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OPTIMIZING VOCATIONAL HUMAN RESOURCE DEVELOPMENT THROUGH AI AND ADAPTIVE LEARNING INTEGRATION: A SYSTEMATIC LITERATURE REVIEW (2019-2025)

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ABSTRACT

This study aims to analyze the integration of Artificial Intelligence (AI) and adaptive learning in vocational education and its implications for vocational human resource development. A Systematic Literature Review (SLR) approach was conducted following PRISMA guidelines, covering peer-reviewed articles published between 2019 and 2025 from Scopus, DOAJ, SpringerLink, and Google Scholar. A total of 10 selected studies were analyzed using thematic synthesis to identify patterns, models, and research gaps. The findings indicate that AI-driven adaptive learning enhances competency development through data-driven personalization, learning analytics, predictive mechanisms, and immersive technologies. A cross-study synthesis reveals that AI improves learning efficiency, skill relevance, and lifelong learning capacity; however, it also exposes a critical imbalance between technical skill development and the limited integration of soft skills. Furthermore, the relationship between adaptive learning systems and workforce outcomes is non-linear and influenced by pedagogical design, institutional readiness, and industry alignment. This study proposes an integrated AI–adaptive learning framework that connects technological, pedagogical, and workforce perspectives, contributing to more adaptive, human-centered, and industry-relevant vocational education systems.

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INTRODUCTION

The advancement of Artificial Intelligence (AI) has increasingly influenced educational innovation by enabling intelligent systems that support automated and personalized learning processes (Silva et al., 2024). This transformation aligns with the growing demand for a workforce capable of adapting to rapid technological changes in the digital economy (Zhang et al., 2026). Vocational education plays a crucial role in preparing such human resources by emphasizing competency-based and industry-relevant training (Cedefop, 2023). However, conventional instructional approaches in vocational education often lack flexibility and fail to accommodate individual learning differences (Al Husaeni et al., 2025). Therefore, more adaptive and learner-centered educational models are required to enhance skill development (Holmes et al., 2023).

Artificial Intelligence provides new opportunities to improve learning systems through predictive analytics and intelligent data processing (Hardaker & Glenn, 2025). By analyzing large volumes of learner data, AI systems can identify patterns and optimize instructional strategies (Khalil et al., 2026). These capabilities support the development of adaptive learning environments that respond to learner needs in real time (David, 2024). In vocational education, such systems can enhance practical skill acquisition by providing personalized training experiences (Lampropoulos & Kinshuk, 2024). Meanwhile, adaptive learning systems enable personalized learning pathways by adjusting content and feedback based on learner performance (Fadieieva, 2023), allowing learners to progress at their own pace and improving engagement and outcomes (Gervacio, 2024; Katona & Gyonyoru, 2025).

Adaptive learning systems enable personalized learning by adjusting content and feedback based on learner performance (R. S. Costa et al., 2021). These systems allow learners to progress at their own pace, improving engagement and learning outcomes (Gjermeni & Prodani, 2024). Empirical evidence suggests that adaptive learning can significantly enhance competency development in digital learning environments (Machkour et al., 2025). In vocational contexts, this approach supports the development of job-specific skills and competencies (Delcker et al., 2025). Thus, adaptive learning contributes to improving the effectiveness of vocational education systems (Sari et al., 2024).

The integration of AI and adaptive learning has led to the development of smart learning environments that provide interactive and immersive experiences (Prasasti et al., 2025). These environments utilize technologies such as virtual simulations and intelligent tutoring systems to enhance learning (Cao et al., 2020). Such innovations enable learners to engage in realistic training scenarios that reflect workplace conditions (Akerson et al., 2024). This is particularly important in vocational education where experiential learning is essential (Winiasri et al., 2020). Consequently, AI-supported learning environments improve workforce readiness and competency development (Dhouib et al., 2025).

Despite these advancements, several challenges remain in the implementation of AI-based learning systems (Familoni et al., 2024). One major issue is the unequal distribution of technological infrastructure, which limits access to advanced learning technologies. Additionally, educators often lack the necessary competencies to effectively integrate AI into teaching practices (Nguyen et al., 2020). These limitations hinder the adoption of AI in vocational education systems (Flores & Chiappe, 2025). Therefore, addressing these barriers is essential to ensure effective implementation (Flores & Chiappe, 2025).

