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PAPER

Bridging the Industry 4.0 Skills Gap: Development of Case-Based Learning Model in AI-Powered Teaching Factory for Automotive Vocational Education

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ABSTRACT

This study aimed to develop a case-based learning (CBL) in artificial intelligence (AI)-powered teaching factory (CAI-TEFA) model to improve Industry 4.0 competencies of automotive vocational education students. The model was designed to address the skills gap between vocational education graduates and industry needs, integrating AI, Internet of Things (IoT), and automation systems. The development used the Research and Development (R&D) method with a 4D framework (define, design, develop, and disseminate), followed by testing through a quasi-experimental design on 68 students of the Automotive Engineering Education Study Program. Moreover, the CAI-TEFA has four main components, namely Initial Ability (basic skills), AI-Integrated Teaching Factory (TEFA) (technological infrastructure), CBL Framework with AI Integration (pedagogical mediator), and dual outcomes in the form of Industry 4.0 Competencies and Enhanced Learning Outcomes. The CAI-TEFA learning framework generates a systematic four-stage syntax with AI support, comprising Real Industry Case Analysis, Problem Identification and Diagnosis, Solution Development and Testing, as well as Implementation and Reflection. The results showed that the CAI-TEFA was highly effective with excellent validity, explaining 30.6% of the variance in Industry 4.0 competencies and 24.8% of Enhanced Learning Outcomes. Quasi-experimental testing showed significant effectiveness, with the experimental group achieving a post-test score of 84.25 compared to the control group at 67.35 and a gain score of 37.10 vs. 21.53 points (t-count 8.672 > t-table 2.000, $p < 0.001$). Furthermore, the model was declared "Highly Practical" with an achievement of 94.58%, showing a transformative contribution to automotive vocational education responsive to Industry 4.0, which could prepare graduates with adaptive skills to face the complexities of modern automotive technology.

KEYWORDS

case-based learning (CBL), AI-powered teaching factory (TEFA), industry 4.0, artificial intelligence (AI)

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1 INTRODUCTION

The Industry 4.0 era has transformed the automotive sector through the adoption of artificial intelligence (AI), the Internet of Things (IoT), and automation, creating a significant skills gap between vocational education graduates and industry demands, particularly in developing countries [8] [20] [24]. Conventional automotive vocational education remains limited by teacher-centered approaches and insufficient exposure to industry-relevant technologies, resulting in graduates with weak problem-solving skills and adaptability [3] [39]. AI offers strong potential to bridge this gap by enabling personalized learning, adaptive feedback, and technology-enhanced training environments. Empirical studies in Indonesia show that AI-based teaching factory (TEFA) models improve technical proficiency, learning efficiency, and industry readiness through individualized learning pathways. Meanwhile, case-based Llarning (CBL) is widely recognized for developing critical thinking and problem-solving through authentic scenarios, although its integration with AI in automotive vocational education remains limited [13] [37].

While TEFA effectively simulates real industrial environments and enhances students' technical and soft skills, conventional implementations still lack personalization and responsiveness to rapid technological change. Therefore, integrating AI-supported CBL within the TEFA framework is essential to address Industry 4.0 challenges. The absence of a comprehensive AI–CBL–TEFA model in the automotive context highlights the need to develop an integrated learning model capable of bridging the Industry 4.0 skills gap and preparing globally competitive vocational graduates [18] [40].

2 LITERATURE REVIEW

2.1 CBL

Case-based learning is a student-centered approach that uses authentic real-world cases to develop critical thinking, problem-solving skills, and the application of theoretical knowledge in practical contexts [11]. Grounded in constructivist theory, CBL promotes active knowledge construction through interaction and reflection, enabling students to simulate workplace practices relevant to vocational education [5] [36]. Integrating AI into CBL within a TEFA environment creates a more adaptive learning paradigm. AI enables personalized case adaptation, real-time feedback, and automated generation of complex automotive scenarios aligned with students' competency levels [20] [54]. In addition, AI-enhanced simulations expose students to complex problems that are difficult to replicate in conventional instruction while supporting data-driven monitoring and assessment of learning progress [2] [16] [40].

2.2 TEFA

Teaching Factory is a production-based learning approach that replicates real industrial standards within educational settings, enabling students to experience authentic workplace conditions in a controlled environment [40]. Based on work-based and experiential learning theories, TEFA promotes technology-driven instruction aligned with the demands of Industry 4.0 [12]. In automotive vocational education, TEFA also provides a strategic platform for integrating AI to create adaptive and industry-responsive learning environments. The integration of AI in TEFA supports personalized learning pathways, real-time feedback, and data-driven optimization of learning processes [30]. Empirical studies indicate that AI-based TEFA improves students' technical skills, learning efficiency, and industry readiness through intelligent learning systems and AI-supported simulations [18]. In automotive contexts, AI applications further enhance practical competencies by analyzing performance in vehicle diagnosis, maintenance, and repair while providing targeted recommendations to improve problem-solving accuracy [6] [23] [26] [31] [45].

2.3 AI

Artificial intelligence has become a key driver of transformation in modern learning systems through the integration of machine learning, natural language processing, and adaptive learning technologies that personalize instruction according to students' needs [1] [31]. Intelligent tutoring systems (ITS) provide adaptive feedback and scaffolding, while learning analytics utilizes big data to analyze learning behavior and predict outcomes [44]. Studies indicate that AI-supported CBL effectively integrates technology into instruction and prepares students for technology-intensive professional environments [34]. In automotive TEFA contexts, AI-enhanced CBL exposes students to authentic industrial scenarios supported by predictive diagnostics, automated maintenance, and process optimization technologies, thereby strengthening problem-solving and industry-relevant competencies. Moreover, AI applications such as ITS, automated assessment, virtual simulations, and learning analytics enhance learning outcomes and support students' readiness for Industry 4.0 workplaces [16] [23] [31].

