Journal of International Education and Development
2025, VOL. 9, NO. 11, 163-169
DOI: 10.47297/wspiedWSP2516-250036.20250911

The Impact and Reconstruction of Artificial Intelligence on Vocational Education Ecosystems: An Analysis Based on Stakeholder Theory

Jie Gan

Pingxiang Health Vocational College, Pingxiang, Jiangxi, 337000, China

ABSTRACT
Artificial intelligence (AI) is rapidly transforming labor markets and skill demands, compelling vocational education and training (VET) systems worldwide to adapt. Existing studies focus on AI's technical or curricular impacts but lack a systemic analysis of how it reshapes stakeholder dynamics within the VET ecosystem. Drawing on stakeholder theory, this study employs a mixed-methods approach, combining systematic literature review, comparative case studies of Germany, Singapore, and China, and qualitative analysis of 42 policy documents. AI exerts asymmetric effects across stakeholders, elevating employer influence, intensifying learner urgency, challenging educator roles, and straining government oversight, while simultaneously fostering new governance models such as data consortia, modular credentials, and AI-enhanced apprenticeships. The paper proposes a dynamic stakeholder-based framework for understanding and guiding AI-driven VET transformation, offering practical strategies for equitable and resilient skills development in the digital age.

KEYWORDS
Artificial intelligence; Vocational Education and Training (VET); Stakeholder theory; Ecosystem transformation; Skills futures; Policy innovation; Digital labor markets

1 Introduction

The advent of artificial intelligence (AI) marks a paradigm shift not only in technological capability but also in the very structure of work and human capital formation. As AI systems increasingly automate routine cognitive and manual tasks while augmenting complex decision-making, the global labor market is undergoing profound restructuring [1]. Occupations once considered stable are being reconfigured, and new hybrid roles, such as AI trainers, data annotators, prompt engineers, and human-AI collaboration specialists, are emerging at an unprecedented pace [2]. These roles demand not only technical fluency but also socio-emotional competencies, ethical reasoning, and adaptive problem-solving, skills that challenge traditional vocational pedagogies rooted in standardized task mastery.

In this context, vocational education and training (VET) systems, historically designed to align closely with industrial needs through fixed curricula and apprenticeship models, face both existential challenges and transformative opportunities [3]. On one hand, AI threatens to render large segments of existing VET content obsolete within years, if not months [4]. On the other, it offers powerful tools for personalization, scalability, and real-time responsiveness to labor market signals. Yet, the discourse surrounding AI in VET remains fragmented and often reactive. Much of the scholarly attention focuses narrowly on curriculum redesign, such as integrating coding, data visualization, or machine learning basics, or on the technical feasibility of AI-powered learning tools like intelligent tutoring systems, automated grading algorithms, or virtual reality simulators [5].

While these contributions are valuable, they often overlook the systemic nature of vocational education as a multi-actor ecosystem. VET is not merely a pipeline from school to work; it is a dynamic network where learners, educators, employers, governments, private training providers, certification bodies, and increasingly, edtech platforms, co-create value through ongoing negotiation, resource exchange, and mutual accountability. AI disrupts this ecosystem not by replacing parts but by rewiring relationships, altering who holds knowledge, who sets standards, and who benefits from innovation.

Consequently, a critical research gap persists: the lack of a holistic analytical framework capable of capturing how AI simultaneously disrupts and reconstructs relationships, incentives, governance structures, and legitimacy claims across this ecosystem [6]. Without such a lens, reforms risk reinforcing existing inequities, favoring large corporations over small businesses, digitally native youth over mid-career workers, or efficiency over equity.

This paper addresses this gap by applying stakeholder theory, a well-established framework in organizational and policy studies, to analyze the multifaceted impact of AI on vocational education. Originally developed to guide corporate strategy, stakeholder theory posits that organizations must consider the interests, power, legitimacy, and urgency of all parties affected by or influencing their operations. Extending this to VET ecosystems allows us to move beyond techno-centric or institution-centric analyses toward a relational understanding of systemic change. Rather than asking "What can AI do for VET?" we ask: "How does AI reshape who matters, whose voice counts, and how value is co-produced in vocational education?"

