

Automation Adoption and AI for Future Employability: The Mediating Roles of AI Literacy and Digital Readiness in Vocational Education

Dr. Rogayah Ali Mousa Sharadgah

Faculty of Educational Sciences, Jerash University, Jordan. r.shradgah@jpu.edu.jo. 0009-0002-2434-6594

Dr. Tareq Atef Ali AL-Shboul

Faculty of Educational Sciences, Jerash University, Jordan. T.Al-shbul@jpu.edu.jo. 0009-0005-3896-0490

Dr. Zaid Daher Khalaf Hazaimah

Faculty of Educational Sciences, Irbid National University, Jordan. z.hazaimah@inu.edu.jo. 0000-0003-2779-5520

Dr. Bassam Ahmad Ajlouni

Faculty of Educational Sciences, Irbid National University, Jordan.
bassam.ajlouni@inu.edu.jo. 0009-0004-1399-4179

Abstract

The rapid development of global artificial intelligence and automation technologies is profoundly reshaping skill demands in the labor market, bringing entirely new transformation challenges to vocational education systems in all countries. This empirical study focuses on the vocational education sector in developing countries, taking Jordan's vocational education and training system as its research setting. Centering on the core variables of AI and automation adoption, AI literacy, digital readiness, and future employability, the study tests the direct effect of AI and automation adoption on AI literacy and digital readiness, as well as the mediating role of these two variables between AI and automation adoption and future employability. This study adopts a quantitative cross-sectional survey to investigate students at Jordan's vocational education institutions, and 257 valid questionnaires were collected. Analysis using the partial least squares structural equation model in SmartPLS 4 shows that all path coefficients are statistically significant: AI and automation adoption exerts a significant positive impact on AI literacy ($\beta=0.533$, $p<0.001$) and digital readiness ($\beta=0.507$, $p<0.001$); both AI literacy ($\beta=0.451$, $p<0.001$) and digital readiness ($\beta=0.441$, $p<0.001$) significantly improve future employability. The mediating effects are confirmed. The model can explain 51.1% of the variance in future employability, indicating strong predictive power. This study not only addresses the gap in empirical literature in this field, but also provides decision-making references for relevant stakeholders.

Keywords: Future Employability; Digital Readiness; AI Literacy; Automation; Vocational Education; PLS-SEM; Jordan.

1. Introduction

The rapid advancement of artificial intelligence (AI) and automation technologies is fundamentally transforming global production systems and labor markets. While the Fourth Industrial Revolution has created significant opportunities for industrial development and innovation, it has also introduced substantial challenges related to workforce adaptability and employment sustainability (Philbeck & Davis, 2018; Dwivedi et al., 2021, Jango and Mohamed, 2025). More recently, the widespread adoption of generative AI has broadened the

scope of automation, placing even occupations previously considered resistant to technological replacement within the reach of rapid technological change (Brynjolfsson et al., 2025, Amayreh et al., 2026). Vocational education institutions, as major providers of skilled human capital for the labor market, are particularly affected by these transformations (Al Matrooshi et al., 2025). Previous studies indicate that traditional vocational education systems often struggle to keep pace with rapid technological developments and evolving labor market demands (Lund et al., 2021; Faishal et al., 2023). Contemporary labor markets increasingly require workers to possess a broad range of competencies that extend beyond technical expertise (Shboul, 2024). Among these competencies, digital readiness has emerged as a critical foundation for enabling individuals to adapt to and effectively utilize emerging technologies (Kutnjak et al., 2020; Chounta et al., 2024). Evidence further suggests that individuals with higher levels of digital readiness possess greater competitive advantages in employment and career development (Sousa & Rocha, 2019; Sánchez-Canut et al., 2023). Nevertheless, existing research examining the antecedents and consequences of digital readiness remains fragmented, particularly within the context of vocational education.

Alongside digital readiness, AI literacy has emerged as an increasingly important and distinct competency in the contemporary technological environment (Al-Zaqeba et al., 2026). AI literacy refers to an individual's ability to understand, critically evaluate, and effectively use AI systems while recognizing their opportunities, limitations, and ethical implications (Southworth et al., 2023; Wu et al., 2024). Recent research further suggests that AI literacy plays an important role in shaping how individuals respond to technological change and utilize AI to enhance job performance and employment opportunities (Al-Zaqeba, 2025, Mustafa & Altrad, 2026). However, the mechanisms through which AI literacy contributes to employability remain subject to debate. While some studies emphasize its direct contribution to workforce competitiveness (Fareri et al., 2020), others suggest that its effects may depend on complementary capabilities, including digital readiness and organizational support (Chowdhury et al., 2022, Ababneh et al., 2023).

Despite the growing body of literature on AI adoption, digital readiness, AI literacy, and employability, several important research gaps remain. First, previous studies have largely examined these constructs independently (Al-Zaqeba & Basheti, 2024, Al-Taani et al., 2025), with limited attention given to their interrelationships within vocational education. Existing research has predominantly focused on higher education institutions, corporate settings, and technology-intensive industries, whereas vocational education (which plays a central role in workforce preparation and development) has received comparatively limited attention (Williamson & Eynon, 2020; Sharadgah et al., 2025).

Second, the mechanisms through which AI and automation adoption influence future employability remain insufficiently understood (Ayoub and Abd Rahman, 2026). Much of the existing research focuses primarily on direct relationships between technological adoption and employment-related outcomes (Al Obaidy et al., 2024). Consequently, the potential mediating roles of AI literacy and digital readiness in transforming technological adoption into enhanced employability have received limited empirical attention (Aloqaily et al., 2024a).

Third, empirical research examining these relationships within the Middle Eastern context, particularly in Jordan, remains scarce. Jordan has increasingly incorporated digital transformation, technological innovation, and vocational education reform into its national economic development agenda and has introduced initiatives aimed at strengthening digital skills within the education system (Al-Qasbi, 2024). Nevertheless, concerns remain regarding whether vocational education students possess sufficient AI-related and digital competencies to meet the rapidly evolving requirements of the labor market. More broadly, there is limited empirical evidence from the Middle East regarding the mechanisms through which AI and automation adoption may influence employability through the development of individual

technological competencies (Hamour et al., 2023, Jebril et al., 2024). Accordingly, this study seeks to address these gaps by examining the relationships among AI and automation adoption, AI literacy, digital readiness, and student employability within the context of vocational education in Jordan. Specifically, the study investigates whether AI literacy and digital readiness mediate the relationship between technology adoption and student employability. By integrating these four constructs into a single conceptual framework, the study aims to contribute to the literature on vocational education, technological transformation, and workforce development, while providing empirical evidence relevant to the development of vocational education policies and practices in Jordan and similar emerging contexts.

2. Literature Review

AI and automation technologies are rapidly expanding across contemporary organizational and educational environments, fundamentally reshaping academic and policy discussions surrounding digital capability development, workforce readiness, and future employability. Against this background, the present study adopts a systematic literature review approach, focusing on four interrelated constructs: AI and automation adoption, digital readiness, AI literacy, and future employability (Al-Hassan, 2023; Almansour et al., 2026; Al-Shouh & Al-Darawsheh, 2024; Al-Zaqeba et al., 2026; Alzeyoudi & Ineizeh, 2025; Ayman, 2025; Elagha et al., 2025; Hazaimah, 2025; Qahman et al., 2026; Maabreh et al., 2026). The review systematically synthesizes and organizes the core literature relevant to these constructs, identifies their conceptual boundaries and interrelationships, and highlights the key theoretical and empirical developments within the field. In doing so, it clarifies the research positioning and underlying logic of the present study and establishes a coherent conceptual foundation for the subsequent analysis of the literature.

2.1 Artificial Intelligence and Automation Adoption

2.1.1 Conceptualization and Definitional Evolution

Since the emergence of the Fourth Industrial Revolution, the conceptualization of artificial intelligence (AI) and automation adoption has undergone significant development. Philbeck and Davis (2018) highlighted a shift from narrow, technology-centered perspectives toward broader and more multidimensional frameworks that incorporate organizational, cognitive, and societal dimensions. Early conceptualizations, largely rooted in information systems and operations management (Shubailat et al., 2024), primarily focused on the implementation of technologies such as machine learning and robotic process automation within specific functional areas, including supply chain management, finance, and customer service (Canhoto & Clear, 2020; Bhattacharya, 2021). However, this relatively narrow perspective was increasingly challenged because it did not adequately capture the broader organizational and institutional transformations associated with AI adoption (Dwivedi et al., 2021; Berente et al., 2021).

More recent research has therefore proposed broader frameworks for understanding AI adoption. Fountaine et al. (2019), for example, conceptualized AI adoption as a progressive organizational process ranging from the implementation of isolated AI applications to the integration of AI across organizational processes and, ultimately, to the development of AI-enabled organizational structures. Similarly, Huang and Rust (2021) proposed a functional framework that categorizes AI according to mechanical, analytical, intuitive, and empathetic capabilities. These categories reflect different forms of human–AI interaction and suggest that AI adoption involves varying levels of organizational transformation and human–machine collaboration.

The emergence of generative AI has further expanded the conceptual boundaries of AI and automation adoption. Unlike earlier forms of automation that primarily focused on routine and

structured tasks, generative AI has increasingly demonstrated the capacity to augment or automate complex cognitive and knowledge-intensive activities (De Cremer et al., 2023; Brynjolfsson et al., 2025). This development has intensified academic interest in understanding how AI adoption may reshape organizational structures, occupational roles, skills, and employment opportunities.

