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ORIGINAL

Smart Teaching Factory: Integrating Extended Reality, Artificial Intelligence, and Animated Simulations for Transformative Vocational Education

Fábrica De Enseñanza Inteligente: Integración de Realidad Extendida, Inteligencia Artificial y Simulaciones Animadas para una Educación Vocacional Transformadora

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ABSTRACT

This study presents the design, implementation, and validation of the Smart Teaching Factory (STF) framework, which integrates Extended Reality (XR), Artificial Intelligence (AI), and animated simulation technologies to enhance vocational education. Targeting 62 electronics engineering students and 6 vocational instructors across three Indonesian public vocational schools, this quasi-experimental mixed-methods study compared the effects of STF-enhanced instruction with conventional methods. Quantitative results from pre- and post-tests revealed significant improvements in student learning outcomes ($p < 0,01$), while SUS usability scores reached 82,5, indicating excellent system acceptance. Interaction analytics from platform logs and classroom observations highlighted elevated student focus, collaboration, and task engagement in the experimental group. The STF model proved effective in delivering competency-based, immersive learning experiences through a data-informed, user-centered platform. These findings demonstrate STF's potential as a scalable, adaptable framework for transforming vocational education in resource-constrained environments.

Keywords: Smart Teaching Factory; Integrating Extended Reality; Artificial Intelligence; Animated Simulation; Vocational Education; Learning Analytics; Usability.

RESUMEN

Este estudio presenta el diseño, la implementación y la validación del marco Smart Teaching Factory (STF), que integra Realidad Extendida (XR), Inteligencia Artificial (IA) y tecnologías de simulación animada para mejorar la formación profesional. Dirigido a 62 estudiantes de ingeniería electrónica y 6 instructores de formación profesional de tres escuelas públicas de formación profesional de Indonesia, este estudio cuasiexperimental de métodos mixtos comparó los efectos de la instrucción mejorada con STF con los métodos convencionales. Los resultados cuantitativos de las pruebas previas y posteriores revelaron mejoras significativas en los resultados de aprendizaje de los estudiantes ($p < 0,01$), mientras que las puntuaciones de usabilidad del SUS alcanzaron 82,5, lo que indica una excelente aceptación del sistema. El análisis de interacción de los registros de la plataforma y las observaciones en el aula destacó un mayor enfoque, colaboración y compromiso con la tarea de los estudiantes en el grupo experimental. El modelo STF demostró ser eficaz para ofrecer experiencias de aprendizaje inmersivas basadas en competencias a través de una plataforma basada en datos y centrada en el usuario. Estos hallazgos demuestran el potencial de STF como marco escalable y adaptable para transformar la formación profesional en entornos con recursos limitados.

Palabras clave: Fábrica de Enseñanza Inteligente; Integración de Realidad Extendida; Inteligencia Artificial; Simulación Animada; Formación Profesional; Analítica del Aprendizaje; Usabilidad.

INTRODUCTION

In light of accelerating technological transformation, Technical and Vocational Education and Training (TVET) systems are under increasing pressure to cultivate competencies aligned with Industry 4.0—such as adaptability, advanced problem-solving, and digital fluency.(1,2) Nevertheless, prevailing instructional practices in many vocational settings remain entrenched in conventional, teacher-centered paradigms, often dominated by rote learning and minimal use of digital technologies.(3,4) This pedagogical inertia limits students' exposure to contemporary tools, constraining their readiness for evolving labor market demands.(4,5)

Despite the growing availability of immersive educational technologies such as Extended Reality (XR), AI-powered tutoring systems, and animated simulations, their adoption in vocational education—especially in Southeast Asia—remains fragmented and inconsistent.(6,7,8) These tools have shown strong potential to enhance procedural understanding, foster experiential learning, and improve learner engagement. However, a cohesive and scalable instructional framework that effectively integrates these technologies while aligning with contemporary learning theories remains underdeveloped.