Our primary research objectives are threefold: (1) To map how AI alters the roles, expectations, strategic behaviors, and perceived legitimacy of key VET stakeholders across different national contexts; (2) To identify emergent patterns of collaboration, conflict, institutional innovation, and resistance in response to AI-driven disruption; and (3) To propose a reconceptualized, empirically grounded model of the AI-integrated vocational education ecosystem that accounts for temporal dynamics, power asymmetries, and normative trade-offs.

Methodologically, we combine systematic literature review with comparative case studies of national VET reforms in Germany, Singapore, and China, three jurisdictions recognized for their advanced digital strategies, mature vocational traditions, and distinct governance philosophies. Germany exemplifies a corporatist, industry-co-governed dual system; Singapore represents a centralized, state-led meritocratic model with strong public-private alignment; and China demonstrates a top-down, pilot-driven approach blending socialist planning with digital capitalism. We supplement this with qualitative analysis of 42 policy documents, white papers, and institutional reports issued between 2020 and 2024, ensuring temporal relevance and alignment with current AI deployment trends, including the rise of generative AI and large language models (LLMs) in educational settings.

The significance of this study is twofold. Academically, it advances stakeholder theory by applying it to a rapidly evolving socio-technical domain characterized by algorithmic mediation, datafication, and platformization. In doing so, it enriches the theory's explanatory power in contexts of technological disruption, particularly by introducing temporal and relational dimensions to the concept of stakeholder salience. Practically, it offers policymakers, VET institutions, industry partners, and civil society actors a diagnostic and design tool to anticipate stakeholder tensions, co-create inclusive transition pathways, and build adaptive governance mechanisms that ensure vocational education remains a vehicle for social mobility, economic resilience, and democratic participation in the age of AI.

2 Related Works

2.1 Technological Determinism vs. Socio-Technical Co-construction in AI-Education Discourse

Early scholarship on AI in education often adopted a technologically deterministic stance, portraying AI as an autonomous force that inevitably reshapes pedagogical practices and institutional structures [7]. Proponents emphasized efficiency gains, personalized learning paths tailored to individual cognitive profiles, automated assessment reducing instructor workload, predictive analytics identifying at-risk students for early intervention, as inherent and universally beneficial outcomes of AI adoption [8]. This perspective assumed a linear, unidirectional relationship between technological input and educational outcome, with minimal consideration of contextual constraints, cultural norms, or human agency. In this view, resistance to AI was framed as irrational or backward-looking, rather than a legitimate response to issues of control, privacy, or pedagogical philosophy.

In contrast, a growing body of recent work advocates for a socio-technical co-construction view, arguing that AI systems are not neutral tools but sociomaterial assemblages embedded within, and actively shaped by, existing institutional norms, power relations, historical legacies, and cultural values [9]. From this standpoint, the impact of AI is not predetermined but negotiated, contested, and reinterpreted through complex interactions among designers, implementers, users, regulators, and even non-human actors like algorithms and data infrastructures [10]. This shift has enabled more nuanced analyses of equity, bias, surveillance, and democratic control in AI-driven education. For instance, studies have shown how facial recognition in online proctoring disproportionately misidentifies students of color, or how recommendation engines in learning platforms reinforce gendered career stereotypes.

Yet, this critical turn remains underutilized in the vocational domain, where pragmatic concerns about employability and economic competitiveness often overshadow deeper questions of justice, autonomy, and epistemic diversity. Vocational education, historically positioned as the "practical" counterpart to academic education, is particularly vulnerable to techno-solutionist narratives that equate digital adoption with modernization [11]. Our study bridges this divide by integrating socio-technical sensitivity with systemic stakeholder analysis.

2.2 Stakeholder Perspectives in Traditional Vocational Education Systems

Traditional VET literature conceptualizes the system as a tripartite partnership among government, industry, and educational institutions, with learners cast as passive beneficiaries or inputs to be processed. In this model, government sets national qualifications frameworks and funding mechanisms; industry defines occupational standards and provides workplace training slots; and institutions deliver curriculum-aligned instruction, often assessed through standardized exams or competency demonstrations. This arrangement assumes stable occupational boundaries, predictable career ladders, and a clear separation between learning and working.

