education, the conducted ethnographic observations of students maintaining "prompt diaries" and engaging in critical reflection provide concrete examples of how theoretical principles manifest in practice.

The observation of "contextual insulation" strategies, where institutions develop highly localized, context-specific assessments, offers an important extension to current theoretical frameworks. While Nikolic *et al.* (2023) discuss assessment integrity challenges, the ethnographic findings reveal a novel approach not yet documented in the literature – the deliberate use of local context as an AI-resistance strategy. This observation suggests that current theoretical models need expansion to account for what we term "contextual defense mechanisms" in assessment design, whereby unique, place-based requirements and culturally embedded tasks function as safeguards against generic or AI-generated responses.

The observed hybrid examination approaches contribute to resolving what Stöhr *et al.* (2024) identify as tensions between traditional and AI-enhanced assessment methods. The ethnographic documentation of successful hybrid implementations provides practical evidence for how theoretical principles of socio-technical integration can be effectively operationalized.

The findings also reveal important contradictions in current research. For instance, while Caccavale *et al.* (2024) report significant faculty resistance to AI integration, the ethnographic observations suggest more nuanced patterns of adaptation, particularly in cases where faculties are provided with structured support systems. This contradiction suggests the need for more sophisticated theoretical models that can account for varying institutional contexts and support structures.

4.1 Emergence of new educational paradigms

The conducted comprehensive analysis reveals the following emerging educational paradigms not yet fully articulated in the literature:

- Reflexive technology integration: Unlike the straightforward adoption patterns described in earlier studies, a more sophisticated approach was observed where institutions continuously adapt their strategies based on immediate feedback and outcomes. This extends beyond the simple feedback loops described by Knoth *et al.* (2024) to include the term "multi-dimensional adaptation mechanisms."
- Contextual technology resilience: The ethnographic observations reveal how institutions develop "contextual technology resilience" – the ability to maintain educational integrity while embracing technological innovation. This goes beyond the resistance strategies documented in current literature to include proactive adaptation mechanisms.

- Hybrid competency development: The emergence of what we might call “hybrid competency frameworks” represents a new educational paradigm where traditional engineering skills are deliberately developed alongside AI literacy. This extends beyond the simple integration patterns described in current literature to include sophisticated competency development strategies.

4.2 Temporal evolution of implementation patterns

A unique pattern emerges by analyzing the temporal progression of AI integration approaches across the literature and the conducted ethnographic observations. Early studies from 2023 show reactive institutional responses focused primarily on preventing misuse (Dai *et al.*, 2023; Neumann *et al.*, 2023). However, by 2024, a significant shift is identified toward “proactive adaptation frameworks,” evidenced in studies like Pham *et al.* (2023b) and the performed ethnographic observations.

4.3 Dialectical tensions in implementation

The performed analysis reveals the following fundamental dialectical tensions not previously identified in the literature:

- The Authenticity-Innovation Paradox: While institutions strive to maintain authentic assessment and learning experiences, they simultaneously push for innovative AI integration. This creates the term “pedagogical cognitive dissonance,” where educators must reconcile seemingly contradictory goals. The ethnographic observation of “contextual insulation” represents one novel resolution to this tension, not previously documented in the literature.
- The Competency-Augmentation Dilemma: A sophisticated tension exists between developing core competencies and leveraging AI augmentation. This goes beyond the simple “cheating versus learning” dichotomy presented in earlier studies (Uhlig *et al.*, 2023) to “augmented competency development” – a new paradigm where traditional skills and AI literacy coevolve.
- The Scale-Customization Conflict: Institutions face competing pressures to scale AI integration while maintaining disciplinary and contextual appropriateness. This tension, which is evident in both ethnographic observations and study by Caccavale *et al.* (2024), suggests the need for the term “scalable contextualization frameworks.”

5. Framework development

The synthesis of ethnographic observations with existing literature reveals several critical insights that both extend and challenge current understanding. In terms of implementation dynamics, the observation of real-time faculty adaptation strategies provides deeper insight into what Pham *et al.* (2023b) describe as institutional transformation processes. The documented evolution of assessment practices reveals how theoretical principles are modified and adapted in response to practical challenges.

