

Integrating AI in teaching factories to advance Indonesian vocational schools

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ABSTRACT

This study aims to develop and evaluate an Artificial Intelligence (AI)-based teaching factory model to enhance students' vocational competencies in alignment with industry standards. It addresses a gap in the existing literature, where teaching factory models and AI applications in education have largely been investigated separately, with limited empirically validated frameworks integrating AI to support adaptive learning and real-time performance assessment in vocational education. In this study, an AI-based teaching factory is operationally defined as a learning environment that utilizes AI to provide personalized instruction, real-time performance analytics, and industry-simulated production workflows. A mixed-methods research approach was employed, comprising needs analysis, system design and development, field trials, and effectiveness evaluation. Instrument validity was assessed using Aiken's V, while reliability was evaluated using Cronbach's alpha. Qualitative data collected through interviews, observations, and document analysis were analyzed thematically to identify patterns related to learning outcomes, implementation processes, and operational challenges. The study was conducted at SMKN 1 Pacet Cianjur and SMKN 11 Bandung in West Java Province, Indonesia. The findings indicate that the proposed AI-based teaching factory model significantly enhances students' problem-solving skills, critical thinking, and readiness for technology-driven workplaces. This study contributes a validated and replicable implementation framework for integrating AI into vocational teaching factories and provides practical recommendations for teacher capacity building, curriculum alignment, and infrastructure development to support sustainable, industry-relevant vocational education.

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INTRODUCTION

Transforming vocational education in Indonesia is a strategic goal to enhance workforce competitiveness in the era of the Fourth Industrial Revolution (Industry 4.0). Vocational high schools (SMKs) play a crucial role in equipping graduates with the skills and knowledge required to meet industry demands and successfully transition into the workforce (Roppertz, 2020). One of the key learning paradigms employed in SMKs is the teaching factory, which bridges the gap between educational practices and industrial needs (Wafroturrohman et al., 2020). The teaching factory model integrates practical production-based learning with the development of technical competencies essential for modern industries (Sulistiani & Yulianto, 2019). Recent advancements in artificial intelligence (AI) have opened new opportunities for enhancing the teaching factory model (Wahjusaputri et al., 2021). However, integrating AI into teaching factories at SMKs faces significant challenges, including infrastructure readiness, teacher proficiency in AI utilization, and resistance to adopting new methods (Wahjusaputri et al., 2024).

In this study, an AI-based teaching factory is operationally defined as a production-oriented learning environment that integrates artificial intelligence to support personalized instruction, real-time student performance analytics, automated feedback, and industry-simulated workflows to enhance vocational competency development. Although previous studies have demonstrated the effectiveness of teaching factories in improving students' technical skills and curriculum–industry alignment, existing research largely examines teaching factories and AI as separate educational innovations. Few empirically validated models systematically integrate AI into teaching factory environments, particularly within the Indonesian vocational education context. This gap highlights the absence of a structured framework that explains how AI can be embedded into teaching factory operations and how such integration impacts learning quality, student competencies, and industry relevance (Casmudi et al., 2022; Suranto et al., 2022).

This study aims to investigate and evaluate the implementation of AI-based teaching factory models in vocational schools across Indonesia (Al-Huwail et al., 2025). Nevertheless, the integration of artificial intelligence (AI) in teaching factories at SMKs is confronted with a range of obstacles, including the preparedness of infrastructure, the proficiency of teachers, and resistance to adopting new methods (Oberc et al., 2020). It seeks to assess the impact of AI integration on learning quality, student skills, and the alignment of education with industry demands. Furthermore, this study identifies challenges encountered during implementation and proposes recommendations for future improvements. The teaching factory is an educational methodology that merges the academic learning environment with a professional industrial setting. Originally developed to address the disparity between institutional education and industry needs, this model enables students to acquire practical, industry-relevant skills through experiential learning that closely mirrors real workplace conditions.