3 MATERIALS AND METHODS

This study employed a mixed-method approach combining Research and Development (R&D) with a quasi-experimental design to develop and evaluate the CAI-TEFA learning model [14]. The development process followed the 4D framework (define, design, develop, and deploy). The effectiveness test involved 68 students from the Automotive Engineering Education Study Program at Padang State University, divided into experimental and control groups (34 students each), during a ten-week implementation using the "Steering, Brake, and Suspension Systems" module in a TEFA environment.

Data were analyzed using SmartPLS 4.0 with Partial Least Squares Structural Equation Modeling (PLS-SEM). The reflective measurement model was evaluated using confirmatory actor analysis (CFA), with model assessment based on average variance extracted (AVE), coefficient of determination (R^2), and the significance of structural path coefficients [7] [17] [43] [46].

3.1 Model effectiveness test design

The effectiveness of the CAI-TEFA learning model was evaluated using a quasi-experimental design involving experimental and control groups. As illustrated in Figure 1, the experimental design compares pre-test and post-test results to determine the impact of the CAI-TEFA model on students' Industry 4.0 competencies and learning outcomes.

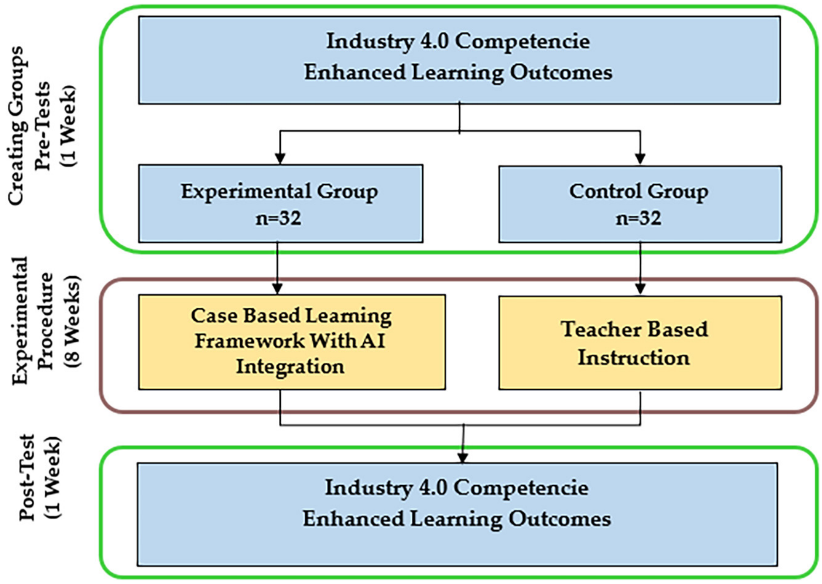

Fig. 1. Experimental design concept for analysis of CAI-TEFA model effectiveness

3.2 Measuring and data collection tools

Industry 4.0 competencies scale. Industry 4.0 competencies in this study were categorized into four dimensions: (1) Digital Literacy, (2) Adaptability and Flexibility, (3) Intelligent and Collaborative Problem-Solving, and (4) Digital Communication [21]. Digital Literacy was based on the DigComp framework, including information and data literacy, communication, content creation, security, and problem-solving skills. Adaptability and Flexibility emphasized continuous learning and innovation, while Intelligent and Collaborative Problem-Solving focused on leadership, teamwork, and strategic thinking. Digital Communication covered cross-cultural communication, knowledge transfer, and conflict management [29].

The competencies were measured using a modified seven-point Likert-scale instrument consisting of 75 items. Reliability analysis showed strong internal consistency with an overall Cronbach's alpha of 0.87 and acceptable subscale reliability for Digital Literacy (0.81), Adaptability and Flexibility (0.78), Intelligent and Collaborative Problem-Solving (0.83), and Digital Communication (0.79), confirming the instrument's reliability for assessing Industry 4.0 competencies in vocational education [21].

Enhanced learning outcomes. The Learning Achievement instrument (Y2.1) was developed to assess students' academic performance and holistic competencies [38]. Initially consisting of 58 pre- and post-test items, the instrument was reviewed by five experts and pilot-tested with 42 students. After psychometric analysis of construct validity, item difficulty, and discrimination, four items were removed, resulting in 54 items with strong reliability ($\alpha = 0.91$), average discrimination index of 0.52, and difficulty level of 0.58. Faster Learning Acquisition (Y2.2) and Enhanced Problem Diagnosis (Y2.3) were measured using a hybrid approach combining 70% process-based assessment and 30% seven-point Likert-scale evaluation [25] [39]. Process-based indicators included time to competency, diagnostic accuracy, problem-solving speed, and performance in workplace simulations [6] [24], while Likert-scale items captured students' perceptions of learning acceleration and diagnostic capability [14]. Assessment validity was ensured through pre–post testing, continuous monitoring, and inter-rater evaluation involving instructors and industry supervisors [28] [38].

4 RESULT

4.1 Results of the development of the CAI-TEFA learning model

As illustrated in Figure 2, the CAI-TEFA model integrates students' initial abilities with AI-integrated TEFA infrastructure to develop Industry 4.0 competencies [3] [21]. The model employs a structured instructional design consisting of four sequential CBL stages: (1) real industry case analysis, (2) problem identification and diagnosis, (3) solution development and testing, and (4) implementation and reflection [5] [11] [36]. CAI-TEFA integrates students' initial competencies, automotive technical skills, basic digital literacy, and conventional problem-solving with AI-integrated TEFA facilities, including AI-powered diagnostics, adaptive learning systems, smart workshops, human–AI collaboration tools, and learning analytics [18], [30], [40]. This integration effectively bridges foundational abilities with advanced Industry 4.0 competencies.

