From Digital Literacy to Artificial Intelligence Competence: An Integrative Review of Competence Development in the Education-To-Work Transition

Yang Chen, Mohamad Zuber bin Abd Majid, Ahmad Firdhaus bin Arham

Universiti Kebangsaan Malaysia p142776@siswa.ukm.edu.my

https://orcid.org/0009-0003-7633-3127

Universiti Kebangsaan（corresponding） Malaysia mzuber@ukm.edu.my

https://orcid.org/0000-0001-5434-5926

Universiti Kebangsaan Malaysia benferdaoz@ukm.edu.my （co_corresponding）

oricd 0000-0002-6740-2077

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ABSTRACT

Digital and artificial intelligence (AI) competence is increasingly important to education–employment transitions, but evidence remains fragmented. This integrative review synthesised 69 Chinese- and English-language thematic sources. Findings show that competence extends beyond technical skills to information processing, problem-solving, critical judgement, ethical responsibility and contextual application. Effective development combines formal curricula, authentic tasks, work-based learning and continuing support, while assessment requires knowledge, performance and process evidence. Employment benefits depend on competence being recognised, applied to occupational tasks and supported by appropriate job matching and organisations. A six-stage framework links resources, competence formation, assessment, task application, job matching and employment outcomes, with inequality, governance and well-being shaping the pathway.

Keywords: digital competence; AI competence; education–employment transition; competence assessment; employability; digital inequality

1. INTRODUCTION

Digital transformation is reshaping education–employment transitions as AI, automation and digital platforms alter occupational tasks. Routine work may decline while demand grows for creativity, judgement, communication and problem-solving (Kolade & Owoseni, 2022). Digitalisation also enables remote work and entrepreneurship but may intensify monitoring, insecurity and work–life conflict (Charles et al., 2022; Cramarenco et al., 2023). Meanwhile, graduates may possess theoretical knowledge and tool familiarity but lack problem-solving, knowledge application and interpersonal competence (Teijeiro et al., 2013). Education often emphasises knowledge and software operation, whereas employers require practical application, collaboration and information evaluation (Spada et al., 2022; Khatri et al., 2025).

Access to AI does not demonstrate competence. Educational value depends on objectives, tasks, teacher judgement and governance (OECD, 2021), supported by infrastructure, content, teacher capability and institutional policy (Arias Ortiz et al., 2025). AI also raises accountability questions when systems influence decisions (Mukhopadhyay & Chakrabarti, 2023). Digital and AI competence must therefore extend beyond operation to system understanding, appropriate selection, verification, risk recognition and responsibility.

Labour-market benefits are conditional. ICT skills are associated with abstract-task-intensive occupations and higher wages, but this does not establish the effects of short-term training (Falck et al., 2021). Job-oriented online learning remains context-specific (Deb et al., 2023), while AI job-search tools may require guidance, training and continuing support (Sanguino et al., 2025). Competence must be developed, demonstrated, applied, recognised and organisationally supported before contributing to employment.

These processes are unequal. Digital inequality concerns access, use conditions, competence and outcomes (Selwyn, 2004), while participation depends on material, digital, human and social resources (Warschauer, 2004). Inequalities vary by socioeconomic position, gender, geography, age, education and language (Martin et al., 2026). Pandemic disruption exposed infrastructure and support gaps (Christanti et al., 2024; Golden et al., 2023); digital exclusion may restrict autonomy and public-service access (Ji & She, 2026); and commercial platforms raise concerns about data control, teacher autonomy and public responsibility (Williamson & Hogan, 2020). Inequality, governance and well-being therefore shape the competence-to-employment pathway.

Research remains fragmented across digital literacy, digital competence, AI literacy and AI competence and often separates definitions, educational mismatch, development, assessment and employment outcomes. This integrative review addresses that fragmentation through three connected themes: competence and education–employment mismatch; competence development and assessment; and translation into employment outcomes. It traces how competence is formed, demonstrated, applied, recognised and converted into employment benefits, while examining inequality, organisational support, governance and job quality as cross-cutting conditions. These themes structure the Results, and the Discussion integrates their implications.

2 METHOD

2.1 Review Design and Scope

This integrative review examined digital and AI competence across education–employment transitions. It included empirical studies, interventions, competence frameworks, assessment instruments, reviews, scholarly chapters and institutional reports from education, human resource development, labour economics, psychometrics and digital inequality research.