However, contemporary critiques highlight the limitations of this static, closed-system view. Studies from the past decade emphasize the increasing fragmentation of labor markets due to platformization, gig work, and project-based

employment; the blurring of boundaries between formal, non-formal, and informal learning; and the rise of learner agency in demanding modular, stackable, and portable credentials [12]. These trends have rendered the tripartite model insufficient, necessitating the inclusion of additional stakeholders such as edtech firms (providing LMS and simulation tools), online learning platforms (offering micro-credentials), professional certification bodies (validating hybrid skills), and learners themselves as active agents shaping their own learning trajectories.

Despite these advances, few frameworks systematically account for how external shocks, like the accelerated deployment of generative AI, reconfigure stakeholder salience, interdependence, and conflict potential. For example, when an AI system predicts that a certain trade will decline in five years, who decides whether to phase out its training program? The government? Employers? Learners already enrolled? Current models lack the granularity to answer such questions.

2.3 Emerging Research on AI and Skills Transformation: Gaps and Opportunities

Recent empirical studies have begun mapping AI's impact on specific occupational clusters. For instance, analyses of manufacturing, logistics, healthcare, and customer service sectors reveal that AI displaces routine perceptual and cognitive tasks but creates demand for "hybrid" competencies combining domain expertise with data interpretation, prompt engineering, AI oversight, and human-machine interaction skills. Some national skills forecasting agencies now incorporate AI exposure indices, measuring the susceptibility of tasks to automation, to guide VET planning and public investment.

Nevertheless, three critical gaps remain. First, most studies treat stakeholders in isolation, e.g., analyzing employer skill demands without considering educator capacity to deliver new content, or assessing learner access without examining infrastructure disparities [13]. Second, there is scant attention to the temporal dimension: how stakeholder relationships evolve during distinct phases of AI adoption (pilot experimentation, scale-up, institutionalization, or backlash). A stakeholder marginalized in the pilot phase may become central during scale-up, and vice versa. Third, the normative question of whose interests dominate in AI-driven VET reforms, corporate efficiency, state control, or learner equity, is rarely addressed explicitly. Without such scrutiny, reforms risk becoming vehicles for platform capitalism rather than public good.

To synthesize these strands, Table 1 compares dominant theoretical orientations in relevant literature.

Table 1 Comparative Theoretical Orientations in AI-VET Research

Dimension	Techno-Determinist View [14]	Socio-Technical View[15]	Stakeholder-Centric View (This Study)
Primary Focus	AI capabilities and efficiencies	Contextual embedding of AI	Inter-stakeholder dynamics under AI disruption
Agency	Technology as driver	Human-technology co-evolution	Stakeholders as strategic, reflexive actors
Change Mechanism	Linear adoption	Negotiated implementation	Power realignment and ecosystem restructuring
Equity Consideration	Implicit or absent	Central, but often post-hoc	Explicitly analyzed via legitimacy, urgency, and inclusion
Temporal Sensitivity	Static	Moderate	High (phases of adoption, feedback loops)

This paper bridges these perspectives by deploying stakeholder theory as an integrative lens. Unlike prior work that treats stakeholders as static categories or background conditions, we analyze them as dynamic actors whose influence, legitimacy, and urgency shift in response to AI-induced uncertainties, opportunities, and threats. Our contribution lies in reframing vocational education not as a delivery mechanism for pre-defined skills, but as a contested, adaptive, and co-evolving ecosystem where AI serves as both disruptor and catalyst for institutional innovation, governance experimentation, and new forms of solidarity.

3 Theoretical Framework and Methodology

3.1 Stakeholder Theory as an Analytical Lens

Stakeholder theory, originally developed in corporate governance, defines stakeholders as "any group or individual who can affect or is affected by the achievement of an organization's objectives." Later extensions introduce three attributes, power (the ability to impose will), legitimacy (socially accepted right to be involved), and urgency (time-sensitive claims requiring immediate attention), to determine which stakeholders command managerial attention. Stakeholders possessing all three attributes ("definitive stakeholders") are prioritized; those with only one or two may be monitored or ignored.

In the context of vocational education ecosystems, we adapt this model to assess how AI alters the salience of each stakeholder group over time. We conceptualize the VET ecosystem not as a single organization but as a polycentric network of interdependent actors engaged in the co-production of human capital, social inclusion, and economic productivity. AI disrupts this network in three interrelated ways:

(1) Epistemic disruption: AI changes the skill content and knowledge bases that define occupational legitimacy. For example, a welder's expertise is no longer just about heat control but also about interpreting sensor data from smart welding helmets.