Despite these advances, important gaps remain in the literature. In particular, the distributional and inequality-related consequences of AI adoption have received comparatively limited attention. Existing research on the labor market effects of automation provides an important foundation for addressing this issue. Acemoglu and Restrepo (2022) developed a framework based on the processes of task displacement and task reinstatement, demonstrating that the employment consequences of technological change may vary across occupations, skill levels, and institutional contexts. Similarly, Bessen et al. (2020) emphasized that the effects of automation on employment and wages are influenced not only by technological capabilities but also by the institutional and regulatory environments in which these technologies are implemented.

2.1.2 Theoretical Frameworks Underpinning AI and Automation Adoption

Research on AI and automation adoption draws upon several interdisciplinary theoretical traditions. However, the literature remains conceptually fragmented, as different studies often emphasize individual, organizational, technological, or societal factors independently. To provide a more integrated understanding, this study draws upon four complementary theoretical perspectives (Aujali, 2026): Technology Acceptance Theory, Institutional Theory, the Resource-Based View (RBV), and Sociotechnical Systems Theory. Together, these perspectives provide a multilevel framework for examining AI adoption across individual, organizational, and broader societal contexts.

At the individual or micro level, Technology Acceptance Theory provides an important explanation of why individuals accept and use new technologies. Constructs such as perceived usefulness, perceived ease of use, and social influence have been widely used to predict technology adoption and behavioral intention. However, technology acceptance models have also been criticized for placing insufficient emphasis on broader contextual factors, including organizational structures, power relations, competitive pressures, and regulatory conditions. These limitations suggest that individual-level explanations alone may not adequately explain the complexity of AI and automation adoption.

At the organizational or meso level, the Resource-Based View and dynamic capabilities perspectives emphasize the importance of organizational resources and capabilities in facilitating successful AI adoption. From this perspective, the effective implementation of AI depends not only on technological investment but also on the organization's ability to develop and coordinate complementary resources, including data infrastructure, technical expertise, human capital, and organizational mechanisms capable of integrating AI-generated insights into decision-making processes. These perspectives therefore highlight the strategic and capability-based dimensions of AI adoption. In the educational context, Ootom (2023) similarly showed that employing artificial intelligence applications in higher education depends on adequate technical infrastructure and institutional support, whereas the shortage of specialized expertise and the high financial costs constitute the main challenges to such adoption.

Institutional Theory further complements these approaches by emphasizing the influence of external institutional forces on organizational behavior. Organizations may adopt AI technologies in response to regulatory requirements, industry norms, competitive pressures, and broader expectations regarding technological innovation. Consequently, AI adoption should not be viewed solely as a rational technological decision but also as a process shaped by institutional environments and social legitimacy.

At the macro and societal level, Sociotechnical Systems Theory provides an additional framework for understanding the broader consequences of AI adoption. This perspective emphasizes that technological systems cannot be separated from the social environments in which they operate. AI adoption may generate challenges related to algorithmic bias, workforce displacement, ethical concerns, and environmental sustainability. Addressing these challenges requires the involvement of multiple stakeholders, including employees, organizations, civil society, and regulatory institutions.

Drawing on interdisciplinary research, Zhang and Lu (2021) identify several persistent challenges associated with AI adoption, including interpretability, scalability, and ethical alignment. Collectively, these theoretical perspectives provide the foundation for understanding AI and automation adoption as a multidimensional phenomenon shaped by individual readiness, organizational capabilities, institutional conditions, and broader sociotechnical considerations. This integrated theoretical landscape provides an important foundation for the conceptual framework of the present study and supports the examination of how AI and automation adoption may contribute to AI literacy, digital readiness, and future employability.

2.2 Digital Readiness

2.2.1 Conceptual Foundations and Measurement Approaches

Digital readiness is a core academic construct that holds both wide influence and central contentious status across multiple academic fields including information systems, education, and human resource management. This paper first systematically sorts out the origin, evolution, measurement frameworks, and core empirical research findings at the organizational level of this construct. Prior research by Kutnjak et al. (2020) was the first to explicitly clarify the core academic value of this construct, whose conceptual roots can be traced back to early studies on technology acceptance and the digital divide; the work of van Laar et al. (2020) provides solid foundational support for this origin lineage of research. The connotation of contemporary digital readiness has expanded beyond a sole focus on individual technical proficiency, evolving into an integrated multi-dimensional construct that covers cognition, motivation, and behavioral orientation.

In terms of measurement research, the five-dimensional organizational-level measurement framework developed by Sousa & Rocha (2019) has become the most widely adopted mature tool in academia today. Regarding empirical results, the study by Jun et al. (2022) confirms that organizational digital readiness can effectively predict employee productivity and team innovation performance. Successive studies by Paschen et al. (2020) and Oehlhorn et al. (2020) jointly support another core conclusion: aligning an organization's digital readiness with its business strategy can significantly improve the actual returns on the organization's AI investments. This full review logically covers the entire process of research on this construct, and all core arguments are supported by authoritative literature from their corresponding fields.

2.2.2 Digital Readiness in Educational and Workforce Contexts

In the field of education and workforce development, academic research focused on digital readiness has accumulated a large body of empirical evidence directly relevant to this study. The core conclusions of existing research form a complete logical framework to support the implementation of the present work. Sousa and Rocha (2019) define digital readiness as a meta-capability that amplifies the returns on investments in other skills, and their study also finds a significant positive correlation between digital learning ability and the sustainable career development capacity of employees in organizations undergoing digital transformation. Zawacki-Richter et al. (2019) and Williamson and Eynon (2020) incorporate this concept into discussions of artificial intelligence (AI) in the education sector, proposing that integrating AI tools into learning scenarios requires teachers and students to meet a baseline level of digital

readiness, which must be designated a core priority for education in the AI era. In the same vein, Alomari et al. (2023) found that e-learning and its dimensions significantly improve the performance of faculty members, which indicates that readiness to engage with digital learning environments translates into tangible performance outcomes. Fareri et al. (2020) further argue that digital readiness has evolved from a source of competitive differentiation into a threshold capability for the knowledge economy's labor market.

Philbeck and Davis (2018) and Lund et al. (2021) place its employment-related impacts within the context of labor market transformation driven by the Fourth Industrial Revolution, noting that as AI and automation continue to penetrate all occupational fields, the gap in employment prospects between workers with varying levels of digital readiness will widen sharply. The empirical findings synthesized in this body of research also confirm that graduates with high digital readiness have shorter job-waiting periods, higher starting salaries, and stronger career mobility. Pinar (2024) supplements and revises the structural narrative outlined above, proposing that the employment-enhancing effect of digital readiness is moderated by the organizational and industrial contexts in which it is applied. Relevant intervention measures must be adapted to local conditions rather than use a universal, one-size-fits-all design to maximize their employment impacts.

2.3 Artificial Intelligence Literacy

2.3.1 Defining and Dimensionalizing AI Literacy

AI literacy has developed into an independent core construct that cannot be overlooked in the interdisciplinary research area spanning digital education, workforce development, and technology ethics. However, academic circles have long faced core disputes over its definitional boundaries. To date, multiple authoritative studies have built integrated research frameworks from different dimensions, gradually clarifying the essential differences between this construct and traditional digital literacy. Williamson and Eynon's 2020 study, from the perspective of the evolutionary history of educational discourse, demonstrated the necessity of establishing AI literacy as an independent educational construct, noting that the new cognitive demands spawned by AI-mediated work and learning scenarios cannot be satisfied by simply expanding the existing digital literacy framework. Wu et al.'s 2024 study further proposed five core dimensions of AI literacy in the era of large language models: conceptual understanding of the limits of AI's capabilities, critical evaluation of AI outputs, ethical reasoning ability for AI application, capacity for efficient human-AI collaboration, and adaptive learning ability that fits with AI iteration. Southworth et al.'s 2023 applied the AI literacy construct to the context of higher business education, arguing that all dimensions of this construct hold unique labor market value and must be integrated into university curricula to adapt to AI-augmented professional environments. Zawacki-Richter et al.'s 2019 study, which synthesized empirical research on AI applications in higher education, further used data to prove that AI literacy has a significantly stronger predictive power for AI-assisted learning outcomes than general digital literacy, while relevant research by Tanveer et al. will be elaborated on in subsequent sections to continue the line of discussion in this field. A 2020 study extended existing analyses of AI literacy to the policy domain, proposing that AI literacy be positioned as a public good tied to fairness and competitiveness, rather than a market-led private investment in skills, and that systematic educational policies be enacted.

2.3.2 AI Literacy in Organizational and Professional Contexts

Organizational-level artificial intelligence literacy (AI literacy) has gradually become a core research topic in the field of technology management. The core logic is as follows: AI literacy is the core foundation supporting human-AI collaboration capabilities, and human-AI collaboration capabilities are the key source for modern enterprises to build core competitive advantages. A 2022 study by Chowdhury and fellow scholars first defined AI literacy as a component of human-AI collaborative intelligence. Their empirical analysis found that

employees with high AI literacy deliver better performance in AI-enabled work scenarios, and this effect operates through three mechanisms: effectively leveraging the capabilities of AI systems, identifying and correcting AI errors, and reasonably overriding inappropriate AI recommendations by integrating context-specific knowledge. In 2023, Albahri and other scholars extended this logic to high-risk medical scenarios, proposing that clinical AI literacy refers to the ability to critically assess the credibility and interpretability of clinical AI recommendations. Their empirical work confirmed that this competency is a significant predictor of patient safety and medical quality in AI-assisted clinical settings, and highlighted the severe social consequences of insufficient AI literacy.