Regarding cultural aspects, the findings extend Strzelecki and ElArabawy’s (2024) work by demonstrating specifically how Australian institutional cultures shape AI integration approaches. The observed variations across different universities suggest that cultural factors operate at multiple levels – institutional, departmental and disciplinary. Similarly, the documentation of faculty members navigating AI integration while maintaining professional standards adds practical depth to Wilson and Nishomoto's (2023) theoretical framework, revealing new dimensions of professional identity formation in the AI era.

This research advances two significant concepts: "contextual insulation" and "guided AI integration." The AI-Inclusive Assessment Design approach aligns with and extends Groothuijsen *et al.*'s (2024) findings in programming education. The observation of the "prompt diary" concept demonstrates concrete implementation mechanisms for AI literacy integration, building upon Knoth *et al.*'s (2024) theoretical emphasis on documented AI use.

The Case Study-Based Resistance Strategy presents an interesting contrast to the current literature. While Nikolic *et al.* (2023) advocate for AI-resistant assessment techniques through technical constraints, the findings reveal how contextual insulation maintains academic rigor through localization. This challenges Savelka *et al.*'s (2023) suggestion that AI tools are becoming increasingly capable of handling complex, contextual problems, as the observations show how deeply embedded local knowledge creates natural barriers to AI use.

The Hybrid Examination approach observed in this study both validates and extends current research. While Wilson and Nishomoto's (2023) work establishes the foundation for assessment transformation, the findings provide specific implementation frameworks for combining different assessment components. Similarly, Pham *et al.*'s (2023b) theoretical framework is extended by demonstrating concrete examples of integrating traditional and AI-enhanced assessment methods in practice.

Hybrid Competency Development: The emergence of "hybrid competency frameworks" represents a new educational paradigm where traditional engineering skills are deliberately developed alongside AI literacy. This extends beyond the simple integration patterns described in current literature to include sophisticated competency development strategies.

5.1 Theory-driven analysis: foundation for multilevel framework development

The integration of AI in higher education requires analysis through multiple theoretical lenses to fully understand the transformative processes occurring at macro, meso and micro levels. The theoretical foundation draws from established frameworks while extending them to address the unique challenges of AI integration.

Individual and Adoption Level Theories: The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology framework provide foundational insights into individual-level adoption patterns, elucidating how perceptions of usefulness (performance expectancy) and ease of use (effort expectancy) drive behavioral intentions. Strzelecki and ElArabawy's (2024) research demonstrate how performance expectancy and effort expectancy influence behavioral intentions to use AI tools. Stöhr *et al.* (2024) large-scale study extends this understanding by revealing varying acceptance patterns across demographic groups, suggesting that traditional TAM frameworks must be expanded to capture the nuanced aspects of AI adoption in engineering education.

Organizational and Implementation Theories: The socio-technical systems theory illuminates the complex interplay between technical capabilities and social structures at the organizational level. Groothuijsen *et al.* (2024) and Pham *et al.* (2023b) demonstrate how technical infrastructure requirements and faculty adaptation patterns interact to create both opportunities and challenges. This theoretical perspective helps explain the term "implementation islands" – the phenomenon where successful practices often remain isolated within institutional contexts.

Cultural-Historical Activity Theory provides crucial insights into how historical and cultural contexts influence implementation strategies. Li *et al.*'s (2024) systematic review demonstrates significant regional variations in adoption patterns, while Stöhr *et al.* (2024) highlight how disciplinary cultures impact implementation approaches. CHAT helps explain the observed “contextual insulation” strategies, where institutions develop locally adapted responses to AI integration challenges.

Professional Identity and Practice Theory emerges as critical for understanding the term “competency-augmentation dilemma”. Wilson and Nishomoto (2023) demonstrate how engineering programs struggle to balance AI assistance with core skill development, while Khatoon *et al.* (2024) explore related ethical considerations. This theoretical framework helps explain the observed tensions between maintaining professional competencies and embracing AI capabilities. Professional Identity and Practice Theory emerges as critical for understanding the term “competency-augmentation dilemma”. Wilson and Nishomoto (2023) demonstrate how engineering programs struggle to balance AI assistance with core skill development, while Khatoon *et al.* (2024) explore related ethical considerations. This theoretical framework helps explain the observed tensions between maintaining professional competencies and embracing AI capabilities.