This study addresses this critical gap by introducing and empirically validating the Smart Teaching Factory (STF)—an integrative pedagogical framework designed to synthesize XR, AI, animated simulations, and embedded learning analytics into a coherent instructional design. The STF is anchored in constructivist learning theory(9), Cognitive Load Theory (CLT),(10) and the Technological Pedagogical Content Knowledge (TPACK) framework,(11,12) the STF offers a comprehensive approach to immersive vocational learning. Unlike prior studies that explore these technologies in isolation,(13,14,15) STF provides a unified, practice-oriented model that supports both students and instructors in technology-enhanced learning environments.

Within the Indonesian vocational education landscape—where many institutions face significant infrastructure limitations and pedagogical constraints—this research demonstrates the feasibility and impact of STF as a pragmatic strategy for driving digital transformation. By deploying STF in public vocational schools (Sekolah Menengah Kejuruan or SMK), the study contributes to both theoretical advancement in immersive learning and practical insights for educational policy and system reform in low- and middle-income countries (LMICs).

The novelty of this study lies in its dual focus on conceptual innovation and empirical validation. Through a rigorous mixed-methods design incorporating pre- and post-tests, System Usability Scale (SUS) evaluation, and interaction-based learning analytics, the research substantiates STF's effectiveness in enhancing learning performance, usability, and behavioral engagement. Ultimately, this study seeks to inform the global discourse on smart, inclusive, and scalable vocational education reform.

Literature Review

Immersive and Intelligent Technologies in Vocational Education

Recent advances in educational technology have significantly reshaped the landscape of vocational education, particularly through the emergence of immersive learning environments and intelligent instructional systems. Technologies such as Extended Reality (XR),(16) Artificial Intelligence (AI),(8,17) animated simulations,(18,19) and learning analytics(20) have each demonstrated individual efficacy in enhancing teaching and learning outcomes. However, despite their respective pedagogical strengths, the integration of these technologies into a unified and pedagogically coherent ecosystem remains underexplored, especially within the context of vocational training.

Extended Reality in Vocational Education

Extended Reality (XR)—encompassing both augmented reality (AR) and virtual reality (VR)—has been increasingly adopted in vocational settings due to its ability to simulate high-risk or cost-prohibitive real-world tasks in controlled digital environments.(21,22,23) XR facilitates authentic, experiential learning that enhances procedural fluency and spatial understanding. For instance, AR in automotive diagnostics allows learners to visualize internal components of complex machinery, while VR simulations are widely used in construction, welding, and safety training.(24) However, most XR applications remain modular and isolated, lacking integration with real-time feedback systems, learner modeling, or data-driven instruction—factors essential for sustained learning gains.

Artificial Intelligence in Personalized Instruction

The use of Artificial Intelligence (AI) in vocational education has primarily centered on adaptive learning platforms, intelligent tutoring systems, and automated assessment tools. AI enables the personalization of learning pathways by analyzing learner behavior, detecting misconceptions, and delivering targeted interventions.(25) Nonetheless, such systems often operate in silos, with limited interoperability with XR environments or simulation tools.(26) Moreover, there is a paucity of research that explores the synergistic integration of AI with immersive media to support both conceptual and procedural knowledge development in vocational domains.

Animated Simulations for Procedural Mastery

Animated simulations have long been valued for their ability to simplify the visualization of complex technical processes—such as engine combustion, electrical circuits, or CNC machining sequences.(16,27) These tools support procedural learning, cognitive scaffolding, and error-free rehearsal of high-stakes tasks.(28) However, their deployment in vocational contexts is often limited to supplementary content rather than as a core component of instructional design. Furthermore, animated simulations are rarely connected to real-time learner analytics or performance feedback systems, limiting their potential to support iterative learning loops.(29)

Learning Analytics and Data-Driven Instruction

Learning analytics offer powerful insights into student engagement, behavioral patterns, and instructional effectiveness.(30) By capturing real-time interaction data, instructors can make informed decisions on instructional pacing, content adaptation, and learner support. However, in practice, analytics are frequently employed in post-hoc evaluations rather than being embedded within the instructional workflow. There is a critical need for models that treat analytics as an integral component of pedagogy, enabling continuous feedback and personalization.