The review combined SALSA (Grant & Booth, 2009), Snyder's (2019) review classification, Whittemore and Knafl's (2005) integrative review process and Torraco's (2005) critical synthesis approach. PRISMA 2020 guided the reporting of source identification and selection (Page et al., 2021). Conceptual and methodological heterogeneity precluded meta-analysis. These five methodological sources informed the review process but were excluded from thematic coding and evidence counts.

2.2 Search Strategy and Study Selection

Scopus, Web of Science, ERIC and CNKI were searched for Chinese and English language publications from January 2000 to May 2026. Google Scholar, institutional websites and backward and forward citation tracking were used to identify additional academic and policy sources, including reports from the OECD, European Commission, International Labour Organization and UNESCO.

Searches combined terms covering digital literacy, digital competence, digital skills, ICT skills, digital fluency, AI literacy and AI competence; education, training, students, graduates, employees and workplaces; and assessment, competence development, skills mismatch, job matching, employability, wages and digital inequality. Equivalent Chinese terms were used. Term selection was informed by Tinmaz et al. (2022), Ng et al. (2021), Cramarenco et al. (2023), Sperling et al. (2024), Lintner (2024), Mikeladze et al. (2024), Nyale et al. (2024) and Martin et al. (2026). Terms within each group related to OR and the groups with AND.

Eligible sources examined digital or AI literacy, skills or competence in relation to education–employment mismatch, development, assessment, occupational application, employment or inequality. Studies limited to algorithms, devices, software performance or general technology adoption were excluded, as were unverifiable materials and sources without accessible full texts. Directly relevant preprints were retained only when no published version was available and were not used to support causal or intervention-effectiveness claims. Published versions replaced corresponding preprints, while findings reported in both reviews and original studies were interpreted only once.

The searches identified 492 records. After 301 duplicates were removed, 191 records underwent title, abstract and, where necessary, full-text screening. A further 122 were excluded, leaving 69 thematic sources. The reference list contains 74 sources because the five methodological sources informed the review design but were not included in the thematic evidence base

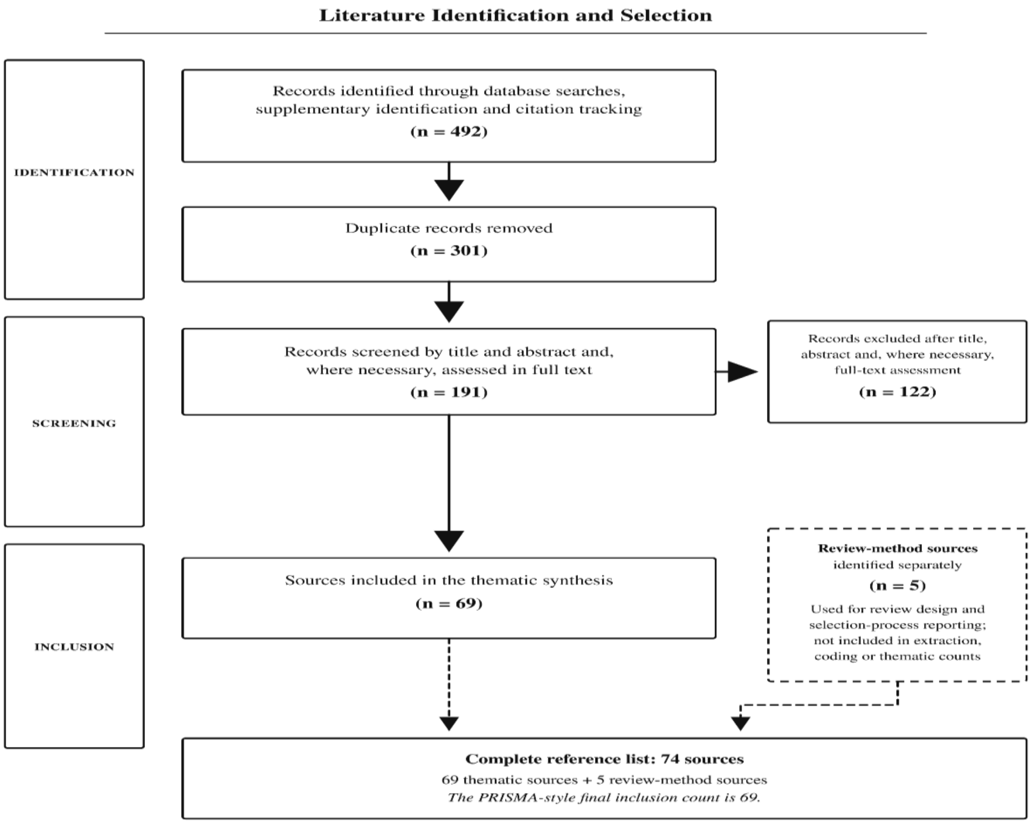

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Figure 2.1. Identification, screening and inclusion of sources

