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Artificial Intelligence and Graduate Employability in Higher Education: A Systematic Review of Competency Development and Career Readiness (2013–2026)

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ABSTRACT

This comparative systematic literature review examines how artificial intelligence (AI) is used in higher education to develop graduate competencies and what evidence links these applications to career readiness and employability. This comparative systematic literature review examines research published between 2013 and 2026, drawing on Scopus and Web of Science. A narrative thematic synthesis compares the periods 2013–2022 and 2023–2026 across pedagogical approaches, competency outcomes, career readiness, and institutional conditions. The synthesis identifies an expansion from specialized instructional and analytical applications toward conversational assistance, generative feedback, and collaborative knowledge production. Reported benefits depend on pedagogical alignment, learner evaluation, self-regulation, and responsible oversight. AI literacy encompasses technical, evaluative, disciplinary, and ethical capabilities, while effective task allocation can preserve opportunities for independent reasoning. However, assisted performance, perceived employability, and actual employment outcomes remain distinct. The review clarifies potential pathways connecting AI-supported education with graduate preparation and identifies priorities for curriculum design, authentic assessment, and university–industry collaboration. Heterogeneous measures and limited longitudinal evidence constrain conclusions about sustained professional transfer and employment benefits.

Keywords: Artificial intelligence; Graduate Employability; Competency Development; Higher Education; Career Readiness

1. INTRODUCTION

The increasing integration of artificial intelligence (AI) into educational and organizational environments is reshaping expectations concerning graduate competencies, professional development, and workforce readiness. Advances in generative AI, large language models (LLMs), and intelligent decision-support systems are creating opportunities for new forms of human technology collaboration while changing the competencies required across professional sectors. Chigbu and Makapela (2025) conceptualized the convergence of Industry 5.0, Education 5.0, and Work 5.0 as a human-centred transformation that connects technological innovation with skills development, sustainability, and workforce inclusion. Similarly, Dasaklis et al. (2026) identified emerging applications of LLMs in human resource management, including recruitment, training, and performance evaluation. These developments have important implications for higher education institutions (HEIs), which are increasingly expected to prepare graduates with disciplinary knowledge alongside digital literacy, analytical capabilities, ethical judgement, and adaptability.

Consequently, graduate talent development requires greater attention to the alignment between educational practices, evolving professional competencies, and labour-market expectations (Singh et al., 2025; Mhaske et al., 2025). Graduate employability is a multidimensional concept encompassing the knowledge, skills, personal capabilities, and contextual resources that support individuals in obtaining employment and adapting to professional environments. Although higher education plays a central role in developing these capabilities, evidence suggests that discrepancies persist between academic preparation and workplace requirements. Nguyen (2026), examining the perspectives of students, lecturers, and employers, identified differences in their assessments of graduate competencies, particularly regarding preparedness for data-driven and AI-integrated work environments.

Likewise, Yaya et al. (2025), in a comparative investigation of accounting undergraduates in Malaysia and Indonesia, found that digital intelligence was positively associated with work readiness and mediated the relationship between accounting competencies and employment preparedness. These findings indicate that disciplinary expertise alone may be insufficient to explain graduate readiness, particularly where professional activities increasingly require the application of digital capabilities. From an institutional perspective, addressing these competency gaps requires educational approaches that connect academic learning with practical professional expectations, including competency-based curricula, experiential learning, and industry engagement (Jackson, 2025; Bunea et al., 2025).

AI-enabled educational practices offer potential mechanisms for strengthening graduate talent development through personalized learning, intelligent feedback, digital competency development, and career-related support. Asad and Anwar (2025), through a narrative review, highlighted the relevance of AI to students' career competencies and resources, including digital literacy, critical thinking, problem-solving, and career exploration. In an applied accounting education context, Abhishek et al. (2026) reported positive relationships between AI-supported pedagogical integration and learning outcomes, with skill development, practical application, and learner engagement contributing to these relationships.

However, the effectiveness of AI integration cannot be attributed solely to technological availability. Dhamak et al. (2026) identified faculty readiness, curriculum design, technological infrastructure, ethical standards, and industry collaboration as interconnected factors influencing AI-enabled competency-based educational reform. Similarly, Pandey and Dash (2026) identified digital and AI literacy, strategic digital vision, and innovation culture as foundational enablers of competency-based training for emerging IT professionals. These studies suggest that the contribution of AI to graduate development depends on how technological capabilities are incorporated into pedagogical practices and supported by institutional strategies.

Nevertheless, AI integration presents institutional, pedagogical, and contextual challenges that may constrain its contribution to employability. Educational institutions differ in technological infrastructure, faculty competencies, curriculum flexibility, and their capacity to establish effective industry partnerships. Research on higher education reform has emphasized the importance of institutional development, curriculum modernization, and alignment with emerging workforce requirements (Mohiuddin et al., 2023; Magagula & Awodiji, 2024). Furthermore, AI-based educational and career-support systems raise concerns about contextual appropriateness, equitable access, and responsible implementation. Eze et al. (2026), evaluating LLM-generated computing career guidance across ten African countries, identified substantial differences in the contextual relevance of competency recommendations, including limitations in recognizing local employment conditions and educational environments.

Chigbu and Makapela (2025) similarly highlighted the potential risks of inequality and deskilling associated with AI-enabled transformation. Such findings indicate that the relationship between AI adoption and graduate employability should not be assumed to be uniformly positive; rather, its implications require examination across institutional settings, disciplinary contexts, and labour-market conditions. The existing literature provides important but differentiated perspectives on AI-enabled education, talent development, and employability. Empirical investigations have examined digital intelligence and work readiness (Yaya et al., 2025), stakeholder perceptions of graduate competency gaps (Nguyen, 2026), and AI-supported educational interventions (Abhishek et al., 2026). Other studies have focused on institutional readiness and competency-based reform (Dhamak et al., 2026), professional training frameworks (Pandey & Dash, 2026), and contextual limitations of AI-based career guidance (Eze et al., 2026).

Prior evidence syntheses have also contributed substantially to this field. In particular, Wu et al. (2026) systematically reviewed 192 publications from Scopus and Web of Science concerning AI and business talent development in higher education, identifying gaps related to AI competencies, curriculum restructuring, institutional support, and the mechanisms through which AI contributes to talent development. Chigbu and Makapela (2025) examined AI-enabled transformation across education, industry, and work, while Wider et al. (2025) mapped research trends concerning postgraduate employment.

Although these studies provide valuable foundations, their respective emphases on business education, broader technological transformation, or postgraduate employment leave room for a more focused, cross-disciplinary examination of how AI-enabled educational and institutional practices relate specifically to graduate competency development and employability.Accordingly, the central research problem is not simply whether AI can support educational innovation, but how, under what conditions, and through which reported mechanisms AI-enabled practices contribute to graduate talent development and employability. Existing research employs diverse conceptualizations of digital competence, AI literacy, career readiness, and employability, while drawing on different populations, disciplinary settings, and research designs. This diversity complicates the comparison of findings and the identification of transferable institutional strategies.