Integration Gaps in Existing Models

While existing studies have shown the promise of each technology independently,(31,32,33) few have successfully integrated XR, AI, animated simulations, and learning analytics into a single, scalable instructional ecosystem. Initiatives such as the Intelligent Virtual Training Environment (IVTE) and AI-augmented VR simulations illustrate conceptual potential but often fall short in scalability, technical interoperability, or usability validation in real-world classrooms. Moreover, most prior models emphasize cognitive outcomes without fully addressing affective and behavioral dimensions such as learner motivation, self-efficacy, collaboration, and confidence—all of which are critical in vocational learning environments.

The integration of multiple technologies also poses challenges in terms of instructional design coherence, infrastructure limitations, and teacher readiness. Particularly in developing contexts such as Indonesia, vocational institutions face barriers related to limited digital infrastructure, professional development, and institutional support, which inhibit the widespread adoption of emerging technologies.(34)

In response to these gaps, this study introduces the Smart Teaching Factory (STF) framework—an integrative, scalable, and pedagogically grounded model for vocational education. The STF synthesizes immersive XR environments, AI-driven tutoring systems, animated simulations, and embedded learning analytics into a cohesive instructional architecture rooted in constructivist learning theory, the TPACK model, and cognitive apprenticeship principles.

Importantly, this study not only conceptualizes the STF framework but also provides a comprehensive empirical validation across multiple dimensions: learning performance (via pre- and post-tests), system usability (using the System Usability Scale, SUS), and behavioral engagement (through interaction analytics and qualitative feedback). Situated within Indonesian public vocational schools, where challenges of digital transformation remain acute, this research contributes to both the theoretical advancement of immersive learning frameworks and the practical reform of global TVET systems.

Each technological layer contributes distinct pedagogical value: XR environments provide immersive, experiential contexts for skill practice; AI modules offer adaptive guidance and performance diagnostics; animated simulations facilitate procedural fluency and conceptual understanding. Collectively, the STF framework enables a personalized, scalable, and data-informed ecosystem that supports deeper learning and professional readiness in vocational settings.

Figure 1 presents the conceptual architecture of the STF, an integrative instructional framework designed to enhance vocational education through the convergence of Extended Reality (XR), Artificial Intelligence (AI), animated simulations, and learning analytics. At the core of the model lies a dynamic feedback loop, in which real-time data from learner interactions are captured via embedded analytics and visualized through system dashboards. These insights inform both automated and instructor-mediated adjustments to instructional pathways, fostering continuous improvement in both content delivery and learner engagement.

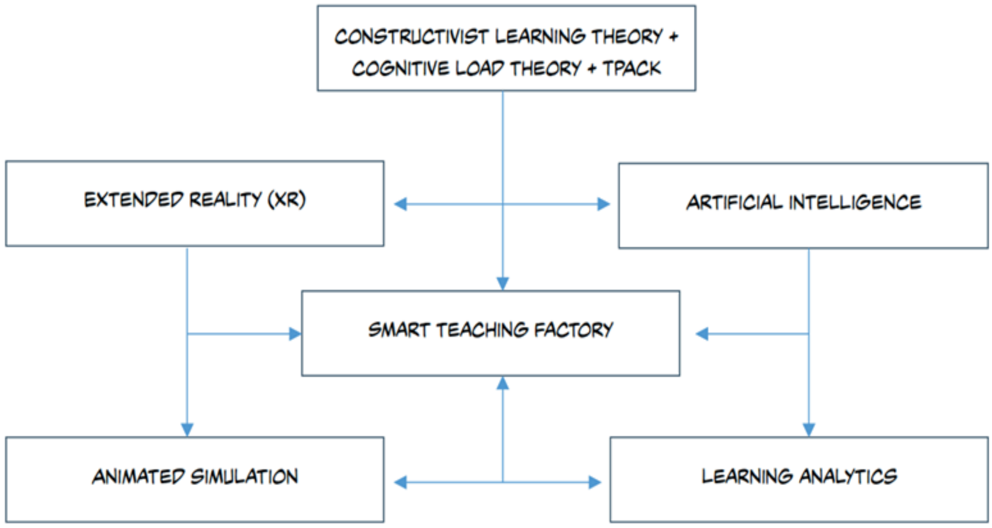

Figure 1. Conceptual Framework of the Smart Teaching Factory (STF)