Adaptive and Dynamic Theories: Adaptive Structuration Theory explains the dynamic processes through which engineering programs adapt AI tools. Huesca *et al.* (2024) research on flipped learning strategies demonstrates how course redesign approaches evolve, while Fuhrmann and Niemetz (2023) document assessment transformation. This framework supports the concept of “structured flexibility frameworks” – approaches that balance standardization with adaptation.

Institutional Theory: Institutional Theory provides insights into organizational change and legitimacy. Caccavale *et al.* (2024) show how institutions adapt their support systems in response to changing needs, while Camacho-Zuñiga *et al.* (2024) demonstrate the importance of multilevel organizational attention. This theoretical perspective helps explain why certain implementation approaches gain legitimacy while others remain peripheral.

Complexity Theory: Complexity Theory helps understand the interactions between different implementation levels. Nikolic *et al.* (2023) multi-institutional study demonstrates how assessment practices evolve through complex interactions between institutional policies, departmental practices and individual innovations. This theoretical perspective supports understanding of how different implementation approaches emerge and evolve.

Theoretical Synthesis: The integration of these theoretical frameworks reveals complex interactions between macro-level institutional factors, meso-level programmatic elements and microlevel individual adaptations. He *et al.* (2024) and Bravo and Cruz-Bohorquez (2024); He *et al.* (2024) demonstrate how different theoretical perspectives complement each other in understanding implementation challenges. This synthesis suggests the need for the term “integrated implementation frameworks” that can capture the complex interplay of factors shaping AI integration in engineering education. Such frameworks must account for the multilevel interactions between institutional policies, departmental practices and individual adaptations, while recognizing the dynamic evolution of implementation practices across these levels. They need to acknowledge how cultural and contextual factors influence adaptation strategies, while maintaining a delicate balance between standardization for consistency and flexibility for local adaptation. This theoretical foundation provides crucial guidance for our framework development, supporting the identification of implementation patterns across different contexts and explaining the observed tensions and paradoxes in AI integration efforts. It offers a robust basis for understanding how adaptation strategies emerge and evolve, while informing practical recommendations for institutions navigating the complex landscape of AI integration in engineering education. The integration of multiple theoretical perspectives enables a more nuanced understanding of how different factors interact and influence implementation success, ultimately contributing to more effective and sustainable AI integration practices.

5.2 Multilevel framework integration

5.2.1 Macro-level analysis: institutional and systemic factors. At the macro level, the integration of AI in engineering education is shaped by broad institutional structures and systemic forces. The socio-technical systems theory helps explain how institutional policies and infrastructures interact with technological capabilities. Caccavale *et al.*'s (2024) highlighted how institutional readiness significantly impacts implementation success. This macro-level challenge is further complicated by what Stöhr *et al.* (2024) describe as varying levels of digital maturity across institutions and regions.

Cultural-Historical Activity Theory proves particularly valuable at this level, helping explain how broader societal and historical forces shape institutional responses. The post-COVID digital transformation has accelerated institutional adoption of AI technologies while simultaneously exposing systemic inequalities in technological infrastructure and readiness (Pham *et al.*, 2023a; Pham *et al.*, 2023b). These macro-level forces create what Camacho-Zuñiga *et al.* (2024) identify as "institutional tensions" between rapid technological advancement and traditional academic structures.

5.2.2 Meso-level analysis: disciplinary and departmental dynamics. The meso level reveals complex interactions between disciplinary characteristics and AI implementation approaches. Adaptive Structuration Theory helps explain how different engineering disciplines modify and adapt AI tools to their specific needs. Groothuijsen *et al.* (2024) demonstrate how programming education develops distinct adaptation patterns, while Bravo and Cruz-Bohorquez (2024) show how civil engineering programs integrate AI tools differently based on their unique disciplinary requirements.