Artificial intelligence (AI) has been widely adopted across various domains, including education, where it has the potential to revolutionize learning processes. AI can automate administrative tasks, personalize learning experiences, and provide real-time, precise feedback to students (Daher & Abu Thabet, 2025). In vocational education, AI can also simulate industry-specific scenarios, creating authentic and immersive learning environments. These capabilities can enhance the teaching factory model by optimizing learning processes, tailoring educational content to individual needs, and strengthening connections between education and industry (Suranto et al., 2022; Z. Wang et al., 2025). Despite these advantages, integrating AI into teaching factories poses several challenges, including the need for robust technological infrastructure, adequate teacher training, and overcoming resistance to change from both educators and students (Ng et al., 2022). Addressing these challenges requires a comprehensive implementation strategy and strong policy support to ensure successful integration (Shiohira, 2021). This is achieved through experiential learning that closely mirrors real-world workplace settings.

Artificial intelligence has found extensive application across diverse domains, including the realm of education (Soeprijanto et al., 2022). However, prior studies primarily focus on technological potential rather than offering empirical evidence on implementation models, pedagogical integration, and measurable learning outcomes in vocational teaching factories (Boersma et al., 2022; Cuzcano-Huarcaya et al., 2023; Nguyen et al., 2022). Integrating artificial intelligence into vocational school teaching factories can yield several advantages, including enhancing learning quality through personalization, optimizing learning process management, and reinforcing the connection between education and industry (J. Wang, 2025). Multiple studies have demonstrated that artificial intelligence may be utilized to create simulations that closely resemble real-world settings in various industries (Ajlouni et al., 2025). This enables students to study in a more authentic and lifelike environment. Nevertheless, the obstacles encountered when integrating AI into educational enterprises encompass the preparedness of technological infrastructure, the proficiency of teachers in harnessing artificial intelligence, and the reluctance to embrace change exhibited by both teachers and pupils (Hiim, 2023). Hence, achieving AI integration in teaching factories necessitates a well-developed implementation plan and robust policy backing.

Therefore, the novelty of this study lies in the development and empirical evaluation of an AI-based teaching factory model specifically designed for SMKs in Indonesia. This research contributes not only practical insights but also a validated implementation framework that advances

methodological and conceptual understanding of AI integration in vocational education. Furthermore, this study identifies implementation challenges, including infrastructure readiness, teacher AI proficiency, and resistance to innovation, and proposes evidence-based recommendations to support sustainable adoption and policy development. By addressing an explicit research gap and offering a replicable integration model, this study seeks to strengthen the alignment between vocational education and industry needs while enhancing the theoretical and practical foundation of AI-supported teaching factory implementation in Indonesia.

METHOD

This study employed the ADDIE framework—analysis, design, development, implementation, and evaluation—to guide the systematic development and evaluation of an artificial intelligence (AI)-based teaching factory model (Ajlouni et al., 2025). ADDIE provides a structured process for designing, developing, implementing, and evaluating educational programs and products (Chang & Zhao, 2025). In this study, the framework was used to organize the development process from the identification of institutional and industry needs to prototype design, validation, field implementation, and evaluation. Each stage was linked to specific objectives, data sources, and evaluation procedures to maintain consistency between model development and empirical assessment. The study adopted a mixed-methods approach, integrating qualitative evidence on contextual needs and implementation experiences with quantitative data on model validity, reliability, and learning outcomes.

The study was conducted at SMKN 1 Pacet, Cianjur, and SMKN 11 Bandung, West Java, Indonesia. Participants included vocational teachers and students who were purposively selected based on their involvement in teaching factory activities and AI-related learning. The study involved XX teachers and XX students. Participant characteristics, including age, gender, field of expertise, teaching experience, and previous exposure to AI technology, were recorded to describe the study sample. Ethical approval was obtained from the institutional research board, and informed consent was obtained from all participants before data collection.