Moreover, improvements in learning engagement, perceived competencies, or educational performance should not automatically be interpreted as evidence of improved employment outcomes. A systematic synthesis is therefore needed to distinguish educational and competency-related outcomes from direct indicators of employability, critically examine the strength of reported relationships, and identify contextual factors that influence their applicability. Against this background, the present study aims to systematically synthesize research on AI-enabled graduate talent development and employability in higher education. Specifically, the review seeks to: (1) identify the principal AI-enabled pedagogical practices and institutional strategies associated with graduate talent development; (2) examine the competencies, career-related capabilities, and employability outcomes reported in existing studies; (3) evaluate the institutional, pedagogical, and contextual conditions that enable or constrain these relationships; and (4) identify conceptual, theoretical, and methodological gaps to inform future research. By integrating evidence across educational and workforce-development perspectives, this review seeks to develop an evidence-informed understanding of the pathways connecting AI-enabled higher education practices with graduate employability. Its anticipated contribution lies in clarifying the relationships among technological integration, institutional capabilities, competency development, and employment preparedness, thereby informing curriculum reform, university–industry collaboration, and responsible AI adoption in higher education.

2. RESEARCH METHODOLOGY

2.1. Research Design and Research Questions

This study adopted a comparative systematic literature review (SLR) to critically examine the evolving role of artificial intelligence (AI) in graduate talent development, competency acquisition, and employability within higher education. The review was structured in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) reporting guidelines to support transparency in literature identification, screening, eligibility assessment, and evidence synthesis. A comparative approach was employed to examine changes in AI-enabled educational practices, graduate competency requirements, and workforce readiness across different stages of technological development.

The review covered publications from January 2013 to November 2026 and distinguished two periods. The first period (2013–2022), representing the pre-generative AI era, examined intelligent tutoring systems, machine learning, learning analytics, adaptive learning technologies, and AI-supported competency development. The second period (2023–2026), representing the generative AI era, focused on the expanding integration of large language models, conversational AI, automated feedback, AI-assisted learning, and intelligent career-support applications. This temporal classification provided a basis for examining how AI applications and their educational implications evolved following the widespread adoption of generative AI.

The comparative synthesis examined relationships among AI-supported pedagogical approaches, graduate competency development, and employability-related outcomes. Particular attention was given to cognitive, technical, digital, and transferable skills, alongside career adaptability and alignment with evolving workforce requirements. Potential limitations, including cognitive offloading, technological dependence, academic integrity concerns, and the transferability of AI-supported competencies to professional environments, were also considered. Rather than assuming that AI adoption directly improved employability, the review distinguished reported educational benefits, measured competency outcomes, and evidence of career readiness or employment-related performance. Accordingly, the review addressed three research questions:

RQ1. How have AI-enabled educational approaches and graduate competency development evolved between the pre-generative AI period (2013–2022) and the generative AI period (2023–2026)?

RQ2. What pedagogical approaches and theoretical frameworks explain the reported opportunities and limitations of AI-supported graduate talent development?

RQ3. What evidence links AI-supported competency development with graduate employability, career readiness, and evolving workforce requirements?

2.2. Search Strategy

Scopus and the Web of Science Core Collection were used as the principal bibliographic databases because of their multidisciplinary coverage of higher education, management, information systems, educational technology, and workforce development. The search targeted English-language publications released between January 2013 and November 2026. The initial database identification yielded 910 records, comprising 590 records from Scopus and 320 from Web of Science.

The search strategy incorporated three interconnected conceptual domains: AI technologies, higher education, and graduate competency development or employability. Search terms included conventional AI applications and emerging generative AI technologies to capture relevant research across both periods. Alternative terminology was incorporated to accommodate differences in how educational, technological, and employment-related concepts were described across disciplines.

The search expression was structured around the following conceptual combination: The search combined three concept groups: AI technologies, higher education, and graduate development. Both general and technology-specific terms is included to accommodate differences in terminology across disciplines. The proposed Scopus and Web of Science (WOS) search string is: TITLE-ABS-KEY ((“artificial intelligence” OR “generative AI” OR “AI-enabled” OR “AI-supported”) AND (“higher education” OR “undergraduate” OR “postgraduate” AND (“work readiness” OR “job readiness” OR “skill development” OR “talent development”))

2.3. Eligibility Criteria

Eligibility criteria are Guided by an adapted Population Concept Context (PCC) framework, eligibility criteria will be determined by study population, educational context, AI application, outcomes, publication characteristics, and research design Table 1.

Table 1. Eligibility Criteria for the Systematic Literature Review

Dimension	Inclusion criteria	Exclusion criteria
Population	University students, graduates, educators, and employers in graduate recruitment contexts	Primary or secondary education and unrelated populations
Phenomenon	AI-supported learning, skills development, AI literacy, career guidance, and workforce preparation	Technical AI applications without educational or employability relevance
Comparison	AI-supported and conventional approaches; 2013–2022 and 2023–2026	Studies without a relevant conceptual or empirical connection
Outcomes	Graduate competencies, employability, professional readiness, adaptability, and cognitive skills	Algorithmic performance alone without human development outcomes
Publication	English-language peer-reviewed empirical studies, systematic reviews, and relevant conceptual research	Editorials, abstracts without full papers, and unrelated publications
Period	January 2013–November 2026	Publications outside the review period

The eligibility framework distinguished studies examining AI adoption or student satisfaction from studies reporting competency development or employability outcomes. Research addressing attitudes toward AI was relevant where its findings were explicitly connected to learning, skills, career preparation, or educational practice. Studies reporting only technology acceptance without such connections were not treated as direct evidence of improved graduate employability.

2.4. Data Extraction and Thematic Analysis

The analytical framework organized the literature according to publication characteristics, AI technologies, educational applications, graduate competencies, and employability-related outcomes. Bibliographic and substantive information was structured around publication year, study context, research design, AI application, theoretical framework, reported competency outcomes, employability-related findings, and identified limitations.

The thematic synthesis was organized into five interrelated dimensions.

Theme 1. AI-enabled pedagogical transformation. This dimension examined intelligent tutoring, adaptive learning, personalized instruction, automated feedback, AI-assisted assessment, conversational learning support, and the changing role of educators in AI-supported environments.

Theme 2. Graduate competency development. This dimension addressed digital literacy, AI literacy, critical thinking, creativity, communication, problem-solving, analytical capabilities, self-regulated learning, and other transferable competencies relevant to graduate development.

Theme 3. Career readiness and employability. This dimension examined career adaptability, professional readiness, recruitment expectations, graduate employability perceptions, employment-related competencies, and evidence connecting educational experiences with workforce preparation.

Theme 4. Human–AI collaboration and developmental risks. This dimension considered cognitive offloading, technological dependence, academic integrity, skill substitution, human oversight, and the potential consequences of excessive reliance on AI-generated outputs for independent learning and professional judgment.