Professional Identity Formation Theory becomes particularly relevant at this level, as departments struggle to maintain disciplinary integrity while embracing technological innovation. Wilson and Nishomoto's (2023) research shows how departments are reconceptualizing assessment practices to focus on understanding and effort rather than just technical correctness. This meso-level adaptation reflects what Knoth *et al.* (2024) describe as the emergence of new forms of disciplinary literacy that combine traditional engineering knowledge with AI competencies.

5.2.3 Microlevel analysis: individual and classroom dynamics. At the micro level, the TAM helps explain individual adoption patterns among students and faculty. Strzelecki and ElArabawy's (2024) research reveals how personal factors such as gender, prior experience and individual attitudes influence AI tool adoption. This individual-level variation is further complicated by what Sajawal and Kittur (2024) identify as differences in self-efficacy and perceived usefulness among different user groups.

The interaction between these levels creates complex dynamics that shape AI integration outcomes. For example, Huesca *et al.*'s (2024) study of flipped learning demonstrates how microlevel classroom practices are influenced by meso-level departmental policies and macro-level institutional support structures. Similarly, He *et al.*'s (2024) analysis shows how individual faculty members' ability to implement AI tools effectively depends on both departmental support systems and institutional resources.

5.2.4 Cross-level interactions and impacts. The interaction between these levels reveals several critical patterns. First, macro-level institutional policies and resources significantly influence meso-level departmental capabilities and microlevel implementation success. Pham *et al.* (2023a, 2023b) demonstrate how institutional digital readiness affects departmental ability to support faculty and student AI use. Second, meso-level disciplinary characteristics shape both macro-level policy requirements and microlevel implementation strategies. This is evidenced in Nikolic *et al.*'s (Nikolic *et al.*, 2023) multi-institutional study, which shows how different disciplines require different assessment approaches and support structures.

The dynamic interaction between these levels also creates what Dunder *et al.* (2024) describe as "implementation feedback loops." Success or failure at the micro level influences departmental policies at the meso level, which in turn affects institutional strategies at the macro level. This multidirectional influence is particularly evident in the evolution of assessment practices, where individual faculty experiences inform departmental policies, which ultimately shape institutional approaches to AI integration.

The findings of this paper culminate in a multilevel framework for AI integration in higher technical and engineering education (Figure 4), synthesizing insights from both the SLR and ethnographic data. This circular, concentric model captures the hierarchical and interdependent nature of AI integration across institutional levels. At the macro level, it identifies three primary dimensions: Policy and Governance, Infrastructure and Support and Strategic Planning. These outer components inform meso-level adaptations (e.g. departmental protocols, faculty development), which in turn support microlevel pedagogical practices. Core elements such as faculty training, assessment design and student engagement are positioned centrally, highlighting their cross-cutting importance. The concentric design emphasizes the interdependent nature of these elements, where success at each level depends on alignment with other levels. Color gradients represent the intensity of implementation requirements, with darker shades indicating core elements requiring more immediate attention.

5.3 Framework application

The practical application of the developed multilevel framework requires a structured yet flexible approach to AI integration in engineering education. The findings of this research indicate that successful implementation depends on four key principles: establishing clear governance structures with defined roles and responsibilities; maintaining a balance between standardization and disciplinary adaptation; recognizing contextual factors, including institutional culture and infrastructure; and integrating multiple theoretical perspectives to ensure comprehensive coverage. These principles must be applied while considering existing technical infrastructure, faculty readiness, student needs and disciplinary requirements. Implementation guidelines should serve as enablers rather than constraints, allowing for discipline-specific adaptations while maintaining consistent quality standards.

Assessment of framework implementation requires a sophisticated approach that addresses both implementation success and educational outcomes. This research suggests a comprehensive assessment strategy that combines quantitative metrics (such as adoption rates and usage patterns) with qualitative evaluation of faculty satisfaction and student engagement. This assessment must monitor professional competency development, including technical skills, professional judgment and ethical decision-making capabilities while maintaining an appropriate balance between traditional and AI-enhanced assessment methods. Successful strategies include hybrid examination approaches, project-based assessments integrating AI tools and portfolio assessments that document both individual capabilities and AI-enhanced work. Regular review and updates of assessment criteria ensure the framework remains relevant as technology and educational needs evolve.