The analysis stage focused on identifying competency requirements, institutional readiness, and contextual conditions relevant to the integration of AI into teaching factory learning (Sukardjo et al., 2023). A qualitative-dominant mixed-methods approach was used at this stage. Data were collected through structured questionnaires ($n = XX$), semi-structured interviews with educators and industry partners ($n = XX$), and curriculum document analysis. Qualitative data were examined through thematic analysis involving open and axial coding to identify recurring patterns related to AI competency requirements, infrastructure readiness, pedagogical challenges, and stakeholder perceptions. Quantitative questionnaire data were used to identify priority competencies and levels of readiness. The integration of these findings provided an empirical basis for determining the competencies, learning requirements, and implementation conditions to be incorporated into the proposed AI-based teaching factory model.

The design stage translated the needs-analysis findings into the conceptual and instructional structure of the model (Srimala et al., 2023). Core competencies, learning workflows, assessment indicators, and AI-supported learning activities were specified in accordance with national vocational standards and relevant industry requirements. AI applications, including intelligent tutoring systems and machine-learning-based tools, were selected to support learning and industry-simulated production activities. At this stage, the latent constructs subsequently examined using partial least squares structural equation modelling (PLS-SEM) were also defined: AI Learning Support, Student Engagement, Skill Competency, Learning Effectiveness, and Industry Alignment. Survey instruments and interview protocols were developed in relation to these constructs so that the instructional components of the model and the subsequent empirical evaluation addressed the same conceptual dimensions.

During the development stage, the design specifications were translated into a prototype consisting of AI-supported learning components, instructional materials, and performance-monitoring tools (Srimala et al., 2023). The prototype and research instruments were reviewed by vocational education specialists, AI practitioners, and industry representatives ($n = XX$) to assess

content accuracy, pedagogical relevance, and alignment with industry requirements. Content validity was examined using Aiken's V , with $V \geq 0.80$ established as the acceptance criterion, while the internal consistency of the questionnaire instruments was assessed using Cronbach's α , with $\alpha \geq 0.70$ as the criterion for acceptable reliability. A pilot trial involving XX vocational students was then conducted to examine the usability, functionality, and instructional clarity of the prototype. Feedback from experts and pilot participants was analysed thematically and used to revise the model and research instruments before field implementation.

Following validation and revision, the prototype was implemented in teaching factory settings at the participating vocational schools (Goodyear et al., 2021). The implementation comprised XX instructional sessions in which students completed industry-simulated production tasks supported by AI-based feedback and performance-monitoring mechanisms. Quantitative data were collected using pre-test and post-test assessments, structured questionnaires prepared for PLS-SEM analysis, and performance-assessment rubrics. Qualitative evidence was collected concurrently through classroom observations, teacher reflective journals, and student interviews to capture learning experiences, engagement patterns, and challenges encountered during implementation. Observation checklists were also used to examine implementation fidelity and consistency in the application of the model across the participating learning settings. The qualitative data were analysed thematically to provide contextual explanations of students' and teachers' experiences and to complement the quantitative measures of model implementation and learning outcomes.

The evaluation stage integrated evidence from the preceding stages to examine the validity, reliability, implementation, and educational outcomes of the AI-based teaching factory model. PLS-SEM was used to examine the hypothesized relationships among AI Learning Support, Student Engagement, Skill Competency, Learning Effectiveness, and Industry Alignment. The measurement model was evaluated using indicator reliability (outer loadings ≥ 0.70), convergent validity based on average variance extracted ($AVE \geq 0.50$), composite reliability ($CR \geq 0.70$), and discriminant validity using the Fornell–Larcker criterion and heterotrait–monotrait (HTMT) ratio. The structural model was evaluated using bootstrapping with 5,000 resamples to assess the significance of the hypothesized paths, R^2 values to examine the variance explained in the endogenous constructs, and Q^2 values to assess predictive relevance (Suyatno et al., 2023). Qualitative evidence from interviews, classroom observations, and reflective journals was then synthesized with the quantitative findings to help explain observed patterns, identify implementation barriers, and provide contextual understanding of the model's performance. Integrating the two forms of evidence enabled the evaluation to address not only quantitative patterns in the model but also how the AI-based teaching factory was experienced and implemented within the participating vocational-school contexts.