Theme 5. Institutional and workforce alignment. This dimension addressed curriculum transformation, faculty readiness, institutional AI literacy initiatives, industry expectations, ethical governance, and the alignment of higher education practices with emerging labor-market requirements.

The five dimensions provided a common analytical structure for organizing findings across the two review periods. Evidence was interpreted according to the outcomes reported by individual studies, with attention to differences between measured performance, self-reported competencies, and conceptual expectations. The thematic structure also supported alignment with the research questions. Technological and pedagogical developments informed RQ1; instructional approaches, theoretical frameworks, and developmental risks informed RQ2; and graduate competencies, career readiness, and workforce alignment informed RQ3.

2.5. Cross-Period Comparative Synthesis

The comparative synthesis distinguished publications from 2013–2022 and 2023–2026 to examine changes in AI applications and their implications for graduate talent development. The comparison considered differences in technological capabilities, pedagogical functions, competency priorities, educational risks, and relationships with workforce requirements. The earlier period provided a baseline for examining AI-supported personalization, intelligent learning systems, learning analytics, and technology-mediated skill acquisition. The later period captured developments in generative AI, including conversational learning support, automated content production, AI literacy, and changing expectations concerning human AI collaboration. The synthesis distinguished three levels of evidence: reported educational applications, observed or perceived competency outcomes, and employability-related outcomes. This distinction reduced the risk of treating technological adoption as equivalent to demonstrated skill development or labor-market success.

2.6. Study Selection and PRISMA Screening

The study selection process was organized according to the identification, screening, eligibility, and inclusion stages of PRISMA 2020. Database identification yielded 910 bibliographic records, including 590 from Scopus and 320 from Web of Science.

Records were considered for deduplication using bibliographic identifiers and publication information, including digital object identifiers, article titles, authors, and publication years. Title and abstract screening were guided by the eligibility criteria presented in Table 1. Particular attention was given to the relationship between AI applications, higher education, graduate competency development, and employability. Publications addressing unrelated educational populations, clinical applications without a higher education connection, or AI systems without relevant human development outcomes were outside the review scope. Full-text eligibility assessment focused on the substantive relevance of each publication to the research questions, the clarity of its educational or professional development context, and the nature of the evidence presented. The final review sample comprised 44 studies.

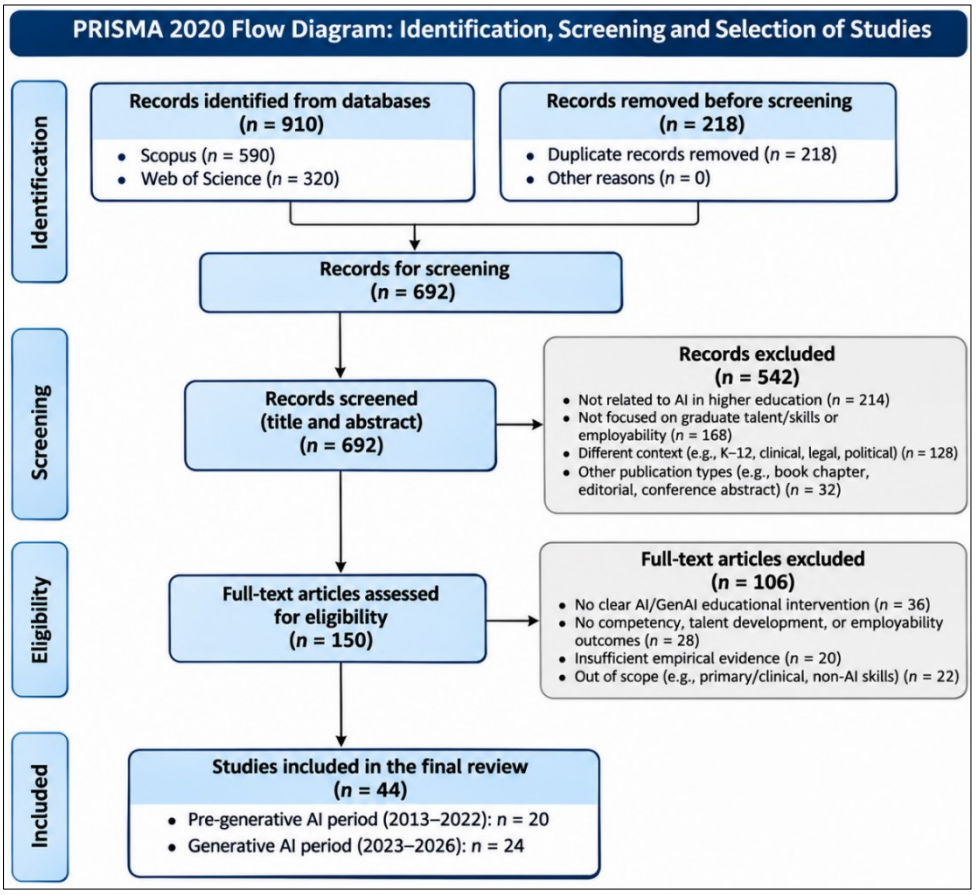

Figure 1. PRISMA 2020 Flow Diagram

2.7. Methodological Scope and Limitations

Several methodological considerations informed the interpretation of the review findings. First, the use of Scopus and Web of Science provided multidisciplinary bibliographic coverage but did not guarantee the inclusion of every relevant publication. English-language and journal-publication restrictions may also have excluded research reported in other languages or publication formats. Second, the literature incorporated heterogeneous educational settings, AI technologies, research designs, and competency measures. These differences limited direct quantitative comparison and supported the use of narrative thematic synthesis rather than pooled effect estimation. Third, the distinction between the pre-generative AI and generative AI periods represented an analytical classification rather than an absolute technological boundary. Some generative approaches preceded 2023, while conventional AI applications continued to be investigated during 2023–2026.

The comparison therefore emphasized changes in research focus and educational applications rather than assuming a complete technological transition. Fourth, many educational studies relied on self-reported AI use, perceived learning benefits, technology acceptance, or employability expectations. Such measures were not treated as equivalent to independently assessed competencies, verified workplace performance, or actual employment outcomes. Finally, the review synthesized the available published evidence rather than establishing causal relationships between AI adoption and graduate employability. Its conclusions were therefore framed around the strength, consistency, and limitations of reported findings, with attention to the need for longitudinal research and direct assessments of graduate competency development and workforce outcomes

3. LITERATURE REVIEW

3.1 Evolution of Artificial Intelligence in Higher Education (2013–2026)

The integration of artificial intelligence (AI) into higher education has evolved from specialized instructional and analytical applications toward increasingly interactive systems supporting personalized learning, knowledge creation, and professional competency development. During the pre-generative AI period (2013–2022), educational applications primarily involved intelligent tutoring systems, adaptive learning, automated assessment, machine learning, and learning analytics. These technologies supported individualized instruction, academic performance monitoring, and data-informed educational decisions, although their functionality was generally organized around specific learning objectives and institutional requirements. Popenici and Kerr (2017) examined the implications of AI for university teaching and learning, highlighting opportunities for educational transformation alongside challenges concerning pedagogical practices and institutional adaptation. Schiff (2021) similarly emphasized that the integration of AI into education requires consideration of its broader pedagogical and societal implications rather than technological capabilities alone.