In 2019, Johansson and Herranen explored the shaping effect of organizational learning environments on AI literacy. Their empirical findings showed that enterprises that embed explicit AI literacy development programs in their human resource systems have a significantly higher average AI literacy level among their professional staff, and experiential learning that combines formal AI education with hands-on AI practice in real scenarios delivers the most prominent development outcomes. In 2020, Wamba-Taguimdje and other scholars supplemented performance evidence from the organizational learning perspective. They empirically verified that enterprise-level AI literacy is a significant predictor of the successful adoption of AI technologies, with its measurement dimensions covering implementation quality, employee engagement, and actual performance gains, and proposed that AI literacy is a core organizational capability that moderates the return on AI investments. In 2023, Trocin and fellow scholars extended this line of research to the dimension of responsible AI, proposing that the ability to identify, challenge, and remediate algorithmic bias and ethical risks is an imperative governance demand that organizations must cultivate, rather than merely a personal competency. This also supported by Obermeyer et al. (2019). Abu Eyadah and Odaibat (2023) likewise proposed a set of ethical standards for employing artificial intelligence in scientific research, emphasizing that the responsible use of AI requires users who are able to recognize and address its ethical implications. At present, relevant research in this field has formed a preliminary context, but the AI literacy distribution gap across occupations and demographic dimensions remains an emerging topic that has not yet been fully explored. In 2020, an anonymous research team found through large-scale text mining of job advertisement texts that demand for AI literacy has extended to non-technical positions including creative industries, social services, and public administration, a scope far broader than the general public commonly recognizes. This gap in AI literacy will impose an employability penalty on the full spectrum of the labor market, and its negative impacts are by no means limited to technical roles alone. A 2021 study by Ulnicane et al. further supplemented this finding: against the backdrop where AI systems already mediate access to economic, social, and political resources, AI literacy must also cover the dimensions of governance and intellectual property, integrating both the ability to use relevant tools and the civic literacy required to participate in governance.

2.4 Future Employability

2.4.1 Reconceptualizing Employability in the Age of AI

AI and automation technologies are driving disruptive changes to the global labor market, and are also pushing the academic community to systematically restructure the concept of future employability. First is the classic framework rooted in traditional human capital theory; Lund et al. (2021) summarize its core elements as formal educational credentials, domain-specific technical skills, and accumulated work experience. Yet the limitations of this framework have long been noted by scholars: Petropoulos (2018) and Wang & Siau (2019) successively proposed that amid technological disruption, a large number of routine cognitive and physical tasks have gradually become automated, so employers' demand profiles for workforce capabilities have fundamentally shifted, and the old framework must be substantially revised.

The contemporary new framework that later emerged identifies adaptability, metacognitive flexibility, and technological complementarity as the core features that sustain labor market resilience in the AI era. This shift is supported by two key studies: a critical study by Benhamou (2020) argued that the core of future employability with long-term value is the metacapability to continuously adapt to technological environments, rather than specific technical skills whose half-lives shrink rapidly as AI iterates. An economic analysis of labor value redistribution by Sohn (2024) further pointed out that AI has shifted the capability premium from prediction and information processing abilities to the judgment, creativity, and relational skills that AI cannot replicate, meaning the future employability landscape must be restructured around AI-complementary skills. However, the field still faces core methodological challenges today. The four existing operational measurement methods sorted out by Baah-Acheamfuor et al. (2023) (self-reported employment perceptions, employer-rated capability assessments, objective labor market outcomes, and expert judgments of occupational automation exposure risk) can only cover partial dimensions of this multi-dimensional construct. This leads to inconsistent conclusions across different studies, so scholars must exercise caution when interpreting the cumulative evidence accumulated in the field. This study builds on the research of scholar Perez (2010), and adopts the techno-economic paradigm transformation framework to explain controversies in labor market measurement: during periods of fundamental technological change, the reshaping of competency profiles cannot be anchored to a stable benchmark, so the future employment readiness of individuals and organizations cannot be reliably assessed.

2.4.2 Empirical Evidence on Future Employability Determinants

A large body of empirical research has produced abundant findings regarding the determinants of future employability amid the wave of AI and automation. These studies collectively outline a profile of core competencies that suit digitally transforming economies, support labor market resilience, and sustain long-term career development. Existing research can be organized along a logical thread: from general requirements, to heterogeneous characteristics, and finally to long-term dynamics. First is empirical evidence on cross-industry general competencies. Fareri et al. (2020) conducted a large-scale systematic analysis of job postings for Industry 4.0 roles, and found that employers across all sectors increasingly rank AI-related capabilities, digital collaboration skills, and data literacy on par with traditional domain expertise. This reflects the systematic restructuring of the competency profile required in the current labor market. Next are research conclusions on industry-specific contextual traits. Lund et al. (2021) recorded notable differences in employability requirements across industries with varying speeds of AI transformation. The healthcare, finance, and logistics sectors saw the sharpest rise in demand for AI-complementary skills and digital readiness, which have become core prerequisites to maintain career retention. Chowdhury et al. (2022) proposed that the labor market value of AI collaboration skills is particularly prominent in knowledge-intensive sectors where human-AI collaboration is widely adopted. AI literacy and digital readiness deliver the highest employment returns in scenarios with the highest rates of AI application. In the vocational education context specifically, Sharadgah et al. (2026) reviewed the literature on AI adoption for future employability, underscoring the growing relevance of this relationship for vocational learners and training systems.

Albahri et al. (2023) found that the widespread use of AI-assisted clinical decision tools has driven up the employment premium of clinical AI literacy, a premium that is already reflected in gaps in employment and career advancement among medical staff. Finally, there is research examining the long-term dynamic dimension. Wang and Siau (2019) and De Felice et al. (2023) both emphasized that a continuous learning orientation and adaptive skills are necessary supplements to static AI literacy. This perspective aligns with the projection put forward by Pinar (2024), who argued that the pace of AI iteration will keep accelerating, continuously reshaping occupational skill requirements. Workers must have the ability to update their skills

quickly to maintain competitiveness throughout their entire careers. Stahl et al. Building on the existing longitudinal research frameworks of the anonymous author (2021) and Shtefan (2025), this paper adds a normative dimension to the prior framework. It proposes that in economies with widespread AI adoption, future employability requires not only the originally necessary technical and cognitive dimensions, but also ethical and civic competencies. These competencies enable workers to participate in AI system governance, and to advance the establishment of labor market institutions that ensure the fair distribution of productivity gains generated by AI.

3. Hypothesis Developments

3.1 Artificial Intelligence and Automation on Digital Readiness

AI and automation technologies have been integrated into the ecosystem of modern organizations at an accelerating pace. This trend has drawn sustained attention from academic circles. In a 2025 study, Sharadgah et al. became the first to link this trend to the core topic of digital readiness, marking the start of systematic sorting of the relevant research lineage. At the level of core constructs, Chounta et al. (2024) define digital readiness as the ability of individuals and organizations to effectively engage with digital tools, platforms, and data-driven processes, positioning it as a core academic construct in the knowledge economy. In terms of theoretical support, Acemoglu and Restrepo (2022) proposed that automation replaces routine cognitive and manual tasks, forcing both labor and management to restructure their technical capabilities, which generates a structural demand for digital readiness. This view aligns with the classic task framework. Bessen et al. (2020) further corroborated this argument, noting that AI and automation will not eliminate all jobs entirely; they only redefine the combination of economically valuable tasks, requiring all types of market entities to continuously update their digital skills.

The positive correlation between enterprises' AI application intensity and organizational digital readiness has also been uniformly verified by cross-sector empirical evidence: Canhoto and Clear (2020) found that enterprises that launch AI integration will simultaneously invest in digital infrastructure, employee capability development, and process restructuring, all three of which are core components of digital readiness. Bhattacharya (2021) also noted that competition in the AI era requires not only the deployment of algorithmic tools, but also the cultivation of a company-wide digital mindset that runs through all decision-making and operational activities. Academic circles have also expanded the boundaries of this construct from multiple dimensions. From the cognitive and creative dimension, generative AI has fostered human-machine collaboration capabilities unforeseen in the pre-AI era, which constitute high-level digital readiness, a claim supported by studies by Fountaine et al. (2019) and Huang & Rust (2021). From the organizational learning perspective, Brynjolfsson et al. (2025) proposed that the iterative feedback loops of AI systems improve digital proficiency across all organizational levels; generative AI, in particular, raises the digital readiness of low-skilled workers, breaking the barrier that complex digital capabilities are exclusive to high-skilled specialists. From the ethical governance dimension, studies by Fenwick & Vermulen (2019) and Nishant et al. (2020) point out that the demand for AI ethical governance gives rise to compliance-related digital readiness, further expanding the connotation and boundary of this construct in scenarios of AI integration. Based on the theoretical derivations and mainstream empirical evidence discussed above, this study formally proposes the core research hypotheses to be tested.

H1: Artificial Intelligence and Automation Adoption positively influences Digital Readiness.

3.2 Digital Readiness on Future Employability

The deep restructuring of the global labor market in the post-pandemic era, combined with the wave of technological penetration driven by the Fourth Industrial Revolution, has made the

linkage mechanism between digital readiness and future employability a core research topic in the field of labor economics. This study sorts out the academic context of this field, first defining the core concept of "future employability" as the comprehensive ability of individuals to adapt to technological iterations in the labor market, and continuously obtain and competently perform job positions. Research on the link between the two is primarily grounded in classic human capital theory. Öziskender & Erdem (2025) point out that academic output on this topic has grown explosively in recent years; van Laar et al. (2020) confirm that the development of future employability relies heavily on a solid foundation of digital capabilities; Sousa & Rocha (2019) verify the explanatory power of human capital theory for this research agenda; Lund et al. (2021) propose that digital readiness is a core support for labor force transformation, as individuals with high digital fluency are better able to avoid the risk of unemployment caused by automation and access emerging job roles that require technology-mediated problem-solving, creativity, and adaptability.