RESULTS AND DISCUSSION

In this section, the research results are explained, and a comprehensive discussion is provided. Results can be presented in figures, graphs, tables, and other formats that make the reader understand easily (Nadzeri et al., 2023; Xue, 2025). The discussion can be made in several sub-sections. The implementation of the artificial intelligence (AI)-based teaching factory model in vocational high schools (SMKs) represents a pivotal step toward integrating AI technology into vocational education. This process involved multiple stages, including identifying, analyzing, testing, measuring, and evaluating the readiness and effectiveness of the model prior to its broader adoption in SMKs across Indonesia (Alasmari, 2025).

Results

Demographic Profile of Students in State SMKs in West Java (Bandung)

The validation process aimed to assess the results of this study, which included the development of an AI-driven teaching factory model to facilitate production-based learning aligned with the demands of industry and the business world (Vázquez et al., 2022). To evaluate the model, a Smart Mobile Application Assessment Model questionnaire was administered via Google Forms. The questions were designed to reflect critical success factors (CSFs) for the model, with a readability

test ensuring that each question was clear and unambiguous for respondents (Riyadi et al., 2023). The questionnaire was distributed to 50 students specializing in software engineering, visual communication design, teaching factory TJKT, hospitality, and agribusiness processing of agricultural products across grades X-XII. A Likert scale was employed, ranging from 1 (very inappropriate) to 5 (very appropriate). This enabled students to evaluate the relevance and appropriateness of the AI-based teaching factory model in aligning with vocational education standards (Weyant, 2022).

Validation and Content Analysis

The questionnaire results were examined using Aiken's V coefficients to evaluate the indicators included in the AI-based teaching factory model. The analysis covered four dimensions—students, technology, teaching, and learning—with coefficients interpreted using the predetermined criterion of $V > 0.80$. Rather than indicating uniformly strong results, the coefficients varied across dimensions and indicators, suggesting that some aspects of the model were more strongly supported than others.

Table 1 presents the item-level coefficients obtained from the model trial. Within the student dimension, relatively high coefficients were recorded for AI support in completing learning tasks (M2, $V = 0.721$) and interactive engagement with learning materials (M9, $V = 0.701$). In contrast, lower coefficients were found for understanding learning materials (M1, $V = 0.406$), developing critical and analytical skills (M4, $V = 0.418$), and receiving faster and more accurate feedback (M5, $V = 0.480$). These results indicate variation in students' responses to different aspects of AI-supported learning.

A similar pattern was observed in the technology dimension. Engagement with educational resources (T2, $V = 0.696$), personalized feedback (T3, $V = 0.685$), and access to supplementary learning materials (T6, $V = 0.680$) received comparatively high coefficients. By contrast, the perceived efficiency of AI in the learning process (T1, $V = 0.460$) and the perceived future role of AI in education (T7, $V = 0.470$) fell below the predetermined threshold. For the teaching dimension, AI support for completing educational tasks recorded the highest coefficient (K2, $V = 0.829$), followed by prompt and accurate feedback (K5, $V = 0.747$). However, students' comprehension of learning materials through AI-supported instruction (K1, $V = 0.447$) remained comparatively low.

The learning dimension showed the most consistently positive pattern. All five indicators exceeded the predetermined threshold, ranging from $V = 0.628$ to $V = 0.759$. Learning motivation recorded the highest coefficient (P2, $V = 0.759$), followed by personalized learning (P1, $V = 0.711$) and interactive engagement with learning materials (P4, $V = 0.709$). Taken together, these results suggest that students responded more positively to the motivational, interactive, and task-support aspects of the AI-based teaching factory than to several indicators related to conceptual understanding, critical and analytical skills, and technological efficiency.