METHOD

This study employed a convergent mixed-methods design, integrating quantitative and qualitative data to evaluate the design, implementation, and impact of the Smart Teaching Factory (STF) framework in vocational education settings. Conducted in three Indonesian public vocational schools (SMKs) with students enrolled in the electronics engineering program, the methodological framework assessed pedagogical effectiveness, system usability, and behavioral engagement through the integration of Extended Reality (XR), Artificial Intelligence (AI), and animated simulations.

Research Design

A quasi-experimental, pretest-posttest non-equivalent group design was adopted to evaluate the impact of STF on students' learning outcomes.[33] This design enabled comparison of performance metrics between an experimental group (exposed to STF) and a control group (receiving conventional instruction).[34] Quantitative data were collected via pre- and post-test assessments, System Usability Scale (SUS) surveys, and digital interaction logs. Qualitative data were gathered through structured classroom observations to assess behavioral engagement and user perceptions, with open-ended interviews providing supplementary insights into learner experiences.

System Architecture and Conceptual Workflow

The STF framework is built upon a centralized Learning Management System (LMS) that integrates four key modules:

- XR-based immersive modules: Delivered using head-mounted displays (HMDs) and mobile AR devices, these modules simulate vocational tasks such as electrical circuit installation, safety procedure execution, transformer wiring, and digital multimeter usage in various diagnostic scenarios.
- AI-driven personalized tutoring: Implemented using rule-based and machine learning algorithms that adjust instructional sequences, task difficulty, and real-time scaffolding based on individual performance in topics such as voltage calculations, circuit troubleshooting, and safety compliance.
- Animated simulations: Procedural animations illustrate key electrical processes—such as AC/DC current flow, motor control circuits, and relay operations—to support conceptual clarity and reduce cognitive load in understanding abstract or invisible electrical phenomena.
- Real-time learning analytics dashboard: This component captures behavioral data (e.g., completion rate, time on task, error frequency in simulation labs) and provides actionable insights for instructors and learners to support adaptive interventions and mastery learning.

The system architecture follows a cyclical workflow consisting of:

- Input: Learner interactions with XR, AI, and simulation modules are captured through the LMS.
- Processing: AI algorithms analyze performance data and adjust the instructional path (e.g., scaffolding complexity, content feedback).
- Output: Dashboards visualize performance trends and recommend interventions (e.g., review modules, collaborative tasks).
- Feedback loop: Instructors use dashboard insights to make real-time pedagogical adjustments.