(2) Power redistribution: Control over data, algorithms, and digital infrastructure grants new forms of influence. Edtech firms that host learning platforms can shape curriculum visibility; employers with real-time workforce analytics can redefine credential validity.

(3) Temporal acceleration: The half-life of skills is shortening, creating urgency around reskilling and lifelong learning, but also anxiety and exclusion for those unable to keep pace.

Stakeholder theory enables us to trace these shifts systematically, moving beyond descriptive accounts to explanatory mechanisms. It allows us to ask: When does a learner become urgent? When does an SME lose legitimacy in standard-setting? How do governments balance the power of multinational tech firms with the needs of local communities?

3.2 Research Design and Data Collection

This study employs a sequential mixed-methods design to ensure depth, breadth, and triangulation.

Phase one involved a systematic literature review following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. We screened 187 peer-reviewed articles (2019 – 2024) from Scopus and Web of Science using Boolean combinations of keywords such as "AI AND vocational education," "stakeholder AND skills transformation," "future of work AND training," and "algorithmic governance AND VET." After applying exclusion criteria (e.g., non-English language, purely technical focus, opinion pieces), 63 empirical or theoretically rigorous studies were selected for thematic coding using NVivo 14. Codes included stakeholder type, AI application, reported impact, and equity considerations.

Phase two consisted of comparative case studies of Germany, Singapore, and China. These cases were selected based on three criteria: (1) high national investment in AI strategy (e.g., Germany's AI Strategy 2023, Singapore's National AI Strategy 2.0, China's Next Generation AI Development Plan); (2) mature VET systems with distinct governance models (Germany's industry-co-governed dual system, Singapore's centralized SkillsFuture ecosystem, China's state-directed "AI+VET" pilots); and (3) availability of recent, publicly accessible policy documentation. For each country, we analyzed 10 – 15 key documents, including national AI strategies, VET reform roadmaps, memoranda of understanding between industry and education ministries, and evaluation reports from pilot programs.

Phase three involved qualitative content analysis of 42 policy and institutional documents published between 2020 and 2024. We focused on explicit references to stakeholders, their responsibilities, rights, and AI-related risks or opportunities. Coding was iterative: initial codes derived from stakeholder theory (power, legitimacy, urgency) were refined through constant comparison. For example, "employer co-design" was coded under power and legitimacy; "learner data privacy" under urgency and legitimacy.

Triangulation across methods ensured validity: literature informed theoretical sensitization; cases provided contextual depth and variation; document analysis revealed institutional discourses and policy logics. Limitations include potential bias in official documents (which tend to emphasize success over failure) and the exclusion of grassroots learner and instructor voices, which future research could address through interviews, focus groups, or participatory observation.

4 Findings and Discussion

4.1 Asymmetric Disruption Across Stakeholder Groups

Our analysis reveals that AI does not impact all stakeholders equally; rather, it produces asymmetric effects that exacerbate or mitigate existing inequalities depending on context.

Learners face heightened uncertainty and stratification. While AI promises personalized upskilling through adaptive learning platforms, it also accelerates credential obsolescence, particularly for those in mid-career transitions or low-resource settings. In Singapore's SkillsFuture initiative, AI literacy modules are widely accessible, yet uptake remains skewed toward younger, urban, digitally native cohorts with reliable internet and devices, exacerbating intergenerational and socioeconomic inequities. Older workers report feeling alienated by interfaces designed for "digital natives," and rural learners in China's western provinces struggle with bandwidth limitations that prevent effective use of AI simulations.

Educators experience simultaneous role erosion and expansion. Traditional instructors report diminished authority as AI tutors handle foundational knowledge delivery, automated feedback, and even basic mentoring. Yet, new roles, such as "learning experience designers" who curate AI-human collaborative scenarios, or "ethics facilitators" who guide discussions on algorithmic bias, are emerging. However, these roles often lack formal recognition, career pathways, or professional development support. German dual-system trainers express concern that AI simulations, while useful for

safety training, cannot replicate the tacit knowledge transmission that occurs through master-apprentice relationships in workshops.