Table 1. Summary of Student Responses to the AI-Based Teaching Factory Model

Dimension	No. of Items	Mean V	Range	Highest-Rated Indicator	Lowest-Rated Indicator
Students	10	0.564	0.406–0.721	M2 (0.721)	M1 (0.406)
Technology	10	0.596	0.460–0.696	T2 (0.696)	T1 (0.460)
Teaching	5	0.662	0.447–0.829	K2 (0.829)	K1 (0.447)
Learning	5	0.701	0.628–0.759	P2 (0.759)	P5 (0.628)
Overall	30	0.618	0.406–0.829	K2 (0.829)	M1 (0.406)

Note. V = coefficient reported for each questionnaire item. Item-level results are available in the complete instrument.

Figure 1 provides a visual comparison of selected indicators representing the main patterns observed across the four dimensions. The learning dimension showed comparatively stronger results, particularly for learning motivation (P2, $V = 0.759$), whereas lower coefficients were observed for technological efficiency (T1, $V = 0.460$) and comprehension of AI-supported instructional content (K1, $V = 0.447$). This contrast suggests that students responded positively to several aspects of AI-

supported learning, particularly motivation and task support, while technological and instructional aspects were less consistently rated.

Qualitative evidence collected during implementation provides additional context for these lower-rated aspects. Participants identified limitations in technological infrastructure, including access to appropriate computers, software and hardware, and reliable internet connectivity, as well as constraints related to institutional funding and external support. These contextual conditions may help explain some of the challenges experienced during implementation; however, they should be interpreted alongside, rather than inferred directly from, the quantitative coefficients. Overall, the combined findings indicate that the model showed encouraging results in learning-related dimensions while also identifying areas requiring further development, particularly technological readiness and the clarity of AI-supported instruction.

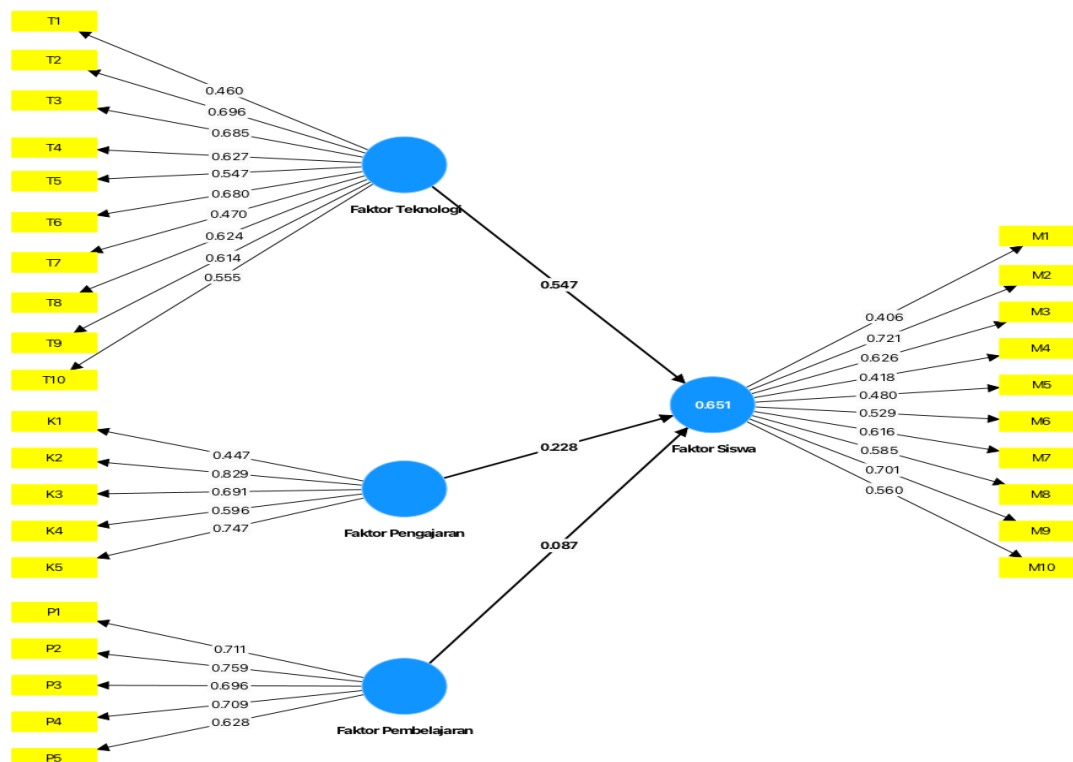


Figure 1. Comparison of Selected Indicators from the AI-Based Teaching Factory Model Trial