Note: Five additional review-method sources informed the research design and reporting procedures but were not included among the 69 thematic sources.

2.3 Data Extraction, Appraisal and Synthesis

Standardised records captured publication context, design, population, competence concepts, educational and occupational settings, development approaches, assessment methods, employment outcomes and study limitations. Extraction was organised around three themes: competence and education–employment mismatch; competence development and assessment; and translation into employment outcomes. Digital resources, organisational support, well-being, platform governance and algorithmic bias were coded as cross-cutting conditions, consistent with Ng et al. (2021) and Sperling et al. (2024). Sources could receive multiple codes without receiving greater evidential weight.

Quality appraisal was adapted to source type. Empirical studies were assessed for alignment among questions, samples, measures, analyses and conclusions; interventions for content, implementation and outcomes; frameworks for conceptual clarity and contextual relevance; reviews for search and synthesis procedures; and institutional reports for issuer, data and scope. Preprints were assessed for verifiability, reporting completeness and publication status. Assessment instruments were examined for validity, reliability, measurement error, invariance and responsiveness. Because AI literacy research relies heavily on self-report (Lintner, 2024), self-assessment, knowledge tests and authentic-task performance were treated as distinct evidence. Methodologically limited studies informed description but not causal conclusions.

Following Whittemore and Knafl (2005), sources were organised in a study–theme matrix and synthesised through descriptive mapping, thematic analysis and cross-study comparison. Comparisons examined competence definitions, educational preparation, employer requirements, assessment evidence, occupational application and employment outcomes. Differences between self-report and performance measures were treated as measurement discrepancies rather than automatically interpreted as competence gaps.

The synthesis followed a common pathway from competence formation and assessment to occupational application, recognition, job matching and employment outcomes. Digital inequality, organisational support, governance and well-being were examined across the pathway, including learning pressure and work–life disruption (Cramarenco et al., 2023) and teacher, institutional and industry conditions (Nyale et al., 2024). This pathway is an analytical synthesis rather than a universal causal sequence.

2.4 Review Limitations

Restricting the review to Chinese- and English-language sources and selected databases may have excluded relevant regional evidence. Supplementary searches broadened coverage but were less reproducible than database searches. Differences in concepts, populations, measures and outcomes prevented effect-size synthesis, while cross-sectional, self-report and short-term studies limited causal interpretation. Preprints received restricted evidential weight. The resulting pathway therefore requires performance-based, longitudinal and cross-contextual validation.

3 RESULTS

The 69 thematic sources produced three connected themes: the changing meaning of digital and AI competence and its mismatch with employment requirements; the development and assessment of competence; and its translation into employment and job-quality outcomes. Across the evidence, competence was not treated as a direct predictor of employment. Its value depended on whether it could be developed, demonstrated, applied to occupational tasks, recognised and supported within labour-market and organisational conditions.

3.1 Competence and Education and Employment Mismatch

Digital capability has expanded from device and software operation to information evaluation, communication, content creation, problem solving and responsible participation. Tinmaz et al. (2022) distinguish digital literacy, competence, skills and thinking, while Mattar et al. (2022) identify overlaps with information, media, computer and data literacy, digital citizenship and 21st century skills. These concepts are related but not interchangeable: skills concern specific operations, literacy adds informed participation, and competence integrates knowledge, skills and attitudes in contextual tasks. Digital competence accordingly combines technical, cognitive and behavioural dimensions (Morgan et al., 2022) with information management, communication, collaboration, creativity and problem solving (Van Laar et al., 2020), mobilised within workplace tasks (Oberländer et al., 2020).