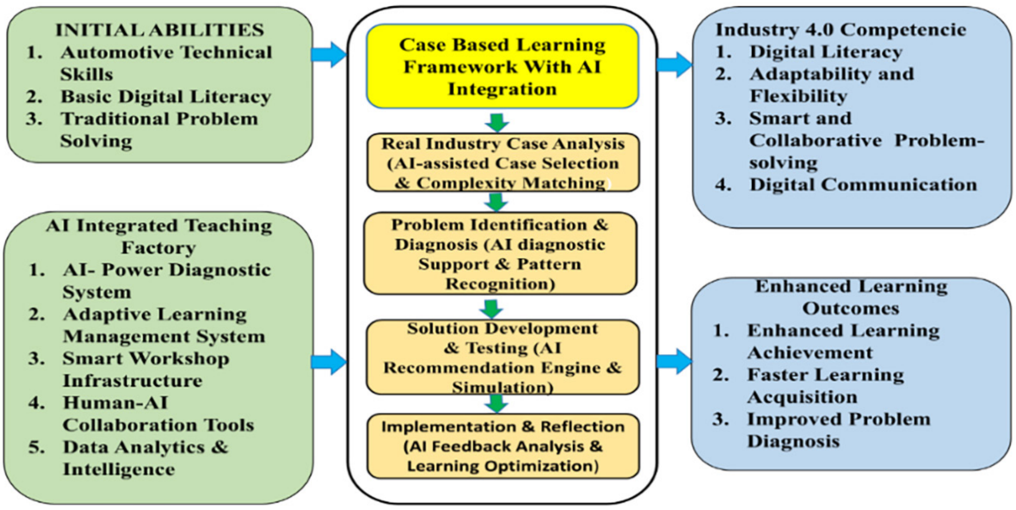

Fig. 2. Final model on the CAI-TEFA learning model

Learning transformation through an AI-integrated CBL framework enhances personalized learning and student engagement by enabling adaptive adjustment of learning content to individual abilities [1] [32] [35]. This framework supports the development of core Industry 4.0 competencies, including digital literacy, adaptability and flexibility, intelligent and collaborative problem solving, and digital communication skills [29]. As a result, the model improves learning outcomes, accelerates learning acquisition, and enhances problem diagnosis, addressing the demands of the modern automotive industry [31].

4.2 Measurement model assessment (MMA)

The measurement model assessment of CAI-TEFA confirmed strong construct validity and reliability. All indicators demonstrated adequate convergent validity, with factor loadings exceeding the 0.70 threshold (0.791–0.912), supported by high Composite Reliability (0.889–0.938) and AVE values (0.692–0.791) [7] [27]. PLS-SEM results identified the AI-integrated CBL framework as the strongest mediating construct ($R^2 = 0.431$), emphasizing its central role within the CAI-TEFA model [36]. This construct showed strong indicator loadings (0.850–0.909), with Real Industry Case Analysis as the most influential indicator (0.909), underscoring the importance of authentic industry contexts in CBL [5] [23]. Structurally, the framework was significantly influenced by Initial Ability (0.417) and AI-Integrated TEFA (0.493) and strongly affected Industry 4.0 competencies (0.553), confirming its mediating function in transforming foundational skills into advanced competencies.

Table 1. Construction validation between variables and indicators in the CAI-TEFA learning model

Variable	Indicator		Factor Loading	Cronbach's Alpha	Composite Reliability (rho_c)	AVE
Initial Abilities (X1)	X1.1	Automotive Technical Skills	0.850	0.814	0.889	0.729
	X1.2	Basic Digital Literacy	0.912			
	X1.3	Traditional Problem Solving	0.795			
AI Integrated TEFA (X2)	X2.1	AI-Powered Diagnostic System	0.791	0.889	0.918	0.692
	X2.2	Adaptive Learning Management System	0.825			
	X2.3	Smart Workshop Infrastructure	0.833			
	X2.4	Human-AI Collaboration Tools	0.802			
	X2.5	Data Analytics & Intelligence	0.904			
Case-Based Learning Framework with AI Integration (M)	M1.1	Real Industry Case Analysis (AI-assisted Case Selection & Complexity Matching)	0.909	0.912	0.938	0.791
	M1.2	Problem Identification & Diagnosis (AI Diagnostic Support & Pattern Recognition)	0.891			
	M1.3	Solution Development & Testing (AI Recommendation Engine & Simulation)	0.850			
	M1.4	Implementation & Reflection (AI Feedback Analysis & Learning Optimization)	0.907			
Industry 4.0 Competencies (Y1)	Y1.1	Digital Literacy	0.842	0.864	0.907	0.709
	Y1.2	Adaptability and Flexibility	0.849			
	Y1.3	Smart and Collaborative Problem-solving	0.835			
	Y1.4	Digital Communication	0.843			
Enhanced Learning Outcomes (Y2)	Y2.1	Enhanced Learning Achievement	0.838	0.842	0.904	0.758
	Y2.2	Faster Learning Acquisition	0.878			
	Y2.3	Improved Problem Diagnosis	0.894			

As presented in Table 1, the MMA confirms the validity and reliability of the CAI-TEFA constructs and their associated indicators. Industry 4.0 competencies exhibited balanced indicator loadings (0.835–0.849), confirming equal contributions of digital literacy, adaptability, collaborative problem-solving, and digital communication, with an R^2 of 0.306 indicating meaningful gains [27]. Enhanced Learning Outcomes demonstrated strong validity, with high factor loadings (0.838–0.894) and an AVE of 0.758, where Enhanced Problem Diagnosis (0.894) emerged as the most responsive outcome to the CAI-TEFA intervention [38]. Structurally, Enhanced Learning Outcomes were directly influenced by AI-Integrated TEFA (0.498) and indirectly through the mediating role of the CBL framework (0.553), yielding an explained variance of $R^2 = 0.248$ [38].