Impact on Student Skills and Learning Quality

Teacher responses provided further evidence regarding the perceived relevance, feasibility, and institutional readiness of the AI-based teaching factory model. As shown in Table 2, the coefficients varied considerably across the 16 indicators, ranging from 0.199 to 0.889. The highest coefficient was recorded for the perceived contribution of AI to productivity and efficiency in teaching factory operations ($V = 0.889$). Relatively high coefficients were also found for alignment with industry skill requirements ($V = 0.724$), opportunities for industry involvement in AI-integrated curriculum development ($V = 0.724$), enhancement of the teaching factory learning experience ($V = 0.724$), and graduate industry readiness ($V = 0.724$). The perceived importance of incorporating AI into the curriculum also received a comparatively high coefficient ($V = 0.702$).

By contrast, lower coefficients were observed for government or institutional support for AI implementation ($V = 0.199$), access to training and resources ($V = 0.470$), opportunities for teaching factory–industry partnerships in developing AI-related skills ($V = 0.484$), and the perceived contribution of AI-supported education to addressing industry challenges related to productivity and efficiency ($V = 0.486$). Perceived industry readiness to employ graduates with AI competencies was also relatively modest ($V = 0.526$). These results reveal a clear contrast between teachers' positive

perceptions of the potential educational and operational benefits of AI and their less favorable assessments of the external conditions required to support its implementation.

Table 2. Summary of Teacher Responses to the AI-Based Teaching Factory Model

Indicator	V
Importance of AI integration in the curriculum	0.702
Alignment of graduate skills with industry requirements	0.724
Strengthening school–industry relationships	0.600
Industry readiness for AI-skilled graduates	0.526
Industry involvement in AI-integrated curriculum development	0.724
Expected benefits of investment in AI-based education	0.669
Student preparation for industry careers	0.603
Contribution to industry productivity and efficiency	0.486
Availability of AI training and resources	0.470
Contribution to teaching factory education and training quality	0.552
Enhancement of the teaching factory learning experience	0.724
Productivity and efficiency of teaching factory operations	0.889
Institutional readiness for AI implementation	0.603
Graduate industry readiness	0.724
Teaching factory–industry partnership for AI-related skills	0.484
Government or institutional support	0.199

Source: Researcher data processing (2024)

Overall, the teacher responses suggest that the perceived potential of AI was stronger than the perceived readiness of the surrounding implementation ecosystem. Teachers generally reported favorable views of AI in relation to curriculum relevance, learning experiences, industry-oriented skills, and teaching factory productivity. However, lower coefficients for training resources, industry partnerships, and government or institutional support point to areas in which implementation conditions were perceived as less developed.

When considered alongside the student findings, the results present a similarly differentiated pattern. Students reported relatively favorable responses for learning motivation, task completion, interaction, and several aspects of AI-supported learning, whereas lower coefficients were found for conceptual understanding, critical and analytical skills, and technological efficiency. The evidence therefore does not uniformly support a claim that the model produced strong improvements across all learning outcomes. Instead, the findings indicate promising responses in selected areas alongside continuing pedagogical, technological, and institutional constraints. These patterns provide a more cautious basis for evaluating the model’s current level of implementation and identifying areas requiring further development.