DigComp 2.2 provides a common foundation through information and data literacy, communication, content creation, safety and problem solving (Vuorikari et al., 2022), but general frameworks only partially represent occupational performance. DigComp gives limited attention to practical data use, fairness and environmental and social consequences (Van Audenhove et al., 2024). Framework based self-report instruments may not demonstrate authentic performance (Tzafilkou et al., 2022), application varies across educational and technological contexts (Reddy et al., 2023), and preservice teacher frameworks require further validation (Rakisheva & Witt, 2023). Workplace models therefore incorporate organisational innovation (Blanka et al., 2022), role specific profiles (Piętowska-Laska & Laska, 2025), industrial equipment, software, production data and occupational standards (Zhao & Wang, 2025), or craftsmanship and agile development (Zhu et al., 2025). Although incompletely validated, these models demonstrate the need to connect general competence with professional systems, workflows and responsibility.

AI literacy extends these foundations through understanding and evaluating AI systems, data, outputs and ethical implications. Ng et al. (2021) organise it around understanding, application, evaluation, creation and ethics, while Choi et al. (2025) emphasise knowledge, practical skills and ethical attitudes, although their preprint remains emerging evidence. Chiu et al. (2024) distinguish basic knowledge from competence involving application, confidence, reflection and continued learning. AI competence consequently adds task and tool selection, verification, bias recognition, coordination between humans and AI, and accountability. Professional applications also include teaching, assessment and learner development (Ng et al., 2023), yet frameworks often privilege theory and tool use over practical judgement and ethics (Sperling et al., 2024). Conceptual and empirical models require stronger authentic validation (Mikeladze et al., 2024), while governance, professional learning and implementation readiness make competence partly institutional (Daher, 2025).

This expansion reframes education and employment mismatch as differences in competence composition, application, occupational context, assessment signals and opportunities for use. Gaps between graduates and employers occur in problem solving, knowledge application, independent work and interpersonal competence (Teijeiro et al., 2013), with variation across disciplines (Pažur Aničić et al., 2023). Graduates may emphasise tools, whereas employers prioritise problem solving, collaboration and work management (Khatri et al., 2025). Malaysian employers similarly reported gaps in communication, problem solving and safety (Tee et al., 2024a), while recognising that digital competence and microcredentials do not demonstrate overall employability (Tee et al., 2024b). Marketing job advertisements also contained broader requirements than university curricula (Spada et al., 2022), while earlier manufacturing research identified differences between universities and industry whose age and sector limit generalisation (Eggert, 2006). Occupational decisions may integrate equipment, data, quality, cost and environmental effects, although Pacana and Siwiec (2025) examined production decisions rather than mismatch directly.

Digitalisation intensifies misalignment as automation increases demand for creativity, judgement and complex problem solving (Kolade & Owoseni, 2022). Digital skills must be combined with occupational knowledge, communication, adaptability and self regulation (Charles et al., 2022; Poláková et al., 2023; Mukherjee, 2023), while AI adds verification, data protection and accountability. Limited practice and weak signals compound the problem: macro level associations between education and employment do not identify effective learning approaches (Picatoste et al., 2018); work integrated learning and digital collaboration are associated with perceived employability or creativity without establishing causality (Adegbite, 2024; Kholifah et al., 2025); and certification may provide only a short term recruitment advantage (Sengupta et al., 2023). Education and employment mismatch is therefore cumulative misalignment among competence content, authentic practice, occupational requirements, assessment evidence and opportunities for application.

3.2 Competence Development and Assessment

The evidence supports a connected process linking foundations, authentic practice, assessment, transfer and continued learning rather than reliance on one course or credential. It favours combining transferable digital, data, safety and AI knowledge with occupational tasks. Reddy et al. (2023) reported a Cohen's d of 0.473 for overall digital literacy following the DLIP intervention, with effects varying across modules. A seven-hour course improved AI knowledge, self reported literacy and empowerment without demonstrating professional application (Kong et al., 2021). Measures of familiarity, anxiety, barriers and intention can guide support but do not establish task competence (Lazar et al., 2020).

AI can support explanations, feedback and error diagnosis, but its value depends on objectives, task design and human oversight (OECD, 2021). AI assisted engineering instruction improved reports, participation and data analysis but not final examinations, while conventional instruction was stronger for some practical problem-solving outcomes (Wan et al., 2025). Reviews likewise identify personalisation and immediate feedback alongside constraints involving teacher preparation, infrastructure, integrity, bias and cultural suitability (Ximenes, 2025). Structured prompts, expert examples and revision can improve AI supported task design, but expert review remains necessary (Li et al., 2026). Product quality, knowledge and independent performance therefore represent distinct outcomes.