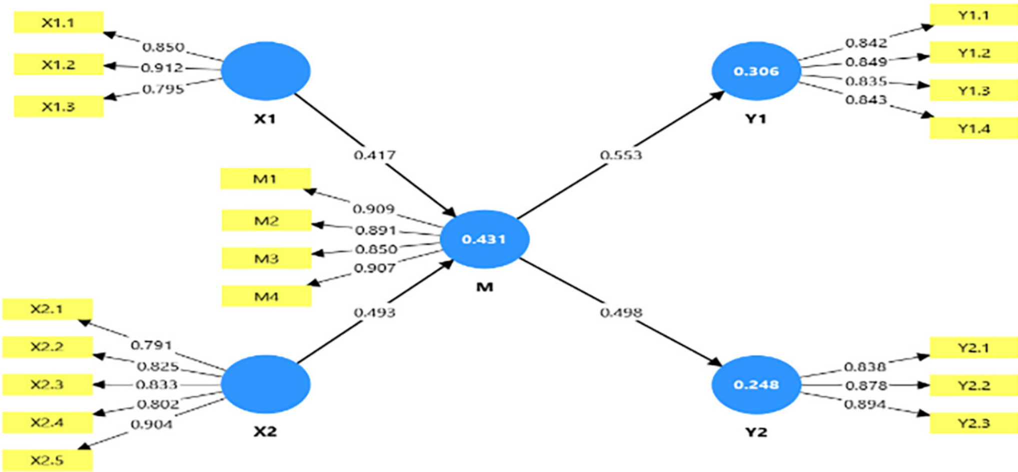

Fig. 3. PLS-SEM output for CAI-TEFA learning model

Figure 3 illustrates the structural model results obtained from the PLS-SEM analysis of the CAI-TEFA learning model. The integrated findings provide a clear framework for implementing CAI-TEFA in automotive vocational education. Consistent with prior studies, AI integration enhances accessibility, inclusiveness, and learning quality through personalized instruction and improved curriculum design. The strong predictive power of the constructs and significant structural paths confirm the model's theoretical robustness and practical applicability [27]. Path analysis shows that AI-integrated TEFA improves learning outcomes both directly and indirectly through the CBL framework and Industry 4.0 competencies, aligning with evidence that multimedia and AI integration enhances learning satisfaction and 21st-century skill development [3]. Effective implementation of CAI-TEFA requires holistic integration of technological infrastructure, pedagogy, and competency development, which is crucial given the 43% skills gap in the automotive sector. Empirical results indicate that this integrated approach strengthens student readiness and employability, helping to mitigate workforce shortages in the modern automotive industry [22].

4.3 Discriminant validity

Table 2. Fornell-Larcker criterion

Predictor	Case-Based Learning Framework with AI Integration (M)	Initial Abilities (X1)	AI Integrated Teaching Factory (X2)	Industry 4.0 Competencies (Y1)	Enhanced Learning Outcomes (Y2)
Case-Based Learning Framework with AI Integration (M)	0.890				
Initial Abilities (X1)	0.433	0.854			
AI Integrated TEFA (X2)	0.507	0.032	0.832		
Industry 4.0 Competencies (Y1)	0.553	0.300	0.239	0.842	
Enhanced Learning Outcomes (Y2)	0.535	0.402	0.475	0.336	0.792

Discriminant validity assessment using the Fornell–Larcker criterion and the HTMT ratio demonstrated strong consistency in confirming the distinctiveness of the CAI-TEFA constructs. As shown in Table 2, all AVE values on the main diagonal (0.792–0.890) exceeded the inter-construct correlations, satisfying the Fornell–Larcker criterion [7]. This result was reinforced by the HTMT analysis in Table 3, where all values were below the recommended threshold of 0.90, with the highest value observed between AI-Integrated TEFA Competencies and Industry 4.0 (0.615). These findings provide robust empirical evidence that each CAI-TEFA construct is measured independently and possesses a distinct conceptual structure.

Table 3. Heterotrait-Monotrait ratio (HTMT)

Predictor	Case-Based Learning Framework with AI Integration (M)	Initial Abilities (X1)	AI Integrated TEFA (X2)	Industry 4.0 Competencies (Y1)	Enhanced Learning Outcomes (Y2)
Case-Based Learning Framework With AI Integration (M)					
Initial Abilities (X1)	0.495				
AI Integrated TEFA (X2)	0.062	0.548			
Industry 4.0 Competencies (Y1)	0.273	0.35	0.615		
Enhanced Learning Outcomes (Y2)	0.378	0.423	0.554	0.557	

The consistency between the Fornell–Larcker and HTMT results provides strong empirical support for the theoretical structure of the CAI-TEFA model. Moderate correlations between the AI-integrated CBL framework and improved learning outcomes (Fornell–Larcker = 0.535; HTMT = 0.378) indicate that AI-supported CBL is both theoretically sound and practically effective, in line with constructivist principles emphasizing authentic, technology-supported vocational learning [38]. The convergent evidence from both tests confirms that each CAI-TEFA construct contributes uniquely without redundancy, forming a well-integrated system. Practically, these findings justify the implementation of CAI-TEFA and support strategic investment in AI infrastructure, CBL development, and TEFA facilities to enhance Industry 4.0 competencies and student learning outcomes.

4.4 Practicality of CAI-TEFA learning model components

As shown in Table 4, all CAI-TEFA components were rated "Highly Practical" by both lecturers and students, indicating strong feasibility for real-world implementation [14]. The syntax component received the highest ratings (lecturers: 4.73 or 94.60%; students: 4.85 or 97.00%), reflecting the ease of applying structured AI-integrated learning in a TEFA environment and supporting systematic instructional design principles [6], [38]. Learning materials also demonstrated high practicality (lecturers: 4.67 or 93.40%; students: 4.49 or 89.80%), confirming overall feasibility, although minor refinement is needed to better accommodate AI-based vocational learning characteristics.

Table 4. Practicality of CAI-TEFA learning model components

Practicality	Practicality Rating	Practicality Percentage	Practicality Category
Learning Model Book			
Lecturer Response	4.52	90.40	Highly practical
Student Response	4.61	92.20	Highly practical
Syntax model			
Lecturer Response	4.73	94.60	Highly practical
Student Response	4.85	97.00	Highly practical
Learning Materials Based on CAI-TEFA Model			
Lecturer Response	4.67	93.40	Highly practical
Student Response	4.49	89.80	Highly practical
Instructor's Manual			
Lecturer Response	4.58	91.60	Highly practical
Student Response	4.71	94.20	Highly practical
Student's Manual			
Lecturer Response	4.54	90.80	Highly practical
Student Response	4.66	93.20	Highly practical

The consistently high practicality ratings from lecturers and students (mean = 4.49–4.85; 89.80%–97.00%) confirm that CAI-TEFA fulfills established practicality criteria for educational product development. These findings indicate ease of use, efficient implementation, and minimal operational constraints in integrating AI with CBL within a TEFA environment. Furthermore, the high practicality demonstrates strong potential for the sustainable long-term adoption of CAI-TEFA in automotive vocational education systems [16].