Sánchez-Canut et al. (2023)'s systematic review of digital competence frameworks confirms that digital readiness is positively correlated with graduates' employment outcomes, as it can shorten job search time and improve career mobility. Petruzzello (2022)'s empirical study of higher education graduates further validates this association, finding that digital readiness scores can significantly predict graduates' perceived employment status and actual employment status six months after graduation. Stahl et al. (2021) add that digital readiness also acts as a meta-competence that enhances the market signal value of job seekers. Paschen et al. (2020) and Oehlhorn et al. (2020) find that this positive effect is more pronounced in transforming industries with widespread adoption of AI workflows, such as finance, healthcare, and logistics. Finally, drawing on Perez's (2010) techno-economic paradigm framework, existing studies note that the current round of technological revolution will grant a labor market premium to individuals with sufficient digital readiness, while phasing out workers who only master skills from the analog era. Building on the relevant theories and empirical evidence outlined in the preceding sections, this study integrates the logic of biased AI employment redistribution proposed by Pinar (2024), draws on supporting work by Williamson & Eynon (2020) and Faishal et al. (2023), synthesizes all lines of argumentation, and puts forward its core hypothesis.

H2: Digital Readiness positively influences Future Employability.

3.3 Artificial Intelligence and Automation on AI Literacy

As artificial intelligence and automation systems fully permeate all sectors of the economy and society, AI literacy, as an independent core competency domain, has gradually entered the purview of academic research and practical circles, becoming a core issue in building workplace competencies for the digital age. Existing research has reached a consensus on the core connotation of AI literacy: Kalantzis and Cope (2025) and Essenfelder (2026) define it as a comprehensive ability to understand, critically assess, and effectively engage with AI systems, their outputs, and their underlying algorithmic logics. The positive correlation mechanism between the intensity of workplace AI technology adoption and the development of group AI literacy proposed in this paper is rooted in empiricism and the sociotechnical learning framework: continuous exposure to AI tools can catalyze the deepening of individuals' AI understanding through iterative use, reflective review, and skill transfer, a logic supported by the studies of Zawacki-Richter et al. (2019) and Tanveer et al. (2020). However, it must be clarified that literacy development is not a passive outcome of technological penetration.

Ulnicane et al. (2021) point out that individuals can only achieve iterative advancement of their literacy if they actively explore the capability boundaries, limitations, and ethical dimensions of AI. Multi-dimensional empirical evidence also supports this mechanism: at the organizational level, Wamba-Taguimdje et al. (2020) found that employees at firms with high AI adoption intensity have significantly higher average AI literacy scores; in the healthcare

setting, Tun et al. (2025) confirmed that medical staff who regularly use clinical AI-assisted tools have far stronger algorithmic reasoning and critical assessment skills than groups with low exposure to such tools; in general workplace contexts, van Laar et al. (2020) noted that firms' investment in AI tools is positively correlated with improvements in employees' critical thinking, which is reflected in the dimensions of data interpretation, output verification, and bias identification; on the ethical dimension, Obermeyer et al. (2019) found that the behavior of questioning biased AI outputs only occurs at high frequency in scenarios where AI is deeply deployed. The education community also echoes this conclusion: Williamson and Eynon (2020) and Southworth et al. (2023) argue that context-embedded cultivation is far superior to disembodied training, and Chee et al. (2025) further point out that AI literacy is a dynamic capability, and adoption intensity is its core structural determinant. Zhang and Lu (2021) found that organizations that proactively implement AI-driven automation strategies invest in employee AI literacy programs in a more systematic manner, forming a mutually reinforcing cycle between the two practices. This paper integrates existing literature in the field to propose that AI automation applications are the primary antecedent of AI literacy development, which leads to this paper's core research hypothesis.

H3: Artificial Intelligence and Automation Adoption positively influences AI Literacy.

3.4 AI Literacy on Future Employability

A broad consensus has emerged among academic and policy communities that AI literacy is a core competency for workers to succeed in the future labor market. Underpinning this consensus is a structural shift in the epistemology of employability (Mustafa & Altrad, 2026), traditional human capital theory, which originally focused on the completion of formal education and the acquisition of specialized technical skills, has undergone adaptive expansion in recent years, incorporating AI literacy into the category of new value-adding human capital for labor markets deeply penetrated by AI. A cross-industry analysis of employment structures by De Felice et al. (2022) shows that workers with AI literacy experience lower job displacement rates and have smoother promotion paths; an empirical study by Chowdhury et al. (2022) verifies that human-AI collaboration capacity, a core subdimension of AI literacy, is positively correlated with workers' objective job performance and subjective promotion expectations; a sector-specific study of the healthcare field by Albahri et al. (2023) finds that medical personnel with high explainable AI literacy boast stronger professional confidence, resilience, and employment prospects; text mining evidence from Fareri et al. (2020) demonstrates that in Industry 4.0 scenarios, employers in the manufacturing, logistics, and professional services sectors are continuously raising the wage premium for AI-related competencies; Dwivedi et al. (2021) and Wang & Siau (2023) add that beyond its technical dimension, AI literacy also covers the ethical, social, and critical thinking dimensions that employers urgently need, to align with the risk management requirements of AI deployment; a forward-looking assessment by Benhamou (2020) proposes that individuals who can critically review AI outputs and participate in responsible AI governance will hold a strategic advantage in the labor market; and a survey of small and medium-sized enterprises by Carayannis et al. (2025) ultimately provides full validation that AI literacy is a top priority in recruitment for digital transformation roles, confirming its market recognition as a differentiated employment asset. The accumulated theoretical and empirical findings from the literature reviewed in this paper are sufficient to support hypotheses for subsequent research.

H4: AI Literacy positively influences Future Employability

3.5 Mediating role of Digital Readiness

This paper puts forward a core review proposition: digital readiness, as a mediating variable, transmits the impact of artificial intelligence and automation adoption on future employability. This proposition extends previous research hypotheses that only focused on the direct effects

of the two aforementioned factors, and it holds both theoretical coherence and empirical support. To clarify the mediating logic, this review draws on three core theories for mediating analysis in the field (the Technology Acceptance Model, the Resource-Based View of the Firm, and the Capability Theory) to confirm that the improvement of employability driven by AI adoption does not occur directly or immediately. Instead, it influences workers' positioning in the labor market through the gradual accumulation of digital readiness literacy. This paper then sorts out empirical studies following a hierarchy from micro to macro, and from general scenarios to specialized subfields, to confirm the rationality of the core mechanism: Gartner et al. (2023) directly verified the mediating attribute of digital readiness, finding that most of the positive effect of technology usage intensity on employee performance can be explained by this variable, and the direct effect of technology is greatly weakened after the mediating variable is added; Patalas-Maliszewska & Kłos (2022) defined digital readiness as a dynamic capability that allows organizations and individuals to respond to AI-related demands, and that can support higher productivity and career performance; Fareri et al. (2020) incorporated this variable into a competence-oriented employment framework, proposing that AI adoption creates conditions for the accumulation of digital readiness, and expands the scope of workers' professional competence; Lund et al. (2021) and Faishal et al. (2023) provided macro-level evidence that regions and industries with higher AI adoption rates have higher levels of workforce digital readiness, which correspond to better employment outcomes including lower structural unemployment rates and higher occupational transition rates; Konttila et al. (2019) and Sousa & Rocha (2019) verified the partial mediating model in the healthcare and business education contexts respectively, proposing that the conversion of technology exposure into employment gains relies on the internalization of digital literacy; Petruzzello (2022) and Sánchez-Canut et al. (2023) confirmed the mediating pathway in studies of graduate populations, pointing out that the impact of digital-intensive environments on employment outcomes can be partially explained by differences in digital readiness. By integrating the aforementioned theoretical rationale and empirical basis, this study proposes its core mediating hypothesis.

H5: Digital Readiness mediates the relationship between Artificial Intelligence and Automation Adoption and Future Employability.

3.6 Mediating role of AI Literacy

In the contemporary field of workforce development research, the mediating role of AI literacy between firms' adoption of AI and automation technologies and employees' future employability is a core proposition that carries both theoretical complexity and practical importance. Mustafa & Altrad (2026) first proposed the core logic of this mediating effect: the gains in employee employability brought by firms' deployment of AI and automation tools are never automatically generated by the technology deployment itself, but rely entirely on employees' internalization of the three core capabilities that constitute AI literacy (Qahman et al., 2026). The two core theoretical foundations that support this mediating path are, first, the knowledge transfer learning models proposed by Zawacki-Richter et al. (2019) and Southworth et al. (2023), and second, the extended human capital theory that incorporates AI literacy, developed by Agrawal et al. (2022) and Wang & Siau (2023). Integrating findings from multiple empirical studies across interdisciplinary contexts fully validates the effectiveness of this mediating model: Chowdhury et al. (2022) and Albahri et al. (2023) confirmed that the pathway through which AI literacy translates into performance and reputational capital to ultimately boost employability holds; Dwivedi et al. (2021) proposed that AI literacy acts as a core link connecting AI's disruptive potential to the high-value reallocation of human capital; De Felice et al. (2022) and Fareri et al. (2020) proved that the AI adoption premium in the labor market stems from AI literacy development rather than technology adoption itself; Berente et al. (2021) and Tanveer et al. (2020) verified the indispensability of this mediating mechanism

by comparing differences in employment outcomes between two types of firms' AI adoption strategies: those that invest in AI literacy and those that neglect this input. The collective support from the above literature completes the preliminary groundwork for the core proposition, and clarifies the full logical context for this study to put forward its final research hypotheses.

H6: AI Literacy mediates the relationship between Artificial Intelligence and Automation Adoption and Future Employability.