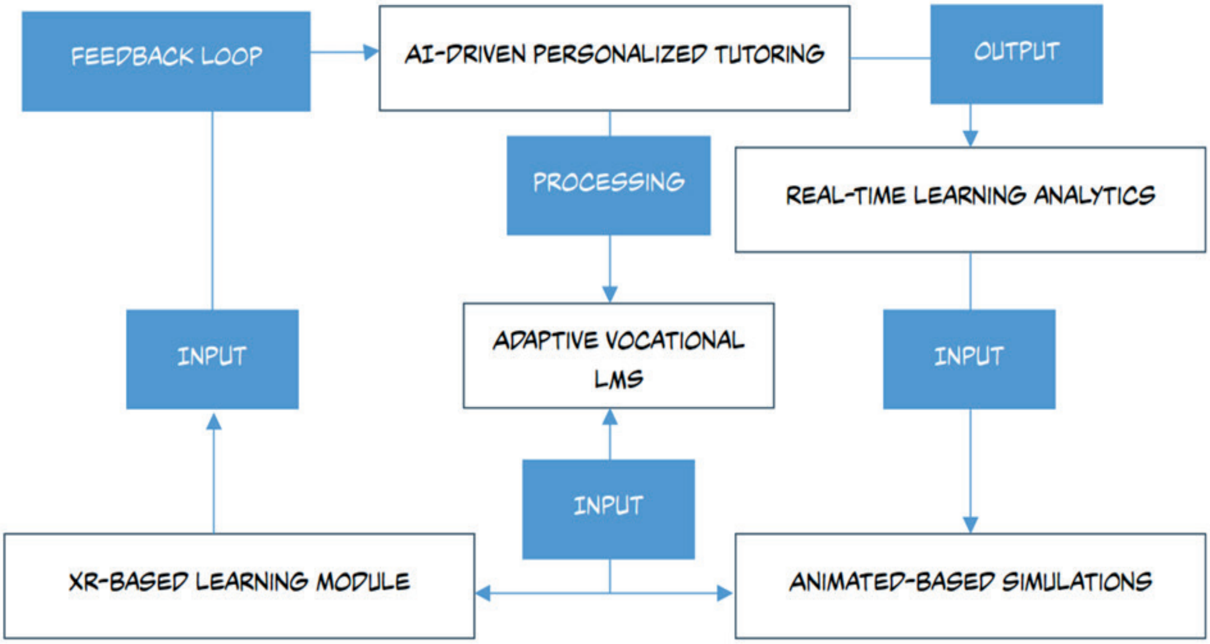

Figure 2. Conceptual Workflow of the Smart Teaching Factory (STF)

Figure 2 depicts the operational flow of the STF model, highlighting the seamless interaction between its technological components. The integration ensures a data-driven, adaptive, and student-centered learning environment, where real-time feedback informs continuous instructional improvements. The workflow supports both automated system responses and human-in-the-loop decision-making.

Participants

The study employed a quasi-experimental, pretest-posttest control group design involving two matched groups of 31 vocational high school students each, enrolled in the electronics engineering program, selected through purposive sampling to ensure comparable demographic characteristics and baseline academic achievement.[36]

- Control Group (n = 31): Students received instruction through conventional classroom methods, including teacher-led lectures, textbooks, and printed handouts.
- Experimental Group (n = 31): Students participated in the Smart Teaching Factory (STF) learning environment, which integrated Extended Reality (XR), Artificial Intelligence (AI)-driven learning support, and animated simulations into the instructional process.

Table 1. Participant Demographics

Group	N	Gender (M/F)	Average Age	Prior XR Experience
Control	31	18 / 13	16,9	Low
Experimental	31	17 / 14	17,0	Moderate

Participants had similar academic standing based on prior semester grades and no prior exposure to AI-based tutoring or formalized XR learning environments. Participation was voluntary, with parental consent obtained for minors. Six vocational instructors (three per group) with at least five years of teaching experience participated, delivering lessons, facilitating classes, and providing feedback. Instructors underwent brief training on the STF implementation protocol to ensure consistency.

Instruments

Three instruments were employed to comprehensively capture cognitive outcomes, system usability, and behavioral engagement:

1. Pre-Test and Post-Test Assessments

To evaluate students' mastery of electrical engineering competencies before and after the intervention, pre-test and post-test assessments were administered to both groups. Each assessment consisted of 30 multiple-choice items aligned with nationally mandated vocational standards. The questions assessed key technical domains such as circuit analysis, schematic interpretation, equipment troubleshooting, and safety compliance. The items were reviewed and validated by a panel of subject-matter experts to ensure content clarity, relevance, and cognitive appropriateness. Tests were administered under standardized conditions, and individual scores were used to quantify learning gains resulting from participation in either the conventional or STF-based instructional approach.[35]

2. System Usability Scale (SUS)

The usability of the Smart Teaching Factory platform was evaluated using a standardized 10-item Likert-scale questionnaire designed to capture student perceptions of system effectiveness and ease of use. The SUS measured key usability dimensions, including system learnability, operational efficiency, interface intuitiveness, and overall user satisfaction. Each item was rated on a 5-point scale, ranging from 1 (strongly disagree) to 5 (strongly agree). A total SUS score was computed for each respondent by applying the established scoring protocol, yielding an aggregate usability index. This instrument was administered exclusively to the experimental group upon completion of the STF learning sessions to assess their experience with the digital learning environment.[36]