5 DISCUSSION

5.1 The effectiveness of implementing the CAI-TEFA Industry 4.0 model in improving Industry 4.0 competencies for students

Based on Table 1 and Figure 3, the CAI-TEFA learning model demonstrates strong effectiveness in preparing students for Industry 4.0 challenges, as indicated by high construct reliability (Cronbach's Alpha = 0.864; Composite Reliability = 0.907) [17]. Students' foundational competencies digital literacy (0.912), automotive technical expertise (0.850), and conventional problem-solving (0.795) contribute substantially, explaining 55.3% of the variance in Industry 4.0 competency development [10]. CAI-TEFA develops four core competencies in a balanced manner: digital capacity (0.842), adaptability (0.849), collaborative problem-solving (0.835), and digital communication (0.843), all of which are critical for contemporary workplaces [22]. The integration of CBL with advanced AI technology enables students to engage with authentic industrial cases and apply solutions aligned with Industry 4.0 standards, strengthening professional readiness in real automotive contexts [39]. Overall, CAI-TEFA explains 30.6% of the variance in Industry 4.0 competencies, confirming its effectiveness in preparing graduates for the modern automotive industry [14].

Effectiveness in digital literacy. CAI-TEFA demonstrated strong effectiveness in enhancing students' digital literacy, as indicated by a high loading score of 0.842, achieved through the integration of technical digital skills, critical technological thinking, and digital ethics [45]. The model contributed substantially to overall academic achievement, explaining 49.8% of the observed effect. This effectiveness is primarily driven by the use of authentic automotive industry digital technologies, enabling students to develop competencies directly applicable in modern industrial environments [20]. The integration of AI within industry-oriented CBL further strengthened digital literacy by exposing students to digital platforms, AI-based diagnostic systems, and collaborative tools reflective of real automotive practices [33]. Strong indicator contributions across the AI-supported CBL cycle from real industry case analysis (0.789) to implementation and reflection (0.823) confirm CAI-TEFA's effectiveness in bridging the Industry 4.0 skills gap and producing digitally competent graduates aligned with global automotive transformation [45].

Effectiveness in adaptability and flexibility. Structural equation modeling results indicate that CAI-TEFA is highly effective in enhancing students' adaptability and flexibility, as reflected by a strong loading score of 0.849. This effectiveness is driven by the integration of AI-based personalized learning, adaptive CBL, and intelligent learning infrastructure that supports continuous adaptive responses [10]. Adaptability and flexibility contributed substantially to overall learning effectiveness, accounting for 49.8% of the observed impact. By exposing students to diverse real-world automotive industry cases and AI-generated scenarios, CAI-TEFA fosters mental agility and flexible problem-solving strategies aligned with Industry 4.0 demands, including electric and autonomous vehicle technologies [19], [20]. Practically, CAI-TEFA explains 30.6% of the variance in adaptability development ($R^2 = 0.306$), confirming the mediating role of the AI-supported CBL framework in transforming foundational skills into cognitive flexibility for addressing complex industrial challenges.

Effectiveness in smart and collaborative problem-solving. CAI-TEFA demonstrated strong effectiveness in enhancing students' smart and collaborative problem-solving competencies, as indicated by a loading score of 0.835. This effectiveness is driven by the synergy between students' foundational competencies, advanced AI-supported analytical infrastructure, and industry-based case learning that promotes collaborative inquiry [4] [17]. Through exposure to authentic automotive industry cases, students engage in human–AI collaboration to identify problems, analyze data, and generate evidence-based solutions, thereby improving both the quality and efficiency of problem-solving processes [1], [16]. These findings confirm CAI-TEFA as a scalable learning model capable of developing collaborative intelligence and human–AI problem-solving skills essential for vocational education in Industry 4.0 contexts [33] [39] [41].

Effectiveness in digital communication. CAI-TEFA demonstrated strong effectiveness in enhancing students' digital communication competencies, as reflected by a loading score of 0.843. This effectiveness is supported by AI-enabled learning environments that facilitate mastery of technical documentation, multimedia presentation, online collaboration, and human–AI interaction, key communication practices in Industry 4.0 contexts [42]. The integration of industry-based case studies provides authentic professional communication experiences and strengthens the linkage between digital communication, collaborative problem-solving, and adaptability [9] [22]. These findings confirm digital communication as a core Industry 4.0

competency and position CAI-TEFA as a scalable model for developing technical and strategic communication skills aligned with modern vocational workplace demands [9] [42].

5.2 Effectiveness of implementing the CAI-TEFA Industry 4.0 model in improving learning outcomes (Y2) for students

CAI-TEFA demonstrated strong effectiveness in improving student learning outcomes (Y2), as evidenced by high reliability and validity indices (Cronbach's Alpha = 0.842; Composite Reliability = 0.904; AVE = 0.758) [27]. Balanced gains were achieved across Learning Achievement (0.838), Faster Learning Acquisition (0.878), and Improved Problem Diagnosis (0.894), indicating the development of integrated learning capacities essential for automotive vocational education. These improvements were driven by two complementary mechanisms: a direct contribution from AI-integrated TEFA infrastructure (49.8%) and an indirect contribution mediated through industry-oriented CBL, both exhibiting strong construct reliability (Cronbach's Alpha = 0.912; Composite Reliability = 0.938; AVE = 0.791) [27]. Overall, CAI-TEFA explained 24.8% of the variance in learning outcomes, confirming its substantial effect size and effectiveness in integrating AI technology with CBL to enhance academic performance, learning efficiency, and diagnostic competence aligned with contemporary automotive industry demands [38] [44].