As AI applications expanded, universities increasingly explored their potential to improve educational delivery and institutional responsiveness. Cantú-Ortiz et al. (2020) discussed AI-oriented educational strategies in the context of digital transformation, while Zhou (2023) examined the integration of AI technologies into higher education. These contributions reflected growing interest in technology-supported instruction, personalization, and educational innovation. Nevertheless, the relationship between AI adoption and graduate competency development remained less straightforward. Humble and Mozelius (2022) critically examined the opportunities and expectations surrounding AI in education, illustrating the need to distinguish anticipated benefits from demonstrated educational outcomes. Consequently, improvements in instructional automation or learning efficiency should not automatically be interpreted as evidence of stronger graduate employability.

Alongside these educational developments, changes in professional environments increased expectations regarding graduates' digital and transferable competencies. Li (2024) emphasized the importance of workforce reskilling and upskilling in response to Industry 4.0 transformations, while Santana and Díaz-Fernández (2023) examined emerging competencies associated with the AI era. These studies provide a broader workforce perspective, suggesting that higher education must respond not only to technological changes in teaching but also to evolving professional requirements. However, evidence concerning workforce skill demands does not independently establish that AI-supported university instruction produces those competencies. This distinction is essential when evaluating the contribution of educational AI to graduate talent development.

The emergence of widely accessible generative AI (GenAI) applications from late 2022 introduced a further transformation in human–AI interaction. Unlike earlier educational systems that frequently relied on structured learner information or predefined instructional activities, large language models enabled students to generate content, obtain conversational explanations, develop ideas, and refine academic work through iterative natural-language interaction. This development expanded the educational role of AI toward writing assistance, collaborative problem-solving, personalized feedback, and simulated professional practice. Tilwani et al. (2026) examined generative AI in relation to personalized learning and transformative skill development within higher education in developing-country contexts, illustrating the growing interest in connecting AI-supported learning with broader educational capabilities. Nevertheless, generative AI should be understood as an extension of educational technologies rather than a complete replacement of adaptive learning and analytical systems.

Recent evidence demonstrates both the educational opportunities and the limitations of generative applications. Shi et al. (2025), in a systematic review of empirical research on large language models in education, identified applications involving intelligent tutoring, learning assistance, accessibility, and skill development. However, their synthesis also highlighted concerns relating to technological reliability, excessive dependence, assessment fairness, and privacy. Similarly, Xia et al. (2026) examined the design of self-regulated learning activities supported by generative AI, emphasizing the importance of pedagogical arrangements that enable learners to manage their own learning processes. These findings suggest that the effectiveness of generative AI depends on how technologies are integrated into educational activities rather than their availability alone.

The growing use of AI in professional education further illustrates its potential contribution to graduate preparation. Martinez et al. (2025) investigated nursing students' experiences with AI-driven virtual patients and identified perceived benefits involving confidence, communication, information gathering, and reflective learning. Such applications demonstrate opportunities for simulated professional interaction, although self-reported experiences cannot establish equivalent improvements in independently assessed workplace competence. Likewise, Symes et al. (2026) identified educational support, critical thinking, information accuracy, and ethical considerations as important themes in postsecondary nursing students' experiences with generative AI. These findings highlight the need to evaluate both the educational functions of AI and students' ability to critically assess its outputs.

Despite these opportunities, generative AI has introduced additional concerns regarding cognitive dependence, academic integrity, and the authenticity of learning outcomes. Kim (2026) addressed AI-induced illusory competence through structured verbal assessment, emphasizing the importance of independently demonstrating clinical reasoning. Yan and Wang (2026) identified tensions involving cognitive engagement, self-regulation, ethical responsibility, and professional identity among undergraduate nursing students using generative AI. Furthermore, Bal and Arseven (2026) examined AI-assisted writing and creativity, highlighting the importance of pedagogical design in balancing technological assistance with independent creative development. Collectively, these studies indicate that effective AI integration requires instructional approaches that preserve student agency, critical evaluation, and demonstrable learning.

The comparison between the pre-generative (2013–2022) and generative AI (2023–2026) periods therefore reveals an expansion in educational functionality and competency expectations. Earlier applications emphasized adaptive instructional support, learning analytics, and structured personalization, whereas more recent technologies have broadened opportunities for conversational assistance, knowledge generation, and human–AI collaboration.

However, these developments have not eliminated the importance of foundational disciplinary knowledge, independent reasoning, or pedagogical oversight. More importantly, evidence of technological adoption, perceived learning benefits, or improved task efficiency should not be equated with sustained competency development or graduate employability. Understanding how AI-supported educational experiences contribute to transferable professional capabilities therefore provides the foundation for examining AI-enabled graduate talent development and competency acquisition in the following subsection.

3.2 AI-Enabled Graduate Talent Development and Competency Acquisition

AI-enabled graduate talent development concerns how higher education prepares students to combine disciplinary expertise with technological understanding, independent judgement, and professional adaptability. Its contribution therefore requires examination beyond technology adoption or frequency of use. Wu et al. (2026), reviewing AI and business talent development in higher education, identified curriculum design and decision-making among prominent research themes, alongside limitations in theoretical development and longitudinal investigation. Their findings provide a foundation for examining how AI-supported educational practices relate to competency acquisition, while highlighting the need to distinguish immediate learning performance from durable graduate capabilities. Digital competence provides an important foundation for engaging with AI, but these constructs should not be treated as equivalent. Shomotova et al. (2026), studying undergraduate students in the United Arab Emirates, found a positive relationship between digital competence and AI literacy, with digital evaluation skills emerging as a particularly important predictor.

However, their observational findings do not establish that increasing technology use independently produces stronger AI literacy. Domain-specific measurement further illustrates the breadth of the construct. Gu et al. (2026) developed an AI literacy scale for design students encompassing technical understanding, tool proficiency, ethical and originality awareness, recognition of AI's value in design, and independent evaluation of outputs. This framework indicates that AI literacy extends beyond operational familiarity to include evaluative and disciplinary capabilities. Nevertheless, validating a measurement instrument does not demonstrate the effectiveness of an educational intervention.

The relationship between AI literacy and competency development also involves the possibility of dependence. Ren and Khan (2026), in a mixed-methods study of music learning, examined associations among generative AI use, domain skills, AI dependence, and musical performance. AI literacy moderated these relationships, strengthening the favourable skill-related pathway while weakening the dependence-related pathway. These findings support examining AI literacy as a condition shaping the outcomes associated with AI use. They do not establish that similar relationships necessarily occur across disciplines or that AI literacy eliminates dependence.