4. Methodology

This study constructs a research framework centered on employability-related propositions in Jordan's vocational education sector. It adopts a quantitative research orientation and cross-sectional survey design, with a core focus on four latent variables: AI and automation adoption, AI literacy, digital readiness, and future employability. The study is implemented within Jordan's vocational education and training (VET) system for the 2025/2026 academic year, covering three types of institutions: secondary vocational schools, technical colleges, and vocational training centers. Jordan is currently advancing digital transformation, AI integration, and workforce development strategies to improve local employment levels and economic competitiveness. This development context provides a reasonable application scenario for this empirical study focused on vocational education. Regarding method appropriateness, this study cites the conclusions of Al-Qasbi (2024) to verify that quantitative methods can support testing of this study's conceptual model and the hypothesized relationships between latent variables via structural equation modeling (SEM). For sampling, the study uses convenience sampling, a common method in education and technology adoption research, to recruit vocational education students from multiple regions across Jordan. A total of 257 valid samples were ultimately collected. This sample size also meets the requirements for partial least squares structural equation modeling (PLS-SEM)- (Alazzam et al. (2026). The questionnaire used in this study is divided into two main modules. The first module collects demographic information including gender, age, education level, and field of study. The second module uses established; validated scales adapted from existing literature. All items are scored on a 1–5 point Likert scale. The adapted scales are not only suited to the context of Jordan's vocational education system, but also fully retain the core connotations of the original concepts.

5. Findings

This study conducts data analysis using SmartPLS 4, following the widely adopted two-step analytical framework standard in the PLS-SEM field. First, we test the indicator loadings, reliability, and various types of validity of the measurement model. We then complete core tests of the structural model, including collinearity and path coefficients, using the bootstrap method with 5,000 subsamples.

5.1 Measurement Model Assessment

This study first tests the measurement model across three major dimensions: indicator reliability, internal consistency reliability, and convergent validity. Drawing on the data from Figure 1, the factor loadings, which range from 0.782 to 0.858, meet the general threshold of 0.7. In the structural model, all four core constructs show positive associations with one another.

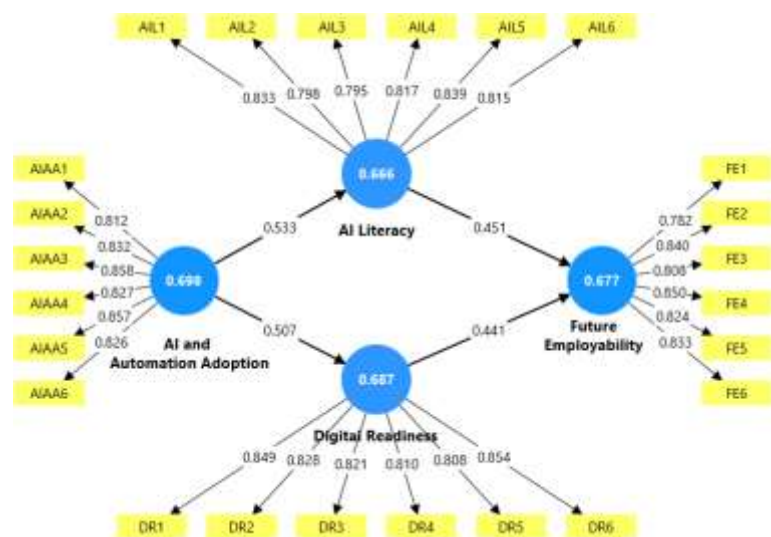


Figure 1. Measurement and Structural Model Results

The regression results shown in Figure 1 of this study indicate that the adoption of artificial intelligence and automation has significant positive effects on AI literacy ($\beta=0.533$) and digital readiness ($\beta=0.507$); in the mediation pathway, the regression coefficients of AI literacy and digital readiness for future employability are 0.451 and 0.441 respectively, both of which are positive. These findings provide preliminary support for the study’s theoretical framework, and follow-up test results including Cronbach’s alpha, composite reliability, and average variance extracted will be reported in Table 1.

Table 1. Reliability and Convergent Validity Assessment

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI Literacy	0.900	0.902	0.923	0.666
AI and Automation Adoption	0.914	0.916	0.933	0.698
Digital Readiness	0.909	0.912	0.929	0.687
Future Employability	0.905	0.908	0.926	0.677

For the measurement model of this PLS-SEM empirical study, this research sequentially conducted tests of reliability, convergent validity, and discriminant validity. All indicators conform to the general standards widely accepted in the PLS-SEM field: as documented in Table 1, Cronbach’s Alpha values range from 0.900 to 0.914, composite reliability ranges from 0.923 to 0.933, and AVE values range from 0.666 to 0.698; discriminant validity was tested simultaneously using the HTMT and Fornell-Larcker criteria, with the HTMT values listed in Table 2 ranging from 0.313 to 0.671. All indicators meet the required thresholds, and this measurement model can support subsequent structural model analysis and hypothesis testing.

Table 2. Heterotrait-Monotrait Ratio (HTMT)

	AI Literacy	AI and Automation Adoption	Digital Readiness	Future Employability
AI Literacy				

AI and Automation Adoption	0.584			
Digital Readiness	0.313	0.550		
Future Employability	0.635	0.671	0.624	

This study additionally adopted the Fornell-Larcker criterion to test the discriminant validity of its measurement scale. Based on the data presented in Table 3, we verified that the square roots of the average variance extracted (AVE) for all constructs, which ranged from 0.816 to 0.836, were all higher than the correlation coefficients between any pair of other constructs. This provides additional supporting evidence confirming that the discriminant validity of this study holds.

Table 3. Fornell-Larcker Criterion

	AI Literacy	AI and Automation Adoption	Digital Readiness	Future Employability
AI Literacy	0.816			
AI and Automation Adoption	0.533	0.836		
Digital Readiness	0.287	0.507	0.829	
Future Employability	0.577	0.612	0.570	0.823

This study was validated using two commonly adopted analytical methods, HTMT and Fornell-Larcker. All constructs can capture unique theoretical concepts, and the measurement model has acceptable discriminant validity.

5.2 Structural Model Assessment

After completing the reliability and validity validation of the measurement model, we conducted the assessment of the structural model. Drawing on three core statistical indicators and integrating the data from Table 4: the AI and automation adoption dimension explains 28.4% of the variance in AI literacy and 25.7% of the variance in digital readiness, respectively; the two constructs together explain 51.1% of the variance in future employability. The judged model's at level of explanatory power based on the authoritative criteria set forth by Hair et al. in 2022.

Table 4. Coefficient of Determination (R²)

	R-square	R-square adjusted
AI Literacy	0.284	0.281
Digital Readiness	0.257	0.254
Future Employability	0.511	0.507

Based on the Cohen's f^2 effect size analysis data from Table 5 of this study, the impacts of all predictor variables, including artificial intelligence and automation adoption, align with prior expectations. All predictor constructs make a substantial contribution to the endogenous constructs.

Table 5. Effect Size (f^2)

	AI Literacy	AI and Automation Adoption	Digital Readiness	Future_Employability
AI Literacy				0.381
AI and Automation Adoption	0.397		0.346	
Digital Readiness				0.364
Future Employability				

This study adopted the blindfolding procedure, and combined data from Table 6 to verify the model's predictive ability. All Q^2 values of the endogenous constructs fell within the range of 0.250–0.350, indicating sufficient predictive relevance. The three constructs, ranked by their Q^2 values.

Table 6. Predictive Relevance (Q^2)

	Q^2_{predict}	RMSE	MAE
AI Literacy	0.276	0.857	0.711
Digital Readiness	0.250	0.872	0.722
Future Employability	0.350	0.813	0.674

The structural model constructed in this paper passed quantitative tests using R^2 , f^2 , and Q^2 , meeting all qualification requirements. It has good explanatory and predictive power, covers four types of core variables, and is only applicable to the research context of vocational education.

5.3 Hypotheses Testing

This study adopted the bootstrapping resampling method built into the SmartPLS software to test the significance of the proposed structural relationships between variables. It incorporates the four direct effect paths included in the model presented in Figure 2, laying the groundwork for the presentation of subsequent research results.

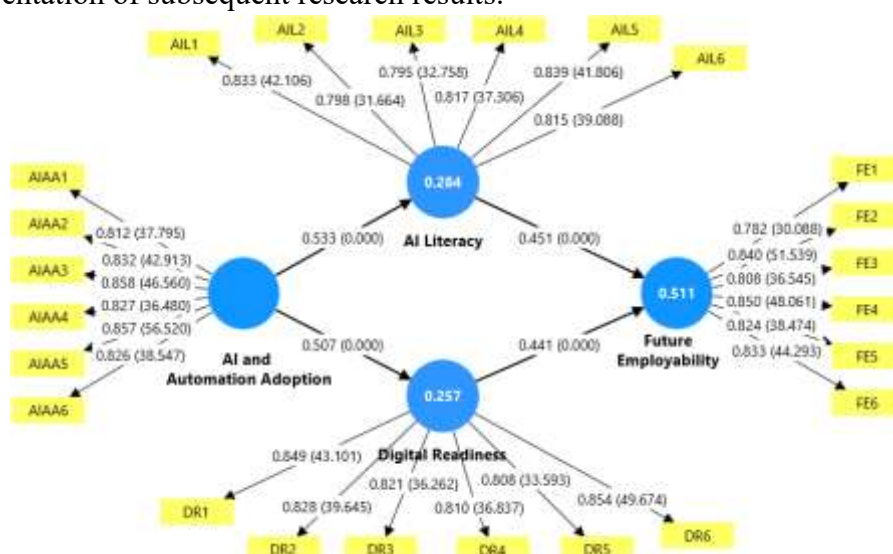


Figure 2. Bootstrapping Results of the Structural Model

This paper presents the bootstrap test results of the structural model in Figure 2, which displays all associations between the study's variables. The detailed statistical results for the relevant hypothesis tests are compiled in Table 7.