Another critical issue is the limited focus on soft skills development in AI-driven learning systems (Maamor et al., 2024). Most systems prioritize technical competencies while neglecting interpersonal and communication skills (Bennett, 2018). This imbalance may lead to graduates who lack essential workplace skills (Yong et al., 2024). In modern work environments, such competencies are crucial for collaboration and problem-solving (Eimer & Bohndick, 2023). Thus, integrating soft skills into AI-based learning systems remains a significant challenge (Luo et al., 2025).

Furthermore, there is often a lack of alignment between adaptive learning systems and industry competency requirements (Prasetyo et al., 2025). Many AI-based learning platforms are developed without sufficient collaboration with industry stakeholders. As a result, a mismatch may occur between educational outcomes and labor market needs (Pavlakou et al., 2025). This gap reduces the effectiveness of vocational education in preparing job-ready graduates (Sukardi & Usman, 2025). Therefore, stronger integration between education and industry is necessary.

In addition, most research on AI and adaptive learning focuses on short-term learning outcomes rather than long-term workforce performance (Adamakis & Rachiotis, 2025). This limit understanding of how AI-based learning systems impact career development and productivity (Vieriu & Petrea, 2025). Longitudinal studies are needed to evaluate the sustainability of competencies developed through adaptive learning (Reihanian et al., 2025). Such research would provide deeper insights into human resource development (Venugopal et al., 2024). Hence, there is a need to expand research perspectives toward long-term impacts (Liden et al., 2025).

The integration of AI and adaptive learning has led to the emergence of smart learning environments that offer interactive and immersive experiences through technologies such as virtual simulations and intelligent tutoring systems (Gligorea, Cioca, Oancea, & Gorski, 2023; Tiwari, 2023). These innovations are particularly relevant in vocational education, where experiential learning is essential for developing job-specific competencies (Hamdani et al., 2021; Lin & Zhang, 2020). Consequently, AI-supported learning environments have the potential to improve workforce readiness and competency development (Yusuf et al., 2024).

Despite these advancements, several challenges remain. These include unequal access to technological infrastructure, limited teacher readiness in integrating AI (Ayanwale et al., 2022), insufficient emphasis on soft skills and weak alignment between learning systems and industry needs. Additionally, many studies focus predominantly on short-term learning outcomes rather than long-term workforce performance, limiting the understanding of how AI-driven learning contributes to sustainable human resource development (Chigbu & Makapela, 2025; Thangaraju & Palani, 2025).

More critically, a significant research gap lies in the absence of an integrative and holistic synthesis that explicitly links AI, adaptive learning, and vocational human resource development within a single conceptual and analytical framework. Existing studies tend to be fragmented and domain-specific, where AI research primarily emphasizes technological capabilities, adaptive learning studies focus on instructional personalization, and vocational HRD research highlights workforce outcomes. This disciplinary separation results in a lack of comprehensive understanding of the causal pathways and interdependencies between these components, particularly in explaining how AI-driven adaptive systems translate into measurable improvements in competency relevance, employability, and long-term workforce adaptability.

Furthermore, prior studies rarely address the multi-level impact of AI and adaptive learning integration, especially the connection between micro-level learning processes (e.g., personalization, feedback mechanisms) and macro-level outcomes (e.g., workforce productivity, career sustainability, and human capital development). There is also limited empirical and conceptual synthesis that captures cross-context variations, particularly in vocational education settings where practical skill acquisition, industry alignment, and experiential learning are critical. This gap indicates the need for a more structured and comprehensive analysis that not only consolidates existing findings but also clarifies the theoretical and practical linkages among these domains.

From a methodological perspective, many studies lack comprehensive synthesis across different research contexts (Hidayat, 2025). Systematic Literature Review (SLR) provides a structured approach to integrate research findings (Lame, 2019). SLR enables researchers to identify trends, gaps, and future directions (Xiao & Watson, 2019). This approach enhances the rigor and reliability of academic research (Siddaway et al., 2019). Therefore, SLR is appropriate for analyzing AI and adaptive learning research (Carrera-Rivera et al., 2022).

The novelty of this study lies in its integrative approach that synthesizes interdisciplinary evidence to elucidate the relationship between AI-driven adaptive learning and vocational human resource development outcomes.