Discussion

The findings provide a nuanced picture of the potential and current limitations of integrating artificial intelligence (AI) into teaching factory learning. Rather than showing uniformly strong outcomes, the results indicate that the model was more positively received in some areas than in others. Students reported relatively favorable experiences related to learning motivation, task completion, interaction with learning materials, and access to learning resources, whereas several indicators associated with conceptual understanding, critical and analytical skills, and technological efficiency received lower coefficients. Teacher responses showed a similar pattern: AI was viewed positively in relation to curriculum relevance, industry-oriented skills, learning experiences, and teaching factory productivity, but considerably weaker responses were observed for training resources, industry partnerships, and government or institutional support. Taken together, these findings suggest that the educational value of an AI-based teaching factory depends not simply on introducing AI technologies but on how effectively technological, pedagogical, and institutional components are integrated.

This interpretation extends previous research on teaching factories and technology-supported vocational learning. [Suranto et al. \(2022\)](#) showed that teaching factory environments can

support the development of employability skills by connecting vocational learning more closely with workplace practices. Research on AI-supported vocational education has similarly highlighted opportunities to improve access to learning resources and develop technology-supported learning environments (J. Wang, 2025). The present study adds to this literature by showing that the perceived benefits of AI integration may not develop evenly across all aspects of vocational learning. Positive responses to motivation, task support, and learning interaction coexist with weaker responses in areas that require deeper conceptual understanding and more developed technological infrastructure. This distinction is important because successful AI integration in vocational education involves more than providing access to digital tools; it also requires those tools to be meaningfully embedded in instructional activities that support the competencies students are expected to develop.

The findings also reinforce the importance of connecting AI-supported teaching factory learning with authentic industry needs. Teaching factories are intended to narrow the distance between school-based learning and workplace practice, and AI integration creates opportunities to extend this connection through industry-relevant projects and digitally supported production activities. The relatively favorable teacher responses concerning curriculum relevance and industry-oriented skills suggest that AI has potential to strengthen this alignment. However, this potential depends on sustained school–industry collaboration to identify relevant competencies and translate them into meaningful learning activities. Project-based tasks involving areas such as machine learning, data analysis, and AI-supported production could provide students with opportunities to integrate theoretical knowledge with practical application, provided that these activities correspond to the occupational context of the vocational program rather than introducing AI as a separate technological component.

At the same time, the lower coefficients for several technological and instructional indicators show that access to AI does not automatically translate into effective learning. The implementation of an AI-based teaching factory requires teachers who can integrate technological tools with vocational pedagogy, provide appropriate guidance, and connect AI-supported activities with clearly defined learning outcomes. This makes teacher professional development an important component of implementation. The findings are broadly consistent with Oberc et al. (2020) in emphasizing that technology-based educational innovation needs to be accompanied by appropriate instructional capacity and implementation support. In practical terms, schools need to consider teacher readiness, mentoring, curriculum coherence, and the availability of functional technological infrastructure alongside decisions about which AI applications to adopt.

The institutional context is equally important. The comparatively low coefficient for government and institutional support ($V = 0.199$), together with lower responses concerning access to AI training and resources and teaching factory–industry partnerships, suggests that implementation challenges extend beyond the classroom. These findings point to a gap between the perceived potential of AI and the conditions available to support its sustained use. Although Ajlouni et al. (2025) discuss opportunities associated with AI-supported educational environments, the present findings indicate that these opportunities need to be interpreted within the specific institutional conditions of Indonesian vocational schools. For SMKN 1 Pacet and SMKN 11 Bandung, the implementation of an AI-based teaching factory therefore needs to be understood as part of a broader ecosystem involving school capacity, infrastructure, industry participation, professional development, and policy support rather than as a stand-alone technological intervention.

School–industry collaboration is particularly relevant in this regard. Hiim (2023) demonstrates that collaboration between vocational schools and workplaces can contribute to more relevant vocational education by strengthening coherence between school-based learning and occupational practice. This perspective is directly relevant to the present study because the effectiveness of an AI-based teaching factory ultimately depends on whether the competencies and learning activities developed in school remain connected to changing workplace practices. Stronger partnerships could support curriculum development, authentic project design, teacher professional learning, access to industry expertise, and opportunities for students to apply AI-related competencies in realistic occupational settings. Thus, the broader implication of the findings is not simply that vocational schools need more AI technology, but that technological innovation needs to

be embedded within a coordinated relationship among curriculum, pedagogy, industry practice, and institutional support.