The multilevel framework presented in this section builds upon the three integration approaches identified in our findings. The AI-Inclusive assessment design approach informs the framework's components related to faculty development and technological infrastructure; the contextual insulation approach shapes the framework's emphasis on discipline-specific adaptation and assessment design; and the hybrid examination approach

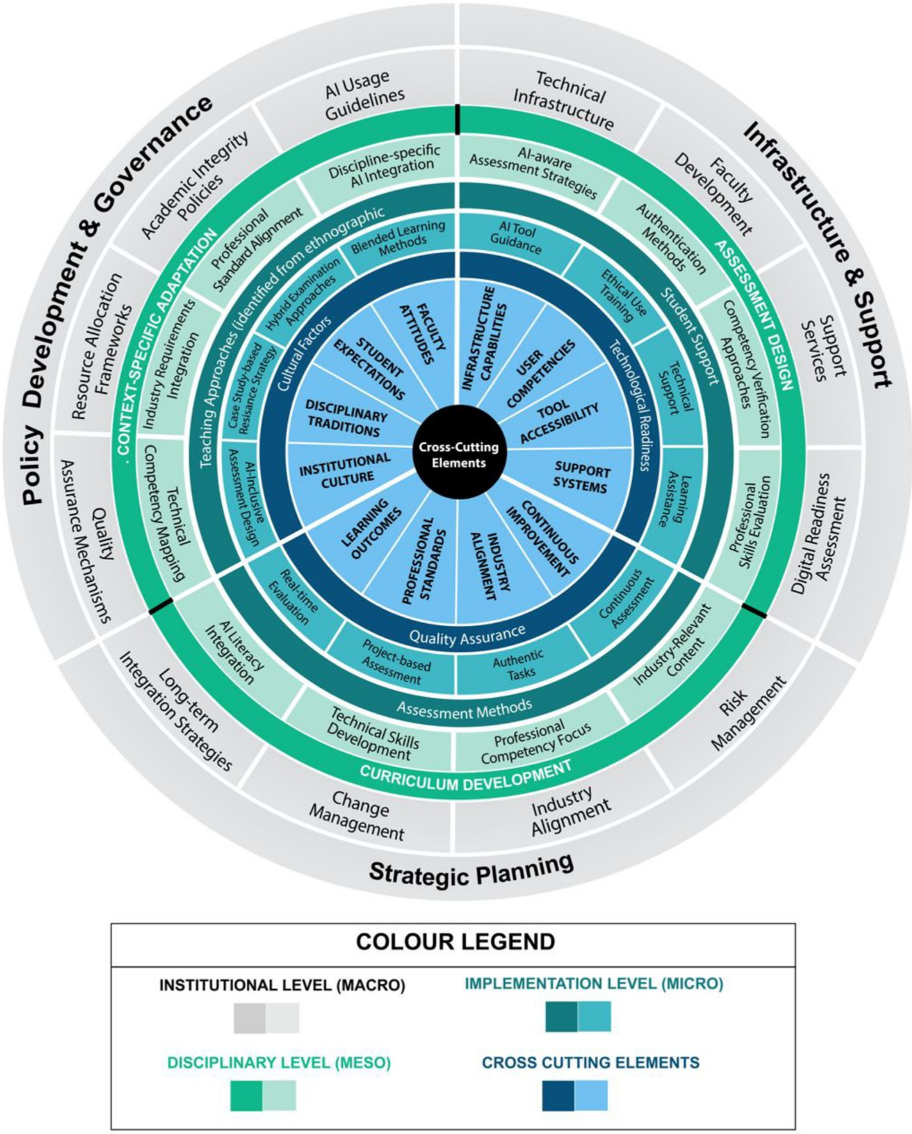

Figure 4. Multilevel framework for AI integration in higher technical and engineering education
Source: Authors' own work

influences the framework's balance between institutional standardization and departmental flexibility. Grounding the framework in these empirically observed approaches ensured that it addresses the practical challenges institutions face when integrating AI while accounting for disciplinary characteristics, cultural contexts and institutional readiness – the key factors identified in the research aims.