Table 7. Path Coefficients and Hypotheses Testing

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
AI and _Automation Adoption -> AI Literacy	0.533	0.536	0.045	11.900	0.000
AI and _Automation Adoption -> Digital Readiness	0.507	0.509	0.046	11.024	0.000
AI Literacy -> Future Employability	0.451	0.452	0.043	10.372	0.000
Digital Readiness -> Future Employability	0.441	0.441	0.045	9.762	0.000

This study completed the core test of mediating effects in the vocational education context. The regression results show that: the effect of artificial intelligence and automation adoption on AI literacy is $\beta=0.533$, $t=11.900$, $p<0.001$; its effect on digital readiness is $\beta=0.507$, $t=11.024$, $p<0.001$; the effects of both AI literacy ($\beta=0.451$, $t=10.372$) and digital readiness ($\beta=0.441$, $t=9.762$) on future employability reach the significance level of $p<0.001$, which verifies the pre-proposed impact transmission chain. This study adopted the bootstrapping method in the SmartPLS software to test the mediating effect. Drawing on the data from Table 8, the study finds that the total indirect effect of AI and automation adoption on future employability, which is transmitted via AI literacy and digital readiness, is $\beta=0.464$, $t=12.330$, $p<0.001$.

Table 8. Indirect Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
AI and _Automation Adoption -> Future Employability	0.464	0.468	0.038	12.330	0.000

The mediating effect test results of this study are detailed in Table 9. Both digital readiness and AI literacy exert significant mediating effects between artificial intelligence and automation adoption and future employability. For digital readiness, $\beta=0.223$, $t=6.475$, $p<0.001$; for AI literacy, $\beta=0.240$, $t=6.950$, $p<0.001$. The mediating effects of both variables are confirmed to hold.

Table 9. Specific Indirect Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
--	---------------------	-----------------	----------------------------	--------------------------	----------

AI and _Automation Adoption -> Digital Readiness -> Future Employability	0.223	0.225	0.034	6.475	0.000
AI and _Automation Adoption -> AI Literacy -> Future Employability	0.240	0.242	0.035	6.950	0.000

The total effect results of all variables in this study are reported in Table 10. All total effects are positive and statistically significant at the $p < 0.001$ level. The three effect values of the core independent variable, AI and automation adoption, are 0.533, 0.507, and 0.464 respectively, and this factor can strengthen vocational education outcomes by improving student abilities.

Table 10. Total Effects

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
AI and _Automation Adoption -> AI Literacy	0.533	0.536	0.045	11.900	0.000
AI and _Automation Adoption -> Digital Readiness	0.507	0.509	0.046	11.024	0.000
AI and _Automation Adoption -> Future Employability	0.464	0.468	0.038	12.330	0.000
AI Literacy -> Future Employability	0.451	0.452	0.043	10.372	0.000
Digital Readiness -> Future Employability	0.441	0.441	0.045	9.762	0.000

This study adopts the Smart-PLS tool and uses the bootstrapping method to test its research hypotheses, relying on three types of indicators: path coefficient β , t-statistic, and p-value. The criteria for confirming any hypothesis follow the authoritative thresholds proposed by Hair et al. in 2022, which require a t-value greater than 1.96 and a p-value less than 0.05. The test results of the six research hypotheses are then reported in sequence: among the four direct path hypotheses, the corresponding statistics of H1 (AI and automation adoption on digital readiness), H2 (digital readiness on future employability), H3 (AI and automation adoption on AI literacy), and H4 (AI literacy on future employability) all meet the threshold requirements, so all four are supported. The two mediating path hypotheses, H5 (the mediating role of digital readiness) and H6 (the mediating role of AI literacy), also passed the test successfully. All research hypotheses in this study are supported. The core conclusion is that the adoption of AI and automation technologies can enhance the future employability of vocational education students through two types of paths; directly improving relevant capabilities, and indirectly fostering AI literacy and digital readiness.

6. Discussion

This study conducts empirical research on the impacts of AI and automation adoption among vocational college students. Its core empirical findings provide solid empirical support for a series of existing studies in the field that emphasize the transformative role of AI and automation for workforce readiness and employability. This study first confirms that the adoption of AI and automation can significantly improve vocational college students' AI literacy and digital readiness. This conclusion aligns with the findings of previous empirical studies by Dwivedi et al. (2021) and Brynjolfsson et al. (2025). Based on this, the study proposes that vocational colleges must move beyond the limits of traditional technical training, and integrate AI-supported learning practices into their daily curricula. This study further finds that AI adoption has a significant positive effect on AI literacy. This result matches the core view put forward by digital capability-driven research (Kutnjak et al., 2020; Chounta et al., 2024) and AI literacy cognitive theory research (Southworth et al., 2023; Wu et al., 2024), which states that effective interaction with AI systems can deepen people's understanding of AI. Accordingly, the study proposes that AI literacy should be listed as a core training goal in vocational education. This study also verifies that both AI literacy and digital readiness can significantly influence students' future employability. This conclusion supports the contemporary employability theory of Lund et al. (2021) and Mustafa & Altrad (2026) proposed against the backdrop of the Fourth Industrial Revolution, proving that in the AI era, employability has long surpassed the scope of traditional vocational skills, and relies more on individuals' ability to collaborate with emerging technologies.

Another core finding of this study is the significant mediating role of both AI literacy and digital readiness, which leads to the preliminary core judgment that the benefits of AI and automation adoption are not directly transmitted to employment outcomes. This study finds that targeted competency development can help students adapt to future workplace environments. This conclusion extends prior research, clarifying the underlying mechanism through which technology adoption supports the building of national workforce reserves. It must be noted that investing in AI technology solely within the education sector is far from sufficient; complementary improvements to students' AI literacy and digital readiness are also required. For vocational education in Jordan and other similar developing economies, policymakers must integrate AI-related competencies into vocational education curricula, and educational institutions need to invest in digital infrastructure, build AI-enabled learning environments, and launch faculty development programs. These measures will close the supply-demand gap between education systems and the labor market, enhance graduates' employability, and support national digital transformation.

7. Conclusion

This study empirically explores the impact of AI and automation adoption on the future employability of vocational education students in Jordan. In the research model, AI and automation adoption is set as the independent variable, AI literacy and digital readiness as mediating variables, and future employability as the dependent variable. The PLS-SEM method is applied to analyze 257 valid student samples collected for the study. The empirical results show that AI and automation adoption can significantly boost students' AI literacy and digital readiness; both mediating variables exert a positive effect on future employability, confirming that the mediating effects hold. This study integrates the four variables into a single conceptual framework, empirically validates the relationships between these variables in the context of Jordan's vocational education setting, and fills a gap in existing literature. At the practical level, this study proposes two types of implementable measures: vocational education institutions should prioritize launching AI-integrated programs that simultaneously cultivate the two core competencies, and national policymakers should introduce national strategies to support AI

education, digital capacity building, and workforce transformation. This study has two limitations: its cross-sectional research design cannot derive causal relationships across the time dimension, and the sample limited only to Jordanian vocational school students restricts the generalizability of the study's conclusions. Future research can adopt longitudinal research designs, recruit larger, more diverse samples, and add moderating variables such as institutional support to deepen related analysis. Ultimately, this study confirms that AI and automation technologies can significantly improve students' future employability when supported by the two core competencies, and vocational education plays a central role in preparing the workforce for the AI era.

References

- Ababneh, A., Almarashdah, M. A., Jebril, I., Al-Zaqeba, M. A. A., & Assaf, N. (2023). Driving sustainable supply chains: Blockchain-enabled eco-efficiency for resilient customs ports. *Uncertain Supply Chain Management*, 11(4), 1719-1734.
- Ababneh, A., Almarashdah, M. A., Jebril, I., Al-Zaqeba, M. A. A., & Assaf, N. (2023). Driving sustainable supply chains: Blockchain-enabled eco-efficiency for resilient customs ports. *Uncertain Supply Chain Management*, 11(4), 1719-1734.
- Abu Eyadah, H., & Odaibat, A. (2023). Suggested ethical standards for employing artificial intelligence in scientific research: An analytical study. *Jerash for Research and Studies Journal*, 24(2), Article 4. <https://digitalcommons.aaru.edu.jo/jpu/vol24/iss2/4>
- Acemoglu, D., & Restrepo, P. (2022). Tasks, automation, and the rise in US wage inequality. *Econometrica**, 90(5), 1973–2016.
- Agrawal, A., Gans, J., & Goldfarb, A. (2022). *Power and prediction: The disruptive economics of artificial intelligence*. Harvard Business Press.
- Al Matrooshi, M. A. M., AlZageba, M. A., & Abdul Hamid, S. (2025). VAT revenues as a mediator between tax evasion and the UAE economy. *International Journal of Digital Accounting and Fintech Sustainability*, 2(2). <https://doi.org/10.70568/IJDAFS.2.2.1>
- Al Obaidy, A. L. A., Alshehadeh, A. R., Al-Khawaja, H. A., Basheti, I. A., & Al-Zaqeba, M. A. A. (2024). Development of a new concept and definition of inheritance risk management in family businesses toward sustainability. *International Journal of Advanced and Applied Sciences*, 11(6), 1-13.
- Alazzam, F., Gharaibeh, Z., Jarah, B., AlJabali, A & Al-Zaqeba, M. (2026). Legal and cybersecurity challenges of integrating artificial intelligence and the internet of things in financial institutions in the United Arab Emirates and Jordan. *International Journal of Data and Network Science*, 10(1), 265-272. <http://dx.doi.org/10.5267/j.ijdns.2025.9.021>
- Albahri, A. S., Duham, A. M., Fadhel, M. A., Alnoor, A., Baqer, N. S., Alzubaidi, L., ... & Deveci, M. (2023). A systematic review of trustworthy and explainable artificial intelligence in healthcare: Assessment of quality, bias risk, and data fusion. *Information fusion*, 96, 156-191.
- Al-Hassan, M. J. (2023). The effect of project-based learning on critical thinking skills among secondary school students. *International Journal of Pedagogy and Professional Human Development Insights*
- Almansour, D. S. M., Almarshedi, M. R. F., Alqahtani, M. B. M., & Mustafa, D. J. H. H. (2026). The Role of Using Artificial Intelligence Applications in Achieving Sustainable Development Goals in the Kingdom of Saudi Arabia. *Universal Journal of Future Intelligence: Innovations and Artificial Intelligence*, 3(1). <https://doi.org/10.70568/r4qstb71>
- Alomari, G., Bani Doumi, F., Al-Kasasbeh, M., Rabee, I., & Alzoubi, H. (2023). The impact of e-learning on faculty members' performance: The mediating role of sustainable development at Police Science Academy in Sharjah. *Jerash for Research and Studies Journal*, 24(2), Article 1. <https://digitalcommons.aaru.edu.jo/jpu/vol24/iss2/1>
- Aloqaily, A. N., Qawasmeh, E. F., Masa'd, F. M., Alrousan, A., & Al-Zaqeba, M. A. A. (2024). The mediating effect of green culture on the relationship between GHRM and green sustainable performance in Jordanian SME logistics companies. *International Journal of Advanced and Applied Sciences*, 11(10), 232-240.
- Al-Qasmi, A. (2024). Navigating the digital transformation in higher education: Opportunities, challenges, and strategic pathways. *Universal Journal of Future Impact of Artificial Intelligence*, 1(4), Article 24. <https://doi.org/10.70568/UJFI1A1.1.4.24>
- Al-Shouh, S. A. H., & Al-Darawsheh, N. A. H. (2024). Applying academic accreditation standards in Jordanian universities in light of e-learning and education. *Universal Journal of Green Human Resources and Sustainable Humanities*, 1(2). <https://doi.org/10.70568/UJGHRSH.1.2.1>