METHOD

This study employed a Systematic Literature Review (SLR) approach to identify and analyze research trends in the integration of Artificial Intelligence (AI) and adaptive learning in vocational education during the 2019–2025 period. The SLR approach was selected to enable a systematic and transparent synthesis of prior studies, facilitating the identification of patterns, research gaps, and future research directions (Yaqin et al., 2024). The review process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure methodological rigor and replicability.

The search strategy was conducted across four major international databases: Scopus, DOAJ, SpringerLink, and Google Scholar. A combination of keywords and Boolean operators was used to enhance search precision, including: "Artificial Intelligence" or "AI" and "Adaptive Learning" and "Vocational Education" or "Technical Education". The search was limited to peer-reviewed journal articles published between 2019 and 2025 to ensure the inclusion of recent and relevant studies. All searches were conducted within a defined time frame and documented to ensure reproducibility.

The study applied explicit inclusion and exclusion criteria. The inclusion criteria were: (1) articles published in peer-reviewed journals; (2) studies focusing on AI and/or adaptive learning in vocational or technical education contexts; (3) empirical or review studies with clear research design; and (4) articles written in English. The exclusion criteria included: (1) duplicate records; (2) conference papers, book chapters, and non-academic publications; (3) studies not related to vocational learners; and (4) articles lacking methodological clarity.

Identification
Records identified (n = 120)

Screening
After duplicates removed (n = 95)

Screening
Records screened (n = 95)
Records excluded (n = 60)

Eligibility
Full text assessed (n = 35)
Excluded (n = 25)

Included
Studies included in review (n = 10)

Figure 1. PRISMA Flow Diagram of the Study Selection Process

The article selection process followed the PRISMA flow procedure, consisting of four stages: identification, screening, eligibility, and inclusion. In the identification stage, all relevant articles were collected from the selected databases. During the screening stage, titles and abstracts were reviewed to assess relevance to the research focus. In the eligibility stage, full-text articles were evaluated based on the predefined criteria, particularly methodological rigor and contextual relevance. Finally, in the inclusion stage, 10 articles met all criteria and were selected as the primary sources for analysis. The detailed selection process is illustrated in a PRISMA flow diagram to enhance transparency.

Subsequently, data from each selected article were systematically extracted and categorized based on the following dimensions:

(a) year of publication,
(b) country of origin,
(c) research objectives,

(d) research methods, and
(e) key findings.

A thematic analysis was then conducted to identify research patterns and emerging trends in the field of integration AI and adaptive learning for vocational students. To ensure data validity and reliability, a cross-checking process was performed between sources, and validation was supported using reference management software (Mendeley) following the APA 7th Edition citation format. Furthermore, a qualitative descriptive analysis was carried out, focusing on global tendencies and thematic contributions of each study. The results were presented in a synthesis table summarizing the authors, year, country, objectives, methods, and key findings of each article to ensure traceability and transparency throughout the review process.

RESULTS AND DISCUSSION

Research Trends in AI and Adaptive Learning (2019-2025)

Table 1. Literature Matrix of AI and Adaptive Learning in Vocational Human Resource Development (2019-2025)

No	Author(s)	Year	Title	Study Focus
1	Zawacki-Richter et al.	2019	Artificial Intelligence in Higher Education: A Systematic Review	Mapping AI research trends in education
2	Tuomi	2019	The Impact of Artificial Intelligence on Learning, Teaching, and Education	AI implications for workforce transformation
3	Chen, Chen, & Lin	2020	Artificial Intelligence in Education: A Review	AI for competency development
4	Ifenthaler & Yau	2020	Learning Analytics for Study Success	Data-driven adaptive learning
5	Tsai et al.	2020	Learning Analytics Adoption in Higher Education	Implementation of adaptive systems
6	Dwivedi et al.	2021	Artificial Intelligence: Multidisciplinary Perspectives	AI and workforce transformation
7	Pérez-Sanagustín	2022	Learning Design and Analytics in Education	Instructional design & analytics
8	Kovanović et al.	2023	Learning Analytics and AI in Education	Adaptive systems & performance
9	OECD	2024	Generative AI in Education: Opportunities and Risks	Policy & HR development
10	UNESCO	2025	AI and the Future of Work and Learning	Workforce readiness

Cross Study Synthesis of AI and Adaptive Learning

The reviewed studies collectively indicate that research on Artificial Intelligence (AI) in education has evolved from initial exploratory mapping toward more application-oriented, data-driven, and impact-focused investigations. A cross-study synthesis reveals three interconnected trajectories: personalization of learning processes, integration of learning analytics, and transformation of workforce competencies.