Employers, particularly large multinational tech firms and industrial conglomerates, gain significant agenda-setting power through data-driven skill definitions. Companies like Alibaba, Siemens, and DBS Bank now co-design micro-credentials based on real-time workforce analytics from their internal HR systems, effectively setting de facto occupational standards. However, small and medium enterprises (SMEs), which constitute over 90% of businesses in most economies, lack the data infrastructure, technical expertise, or bargaining power to participate. This risks creating a two-tier VET system: one for employees of AI-savvy corporations, another for the rest.

Governments struggle to balance innovation promotion with regulatory oversight and social protection. China's "AI+ VET" pilot zones encourage rapid experimentation with generative AI in classrooms but offer limited safeguards against algorithmic bias in learner tracking or opaque credentialing. Conversely, the European Union's AI Act imposes strict transparency and human oversight requirements, which, while protective, may slow adoption in time-sensitive sectors like emergency medical training or renewable energy installation.

To visualize these shifting dynamics, Figure 1 maps the relative salience (on a 1 – 5 scale) of five core stakeholder groups, learners, educators, employers, governments, and training providers, in Germany, Singapore, and China before and after AI integration. The figure reveals notable cross-national patterns: in all three contexts, employer power increases significantly post-AI, while learner urgency spikes but legitimacy remains uneven. Educator power declines modestly, though legitimacy is preserved in Germany due to strong union protections. Government legitimacy remains high, but urgency varies, highest in China (due to state-led urgency), moderate in Singapore, and lower in Germany where consensus-building slows response.

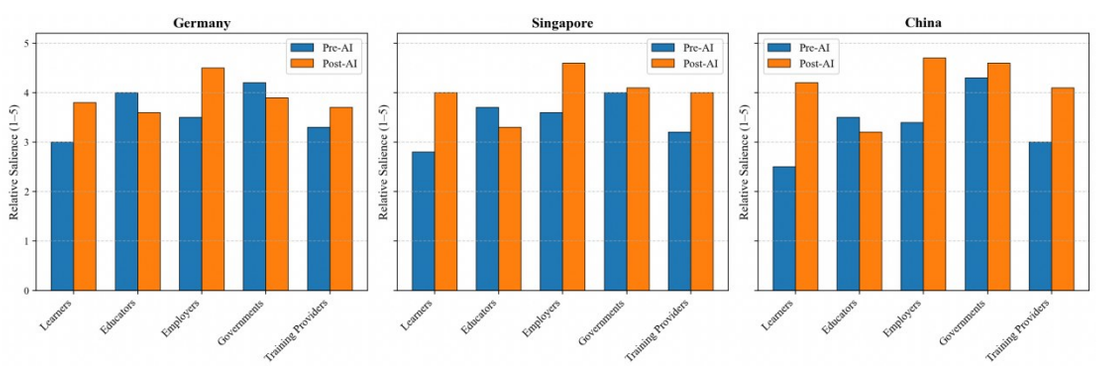

Figure 1 Relative salience (on a 1–5 scale) of core stakeholders in vocational education ecosystems in Germany, Singapore, and China before and after AI integration

4.2 Emergent Ecosystem Reconfigurations

In response to these pressures, new governance and collaboration models are arising, reflecting attempts to rebalance stakeholder salience.

First, data-sharing consortia: In Germany, the Federal Institute for Vocational Education and Training (BIBB) facilitates partnerships among industry associations (e.g., BDI, ZDH), chambers of commerce, and VET schools to jointly operate anonymized, GDPR-compliant skill-demand dashboards fed by AI analytics from job portals and company HR systems. This enables agile, evidence-based curriculum updates while preserving data sovereignty.

Second, modular credential ecosystems: Singapore's MySkills platform, integrated with the national digital identity system, allows learners to stack AI-verified micro-credentials from universities, polytechnics, private bootcamps, and even employers. These credentials are portable, verifiable via blockchain, and mapped to national skills frameworks, decoupling learning from single institutions and empowering learner choice.

Third, adaptive apprenticeship models: In China's Shenzhen and Suzhou pilot zones, traditional apprenticeships in advanced manufacturing are being enhanced with AI-powered virtual reality simulations. Trainees practice high-risk tasks, such as calibrating industrial robots or troubleshooting AI-driven CNC machines, in immersive virtual environments before workplace deployment, reducing accidents and accelerating competence acquisition.