- Al-Taani, A. H. M., Al-Zaqeba, M. A. A., Al-Khawaja, H. A., Shubailat, O. M., Elhesenat, L. A., & Al-Rashdan, M. T. (2025). The influence of tax and customs policies on the success of supply chains: Evidence from Jordan. *International Journal of Advanced and Applied Sciences*, 12(9), 241-251.
- Al-Zaqeba, M. A. A. (2025). Taxation and customs strategies towards enhancing environmental responsibility. In *Green Finance and Energy Transition: Innovation, Legal Frameworks and Regulation* (pp. 595-603). Cham: Springer Nature Switzerland.
- Al-Zaqeba, M. A. A., & Basheti, I. A. (2024). Measurement problems in interest-free financial instruments. *Pakistan Journal of Life and Social Sciences*, 22(1), 5558-5575.
- Al-Zaqeba, M. A. A., Pitchay, S. A., & Hamid, H. A. (2026, April). AI-enabled adaptive learning for workforce-ready: A bibliometric analysis using VOSviewer. In *2026 International Conference on Artificial Intelligence for Sustainable Engineering and Innovation (AISEI)* (pp. 263–271). IEEE.
- Al-Zaqeba, M. A. A., Pitchay, S. A., & Hamid, H. A. (2026, April). AI-Enabled Adaptive Learning for Workforce-Ready: A Bibliometric Analysis using VosViewer. In *2026 International Conference on Artificial Intelligence for Sustainable Engineering and Innovation (AISEI)* (pp. 263-271). IEEE.
- Alzeyoudi, M. A. R. K., & Ineizeh, N. I. A. A. (2025). Empowering Human Capital in the Age of Artificial Intelligence: A Strategic Analysis of AI-Driven Human Resource Skills Development in UAE. *Universal Journal of Green Human Resources and Sustainable Humanities*, 2(2). <https://doi.org/10.70568/5r4wnd14>
- Amayreh, M. S., Al-Zaqeba, M. A. A., Al-Sheyyab, K. O., Aloqaily, A. N., Jarah, B. A. F., & Al-Jamal, W. Q. (2026, April). Legal and Economic Perspectives Under Malaysia's MADANI Framework: ESG, and AI. In *2026 International Conference on Artificial Intelligence for Sustainable Engineering and Innovation (AISEI)* (pp. 423-431). IEEE.
- Aujali, F. A. (2026). The impact of technology on management performance in Libya: A PRISMA-guided systematic review of evidence published from January 2020 through 31 May 2026. *Universal Journal of Green Human Resources and Sustainable Humanities*, 3(1). <https://doi.org/10.70568/UJGHRSH3.1.26.5>
- Aung, Y. Y., Wong, D. C., & Ting, D. S. (2021). The promise of artificial intelligence: a review of the opportunities and challenges of artificial intelligence in healthcare. *British medical bulletin*, 139(1), 4-15.
- Ayman, I. S. A. (2025). The impact of blended learning techniques on enhancing critical thinking skills in Arabic language education: A comparative study of traditional and blended educational systems. *International Journal of Pedagogy and Professional Human Development Insights*, 1(1). <https://doi.org/10.70568/IJPHDI.1.1.5>
- Ayoub, T. K. B., & Abd Rahman, N. B. (2026). From digital technology to sustainable performance: The mediating role of lean management in Malaysia's phone waste management systems. *Universal Journal of Future Intelligence: Innovations and Artificial Intelligence*, 3(1). <https://doi.org/10.70568/UJFIIAI.3.1.1>
- Baah-Acheamfuor, K., Qutieshat, A., & Yangailo, T. (2023). Critical Review: Measures of Digital Competency Related to Employability. *Economia Aziendale Online*, 14(2), 379-391.
- Benhamou, S. (2020). Artificial intelligence and the future of work. *Revue d'économie industrielle*, (169), 57-88.
- Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS quarterly*, 45(3), 1433-1450.
- Bessen, J., Goos, M., Salomons, A., & van den Berge, W. (2020). Automation: A guide for policymakers. *Economic Studies at Brookings Institution: Washington, DC, USA*, 17.
- Bhattacharya, D. (2021). Competing in the Age of AI: Strategy and Leadership When Algorithms and Networks Run the World: Marco Iansiti and Karim R. Lakhani, Boston, MA, Harvard Business Review Press, 2020, 267 pp., US \$32.00 (Hardback), ISBN 9781633697621.
- Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. *The Quarterly Journal of Economics*, 140(2), 889-942.
- Canhoto, A. I., & Clear, F. (2020). Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. *Business Horizons*, 63(2), 183-193.
- Carayannis, E. G., Dumitrescu, R., Falkowski, T., Papamichail, G., & Zota, N. R. (2025). Enhancing SME resilience through artificial intelligence and strategic foresight: A framework for sustainable competitiveness. *Technology in Society*, 81, 102835.
- Chee, H., Ahn, S., & Lee, J. (2025). A competency framework for AI literacy: Variations by different learner groups and an implied learning pathway. *British Journal of Educational Technology*, 56(5), 2146-2182.
- Chounta, I. A., Ortega-Arranz, A., Daskalaki, S., Dimitriadis, Y., & Avouris, N. (2024). Toward a data-informed framework for the assessment of digital readiness of higher education institutions. *International Journal of Educational Technology in Higher Education*, 21(1), 59.
- Chowdhury, S., Budhwar, P., Dey, P. K., Joel-Edgar, S., & Abadie, A. (2022). AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework. *Journal of business research*, 144, 31-49.