First, AI consistently emerges as a core driver of personalized learning environments. Empirical evidence demonstrates that adaptive learning systems improve learning efficiency by dynamically adjusting instructional content, pacing, and feedback based on learner performance and behavioral data. Monika et al., (2024) found that AI-supported adaptive systems significantly enhance competency mastery by reducing irrelevant content exposure and focusing on individualized learning needs. This is reinforced by Ifenthaler & Yau, (2020), who show that continuous monitoring through learning analytics enables timely intervention and supports individualized learning progression. These findings collectively indicate that personalization is not merely a technological feature, but a pedagogical mechanism that reshapes how competencies are developed in vocational contexts.

Second, learning analytics functions as the operational backbone of AI-driven adaptive learning systems. Across multiple studies, analytics enables the transformation of raw learner data into actionable insights that inform instructional design and decision-making. Alfredo et al., (2024) demonstrate that institutions implementing analytics-based adaptive systems experience improved learner engagement and progression, while Dai et al., (2025) highlight the role of predictive analytics in identifying at-risk learners and enabling early intervention strategies. However, cross-study synthesis also reveals that the effectiveness of analytics is contingent upon data quality, system integration, and institutional capacity, suggesting that technological capability alone is insufficient without proper implementation strategies.

Third, the literature consistently highlights the role of AI in reshaping workforce competencies and labor market expectations. Empirical and policy-oriented studies indicate that AI is accelerating the demand for digital literacy, adaptability, and lifelong learning capabilities. However, a deeper synthesis reveals a structural imbalance while AI-driven systems effectively support technical skill acquisition, they often underemphasize the development of soft skills such as communication, collaboration, and critical thinking. This imbalance suggests that current implementations of AI in education may not fully align with the holistic competency requirements of modern workplaces (Ali et al., 2025; Hooshyar et al., 2025; Pronello, 2026).

Importantly, integrating these three trajectories reveals that the relationship between AI-driven adaptive learning and vocational human resource development is complex, multi-layered, and non-linear. Improvements in learning efficiency at the micro level (e.g., personalization, feedback) do not automatically translate into macro-level outcomes such as employability and workforce readiness. Instead, this relationship is mediated by contextual variables including pedagogical design, institutional readiness, and alignment with industry needs.

Synthesized Models of AI Integration in Adaptive Learning

A synthesis of the reviewed literature identifies four dominant models of AI integration, each representing a distinct functional role within adaptive learning systems.

The personalization model focuses on tailoring learning pathways based on learner profiles, performance data, and behavioral patterns. Empirical evidence from Tan et al., (2025) suggests that this model significantly enhances learning efficiency by reducing cognitive overload and focusing on relevant competencies. However, its effectiveness is highly dependent on the accuracy and completeness of learner data.

The adaptive feedback model emphasizes real-time, automated feedback mechanisms that enable iterative learning. Weber et al., (2025) demonstrate that immediate feedback accelerates skill acquisition, particularly in vocational training contexts that require repeated practice and correction. This model aligns strongly with experiential learning principles.

The predictive analytics model extends the role of AI by enabling forecasting of learning outcomes and identification of at-risk learners. Tahir et al., (2025) found that predictive systems improve retention and performance through early intervention strategies. Nevertheless, this model introduces ethical concerns related to algorithmic bias, transparency, and fairness, particularly when decisions are based on opaque data processes.

The immersive learning model, integrating AI with VR and AR technologies, represents a more advanced form of adaptive learning. Won et al., (2023) show that simulation-based environments significantly enhance experiential learning and job readiness by replicating real-world work scenarios. However, implementation remains constrained by cost, infrastructure, and scalability issues.

Across these models, a critical synthesis emerges: AI transforms learning systems from static instructional environments into dynamic, data-driven ecosystems. This transformation shifts the role of educators from knowledge transmitters to facilitators, mentors, and interpreters of learning data. However, excessive reliance on automation risks reducing human interaction, which remains essential in vocational education.