Critical thinking in AI-supported learning involves evaluating the reliability, relevance, and implications of generated information. Lau et al. (2026) developed and validated a critical thinking in AI use scale organized around verification, motivation, and reflection. Their findings connect critical engagement with observable verification practices and accuracy in an AI-assisted fact-checking task. The study therefore offers a more specific basis for assessing critical AI engagement than reliance on general confidence or tool-use frequency alone. Within cybersecurity education, Elkhodr and Gide (2025) described the SAGE framework, which requires students to generate, critique, and refine AI-assisted outputs within tutorial and assessment activities.

This case study illustrates how disciplinary evaluation can be incorporated into AI-supported learning, although its findings should be interpreted within the implementation context.Rodger et al. (2025), in a discussion paper on healthcare education, similarly emphasize concerns about AI literacy gaps and professional competence. Their contribution supports the rationale for oversight rather than providing direct evidence of measured learning gains.

AI-supported creativity requires consideration of both the quality of the output and the learner's contribution to its development. Du and Qiao (2026) examined an AI-powered, scenario-based design thinking approach associated with improvements in university students' creativity, entrepreneurial competencies, and entrepreneurial identity. These findings concern an integrated pedagogical approach; they should not be interpreted as evidence that access to AI alone produces equivalent outcomes. Collaborative problem-solving also requires attention to the process of interaction. Christopoulos et al. (2026) investigated how group prompting develops over time and relates to task effectiveness. Their focus on observable behaviour provides a useful basis for examining how learners formulate problems and interact with AI during collaborative tasks. However, successful completion of an assisted task remains distinguishable from the ability to solve a new problem independently.

The relevance of AI-enabled learning to graduate development ultimately depends on whether acquired capabilities can be applied across unfamiliar tasks and professional settings. Hendrawan and Lestari (2026) examined AI literacy and graduate employability through a survey of final-year university students, incorporating career adaptability and growth mindset into their analytical model. This approach draws attention to adaptive resources alongside technical capabilities, although survey-based relationships cannot independently demonstrate subsequent employment success. Mustafa and Altrad (2026) similarly examined AI adoption, future-ready skills, and employability using a cross-sectional student survey. Their model identified future-ready skills as a mediating construct, but also reported a negative relationship between AI literacy and adoption. This finding cautions against assuming that stronger literacy necessarily corresponds to more frequent adoption or uniformly favourable outcomes. Table 2 summarizes the competency domains and the distinctions needed when interpreting the available evidence.

Table 2. Competency Domains and Evidence Considerations In AI-Enabled Graduate Development

Competency Domain	Focus of Competency Development	Evidence Consideration	Reference
Digital and AI literacy	Technical understanding, responsible use, disciplinary application, and evaluation of outputs	Distinguish tool familiarity and self-reported literacy from demonstrated capability	Gu et al. (2026); Shomotova et al. (2026)
Critical thinking	Verification, reflective judgement, and disciplinary evaluation	Distinguish scale validation and contextual implementation findings from evidence of lasting cognitive development	Elkhodr and Gide (2025); Lau et al. (2026)
Creativity	Idea development, originality, and refinement within authentic tasks	Separate the contribution of AI from the wider instructional approach	Du and Qiao (2026)
Collaborative problem-solving	Problem formulation, group interaction, and evaluation during AI-assisted tasks	Distinguish assisted task effectiveness from independent problem-solving and transfer	Christopoulos et al. (2026)
Transferable professional competencies	Career adaptability, future-ready skills, and application across contexts	Separate student-reported employability from observed employment outcomes	Hendrawan and Lestari (2026); Mustafa and Altrad (2026)

3.3 AI-Supported Pedagogical Approaches and Theoretical Frameworks

AI-supported graduate development requires instructional designs that connect technological capabilities with learning objectives, assessment, and opportunities for reflection. The literature approaches this relationship through complementary perspectives on knowledge construction, learner regulation, motivation, human–AI collaboration, and educator readiness. These perspectives address different questions: how students learn with AI, how they monitor its contributions, what sustains their engagement, and how educators integrate it into disciplinary teaching.

AI-supported active learning can combine inquiry, experimentation, feedback, and revision within authentic disciplinary tasks. Bilotta et al. (2026), for example, developed a pilot framework for digital manufacturing education that integrated AI feedback, peer review, and guided reflective journals. The study illustrates how automated assistance can operate within a broader sequence of design activities. However, its short duration and pilot setting limit conclusions about sustained competency development and transfer to professional practice. Programming education provides a related perspective on instructional alignment. Nathaniel et al. (2025), reviewing 40 empirical studies, identified intentional teaching strategies, assessment design, and structured integration as important conditions for incorporating generative AI while preserving foundational programming capabilities. Their synthesis also highlighted the risk that reliance on generated solutions could weaken opportunities to practice programming logic and higher-order thinking. These findings support evaluating feedback through how learners interpret, verify, and apply it, alongside the accuracy or speed of the generated response.

Constructivist approaches emphasize learners' active interpretation and application of information. Alam et al. (2026) applied a constructivist learning perspective to generative AI integration in higher education, highlighting its supportive role and the need for curriculum adaptation and clearer institutional guidance. Within this perspective, AI-generated explanations and examples can become resources for inquiry when students connect them with prior knowledge, disciplinary evidence, and practical experience.

Self-regulated learning adds attention to how students plan tasks, monitor understanding, evaluate feedback, and revise their strategies. Nathaniel et al. (2025) incorporated self-regulation into their proposed pedagogical framework, connecting AI integration with deliberate learning processes. For graduate development, this perspective directs assessment toward students' decisions about when to seek assistance, how to check a response, and whether they can explain or reproduce the underlying reasoning. The availability of immediate assistance therefore makes the monitoring of learning processes particularly relevant.

Self-Determination theory provides a framework for examining autonomy, competence, and relatedness in AI-supported learning. Setiawan et al. (2026), in a scoping review, found that need satisfaction and need frustration coexisted across the literature, with instructional design emerging as a consistent boundary condition. Their synthesis indicates that motivational consequences depend on the interaction among tool design, instructional scaffolding, and learner characteristics. The predominance of cross-sectional evidence also limits conclusions about how these relationships develop over time. Motivational explanations also apply to educators. Luo and Day (2026) combined Self-Determination Theory with the Unified Theory of Acceptance and Use of Technology to investigate lecturers' intentions and use of generative AI.

Their findings connect adoption with motivational needs, facilitating conditions, and individual attributes. Because the study concerns lecturers, its contribution lies in explaining conditions for implementation; student competency outcomes require separate evaluation. Human–AI collaboration shifts attention toward how people coordinate their judgement with technological assistance. Ganuthula and Balaraman (2025) proposed an Artificial Intelligence Quotient framework for assessing abilities exercised through collaboration with AI. This provides a conceptual basis for examining assisted performance, although a proposed assessment framework does not itself establish the effectiveness of a classroom intervention. In higher education, the relevant questions include how learners allocate tasks, evaluate contributions, and retain responsibility for their final decisions.