6. Implications, limitation and future direction

6.1 Theoretical and practical implications

The findings of this research make several novel theoretical contributions to understanding AI integration in higher education through the synthesis of ethnographic observations and existing literature. The introduction of concepts such as “contextual insulation” and “prompt diary” methodologies extends beyond current theoretical frameworks, providing new ways to conceptualize and implement AI integration in educational settings. Particularly significant is the documentation of temporal dynamics in AI integration – an aspect largely overlooked in existing research that typically provides snapshot analyses. The longitudinal observations reveal organic, bottom-up development of faculty support systems and the evolutionary nature of student adaptation to AI tools, challenging the static implementation models prevalent in current literature.

While previous research such as Caccavale *et al.* (2024) identifies faculty preparedness gaps, and Stöhr *et al.* (2024) documents student attitudes, the findings uniquely capture the dynamic, iterative nature of AI integration in engineering education. Observing how assessment strategies evolve through multiple iterations, alongside documentation of organic faculty development patterns and student adaptation processes, provides a more nuanced theoretical understanding of AI integration as a dynamic, evolving process rather than a static implementation challenge. These insights suggest the need for more sophisticated theoretical frameworks that can account for the temporal and evolutionary aspects of AI integration in higher education.

The practical implications of the findings emphasize the importance of developing “contextually optimized AI integration approaches”. The ethnographic observations reveal how different engineering courses require distinct strategies – from “guided AI integration” in programming courses to “creative augmentation frameworks” in design-focused courses. These approaches demonstrate the effectiveness of discipline-specific AI-aware assessment frameworks that maintain academic rigor while leveraging AI capabilities.

This study also has several policy-level implications. Based on the findings, we propose the following recommendations to guide institutions in the effective integration of AI in higher education:

- *develop adaptive governance frameworks:* institutions should create flexible governance structures for AI integration, allowing regular policy updates based on feedback and balancing standardization with discipline-specific needs;
- *implement tiered support systems:* policies should mandate support systems at institutional, departmental and course levels, including funding for faculty development, infrastructure and ongoing implementation assessments;
- *establish cross-disciplinary AI committees:* institutions should form committees with diverse disciplinary representation to develop and oversee AI integration policies that cater to different academic areas;
- *create dynamic assessment policies:* revise traditional assessment policies to include AI integration, focusing on defining appropriate AI use rather than preventing misuse; and
- *develop national guidelines with local flexibility*: authorities should establish national guidelines for AI integration, encouraging local adaptation based on institutional and disciplinary needs.

These recommendations advocate for “structured flexibility,” providing clear direction while allowing room for innovation and adaptation within disciplines and local contexts, or regional variations and differences, enabling more systematic and sustainable AI integration.

6.2 Limitations of the study

This study's primary limitation lies in its ethnographic scope, which is based on observations from a limited number of Australian institutions. While this provides valuable deep contextual insights, this geographic concentration represents a significant limitation. Educational practices, cultural contexts and policy frameworks may vary significantly across countries and regions. The specific regulatory structures, cultural attitudes toward technology and institutional arrangements in Australian higher education may not be fully generalizable to universities in other countries, particularly in North America, Europe or other parts of Asia. As a result, this study may not fully capture the broad spectrum of AI integration strategies at program or school levels globally. Caution should be taken when generalizing the findings, particularly those derived from the ethnographic observations, as these are specific to the Australian context. Another limitation of this study is the bibliometric analysis, which relied solely on the Scopus database, potentially missing relevant studies indexed in other databases such as Web of Science or Google Scholar.

6.3 Future directions and strategic recommendations

The integration of AI in engineering education demands proactive and strategic approaches that balance institutional support with individual innovation for future developments. This research highlights the necessity of "structured flexibility frameworks" that can dynamically adapt to emerging technologies while maintaining educational integrity.

The primary strategic priorities center on three critical dimensions: context-aware integration frameworks, faculty development and infrastructure adaptability:

(1) Context-aware integration requires developing "adaptive integration matrices" that are tailored to specific disciplinary needs. These matrices must consider course-specific characteristics, learning objectives and professional competency requirements, recognizing that different disciplines require unique AI integration strategies.