Effectiveness in enhanced learning achievement. CAI-TEFA demonstrated strong effectiveness in improving student learning achievement, with an effectiveness score of 0.838, consistent with prior evidence on AI-based learning effectiveness [38]. This improvement was driven by the integration of AI-powered adaptive learning support, industry-based CBL, intelligent TEFA infrastructure with AI-driven diagnostics and analytics [18], [40], and the integration of cognitive learning with hands-on practice, enabling simultaneous development of theoretical understanding and practical competence required in Industry 4.0 contexts. By embedding Industry 4.0 competencies into the learning process, CAI-TEFA strengthens the linkage between academic achievement and professional readiness [21]. Overall, the model explains 24.8% of the variance in learning outcomes, indicating a substantial contribution to producing job-ready graduates with strong analytical, problem-solving, and lifelong learning capabilities for the modern automotive industry [2].

Effectiveness in faster learning acquisition. CAI-TEFA demonstrated strong effectiveness in enhancing Faster Learning Acquisition, as reflected by a high factor loading of 0.878, confirming the effectiveness of the integrated learning approach. This improvement was achieved through the integration of AI-driven personalization, authentic CBL, and smart infrastructure that collectively accelerated cognitive processing, practical skill acquisition, and knowledge transfer [1]. The significant structural relationship between Faster Learning Acquisition and overall learning effectiveness (path coefficient = 0.498) indicates that CAI-TEFA not only accelerates learning speed but also strengthens diagnostic skills and academic achievement [15] [38]. Supported by strong psychometric properties (Cronbach's Alpha = 0.912), CAI-TEFA establishes a sustainable and adaptive learning ecosystem aligned with lifelong learning principles, providing graduates with a competitive advantage in adapting to technological changes in Industry 4.0-oriented automotive environments [11] [36].

Effectiveness in improved problem diagnosis. CAI-TEFA demonstrated strong effectiveness in improving students' diagnostic skills, as indicated by a high factor loading for Improved Problem Diagnosis (0.894). This improvement was supported by the integration of analytical thinking, pattern recognition, and technology-assisted diagnostic reasoning within an AI-powered learning environment [11] [36]. The combination of AI-assisted diagnostic systems, CBL, and smart workshop infrastructure provided authentic industrial contexts that enhanced students' diagnostic competence [4] [31]. The significant structural relationship between Improved Problem Diagnosis and enhanced learning outcomes (path coefficient = 0.498) indicates that CAI-TEFA not only strengthens diagnostic abilities but also supports faster learning acquisition and improved academic achievement [14] [30]. With high construct reliability (0.912), the model helps prepare graduates with industry-ready diagnostic competencies aligned with Industry 4.0 workforce demands [7] [33].

Generalization of findings. The findings of this study provide broader implications beyond the specific context of automotive vocational education. The CAI-TEFA model demonstrates that integrating AI with CBL and TEFA environments can create an adaptive and industry-aligned learning ecosystem. Although implemented in automotive engineering education, the instructional principles of CAI-TEFA AI-supported case analysis, adaptive learning pathways, and industry-simulated work environments are applicable to other technical and vocational fields such as mechanical engineering, manufacturing technology, and electrical engineering. By enabling personalized feedback, data-driven learning analytics, and authentic problem-solving experiences, CAI-TEFA can serve as a scalable instructional framework for vocational education systems seeking to develop Industry 4.0 competencies, digital literacy, and collaborative problem-solving skills.

6 CONCLUSION

This study developed the CAI-TEFA learning model consisting of four stages: Real Industry Case Analysis, Problem Identification and Diagnosis, Solution Development and Testing, and Implementation and Reflection. The model proved effective in improving Industry 4.0 competencies of automotive vocational education students, supported by strong construct validity (Cronbach's Alpha 0.814–0.912, Composite Reliability 0.889–0.938, AVE 0.692–0.791). SEM results indicated significant effects on Industry 4.0 competencies (path coefficient = 0.553, R^2 = 0.306) with balanced contributions from adaptability and flexibility, digital communication, digital literacy, and smart problem-solving. Enhanced Learning Outcomes were also significant (path coefficient = 0.498, R^2 = 0.248), particularly in Improved Problem Diagnosis and Faster Learning Acquisition. CAI-TEFA integrates AI-powered TEFA environments with CBL to create an adaptive and industry-aligned learning ecosystem. The model demonstrated strong discriminant validity (HTMT 0.062–0.615) and high practicality (89.80%–97.00%), indicating its feasibility for implementation. Overall, CAI-TEFA provides a scalable instructional framework for developing Industry 4.0 competencies and preparing vocational graduates with both technical and digital skills required in modern industry.

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8 DECLARATION OF CONFLICTING INTERESTS

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this paper.

9 REFERENCES

[1] M. R. M. Amin, I. Ismail, and V. M. Sivakumaran, "Revolutionizing education with artificial intelligence (AI)? Challenges and implications for Open and Distance Learning (ODL)," *Social Sciences & Humanities Open*, vol. 11, p. 101308, 2025. https://doi.org/10.1016/j.ssaho.2025.101308

[2] M. Ansar and G. George, "Artificial Intelligence-enabled project-based learning to augment subject comprehension among commerce graduates," in *Prompt Engineering and Generative AI Applications for Teaching and Learning*, IGI Global Scientific Publishing, 2025, pp. 143–160. https://doi.org/10.4018/979-8-3693-7332-3.ch009

[3] N. A. B. Anwar and A. D. Minghat, "Industrial engineering students' readiness towards Industrial Revolution 4.0 at technical and vocational university: Literature review," *ASEAN Journal for Science Education*, vol. 3, no. 1, pp. 95–112, 2024.