- De Cremer, D., Bianzino, N. M., & Falk, B. (2023). How generative AI could disrupt creative work. *Harvard Business Review*, 13, 13.
- De Felice, F., Petrillo, A., De Luca, C., & Baffo, I. (2022). Artificial Intelligence or Augmented Intelligence? Impact on our lives, rights and ethics. *Procedia Computer Science*, 200, 1846-1856.
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International journal of information management*, 57, 101994.
- Elagha, T. B. J., Al-Zaqeba, M. A. A., Bin Wahid, M. A., & Bin Harun, M. S. (2025). The Moderating Effect of Family Ownership Concentration Between Board of Directors Effectiveness and Risk Management Disclosure in Palestine Stock Exchange. *International Journal of Digital Accounting and Fintech Sustainability*, 2(1). <https://doi.org/10.70568/26dkr754>
- Essenfelder, R. (2026). From Enchantment to Responsibility: Cultivating Ethical Action through Critical AI Literacy in Education.
- Faishal, M., Mathew, S., Neikha, K., Pusa, K., & Zhimomi, T. (2023). The future of work: AI, automation, and the changing dynamics of developed economies. *World Journal of Advanced Research and Reviews*, 18(3), 620-629.
- Fareri, S., Fantoni, G., Chiarello, F., Coli, E., & Binda, A. (2020). Estimating Industry 4.0 impact on job profiles and skills using text mining. *Computers in industry*, 118, 103222.
- Fenwick, M., & Vermeulen, E. P. (2019). Technology and corporate governance: Blockchain, crypto, and artificial intelligence. *Tex. J. Bus. L.*, 48, 1.
- Fountain, T., McCarthy, B., & Saleh, T. (2019). Building the AI-powered organization. *Harvard business review*, 97(4), 62-73.
- Hamour, H. M. J. A., ALensou, J., Abuzaid, A., Alheet, A., Madadha, S., & Al-Zaqeba, M. (2023). The effect of strategic intelligence, effective decision-making and strategic flexibility on logistics performance. *Uncertain Supply Chain Management*, 11(2), 657-664.
- Hazaimh, Z. D. K. (2025). The Degree of Vocational Education Teachers' Utilization of Digital Skills from Their Perspective in Qasabat Irbid. *International Journal of Pedagogy and Professional Human Development Insights*, 1(2). <https://doi.org/10.70568/7fp8yj29>
- Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the academy of marketing science*, 49(1), 30-50.
- Jango, W. A., & Mohamed, Y. (2025). Evaluation of the Arabic language curriculum for seventh grade in light of technological trends from the perspective of Arabic language teachers and department heads in Al Ain City. *International Journal of Pedagogy and Professional Human Development Insights*, 1(1). <https://doi.org/10.70568/IJPHDI.1.1.2>
- Jebri, I., Al-Zaqeba, M., Al-Khawaja, H., Obaidey, A. L. A. A., & Marashdah, O. (2024). Enhancing estate governance using blockchain technology through risk management in estate governance of business sustainability. *International Journal of Data and Network Science*, 8(3), 1649-1658.
- Johansen, B., & Euchner, J. (2013). Navigating the VUCA world. *Research-Technology Management*, 56(1), 10-15.
- Johansson, J., & Herranen, S. (2019). The application of artificial intelligence (AI) in human resource management: Current state of AI and its impact on the traditional recruitment process.
- Jun, W., Nasir, M. H., Yousaf, Z., Khattak, A., Yasir, M., Javed, A., & Shirazi, S. H. (2022). Innovation performance in digital economy: does digital platform capability, improvisation capability and organizational readiness really matter?. *European Journal of Innovation Management*, 25(5), 1309-1327.
- Kalantzis, M., & Cope, B. (2025). Literacy in the time of artificial intelligence. *Reading Research Quarterly*, 60(1), e591.
- Konttila, J., Siira, H., Kyngäs, H., Lahtinen, M., Elo, S., Kääriäinen, M., ... & Mikkonen, K. (2019). Healthcare professionals' competence in digitalisation: A systematic review. *Journal of clinical nursing*, 28(5-6), 745-761.
- Kutnjak, A., Pihir, I., & Furjan, M. T. (2020). Assessing digital transformation readiness using digital maturity indices. In *Central European Conference on Information and Intelligent Systems* (pp. 307-314). Faculty of Organization and Informatics Varazdin.
- Lund, S., Madgavkar, A., Manyika, J., Smit, S., Ellingrud, K., Meaney, M., & Robinson, O. (2021). The future of work after COVID-19. *McKinsey global institute*, 18.
- Maabreh, H. M. A., Che Abdul Rahman, M. R., & Jamil, A. H. (2026). The effect of earnings management on financial performance through tax avoidance in Jordan's tourism-linked service ecosystem. *Social Science Forum*, 10(9), 106-126. <https://doi.org/10.10118/SSFJ/2610907>
- Mustafa, S. A., & Altrad, A. (2026). Transforming Higher Education Through AI Literacy: A Structural Model for SDG 4, Future-Ready Skills, and Graduate Employability.

- Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International journal of information management*, 53, 102104.
- Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, 366(6464), 447-453.
- Oehlhorn, C. E., Maier, C., Laumer, S., & Weitzel, T. (2020). Human resource management and its impact on strategic business-IT alignment: A literature review and avenues for future research. *The Journal of Strategic Information Systems*, 29(4), 101641.
- Otoom, N. M. (2023). Requirements for employing artificial intelligence applications in higher education and its challenges. *Jerash for Research and Studies Journal*, 24(2), Article 6. <https://digitalcommons.aaru.edu.jo/jpu/vol24/iss2/6>
- Öziskender, E., & Erdem, Z. (2025). The Impact of Post-Pandemic Digital Transformation on Labor Markets. *Premium e-Journal of Social Sciences (PEJOSS)*, 9(56), 572-591.
- Paschen, J., Wilson, M., & Ferreira, J. J. (2020). Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel. *Business Horizons*, 63(3), 403-414.
- Patalas-Maliszewska, J., Kłos, S., & Dostatni, E. (2022). Sustainable business model integrated with the enterprise resource planning system: SBM-ERP. *Bulletin of the Polish Academy of Sciences. Technical Sciences*, 70(6).
- Perez, C. (2010). Technological revolutions and techno-economic paradigms. *Cambridge journal of economics*, 34(1), 185-202.
- Petropoulos, G. (2018). The impact of artificial intelligence on employment. *Praise for work in the digital age*, 119(4), 121-127.
- Petruzzello, G. (2022). Exploring perceived employability of university students and graduates. 10.48676/unibo/amsdottorato/10353
- Philbeck, T., & Davis, N. (2018). The fourth industrial revolution. *Journal of International Affairs*, 72(1), 17-22.
- Pinar, A. (2024). Technological unemployment and the AI revolution: An investigation on macroeconomic consequences. *Econharran*, 8(14), 15-26.
- Qahman, A. I., Alzaqebah, M., Jawarneh, S., Al-Zaqeba, M. A. A., Al-Taani, A. H. M., Aloqaily, A. N., & Almatrooshi, M. A. (2026). Design and development of an intelligent system based on artificial intelligence and machine learning using customs digital indicators. *International Journal of Data and Network Science*, 10(1), 251-264.
- Sánchez-Canut, S., Usart-Rodríguez, M., Grimalt-Álvaro, C., Martínez-Requejo, S., & Lores-Gómez, B. (2023). Professional digital competence: Definition, frameworks, measurement, and gender differences: A systematic literature review. *Human Behavior and Emerging Technologies*, 2023(1), 8897227.
- Sharadgah, R. A. M., Al-Shaboul, T. A., & Hazaimah, Z. D. (2025). The role of digital transformation on the performance of vocational education teachers in public schools in Irbid Governorate from their perspective. *International Journal of Pedagogy and Professional Human Development Insights*, 2(1), Article 625. <https://doi.org/10.70568/IJPPHDI.2.1.625>
- Sharadgah, R. A. M., Al-Shboul, T. A. A., Hazaimah, Z. D. K., & Ajlouni, B. A. (2026). AI adoption for future employability in vocational education: A literature review. *Social Science Forum*.
- Shboul, T. (2024). Adopting the BTEC framework in vocational education: A pathway to elevating employability skills and meeting labor market needs. *International Journal of Pedagogy and Professional Human Development Insights*, 1(1), Article 424. <https://doi.org/10.70568/IJPPHDI.1.1.424>
- Shtefan, A. (2025). Sui Generis Protection of AI-Generated Outputs in Ukraine. *InterEULawEast: Journal for the international and european law, economics and market integrations*, 12(2), 79-103.
- Shubailat, O. M., Al-Zaqeba, M. A. A., Madi, A., & Khairi, K. F. (2024). Investigation the effect of digital taxation and digital accounting on customs efficiency and port sustainability. *International Journal of Data and Network Science*, 8(1), 61-68.
- Sohn, I. (2024). Power and Prediction: The Disruptive Economics of Artificial Intelligence. *Foresight: The International Journal of Applied Forecasting*, (72).
- Sousa, M. J., & Rocha, Á. (2019). Digital learning: Developing skills for digital transformation of organizations. *Future Generation Computer Systems*, 91, 327-334.
- Southworth, J., Migliaccio, K., Glover, J., Glover, J. N., Reed, D., McCarty, C., ... & Thomas, A. (2023). Developing a model for AI Across the curriculum: Transforming the higher education landscape via innovation in AI literacy. *Computers and Education: Artificial Intelligence*, 4, 100127.
- Stahl, B. C., Andreou, A., Brey, P., Hatzakis, T., Kirichenko, A., Macnish, K., ... & Wright, D. (2021). Artificial intelligence for human flourishing—Beyond principles for machine learning. *Journal of Business Research*, 124, 374-388.
- Tanveer, M., Hassan, S., & Bhaumik, A. (2020). Academic policy regarding sustainability and artificial intelligence (AI). *Sustainability*, 12(22), 9435.
- Trocin, C., Mikalef, P., Papamitsiou, Z., & Conboy, K. (2023). Responsible AI for digital health: a synthesis and a research agenda. *Information Systems Frontiers*, 25(6), 2139-2157.

- Tun, H. M., Rahman, H. A., Naing, L., & Malik, O. A. (2025). Trust in artificial intelligence–based clinical decision support systems among health care workers: systematic review. *Journal of Medical Internet Research*, 27, e69678.
- Ulnicane, I., Knight, W., Leach, T., Stahl, B. C., & Wanjiku, W. G. (2021). Framing governance for a contested emerging technology: insights from AI policy. *Policy and Society*, 40(2), 158-177.
- Van Laar, E., Van Deursen, A. J., Van Dijk, J. A., & De Haan, J. (2020). Determinants of 21st-century skills and 21st-century digital skills for workers: A systematic literature review. *Sage Open*, 10(1), 2158244019900176.
- Wamba-Taguimdje, S. L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. *Business process management journal*, 26(7), 1893-1924.
- Wang, W., & Siau, K. (2019). Artificial intelligence, machine learning, automation, robotics, future of work and future of humanity: A review and research agenda. *Journal of Database Management (JDM)*, 30(1), 61-79.
- Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. *Learning, Media and Technology*, 45(3), 223-235.
- Wu, D., Chen, M., Chen, X., & Liu, X. (2024). Analyzing K-12 AI education: A large language model study of classroom instruction on learning theories, pedagogy, tools, and AI literacy. *Computers and Education: Artificial Intelligence*, 7, 100295.
- Zawacki-Richter, O., Marin, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—where are the educators?. *International journal of educational technology in higher education*, 16(1), 39.
- Zhang, C., & Lu, Y. (2021). Study on artificial intelligence: The state of the art and future prospects. *Journal of Industrial Information Integration*, 23, 100224.