Pedagogical integration models address the educator knowledge needed to support these activities. Karataş and Ataç (2025) examined TPACK and AI-TPACK among preservice English teachers, identifying variation across knowledge components and comparatively weaker ethical knowledge within AI-TPACK. Their findings reinforce the importance of connecting technological familiarity with pedagogical, disciplinary, and ethical understanding. Ghabban et al. (2026), drawing on technology acceptance and experiential learning perspectives in business education, similarly examined educational uses of AI alongside institutional, ethical, and behavioural concerns. Together, these approaches help explain implementation conditions while leaving the development of transferable graduate capabilities as a distinct empirical question.

3.4 Artificial Intelligence, Career Readiness, and Graduate Employability

AI-enabled graduate development requires a clear distinction between competency acquisition, career readiness, and employability. Career readiness concerns preparation for entering professional environments, whereas employability encompasses capabilities and contextual resources supporting access to, participation in, and progression through employment. Consequently, confidence in using AI, perceived work readiness, and actual employment outcomes represent related but distinct indicators. Empirical research identifies several potential connections between AI-supported learning and career preparation. Dahri et al. (2025), using survey data from students at Universiti Teknologi Malaysia, reported relationships among ChatGPT output quality, personalized learning, cognitive skills, career-relevant knowledge, and career readiness. However, their survey-based structural model does not establish that these relationships produce improved employment outcomes after graduation.

Hendrawan and Lestari (2026) similarly examined AI literacy and employability through career adaptability and growth mindset, highlighting the relevance of adaptive resources alongside technological capabilities. Mustafa and Altrad (2026) investigated future-ready skills as a pathway connecting AI adoption with employability. These studies support examining intermediate capabilities while retaining the distinction between reported preparedness and observed labour-market outcomes.

The relevance of these capabilities also depends on their alignment with professional expectations. Nguyen (2026) examined graduate competency gaps through student, lecturer, and employer perspectives, providing a basis for comparing educational preparation with workplace requirements. Such comparisons can help identify whether AI-supported curricula address authentic professional tasks rather than technological familiarity alone. For the present review, evidence of career readiness will therefore be interpreted according to its measurement source, disciplinary context, and proximity to employment. Student perceptions, employer assessments, demonstrated task performance, and post-graduation employment records will be considered separately.

3.5 Challenges and Risks of AI-Enabled Graduate Development

The contribution of AI to graduate development depends partly on how educational practices manage cognitive, ethical, and institutional risks. Rodríguez-Montoya et al. (2026), in a systematic thematic synthesis, identified concerns involving skill erosion, assessment, misinformation, privacy, inequality, and institutional preparedness. These findings provide a basis for examining interacting risk domains, although the consequences of individual risks depend on the technology, learning activity, and implementation context.

Delegating tasks to AI can alter opportunities for learning, but offloading should not automatically be interpreted as harmful. Lai et al. (2026) compared different allocations of writing and evaluation tasks between learners and generative AI. Their findings indicated benefits when AI produced initial drafts and learners retained responsibility for feedback and revision. The educational issue is therefore which cognitive activities students continue to perform and how these activities support learning. Claims about lasting skill loss require assessments of independent performance and retention rather than inference from AI use alone.

Reliance becomes problematic when students cannot explain, verify, or reproduce the reasoning underlying AI-assisted work. Ren and Khan (2026) examined associations between AI use, domain skills, and dependence, while Lau et al. (2026) provided a framework for assessing verification, motivation, and reflection during AI interaction. Together, these perspectives support examining whether assistance develops evaluative capability or substitutes for opportunities to practice it. AI-generated submissions create challenges in establishing authorship and determining what students have learned. Alalwani (2026) documented faculty concerns about academic integrity, assessment, and students' reliance on generated content. These findings represent educators' perceptions rather than direct measurements of competency decline. Ying (2026), reviewing student perspectives, identified an ethical grey area in which students interpret and negotiate acceptable AI use.

This suggests that assessment policies require clear expectations, student participation, and alignment between permitted assistance and the capabilities being assessed. Inaccurate or biased outputs become educational risks when learners accept them without appropriate verification. The implications are particularly relevant where disciplinary decisions carry consequences for other people. Rodger et al. (2025), discussing healthcare education, emphasize the importance of AI literacy and responsible professional judgement. Such arguments establish the rationale for oversight; evidence of actual professional harm requires separate investigation. Institutional policies influence how students and educators understand acceptable use, responsibility, and access. Dabis and Csáki (2024), analysing early university policy responses, identified accountability, human oversight, transparency, and inclusiveness as central ethical considerations. Qomariyah and Heriyanni (2026) also found differences between STEM and non-STEM students in several adoption-related dimensions, including facilitating conditions and ethical anxiety. These findings support context-sensitive implementation rather than assuming uniform readiness across disciplines. Table 3 summarize risks and evaluation priorities in AI-enabled graduate development.

Table 3. Risks and Evaluation Priorities in AI-Enabled Graduate Development

Risk Domain	Educational Concern	Evaluation or Response Priority
Cognitive offloading	Students may delegate activities needed for learning	Examine task allocation, learner evaluation, independent performance, and retention
Technological dependence	Assisted performance may exceed independent capability	Assess verification, explanation, self-regulation, and performance without assistance
Academic integrity	Submitted work may provide an incomplete indication of student competence	Clarify permitted assistance and assess reasoning, revision, and authorship
Misinformation and bias	Inaccurate outputs may influence disciplinary decisions	Require evidence checking, contextual judgement, and accountable human oversight
Governance and unequal access	Policies, training, and technological resources may differ across groups	Examine access conditions, disciplinary needs, policy clarity, and implementation support

3.6 Research Gaps

The preceding literature identifies several issues requiring systematic examination across AI-enabled graduate development and employability research. Jaldemark et al. (2025) characterize AI and education research as fragmented, frequently tool-specific, and shaped by short-term perspectives. Their educational ecology approach connects individual learning with curricula, institutions, policy, and wider social conditions. Building on this perspective, the present review will examine five related gaps.

First, cross-disciplinary comparability remains uncertain. Studies use different technologies, learning activities, competency definitions, and assessment instruments. The review will examine which findings can be compared across disciplines and which depend on particular tasks, populations, or professional requirements. Second, educational outcomes require clearer separation from employment outcomes. Studies such as Dahri et al. (2025), Hendrawan and Lestari (2026), and Mustafa and Altrad (2026) examine career-related relationships through student surveys. Their findings motivate further investigation of whether perceived readiness corresponds with demonstrated capabilities, employer evaluations, and employment trajectories. The review will identify the extent to which these different outcome types are represented rather than treating them as interchangeable.

Third, the connections between learning processes and professional transfer need clarification. Technological adoption, learner motivation, competency development, career adaptability, and employment participation operate at different analytical levels. A proposed relationship between them does not establish a causal sequence. The synthesis will distinguish directly examined relationships from theoretical propositions and identify where longitudinal or comparative evidence is needed. Fourth, instructional safeguards require evaluation according to specific learning tasks. Lai et al. (2026) demonstrate why the allocation of cognitive responsibility matters: selected forms of offloading can support learning when students retain evaluative and revision activities. Accordingly, the review will compare the evidence for structured prompting, verification, reflective assessment, and other safeguards without assuming that every recommended practice has been empirically validated.