The findings should nevertheless be interpreted with caution. The study was conducted in a limited number of vocational-school settings, and the implementation period was relatively short. In addition, several outcomes were examined through perception-based instruments, which provide valuable information about participants' experiences but do not by themselves establish changes in students' higher-order thinking, practical competence, or workplace performance. The coefficients reported in the study should therefore not be interpreted as effect sizes or as direct evidence that AI caused improvements in learning outcomes. These limitations restrict both causal interpretation and the extent to which the findings can be generalized to other vocational-school contexts.

Future research should consequently examine the model across a broader range of SMKs, vocational specializations, and institutional conditions. Longer-term implementation would make it possible to investigate whether initial improvements in motivation, engagement, and task support translate into sustained gains in practical competence and workplace readiness. Future studies could also combine performance-based assessments, pre-test–post-test measures, classroom observations, interviews, and employer evaluations to distinguish perceived benefits from measurable learning outcomes. Further attention should be given to teacher AI competence, infrastructure readiness, school–industry collaboration, and institutional support as conditions that may influence implementation. Such research would provide a stronger empirical basis for determining not only whether an AI-based teaching factory is effective, but also under what conditions, for whom, and through which learning processes it is most effective.

Overall, the study positions the AI-based teaching factory as a promising but still developing approach to vocational learning. Its contribution lies less in demonstrating that AI is inherently effective than in showing that its educational value is closely connected to the environment in which it is implemented. The findings therefore shift attention from technology adoption alone toward the interaction among AI, vocational pedagogy, teacher capacity, industry relevance, and institutional readiness. For vocational schools seeking to prepare students for increasingly digital workplaces, this integrated perspective provides a more realistic basis for developing AI-supported teaching factory models that are educationally meaningful and sustainable.

CONCLUSION

This study developed and evaluated an AI-based teaching factory model within the vocational education contexts of SMKN 1 Pacet and SMKN 11 Bandung. The findings indicate that the model showed promising results in selected aspects of vocational learning, particularly learning motivation, task support, interaction with learning materials, and the perceived relevance of AI to industry-oriented learning. However, these positive responses were not consistent across all indicators. Lower coefficients for conceptual understanding, critical and analytical skills, technological efficiency, access to training resources, industry partnerships, and government or institutional support indicate that effective AI integration depends on more than the availability of technology. The study therefore contributes context-specific evidence that the educational value of an AI-based teaching factory is shaped by the interaction among technology, vocational pedagogy, teacher capacity, curriculum–industry alignment, infrastructure, and institutional support. These findings have practical implications for vocational schools seeking to integrate AI into teaching factory environments: implementation should be accompanied by teacher professional development, appropriate technological infrastructure, curriculum integration, and sustained collaboration with industry and relevant institutional stakeholders.

These conclusions should be interpreted within the scope of the study. The research was conducted in two vocational schools, over a relatively limited implementation period, and several outcomes were examined using perception-based measures; consequently, the findings should not be interpreted as evidence of causal effects or generalized to vocational schools with substantially different institutional conditions. Future research should evaluate the model across larger and more diverse samples, vocational specializations, and institutional settings and should employ longer-term designs that combine perception data with objective and performance-based measures of students'

practical competence, higher-order thinking, and workplace readiness. Longitudinal and mixed-methods studies could also examine how teacher AI competence, infrastructure readiness, school–industry collaboration, and institutional support influence implementation over time. Such evidence would provide a stronger basis for refining the model and determining the conditions under which AI-supported teaching factories can contribute meaningfully and sustainably to vocational learning and workforce preparation.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial or non-financial interests that could have appeared to influence the work reported in this paper.

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