These innovations reflect a broader shift from hierarchical, top-down coordination to networked, co-creative governance. Crucially, they succeed only when stakeholder salience is actively managed, for example, by granting SMEs subsidized access to AI tools, involving learners in platform design through user councils, or establishing independent ethics review boards for AI-VET applications.

4.3 Theoretical Implications: Beyond the Tripartite Model

Our findings fundamentally challenge the enduring tripartite model of VET. AI introduces at least two new core stakeholders: edtech platforms (as infrastructure providers that mediate access, visibility, and assessment) and data intermediaries (as trust brokers that manage consent, anonymization, and interoperability). Moreover, the attributes of salience are highly fluid: a learner may gain urgency during mass layoffs in an AI-automated sector but lose power in curriculum design forums dominated by industry representatives.

This supports a reconceptualization of VET as a dynamic stakeholder field, a term borrowed from organizational sociology, where AI acts as a boundary object: simultaneously a technical artifact, a policy instrument, and a social mediator that different groups interpret and mobilize according to their interests. The strength of stakeholder theory lies in explaining why some reforms fail (e.g., when governments ignore employer legitimacy in credential design) and others thrive (e.g., when urgency around green skills is shared across learners, educators, and policymakers).

To capture this complexity, Figure 2 presents our proposed reconceptualized model of the AI-integrated VET ecosystem. At the center lies the learner, surrounded by concentric layers: inner layer (core stakeholders: educators, employers, government), middle layer (enablers: edtech, certification bodies, unions), and outer layer (macro forces: labor market trends, AI ethics frameworks, global standards). Arrows indicate bidirectional flows of data, resources, influence, and feedback, emphasizing co-evolution rather than linear causality. The model explicitly incorporates temporal dynamics (e.g., "skill half-life") and equity safeguards (e.g., "inclusion mechanisms"), offering a practical blueprint for ecosystem design.

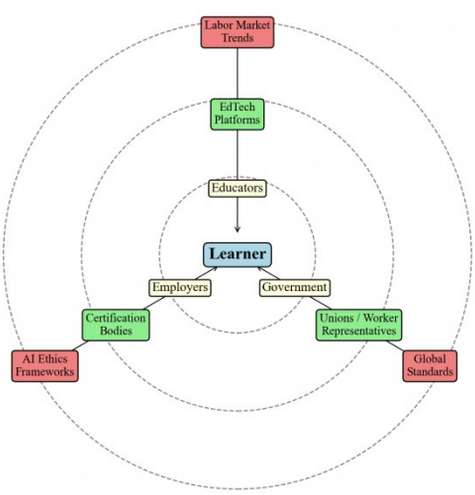

Figure 2 Reconceptualized AI-Integrated VET Ecosystem Model

Compared to prior socio-technical studies, our framework offers greater predictive and diagnostic utility by specifying which stakeholders are likely to resist or champion AI integration based on shifting salience attributes. This moves the field from post-hoc critique toward proactive, anticipatory ecosystem design, a crucial capability in an era of accelerating technological change.

5 Conclusion

This study demonstrates that artificial intelligence is not merely a technological add-on or efficiency tool for vocational education but a systemic force that reconfigures stakeholder roles, power balances, value creation logics, and even the moral foundations of skills development. By applying and extending stakeholder theory to the AI-VET nexus, we provide a robust, empirically grounded analytical framework for understanding these dynamics across diverse national and institutional contexts.

Our key contributions are threefold. Theoretically, we advance stakeholder theory by operationalizing it in a socio-technical ecosystem undergoing rapid, algorithmically mediated disruption. We introduce temporal and relational dimensions to salience assessment, showing how power, legitimacy, and urgency evolve across phases of AI adoption and vary by stakeholder positionality. Empirically, we document concrete mechanisms of ecosystem reconstruction, from cross-sectoral data consortia to portable micro-credential platforms, that offer transferable lessons for policymakers seeking to build responsive, inclusive VET systems. Practically, we caution against techno-solutionism: successful AI integration requires deliberate, ongoing stakeholder engagement, especially with historically marginalized groups such as SMEs, mid-career learners, rural populations, and non-traditional students.