Impact on Vocational Human Resource Development

The integration of AI and adaptive learning has significant implications for vocational human resource development, particularly in enhancing efficiency, relevance, and sustainability of competency development.

From an efficiency perspective, adaptive learning systems streamline the learning process by focusing on individual competency gaps. Afreen et al., (2025) found that AI-driven learning reduces redundant instruction and accelerates skill mastery. This is particularly beneficial in vocational education, where time-efficient skill acquisition is critical.

In terms of relevance, AI enables better alignment between educational outcomes and industry demands. Ramachandran et al., (2024) demonstrate that data-driven learning systems improve the accuracy of skills mapping, ensuring that graduates possess competencies that match labor market needs. However, this alignment is not always consistent, particularly when educational systems lack direct collaboration with industry stakeholders.

From a sustainability perspective, AI supports lifelong learning by enabling flexible and continuous skill development. Ahn, (2024) highlight that adaptive systems encourage learners to engage in self-directed and continuous learning, which is essential in rapidly evolving labor markets.

Despite these benefits, a critical synthesis reveals a paradox. While AI enhances technical and digital competencies, it may simultaneously weaken the development of interpersonal, collaborative, and reflective skills. Bauer et al., (2025) argue that over-reliance on AI-driven systems can reduce opportunities for social interaction and experiential learning, which are essential for holistic competency development.

Thus, the impact of AI on vocational HRD is dualistic: it increases efficiency and precision, but also introduces risks related to the erosion of human-centered learning dimensions.

Integrated Framework of AI Adaptive Learning in Vocational HRD

To address the fragmentation identified in previous studies, this research proposes an integrated framework that conceptualizes the relationship between AI, adaptive learning, and vocational HRD.

The framework consists of three interconnected layers. The input layer includes learner data, profiles, and contextual variables such as institutional readiness and technological infrastructure. The process layer involves AI mechanisms, including analytics, prediction, personalization, and feedback systems. The output layer focuses on outcomes, including competency development, employability, and workforce readiness.

This framework emphasizes that the effectiveness of AI-driven adaptive learning depends on the alignment between technological systems and pedagogical strategies. Empirical evidence supports the notion that without such alignment, technological innovation may not translate into meaningful educational outcomes (Alenezi, 2024; Gligorea, Cioca, Oancea, Gorski, et al., 2023).

Implementation Challenges and System Readiness

A cross-study synthesis identifies four major challenges that limit the effectiveness of AI integration in vocational education.

First, infrastructure inequality remains a significant barrier, particularly in developing regions (Enneking et al., 2025). Second, educator readiness is often limited, as many teachers lack the necessary competencies in AI and data literacy (Prilop et al., 2025). Third, high implementation costs hinder the scalability and sustainability of AI systems (Costa et al., 2025). Fourth, ethical concerns, including data privacy, algorithmic bias, and transparency, present critical challenges that must be addressed (Ali et al., 2024).

These findings suggest that the primary limitation is not technological capability, but rather the readiness of the broader educational ecosystem. Therefore, successful implementation requires a holistic approach that integrates infrastructure, human capacity, policy support, and ethical governance.

Table 2 summarizes the synthesized forms of AI integration in adaptive learning, highlighting their core mechanisms, learning impacts, and implications for vocational human resource development.

Table 2. Forms of AI in Adaptive Learning and Their Implications for Vocational Human Resource Development

No	Form of AI Integration	Core Mechanism	Learning Impact	HR Development Impact	Critical Issue
1	Data-driven personalization	Learner data analysis and adaptive content delivery	Individualized competency acquisition based on learner needs	Accelerates competency development aligned with industry requirements	Risk of over-specialization
2	Adaptive feedback systems	Real-time feedback and automated correction	Iterative learning and continuous skill refinement	Improves technical skill mastery in vocational training	Limited deep reflection
3	Predictive analytics	Performance prediction and early intervention mechanisms	Identification of at-risk learners and learning gaps	Reduces competency gaps and improves workforce preparedness	Bias and transparency issues
4	Immersive technologies (VR/AR + AI)	Simulation-based experiential learning environments	Contextual and hands-on learning experiences	Enhances job readiness and practical skill development	High cost and infrastructure limitations
5	Automated decision-making systems	Algorithm-driven learning pathway optimization	Flexible and dynamic learning processes	Supports continuous and adaptive competency development	Reduced educator control
6	AI-controlled learning systems	Algorithm as the primary learning regulator	Structured and optimized learning progression	Increases efficiency of training and learning systems	Weakening of social and soft skills