Fifth, contextual transferability requires explicit attention. Differences in institutional resources, educator preparation, disciplinary expectations, language, and local employment conditions may influence implementation. Evidence from a single institution or professional field cannot establish applicability elsewhere. The review will therefore examine these conditions as potential explanations for variation in reported outcomes. Together, these gaps define the contribution of the present study: a systematic examination of the practices, mechanisms, outcomes, and contextual conditions connecting AI-enabled higher education with graduate development and employability.

The review procedures set out in Section 2 will guide this synthesis, while the final framework will distinguish supported relationships, conditional findings, and unresolved evidence gaps.

4. RESULTS

4.1. Cross-Period Comparison of Educational Applications

The identifiable literature discussed in the manuscript indicates an expansion in the educational functions attributed to AI. Earlier contributions examine teaching support, institutional adaptation, and the implications of intelligent educational technologies. Popenici and Kerr (2017), for example, consider changes in teaching, learning, student support, and administration, alongside challenges for university practice. Humble and Mozelius (2022) distinguish the educational promises of AI from expectations that may exceed the available evidence. These publications establish a historical perspective, although they do not independently demonstrate improvements in graduate employment.

Later studies examine more direct interaction between learners and generative systems. Applications include conversational assistance, content generation, feedback, design activities, and collaborative problem-solving. The resulting analytical distinction concerns how learners participate in producing and evaluating knowledge. Whereas earlier applications frequently organized support around specified instructional functions, generative applications allow learners to formulate requests, revise outputs, and negotiate alternative responses through natural-language interaction.

This comparison identifies changes in educational application and assessment requirements. It does not establish that the later technologies are more effective, because the cited studies differ in population, task, design, and outcome measurement. Table 4 summarizes the contrast as an interpretive framework for the temporal comparison.

Table 4. Interpretive Comparison of AI-Supported Educational Applications Across the Two Periods

Comparison Dimension	Earlier Applications Discussed in The Manuscript	Generative Applications Discussed in The Manuscript
Educational functions	Tutoring, adaptation, assessment, analytics, and instructional support	Conversational assistance, content generation, feedback, and co-creation
Learner interaction	Engagement with structured instructional functions	Iterative prompting, evaluation, revision, and integration of outputs
Competency focus	Disciplinary learning, digital capabilities, and technology-supported performance	AI literacy, verification, creativity, self-regulation, and collaborative judgement
Assessment concern	Whether system-supported performance reflects learning	Whether generated work demonstrates students' own understanding and contribution
Continuing requirement	Pedagogical alignment and appropriate evaluation	Pedagogical alignment, appropriate evaluation, and explicit responsibility for AI-assisted work

4.2 Pedagogical Arrangements and Competency Development

Three relationships emerge from the identifiable studies: the connection between digital and AI literacy, the importance of retaining evaluative responsibility, and the distinction between assisted performance and independent capability. First, AI literacy involves more than operational familiarity. Shomotova et al. (2026) reported a positive relationship between digital competence and AI literacy, with digital evaluation skills emerging as an important predictor.

Gu et al. (2026) further distinguished technical understanding, tool proficiency, ethical and originality awareness, recognition of AI's disciplinary value, and independent evaluation of outputs. These studies contribute evidence about competency structure and measurement. They do not, by themselves, establish which instructional approach most effectively develops those competencies. Second, the allocation of responsibility between learners and AI matters. Lai et al. (2026) found that selected task-offloading arrangements supported writing development, with particular benefits when learners evaluated and revised AI-generated drafts. This finding qualifies a simple interpretation of offloading as skill substitution: delegating initial production can retain educational value when learners continue to perform demanding evaluative activities. Its applicability remains bounded by the writing tasks and instructional arrangements investigated.

Third, evidence concerning AI-assisted tasks requires attention to the capabilities actually assessed. Lau et al. (2026) linked critical thinking in AI use with verification practices and performance in an AI-assisted fact-checking task. Christopoulos et al. (2026) examined the development of collaborative prompting behaviour during problem-solving. These contributions extend evaluation beyond adoption or satisfaction by examining how people interact with generated information. However, performance during an assisted activity remains distinguishable from independent performance on a subsequent task.

The studies therefore support examining instructional processes alongside outcomes. Feedback provision, learner verification, revision, and collaborative evaluation provide identifiable activities through which competency development can be investigated. Their presence should be established from study procedures rather than inferred from the availability of an AI tool.

4.3 Career Readiness and Employability-Related Evidence

The career-related studies cited in the manuscript primarily provide evidence about relationships among reported educational experiences, competencies, adaptive resources, and preparedness. Dahri et al. (2025) associated ChatGPT output quality and personalized learning with cognitive skills and career-relevant knowledge. Their model also linked cognitive skills with career readiness. The measured relationships concern student-reported constructs and do not establish subsequent employment outcomes. Mustafa and Altrad (2026) examined AI adoption, future-ready skills, and employability through a cross-sectional survey. Their results supported a mediating role for future-ready skills, while also identifying a negative relationship between AI literacy and adoption. Consequently, the findings do not support a uniformly positive sequence in which stronger literacy necessarily produces greater adoption and improved employability.

Hendrawan and Lestari (2026) examined a complementary model incorporating career adaptability and growth mindset, directing attention to psychological resources alongside technological capabilities. Table 5 distinguishes the contributions of selected cited studies according to their evidence type. These examples require confirmation against the final included-study register before being presented as members of the systematic review sample.

Table 5. Evidence Types Represented by Selected Studies Cited in The Manuscript

Study	Evidence Examined	Contribution to the Synthesis	Interpretation Boundary
Gu et al. (2026)	Development and validation of a design-specific AI literacy scale	Clarifies dimensions of disciplinary AI literacy	Instrument validation does not establish intervention effectiveness
Shomotova et al. (2026)	Relationships between digital competence and AI literacy	Identifies relevant learner capabilities	Observational relationships do not establish developmental causation
Lai et al. (2026)	Alternative task-offloading arrangements in writing feedback	Examines the allocation of learner and AI responsibilities	Findings concern a specific instructional context
Lau et al. (2026)	Critical thinking measurement and AI-assisted verification	Connects evaluative tendencies with task behaviour	Findings do not directly establish graduate employment benefits
Dahri et al. (2025)	Student-reported learning and career-readiness relationships	Examines educational pathways to preparedness	Career readiness is distinct from observed employment
Mustafa and Altrad (2026)	AI adoption, future-ready skills, and employability constructs	Examines a proposed intermediate pathway	Cross-sectional modelling cannot establish a causal sequence
Hendrawan and Lestari (2026)	AI literacy, career adaptability, growth mindset, and employability	Includes adaptive resources in career preparation	Survey findings require validation against later employment outcomes

5.0 DISCUSSION

5.1 Changing Educational Functions and Responsibilities

The temporal comparison suggests that the development of generative AI has expanded both the activities available to learners and the responsibilities required of them. Conversational and generative systems can participate in drafting, explanation, design, and problem-solving. These functions make it necessary to examine how students evaluate contributions and retain responsibility for their decisions. While prior empirical research in organizational settings demonstrates that targeted talent attraction, development, and retention strategies significantly enhance employee performance behaviour via intermediate capability outputs (Al-Hussaini et al., 2019), higher education institutions increasingly mirror this pipeline through AI-enabled curricula. Specifically, adaptive learning platforms and AI-driven competency assessments operationalize talent development at the pre-employment stage, ensuring that pedagogical interventions yield verifiable skill outputs aligned with dynamic labor market demands.