[4] S. Aslan *et al.*, "An early investigation of collaborative problem solving in conversational AI-mediated learning environments," *Computers and Education: Artificial Intelligence*, vol. 8, p. 100393, 2025. https://doi.org/10.1016/j.caeai.2025.100393

[5] A. Aydın, "A structured educational model to improve the education of nurses: Case-based learning," *Perioperative Care and Operating Room Management*, vol. 40, p. 100504, 2025. https://doi.org/10.1016/j.pcorm.2025.100504

[6] M. H. A. Bakar, N. H. M. Ghafar, and F. Abdullah, "Exploring the integration of artificial intelligence in technical and vocational education and training (TVET): Applications, benefits, challenges, and future prospects," *Borneo Engineering & Advanced Multidisciplinary International Journal*, vol. 3, no. 3, pp. 57–63, 2024. https://doi.org/10.30574/ijsra.2024.12.1.0971

[7] J. M. Becker, J. H. Cheah, R. Gholamzade, C. M. Ringle, and M. Sarstedt, "PLS-SEM's most wanted guidance," *International Journal of Contemporary Hospitality Management*, vol. 35, no. 1, pp. 321–346, 2022. https://doi.org/10.1108/IJCHM-04-2022-0474

[8] C. F. Buciuman and S. Potra, "Revolutionizing education in Industry 4.0: Eye-tracking and AI for personalized learning," *Procedia Computer Science*, vol. 253, pp. 1658–1667, 2025. https://doi.org/10.1016/j.procs.2025.01.228

[9] I. A. Bykov and M. V. Medvedeva, "Media literacy and AI-technologies in digital communication: Opportunities and risks," in *2024 Communication Strategies in Digital Society Seminar (ComSDS)*, 2024, pp. 21–24. https://doi.org/10.1109/ComSDS61892.2024.10502053

[10] M. T. Chandio, N. Zafar, and G. M. Solangi, "Bloom's taxonomy: Reforming pedagogy through assessment," *Journal of Education and Educational Development*, vol. 8, no. 1, pp. 109–140, 2021. https://doi.org/10.22555/joeed.v8i1.308

[11] M. C. Chang, "Historical and theoretical foundations of case-based learning: Situated cognition and collaborative learning theory," in *Designing Technology-Mediated Case Learning in Higher Education: A Global Perspective*, Springer Nature Singapore, 2023, pp. 49–68. https://doi.org/10.1007/978-981-19-5135-0_4

[12] J. Chelini and D. Richert, "Teaching engineering design for Industry 4.0 using a cyber-physical learning factory," *IFAC-PapersOnLine*, vol. 56, no. 2, pp. 4699–4704, 2023. https://doi.org/10.1016/j.ifacol.2023.10.994

[13] Y. Chen and H. Luo, "What makes a better case? Impact of case familiarity and story ending on online case-based learning," *Thinking Skills and Creativity*, vol. 56, p. 101769, 2025. https://doi.org/10.1016/j.tsc.2025.101769

[14] E. G. Creamer, *Visual Displays in Qualitative and Mixed Method Research: A Comprehensive Guide*. Boca Raton, FL, USA: Taylor & Francis, 2024. https://doi.org/10.4324/9781003303602

[15] A. Cunska, "Effective learning strategies and Artificial Intelligence (AI) support for accelerated math acquisition," in *European Proceedings of International Conference on Education and Educational Psychology*, 2020. https://doi.org/10.15405/epiceepsy.20111.11

[16] I. Daniyan, K. Mpofu, M. Oyesola, B. Ramatsetse, and A. Adeodu, "Artificial intelligence for predictive maintenance in the railcar learning factories," *Procedia Manufacturing*, vol. 45, pp. 13–18, 2020. https://doi.org/10.1016/j.promfg.2020.04.032

[17] G. Dash and J. Paul, "CB-SEM vs. PLS-SEM methods for research in social sciences and technology forecasting," *Technological Forecasting and Social Change*, vol. 173, p. 121092, 2021. https://doi.org/10.1016/j.techfore.2021.121092

[18] M. H. Dehbozorgi *et al.*, "AI education for tomorrow's workforce: Leveraging learning factories for AI education and workforce preparedness," in *2024 IEEE 8th Forum on Research and Technologies for Society and Industry Innovation (RTSI)*, 2024, pp. 677–682. https://doi.org/10.1109/RTSI61910.2024.10761217

[19] T. Denton, *Advanced Automotive Fault Diagnosis: Automotive Technology: Vehicle Maintenance and Repair*. London: Routledge, 2020. https://doi.org/10.1201/9780429317781

[20] W. Ding, "Novel AI-based teaching model for advancing automotive styling design education to meet industry demands," *International Journal of Mechanical Engineering Education*, 2025. https://doi.org/10.1177/03064190251350152

[21] M. Ghobakhloo, "Industry 4.0, digitization, and opportunities for sustainability," *Journal of Cleaner Production*, vol. 252, p. 119869, 2020. https://doi.org/10.1016/j.jclepro.2019.119869

[22] R. K. Ghosh, A. Banerjee, P. Aich, D. Basu, and U. Ghosh, "Intelligent IoT for automotive Industry 4.0: Challenges, opportunities, and future trends," in *Intelligent Internet of Things for Healthcare and Industry*, U. Ghosh, C. Chakraborty, L. Garg, and G. Srivastava, Eds., 2022, pp. 327–352. https://doi.org/10.1007/978-3-030-81473-1_16

[23] C. S. A. Gong, C. H. S. Su, Y. H. Chen, and D. Y. Guu, "How to implement automotive fault diagnosis using artificial intelligence scheme," *Micromachines*, vol. 13, no. 9, p. 1380, 2022. https://doi.org/10.3390/mi13091380

[24] Ö. F. Görçün, A. R. Mishra, A. Aytekin, V. Simic, and S. Korucuk, "Evaluation of Industry 4.0 strategies for digital transformation in the automotive manufacturing industry using an integrated fuzzy decision-making model," *Journal of Manufacturing Systems*, vol. 74, pp. 922–948, 2024. https://doi.org/10.1016/j.jmsy.2024.05.005

[25] N. Góngora, D. Malagón, and M. A. V. Peña, "Assessment of using software for the acquisition of problem-solving skills in mechanical engineering students," *Ingeniería y Universidad*, vol. 26, p. 21, 2022. https://doi.org/10.11144/Javeriana.iued26.ausa