Teachers require technical, pedagogical and ethical competence to organise collaboration between humans and AI and assess processes as well as products (Ng et al., 2023). Preservice teachers viewed AI as supportive rather than a substitute for interaction, but perception based evidence did not demonstrate improved teaching performance (Altinay et al., 2024). Governance, professional learning and partnerships shape implementation readiness (Daher, 2025), while devices, connectivity, platforms, teacher competence and policy form an interdependent system (Arias Ortiz et al., 2025). Accountability also requires learners to disclose AI contributions, verify consequential claims and explain revisions because of risks involving errors, bias, dependence and plagiarism (Yusuf et al., 2024). Recruitment data may inform curriculum renewal but only partially represent actual work (Nyale et al., 2024).

Work based learning provides a more direct setting for transfer. It was associated with perceived employability, although digital literacy was only a weak partial mediator (Adegbite, 2024). Zhao and Wang (2025) proposed a pathway linking assessment, learning, practice and evaluation through diagnosis, differentiated curricula, collaboration between universities and industry, mentoring and AI coaching, but it requires longitudinal evaluation. Informal and peer learning also support adaptation (Picatoste et al., 2018), while organisational time and support are important because continued upskilling may intensify obsolescence pressure and conflict between work and personal life (Cramarenco et al., 2023).

Assessment determines whether development produces credible evidence. Five evidence levels emerged: perception and readiness, knowledge, task performance, behavioural transfer and external outcomes. Self report captures confidence and perceived competence; tests assess specified knowledge; performance tasks demonstrate application in sampled activities; portfolios, process records and observation indicate transfer; and longitudinal data connect competence with external outcomes. Employment and income remain influenced by contextual conditions and are not direct measures of competence.

Self report is efficient for diagnosis but sensitive to self awareness, reference standards and social desirability. The Student Digital Competence Scale covers information access, creation, communication, data management, evaluation and protection (Tzafilkou et al., 2022), while Morgan et al. (2022) reported lower perceived information evaluation ability than online communication. Neither finding demonstrates performance. Lintner (2024) similarly found that 13 of 16 AI literacy instruments relied mainly on self report and only three used performance measures. Validation focused on structural validity and internal consistency, with weaker evidence for content validity, reliability, measurement error, responsiveness and cross cultural validity.

Knowledge tests provide stronger evidence but still limit interpretation. Hornberger et al. (2023) assessed AI applications, machine learning, training data, representativeness, black box problems and ethics, but not open-ended tool selection, verification or responsibility. Chiu et al. (2024) distinguished understanding, impact, ethics, collaboration, reflection and confidence, which should not be combined without empirical support. Performance tasks assess application more directly. Pagani et al. (2016) used authentic web content to test source evaluation and online risk judgement, but the tasks did not demonstrate workplace transfer. Professional assessment is therefore better represented by complementary projects, portfolios, products, observation and interviews (Dowlen, 2016).

Generative AI further complicates assessment because a strong product may conceal weak understanding. Unaided tasks can assess foundations and independent judgement, while tasks involving humans and AI can assess the fit between tools and tasks, verification, revision and responsibility. Process records, oral explanation and live correction provide evidence of authorship and reasoning, although logs may be incomplete or dependent on platforms. Occupational measures also require contextualisation. Manufacturing indicators (Zhao & Wang, 2025) and the digital craftsperson scale (Zhu et al., 2025) incorporate professional systems but do not independently establish authentic performance, stability or occupational prediction.

Validity depends on score use as well as instrument design. Assessment requires adequate content coverage, reliability, measurement error, invariance, task sampling, scoring and interrater agreement. Devices, connectivity, AI versions, permissions and prior experience should be documented because scores may otherwise reflect technological conditions. Although not evidence about digital competence, Hanushek and Rivkin (2010) illustrate the risks of measurement error and model dependence in high-stakes interpretation. Overall, assessment is strengthened by combining knowledge, performance and process evidence rather than substituting one score for another.

3.3 Translation into Employment Outcomes

The reviewed evidence suggests that employment returns depend on competence being applied, recognised and organisationally supported. Organisational uptake requires suitable technologies, processes, tasks, authority, teamwork, management and learning opportunities. Blanka et al.'s (2022) DigiTransComp framework connects employee competence with digital transformation. Among 999 firms in 27 countries, organisational digital capabilities affected performance indirectly through technological capabilities rather than directly (Heredia et al., 2022). Firm-level performance, however, does not establish individual wage or career returns.