This interpretation extends the historical comparison beyond a contrast between technological generations. Earlier concerns about educational quality, teacher roles, and institutional adaptation remain relevant. Generative applications add questions about authorship, verification, and the visibility of learners' reasoning. The educational contribution therefore depends on the relationship between technological functionality and the capabilities that an activity requires students to exercise.

RQ1, the principal interpretive contribution is an expansion in the forms of human–AI interaction. This should not be presented as proof of superior learning effectiveness in the later period. Such a conclusion would require comparable populations, tasks, measures, and research designs across both periods.

5.2 Cognitive Responsibility as a Pedagogical Mechanism

The findings concerning verification and task allocation suggest that cognitive responsibility provides a useful connection between pedagogical design and competency development. Learners may receive extensive assistance while continuing to undertake demanding intellectual work through evaluation, comparison, justification, and revision. Lai et al. (2026) illustrate why this distinction matters. Their findings challenge the assumption that delegating initial production necessarily weakens learning. The arrangement of responsibilities determines whether students continue to practise the capabilities targeted by instruction. Similarly, evidence on critical thinking in AI use directs attention to what learners do with generated information rather than the frequency with which they obtain it. For RQ2, constructivist, self-regulatory, and motivational perspectives can explain complementary aspects of this process. Knowledge construction concerns interpretation and application; self-regulation concerns planning and monitoring; and motivational perspectives concern engagement and autonomy. Their combined analytical value lies in identifying testable mechanisms. Invoking a theory alone does not establish that the proposed mechanism occurred.

5.3 Connecting Competencies with Graduate Employability

The synthesis supports a staged interpretation of the relationship between AI-enabled education and employability. Educational practices may influence task engagement and competency development; those capabilities may support career preparation; and their employment relevance depends on opportunities, professional expectations, and the conditions of application. Each relationship requires its own evidence. This interpretation addresses RQ3 while avoiding the conflation of proximal and distal outcomes. A student may report greater confidence or work readiness without demonstrating stronger independent performance. Demonstrated performance in an academic task may also fail to transfer to a professional setting with different constraints. Employment outcomes additionally depend on factors beyond educational capability, including recruitment practices and labour-market conditions.

AI literacy should therefore be understood as a capability whose value depends partly on application. The negative literacy–adoption relationship reported by Mustafa and Altrad (2026) reinforces the need to separate understanding from frequency of use. More informed learners may make different decisions about when AI assistance is appropriate; this explanation remains a proposition requiring further investigation rather than an established mechanism.

5.4 Implications for Higher Education Management

Universities can use these distinctions to align AI initiatives with explicit developmental objectives. Curriculum decisions should identify the capabilities students must demonstrate, the assistance permitted, and the evidence required to assess learning. Activities involving generated drafts or solutions can retain developmental value when students must verify evidence, explain revisions, and justify decisions. Assessment can combine AI-assisted work with opportunities to demonstrate independent understanding. Appropriate approaches may include explanation of decision processes, evaluation of competing outputs, revision records, and performance on unfamiliar tasks. Their effectiveness should be evaluated within the relevant discipline rather than assumed from their format. Institutional monitoring should also distinguish adoption indicators from developmental outcomes. Tool access, usage, and satisfaction can describe implementation, but competency assessment and career-related follow-up are needed to evaluate educational contribution. University–industry collaboration can strengthen this evaluation by connecting academic tasks with professional requirements and incorporating employer perspectives.

5.5. Limitations and Future Research

The principal limitation of the current draft is the absence of a reconciled study register linking all 44 included publications to their extraction and appraisal records. Consequently, publication distributions, thematic frequencies, study overlap, and formal quality-appraisal findings cannot yet be reported reliably. The temporal comparison remains interpretive until the included publications and their period assignments are confirmed. Further limitations concern heterogeneous outcome definitions, disciplinary settings, and research designs. These differences restrict direct comparison and prevent the estimation of a common effect from the evidence currently documented. Self-reported readiness and employability measures also require careful separation from demonstrated competence and actual employment. Future research should investigate whether capabilities developed during AI-assisted learning persist when assistance is reduced and transfer to unfamiliar professional tasks. Comparative studies should examine different allocations of learner and AI responsibility, while longitudinal designs should connect educational experiences with later workplace assessments and employment trajectories. This would strengthen understanding of how AI-enabled higher education contributes to graduate development under identifiable institutional and labour-market conditions.

6. CONCLUSION AND RECOMMENDATIONS

This review examined AI-enabled graduate talent development and employability in higher education, focusing on changes in educational applications, competency requirements, pedagogical approaches, and career preparation. The literature indicates an expansion from specialized instructional and analytical applications toward conversational assistance, generative feedback, content creation, and collaborative problem-solving. These developments broaden opportunities for learning while increasing the importance of verification, ethical judgement, and independent reasoning. The central conclusion is that AI's contribution to graduate development depends on how educational practices allocate responsibility between learners, educators, and technological systems. AI-supported activities can create opportunities for competency development when students remain actively involved in evaluating evidence, explaining decisions, and revising outputs. Technological access, frequent use, and successful completion of assisted tasks provide insufficient grounds for assuming durable learning or professional competence. The review also highlights the need to distinguish competency development, career readiness, perceived employability, and actual employment outcomes. Evidence concerning confidence, adaptive resources, and educational performance can clarify potential pathways toward workforce preparation, but it does not independently establish improved employment prospects.

The transfer of AI-supported learning into professional capability remains a question requiring direct assessment. For higher education institutions, the findings support aligning AI integration with disciplinary learning objectives, authentic assessment, faculty development, responsible-use policies, and industry expectations. Evaluation should examine both students' ability to collaborate effectively with AI and their capacity to exercise judgement independently. Institutional strategies should also account for differences in access, learner preparation, and local professional contexts. The diversity of research designs, technologies, and outcome measures limits generalisation and causal interpretation. Future research should prioritize longitudinal follow-up, comparative instructional evaluations, independent competency assessments, and employer-informed measures of professional performance. Such evidence is necessary to establish when, how, and under what conditions AI-enabled higher education contributes to sustained graduate development and employability.

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