(2) Faculty development transcends basic tool training, evolving into a comprehensive "multi-dimensional faculty empowerment" approach. This strategy combines technical and engineering proficiency with pedagogical innovation, enabling educators to create hybrid learning environments, design sophisticated assessment methodologies and effectively leverage AI capabilities while preserving academic integrity.

(3) Infrastructure development must be equally adaptive, supporting evolving AI integration needs while maintaining robust security and ethical standards. This involves developing digital platforms for AI-enhanced learning, implementing secure assessment environments and establishing data analytics systems to monitor implementation effectiveness.

To implement these strategic priorities, institutions should take immediate action. This includes establishing AI Integration Task Forces with diverse stakeholder representation, developing comprehensive faculty support programs and creating clear guidelines for AI tool integration across disciplines. Success hinges on sustained institutional commitment, active engagement from faculty and students and continuous evaluation and refinement of implementation strategies.

Future studies should address several critical research priorities that emerge from the findings of this work. First, there is a pressing need for longitudinal studies examining the long-term impact of AI integration strategies on learning outcomes, professional skill development and career readiness. Such studies should track student cohorts through their academic journey and into early career stages to understand how different AI integration approaches influence professional development. Second, cross-cultural comparative analyses are essential to understand how cultural and institutional factors influence AI integration success, particularly as engineering education becomes increasingly globalized. To address the limitation regarding the Australian context, future research should also include comparative studies across diverse geographic and cultural contexts, enabling the identification of both universal principles and region-specific adaptations for effective AI integration. Third, research should focus on developing and testing sophisticated implementation frameworks that can guide institutions in creating context-appropriate integration strategies, with particular attention to assessment innovation and quality assurance mechanisms. Additionally, investigation into new forms of assessment that effectively evaluate student learning in AI-enhanced environments while maintaining academic integrity is crucial. Finally, future bibliometric analyses should expand to include multiple databases beyond Scopus, ensuring comprehensive coverage of relevant literature across different academic sources.

7. Conclusion

The integration of AI technologies in engineering education represents a fundamental transformation requiring a sophisticated understanding across multiple organizational levels. Our comprehensive analysis, combining SLR and bibliometric analysis with ethnographic observations, reveals that successful AI integration demands more nuanced, context-specific approaches than previously recognized in the literature. The bibliometric analysis specifically reveals that ChatGPT dominates current research attention in higher education AI integration, though other AI tools exist and may prove more effective for different contexts and course features – an area requiring further research and testing.

The knowledge gap between current research focus and practical implementation needs underscores the importance of adopting a methodology that combines and compares literature findings with actual implementation practices in educational settings. To this end, our dual methodological approach is instrumental in examining how theoretical insights from literature materialize in practical teaching contexts and identifying areas where real-world experiences challenge or extend existing frameworks. Through this approach, we identified three distinct integration approaches that emerged from our ethnographic observations: AI-inclusive assessment design, case study-based resistance strategies and hybrid examination models.

Our research makes three significant theoretical contributions to the field. First, we identify three fundamental dialectical tensions – the Authenticity-Innovation Paradox, the Competency-Augmentation Dilemma and the Scale-Customization Conflict – that provide a framework for understanding how different courses must balance competing demands. Second, our multilevel analysis framework, examining macro (institutional), meso (disciplinary) and micro (course-specific) factors, demonstrates the importance of what we term “contextual calibration” in implementation success. Third, we introduce the concept of “adaptive resilience” in course design, showing how different engineering disciplines have developed unique approaches to maintaining educational integrity while embracing AI capabilities.

While our ethnographic findings are specific to the Australian context, the bibliometric analysis revealed significant regional and cultural variations in AI implementation worldwide, highlighting the need for frameworks that can be adapted to different educational contexts. Our strategic recommendations emphasize the need for context-aware integration frameworks, comprehensive faculty development programs and adaptive infrastructure to support evolving AI integration needs.

The rapid evolution of both AI technologies and educational practices necessitates continuous adaptation and refinement of integration strategies. However, our research provides a robust foundation for understanding and implementing AI integration in technical and engineering education, while acknowledging that the path forward requires ongoing dialogue between educators, administrators and students to ensure that AI integration serves the fundamental goals of technical and engineering higher education while preparing graduates for an increasingly AI-enhanced professional environment.

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