Recognition and matching form a second condition. Alignment between graduate capabilities and employer requirements has been associated with improved employment prospects, although much of the evidence relies on perceptions (Teijeiro et al., 2013). Credentials may reduce recruitment uncertainty but cannot replace task evidence. Graduates narrowly passing a programming-certification threshold obtained a short-term job-search advantage but no significant long-term employment or income benefit (Sengupta et al., 2023). AI can analyse vacancies and recommend positions, but it does not eliminate mismatch. Among 1,039 European participants, AI job-search tools showed no stable significant relationship with field-of-study–job matching (Sanguino et al., 2025). The cross-sectional design does not establish ineffectiveness but indicates that technological matching cannot be separated from reliable competence data, guidance, training and mentoring.

Economic evidence indicates labour-market value for digital competence, although its magnitude and mechanisms vary. Across 19 countries, ICT skills were associated with higher wages, movement into abstract-task-intensive occupations and reduced routine and physical work; occupational selection accounted for approximately two-thirds of the estimated wage effect (Falck et al., 2021). The measure represented technology-rich problem-solving rather than comprehensive digital or AI competence and did not estimate the effect of short-term training. Across 32 European countries, communication and collaboration, content creation and safety were associated with national employment rates (Đorđević et al., 2025). These aggregate relationships do not predict individual employment and may also reflect economic development, education and labour-market institutions.

Returns also differ across skills and groups. Sri Lankan labour-force data associated digital literacy with income, with variation by age, gender, education, employment and residence, although measurement and endogeneity limited causal interpretation (Perera et al., 2026). Chinese rural data linked digital skills with income, particularly online business, work and learning skills, through possible employment, entrepreneurship and credit channels (Wang et al., 2025). Digital literacy was also associated with a lower risk of returning to poverty, with employment channels stronger than entrepreneurship and learning literacy more influential than entertainment literacy (Zhou et al., 2024). These observational findings suggest that returns depend on competence type and local access to jobs, markets, finance and infrastructure.

Digital inequality operates throughout this process. It includes conditions of access, use, competence and outcomes rather than device availability alone (Selwyn, 2004). Meaningful participation also depends on appropriate content, language, knowledge and family, community and institutional support (Warschauer, 2004). Workplace research has concentrated more on access and skill gaps than on the longer relationship among motivation, self-efficacy, application and employment (Martin et al., 2026). Similar courses, assessments or credentials may therefore produce different returns across regions and groups.

Employment quantity cannot substitute for quality. Digitalisation may create remote, platform and entrepreneurial opportunities while increasing monitoring, insecurity, income volatility and inadequate social protection (Charles et al., 2022). AI-related upskilling may also intensify cognitive demands, stress and work–life conflict (Cramarenco et al., 2023). Relevant outcomes therefore include stability, autonomy, career development, social protection and well-being alongside employment and income.

Table 3.1 integrates the three Results themes into a six-stage pathway. It represents an analytical synthesis of heterogeneous evidence rather than a causal sequence validated by a longitudinal study.

Table 3.1 Analytical Competence-to-Employment Pathway

Stage	Core mechanism	Main constraint
Resources and opportunities	Access to technology, learning, practice and support	Resource, language, regional and group inequality
Competence formation	Digital and AI foundations combined with authentic and work-based learning	Weak task alignment, limited practice and insufficient guidance
Assessment and signalling	Knowledge, performance and process evidence, supported where appropriate by credentials	Self-report dependence, incomplete validity evidence and weak signals
Occupational application	Integration with professional knowledge, technologies, workflows and responsibility	Limited experience, task mismatch and inadequate authority
Matching and organisational uptake	Recognition, suitable jobs, integrated systems and management support	Biased matching, inflexible processes and weak organisational support
Employment and job quality	Employment, income, mobility, stability, autonomy and well-being	Labour-market segmentation, platform risks, weak protection and unequal returns

Taken together, the findings identify a conditional pathway in which competence must be developed through learning and practice, demonstrated through credible assessment, applied in occupational tasks, recognised and matched with suitable work, and supported organisationally before employment benefits can emerge. Inequality, governance and job quality shape every stage.