[26] H. Maksum, W. Purwanto, Siman, S. Triono, and H. Hasan, "Enhancing student achievement through a digital learning module: The TEFA-T model in a teaching factory of automotive vocational education," *Int. J. Interact. Mobile Technol. (iJIM)*, vol. 19, no. 6, pp. 115–127, 2025. https://doi.org/10.3991/ijim.v19i06.53799

[27] J. F. Hair Jr, G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. P. Danks, and S. Ray, *Partial Least Squares Structural Equation Modeling (PLS-SEM) using R: A Workbook*. Cham: Springer Nature, 2021, p. 197. https://doi.org/10.1007/978-3-030-80519-7

[28] P. V. Harisankar, S. Malik, and J. Nagarkar, "Analyzing the impact of AI on knowledge acquisition of students," in *2024 International Conference on Current Trends in Advanced Computing (ICCTAC)*, 2024, pp. 1–6. https://doi.org/10.1109/ICCTAC61556.2024.10581301

[29] M. Hernandez-de-Menendez, R. Morales-Menendez, C. A. Escobar, and M. McGovern, "Competencies for Industry 4.0," *International Journal on Interactive Design and Manufacturing (IJIDeM)*, vol. 14, no. 4, pp. 1511–1524, 2020. https://doi.org/10.1007/s12008-020-00716-2

[30] R. Hoffmann *et al*., "Artificial intelligence for quality assurance and troubleshooting in industry," in *Proceedings of the Upper-Rhine Artificial Intelligence Symposium 2024*, 2024, pp. 69–76. https://doi.org/10.60643/urai.v2024p69

[31] M. N. Hossain, M. M. Rahman, and D. Ramasamy, "Artificial intelligence-driven vehicle fault diagnosis to revolutionize automotive maintenance: A review," *CMES – Computer Modeling in Engineering & Sciences*, vol. 141, no. 2, pp. 951–996, 2024. https://doi.org/10.32604/cmes.2024.056022

[32] D. Johnson, The Role of Work-Based Learning in Developing Future Skills and Johnson, R., Smith, A., & Brown, L. (2023). Artificial intelligence in vocational education: Adaptive learning systems and their impact on student outcomes. *International Journal of Educational Technology*, vol. 18, no. 2, pp. 78–95, 2024.

[33] S. S. Kamran *et al*., "Artificial intelligence and advanced materials in automotive industry: Potential applications and perspectives," *Materials Today: Proceedings*, vol. 62, pp. 4207–4214, 2022. https://doi.org/10.1016/j.matpr.2022.04.727

[34] J. Katona and K. I. K. Gyonyoru, "Integrating AI-based adaptive learning into the flipped classroom model to enhance engagement and learning outcomes," *Computers and Education: Artificial Intelligence*, vol. 8, p. 100392, 2025. https://doi.org/10.1016/j.caeai.2025.100392

[35] R. Lavi and D. Marti, "A proposed case-based learning framework for fostering undergraduate engineering students' creative and critical thinking," *Journal of Science Education and Technology*, vol. 32, no. 6, pp. 898–911, 2023. https://doi.org/10.1007/s10956-022-10017-w

[36] N. O. N. G. Liqiao, "A case study on based on VR-based inquiry learning: Microcomputer assembly example," *Sustainable Futures*, p. 100891, 2025. https://doi.org/10.1016/j.sftr.2025.100891

[37] C. A. Mertler, *Introduction to Educational Research*. Thousand Oaks, CA, USA: Sage Publications, 2024.

[38] H. Middleton, "Developing problem-solving skills," in *Developing Vocational Expertise*, London: Routledge, 2020, pp. 135–152. https://doi.org/10.4324/9781003115342-8

[39] D. Mourtzis, N. Panopoulos, and J. Angelopoulos, "A hybrid teaching factory model towards personalized education 4.0," *International Journal of Computer Integrated Manufacturing*, vol. 36, no. 12, pp. 1739–1759, 2023. https://doi.org/10.1080/0951192X.2022.2145025

[40] O. Morales Matamoros, J. G. Takeo Nava, J. J. Moreno Escobar, and B. A. C. Ceballos, "Artificial intelligence for quality defects in the automotive industry: A systemic review," *Sensors*, vol. 25, no. 5, p. 1288, 2025. https://doi.org/10.3390/s25051288

[41] S. Mumtaz, "Future of digital communication," *Journal of Advanced Digital Communications*, vol. 1, no. 1, p. 024, 2024. https://doi.org/10.53941/jadc.2024.100001

[42] N. Al-Huwail, A. Al-Hunaiyyan, S. Alainati, and A. Alhabshi, "Artificial intelligence in education: Perspectives and challenges," *Int. J. Interact. Mobile Technol. (iJIM)*, vol. 19, no. 4, pp. 26–47, 2025. https://doi.org/10.3991/ijim.v19i04.52117

[43] T. N. Nguyen and H. T. Truong, "Trends and emerging themes in the effects of generative artificial intelligence in education: A systematic review," *Eurasia Journal of Mathematics, Science and Technology Education*, vol. 21, no. 4, p. em2613, 2025. https://doi.org/10.29333/ejmste/16124

[44] G. Nithyanandam, J. Munguia, and M. Marimuthu, "'Digital literacy': Shaping Industry 4.0 engineering curriculums via factory pilot-demonstrators," *Advances in Industrial and Manufacturing Engineering*, vol. 5, p. 100092, 2022. https://doi.org/10.1016/j.aime.2022.100092

[45] S. Alainati, A. Al-Huwail, and A. Al-Hunaiyyan, "Artificial intelligence in education: Opportunities and challenges," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 18, no. 3, pp. 4–17, 2024.

[46] H. Maksum, W. Purwanto, S. Triono, and H. Hasan, "Enhancing student achievement through digital learning modules in a teaching factory model," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 19, no. 6, pp. 115–127, 2025. https://doi.org/10.3991/ijim.v19i06.53799

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