For practice, we recommend three actionable steps: (1) VET authorities should establish multi-stakeholder observatories, inclusive forums that monitor AI's labor market impacts in real time and co-design responsive interventions; (2) Educational institutions must invest in educator upskilling not just in AI tools, but in facilitating human-AI collaborative learning, ethical deliberation, and adaptive pedagogy; (3) Governments must enact smart regulation that ensures algorithmic transparency, data privacy, and anti-discrimination safeguards while incentivizing inclusive innovation through grants, tax credits, or public procurement preferences for SME-partnered AI-VET solutions.

Future research should explore longitudinal effects of AI on graduate employability and wage trajectories; conduct comparative studies in Global South contexts where digital divides are starker; and investigate learner agency through participatory action research that centers marginalized voices. Additionally, the rise of generative AI and LLMs demands new inquiry into how synthetic content, automated assessment, and AI co-creation reshape epistemic authority in vocational domains.

Only through such sustained, multi-level, and ethically grounded inquiry can vocational education fulfill its historic promise, not just as a conveyor belt to jobs, but as an engine of equitable adaptation, human dignity, and democratic resilience in the AI era.

About the Author

Jie Gan, graduated from The University of Sydney with a master's degree in marketing, and is currently working at PingXiang health vocational college.

References

[1] Resmi K. R., Joseph A., George B., Job D., & Cyriac S. (2025). How AI Is Transforming Teaching and Learning in Vocational Programs. In Innovative Approaches in Vocational and Regional Education (pp. 87-118). IGI Global Scientific Publishing.

[2] Hutson J. (2025). From Displacement to Design: Reframing Work, Skills, and Education for the AI-Transformed Economy A Review. ISRG Journal of Economics and Finance, 2(5).

[3] Ghosh L., & Ravichandran R. (2024). Emerging technologies in vocational education and training. Journal of Digital Learning and Education, 4 (1), 41-49.

[4] Barbas M. P., Vieira A. T., Branco P. D., & Casimiro E. (2025). Strategies for Applying AI in Vocational Education and Training. Predict: Preliminary Results and Impact. Calitatea Vieții, 36(1), 1-12.

[5] Thakur G. S. M., Banerjee A., & Sarkar P. (2025). AI in Vocational Education and Training: Technologies and Applications. In Transforming Vocational Education and Training Using AI (pp. 49-72). IGI Global Scientific Publishing.

[6] Jing Z. (2024). Challenges and Opportunities for the Development of Vocational Education in the Age of Artificial Intelligence: A Study Based on Educational Ecology Theory. Journal of Exploration of Vocational Education, 1(1), 101-121.

[7] Konstantinidis A. (2025). A Metaphor for Rethinking Artificial Intelligence in/and Education. Journal of Interactive Media in Education, 2025(1).

[8] Su Q. (2025). AI-Enabled personalized learning ecology construction and its implications for prevocational education. In Itm Web of Conferences (Vol. 77, p. 01034). EDP Sciences.

[9] Mossin E. A., Martins G. A., Gouveia R. C., & Pantoni R. P. (2025). Reflections on artificial intelligence in the light of the foundations of vocational education. Educação em Revista, 41, e53835.

[10] Linderoth C., Hultén M., & Stenliden L. (2024). Competing visions of artificial intelligence in education—A heuristic analysis on sociotechnical imaginaries and problematizations in policy guidelines. Policy Futures in Education, 22(8), 1662-1678.

[11] Li S. (2024, December). The Transformation of Vocational Education in the Context of Deep Learning Theory: Actual Dilemma and Practical Path. In 4th International Conference on New Media Development and Modernized Education (Nmdme 2024) (pp. 193-201). Atlantis Press.

[12] Herrero C., Arroyo S. A., Castaño M. J., Centeno C., Coenen J., Mccoshan A., ... & Zubizarreta, P. A. (2025). Supporting the digital transformation of Vocational Education and Training.

[13] Basheer N., Ahmed V., Bahroun Z., & Anane C. (2025). Sustainability assessment in higher education institutions: exploring indicators, stakeholder perceptions, and implementation challenges. Discover Sustainability, 6(1), 1-25.

[14] Joyce S., Umney C., Whittaker X., & Stuart M. (2023). New social relations of digital technology and the future of work: beyond technological determinism. New technology, work and employment, 38(2), 145-161.

[15] Riesen E. (2025). A sociotechnological-system approach to AI ethics. AI & Society, 1-13.