The synthesis presented in Table 2 indicates that data-driven personalization enables adaptive learning systems to significantly improve learner performance by tailoring instructional content to individual needs, as evidenced by increased learning outcomes in AI-supported environments (Tan et al., 2025). Empirical studies further demonstrate that personalized adaptive systems can enhance competency acquisition rates by allowing learners to focus on specific skill gaps, thereby improving efficiency in vocational training contexts (Singh et al., 2025).

Adaptive feedback systems have been shown to improve learning effectiveness by providing immediate and continuous feedback, which supports iterative skill development in technology-enhanced learning environments (Wang & Liu, 2025). In vocational settings, real-time feedback has been empirically linked to improved technical skill mastery, particularly in simulation-based and practice-oriented learning scenarios (Wu et al., 2026).

The use of predictive analytics allows institutions to identify students at risk of failure and implement early interventions, which has been shown to significantly improve retention and academic performance (Hlosta et al., 2022). Empirical findings also indicate that predictive models contribute to reducing competency gaps by enabling targeted support for learners with lower performance levels.

Immersive technologies such as AI-supported virtual reality have been found to enhance experiential learning by providing realistic simulations that improve knowledge retention and skill transfer (Radianti et al., 2020). Experimental studies further reveal that VR-based learning environments can significantly increase learner engagement and practical competence, particularly in technical and vocational education (Rafiq et al., 2022). Automated decision-making systems enable adaptive learning platforms to dynamically adjust learning pathways, which has been associated with improved learning efficiency and better alignment with learner progress (Sajja et al., 2025). Empirical research suggests that such systems support continuous skill development by enabling flexible and adaptive learning trajectories in digital learning environments.

However, empirical studies also highlight that increased reliance on AI systems may reduce educator involvement in the learning process, potentially affecting instructional quality and learner support. Research further indicates that excessive dependence on algorithm-driven systems can limit opportunities for social interaction, which is essential for developing communication and collaboration skills in vocational human resources (Zhai et al., 2024). From a critical perspective, empirical evidence suggests that while AI enhances learning efficiency, it may simultaneously introduce challenges related to learner autonomy and critical thinking development. Therefore, studies emphasize the need for balanced integration strategies that combine AI-driven efficiency with human-centered pedagogical approaches to ensure holistic vocational human resource development (Singh et al., 2026).

CONCLUSION

This study highlights that the integration of Artificial Intelligence (AI) and adaptive learning in vocational education represents a transformative approach to optimizing human resource development. AI-driven systems enable more personalized, efficient, and data-informed learning processes, which contribute to faster competency acquisition and improved alignment with industry demands. Through mechanisms such as personalization, adaptive feedback, predictive analytics, and immersive learning environments, vocational education is increasingly able to support the development of technical skills and workforce readiness in a more targeted manner.

However, the findings also reveal that the current implementation of AI in adaptive learning is still predominantly focused on learning efficiency rather than the broader objective of optimizing human resource outcomes. The limited integration of human resource development perspectives, the insufficient alignment with real industry practices, and the underdevelopment of soft skills indicate that the potential of AI has not yet been fully realized in vocational contexts.

Furthermore, the study identifies a critical tension between technological efficiency and human-centered learning. While AI enhances adaptability and performance, it also risks reducing learner autonomy, social interaction, and the development of interpersonal competencies, which are essential in modern workplaces. This suggests that the effectiveness of AI integration depends not only on technological advancement but also on the ability to balance digital innovation with pedagogical and humanistic considerations.

Therefore, optimizing vocational human resource development through AI and adaptive learning requires a more holistic approach that integrates technology, pedagogy, and industry collaboration. Future research should focus on developing models that connect AI-driven learning systems with workforce performance indicators, as well as ensuring the inclusion of both technical and soft skills in competency development. By addressing these challenges, vocational education can more effectively prepare human resources that are not only technically competent but also adaptable, collaborative, and aligned with the evolving demands of the global workforce.

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