4. DISCUSSION

4.1 Integrated Interpretation of the Competence-to-Employment Pathway

The review identifies digital and AI competence as a contextual capability rather than a collection of technical skills. Digital competence integrates information processing, communication, collaboration, problem-solving and responsible participation, while AI competence adds system understanding, output verification, human–AI coordination and accountability. Competence therefore depends not only on what individuals know but also on whether they can apply that knowledge within specific tasks, technologies and professional standards.

This interpretation reframes education–employment mismatch as an alignment problem rather than a simple competence deficit. Educational content and assessment may emphasise knowledge and software operation, whereas workplaces require integrated task completion, collaboration, exception handling and responsibility. Workplace competence accordingly combines technical operations with information management, critical thinking, creativity and problem-solving (Van Laar et al., 2020). Employer evidence also indicates demand for data handling, problem-solving, content creation, safety and collaboration (Tee et al., 2024a). National competence–employment associations support broad labour-market relevance but cannot establish individual or course-level effects (Đorđević et al., 2025).

The competence-to-employment pathway explains why competence alone does not guarantee employment benefits. Learning, assessment, occupational application, recognition, job matching and organisational support are interconnected rather than strictly linear: workplace experience may reshape competence, assessment may reveal development needs, and technological change may require renewed learning. The pathway is therefore an integrated analytical explanation, not a universal taxonomy or validated causal model. It connects areas often examined separately and clarifies why isolated courses, AI platforms or credentials cannot independently resolve education–employment mismatch.

4.2 Curriculum, Assessment and Qualification Reform

Curriculum renewal should combine vacancy data, employer surveys, graduate tracking, occupational standards and task analysis because each provides only a partial view of work. General competence frameworks can establish transferable foundations but cannot replace occupational analysis. Industrial models incorporate equipment, production data, enterprise systems and professional standards (Zhao & Wang, 2025), while digital-craftsperson models connect professional foundations with digital literacy, agile transformation and continued development (Zhu et al., 2025). These approaches improve contextual relevance but still require validation against authentic performance. DigComp also gives uneven attention to practical data use, equity and environmental consequences (Van Audenhove et al., 2024).

Curricula should consequently be organised around complete tasks integrating problem definition, data use, tool selection, AI verification, collaboration and risk judgement under constraints of quality, cost, time and accountability. Projects, portfolios, products, presentations, interviews and performance tasks can provide complementary evidence when validity, fairness, authorship and occupational relevance are addressed (Dowlen, 2016). Authenticity requires correspondence among the intended competence, task demands and assessment evidence rather than the reproduction of every workplace condition.

AI-supported learning should progress from tool use to system understanding, strategic application, verification, ethics and reflection (Chiu et al., 2024; Choi et al., 2025). Learners should disclose AI contributions, document consequential verification and revision, and justify final decisions. Structured objectives, expert examples and iterative revision can improve AI-assisted task design, but disciplinary accuracy, cultural suitability, fairness and feasibility still require human review (Li et al., 2026; OECD, 2021).

Assessment must distinguish confidence, knowledge and demonstrated performance. Self-report can identify perceived competence and learning needs but should not determine high-stakes decisions, particularly because AI-literacy instruments provide uneven evidence for content validity, reliability, measurement error, responsiveness and cross-cultural comparability (Lintner, 2024). Knowledge tests, situational judgement, performance tasks, process records and professional feedback should therefore be combined according to the intended interpretation. Unaided tasks can assess foundational knowledge and independent judgement, while human–AI tasks can examine tool selection, verification, revision and responsibility. Process evidence, oral explanation and live revision are especially important when a strong product may conceal weak understanding or uncertain authorship.

Qualifications and microcredentials can document short or work-based learning but do not necessarily demonstrate employability (Tee et al., 2024b). Certification may provide an initial recruitment signal without sustained employment or income benefits (Sengupta et al., 2023). Credentials should therefore specify standards, task content, proficiency and assessment methods and be connected with portfolios, placements and occupational requirements (Dowlen, 2016; Mukherjee, 2023). Technical verification confirms that a credential exists, not that its assessment was authentic or that learning transfers to work (OECD, 2021).

4.3 Institutional Readiness, Governance and Equity

Reform depends on teacher and institutional readiness as well as curriculum design. Teachers must connect technology with disciplinary aims, learner differences and assessment requirements. Existing frameworks offer useful dimensions but provide limited evidence concerning classroom judgement, longitudinal development and cross-cultural application (Rakisheva & Witt, 2023; Sperling et al., 2024; Mikeladze et al., 2024). Professional learning should therefore cover verification, assessment design, privacy, academic integrity, fairness and responsibility rather than tool operation alone.

Institutional readiness requires infrastructure, technical support, curriculum time, data policies and continuing review. The EQUIP framework links ethical governance, professional development, partnerships and implementation readiness (Daher, 2025), while system-readiness research connects students, teachers, policy, infrastructure and data governance (Kulesa et al., 2025). Devices, connectivity, teacher capability and governance must likewise be treated as an interdependent system (Arias Ortiz et al., 2025). Because these frameworks guide implementation without establishing causal effectiveness, institutions should monitor both implementation conditions and learner outcomes.

Platform governance should address data minimisation, intellectual property, cross-border transfer, portability, provider dependence, human oversight, incident reporting, correction, appeals and exit arrangements. Commercial platforms may expand access while increasing private influence over curricula, assessment and learner data (Williamson & Hogan, 2020). AI recommendations affecting education or employment should therefore remain explainable and subject to human review.

Equity must be evaluated across access, meaningful use, competence and outcomes (Selwyn, 2004). Participation depends on material, digital, human and social resources rather than connectivity alone (Warschauer, 2004). The long-term relationship among motivation, competence application and employment remains underexamined (Martin et al., 2026), while AI-related upskilling may increase stress, insecurity and work–life conflict (Cramarenco et al., 2023). Institutions and employers should provide differentiated support and protected learning time and monitor workload, autonomy, well-being and job quality.

Responsibility is consequently distributed. Educational institutions should connect foundations with authentic tasks and career guidance; assessment bodies should produce verifiable occupational evidence; employers should provide suitable technologies, feedback and continued development; and governments should support infrastructure, employment services, social protection and algorithmic governance. Coordination is essential because failure at one stage can prevent competence from producing equitable employment benefits.

4.4 Evidence Limitations and Research Priorities

Four limitations characterise the evidence base. First, frequent reliance on cross-sectional self-report data limits conclusions about task performance. Second, educational research often measures short-term knowledge, confidence or product quality without tracing occupational transfer. Third, individual-, organisational- and national-level findings are not interchangeable: firm performance does not establish employee returns, and national associations do not predict individual employment. Fourth, direct evidence connecting AI competence with employment, income and job quality remains limited. Conceptual, measurement and governance frameworks also require stronger validation across institutions, industries and regions.

Future research should follow learners from curricula, projects, placements and certification into task performance, employment, career development and well-being. It should combine knowledge tests, authentic tasks, process records, organisational data and longitudinal employment information and examine how recognition, job matching and organisational support mediate outcomes. Research should also compare independent and AI-assisted performance; test the fairness, responsiveness, invariance and predictive validity of assessment and matching; and evaluate teacher development, microcredentials and governance arrangements separately and in combination. Differences by gender, education, region, industry and employment type should be examined without assuming equal returns from equivalent competence.

5. CONCLUSION

Digital and AI competence is not demonstrated by access, confidence or tool operation alone. It involves the integration of knowledge, technical skills, critical judgement, collaboration and ethical responsibility within contextualised tasks. AI extends digital competence by requiring understanding of system limitations, appropriate tool selection, output verification, human–AI coordination and accountability.

Education–employment mismatch arises when competence definitions, curricula, practice opportunities, assessment evidence and occupational requirements are misaligned. Addressing it therefore requires more than additional courses or credentials. Competence must be developed through authentic and work-based learning, demonstrated through complementary knowledge, performance and process evidence, applied in occupational tasks, recognised through recruitment and qualifications, and supported by organisational systems.

The review's principal contribution is an integrated competence-to-employment pathway linking resources, competence formation, assessment, occupational application, matching and employment outcomes. Digital inequality, governance, organisational support and job quality affect every stage. The pathway is an analytical synthesis rather than a validated causal model, but it explains why similar competence may produce different outcomes across learners, occupations and regions.

Effective reform requires a coordinated and revisable system connecting occupational demand, authentic curricula, credible assessment, transparent qualifications and suitable work. Institutional readiness, platform governance, equity and well-being must support this system. No single course, platform, credential or policy can achieve these outcomes independently.

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