3. Observation Rubric

To capture behavioral engagement during the learning process, structured classroom observations were conducted using a predefined rubric. Observers documented key indicators such as student collaboration, active participation, and sustained engagement throughout the sessions. Observational data were collected in real time during both traditional and STF-based instructional activities. The rubric included qualitative descriptors for each behavioral category, enabling consistent interpretation across sessions. Observers recorded both frequency and quality of student actions, providing rich contextual insights into how learners interacted with peers, instructors, and learning technologies. These data served to triangulate quantitative findings and offer a holistic understanding of learner engagement under each instructional condition.[37,38]

Table 2. Instrumentation Overview

Instrument	Purpose	Format	No. of Items
Pre/Post Test Assesments	Measure content mastery	Multiple Choice	30
System Usability Scale	Evaluate platform usability	SUS (Likert Scale)	10
Observation Rubric	Monitor behavioral engagement	Open-ended rubric	6

Data Processing Flow

All digital learning interactions, including metrics such as time-on-task, frequency of quiz attempts, and XR engagement logs, were automatically recorded through the integrated Learning Management System (LMS). These data were analyzed using descriptive statistics and inferential techniques, specifically paired-sample t-tests, to assess changes in student performance and usability perceptions across conditions.[39,40]

The data collection was carried out in four sequential phases. During the Pre-Intervention phase (Week 1), participants completed a baseline knowledge assessment (pre-test), and the experimental group received an orientation session on how to navigate and utilize the STF platform. The Intervention Phase (Weeks 2 to 4) involved two distinct instructional treatments: the control group engaged in conventional, lecture-based instruction supplemented by worksheets, while the experimental group completed modules within the STF system, including immersive XR simulations, AI-assisted guidance, and collaborative learning scenarios enhanced by animated visualizations.

Concurrently, during the Observation Phase, trained evaluators conducted structured classroom observations using standardized rubrics to document student behaviors such as peer collaboration, system navigation, and participation. Observational data were collected weekly to capture trends in learner engagement throughout the instructional period.

In the post-intervention phase (Week 5), all participants completed a post-test to measure learning gains. In addition, students in the experimental group responded to the System Usability Scale (SUS), and full interaction logs were extracted from the STF analytics dashboard for further analysis. Qualitative observation data were thematically coded, and the full data processing sequence—from raw learner activity to actionable instructional insights—is visualized in figure 3.

Figure 3. Learning Data Processing Flow

Figure 3 illustrates the end-to-end data cycle within the Smart Teaching Factory (STF) system—starting from student interactions with XR, AI, and animated modules; progressing through backend data acquisition and processing; then analyzed via embedded learning analytics tools; and finally interpreted through dashboards and usability metrics to inform instructional design and system refinement.

Data Analysis

This study employed a combination of quantitative and qualitative analytical techniques to ensure a comprehensive understanding of the effectiveness of the Smart Teaching Factory (STF) framework.

The quantitative analysis involved two key statistical procedures. First, paired-sample t-tests were used to compare pre-test and post-test scores within each group, allowing for the measurement of individual learning gains over time.[40] Second, independent-sample t-tests were applied to assess the statistical significance of performance differences between the experimental and control groups.[39] Additionally, data from the System Usability Scale (SUS) were analyzed to calculate mean usability scores and standard deviations. The usability outcomes were further interpreted based on established benchmarks, where a mean score equal to or above 68 indicates acceptable system usability.

The qualitative analysis was conducted through thematic coding of structured classroom observation notes. Using qualitative analysis software (NVivo 12),[41] emergent themes related to learner engagement, collaboration, system interaction, and motivational behavior were identified. Coding followed an inductive process, ensuring that patterns were grounded in actual student behavior during the intervention. To enhance the credibility and depth of the findings, triangulation was employed by cross-referencing qualitative insights with quantitative test results and usability outcomes. This mixed-method approach provided both statistical validity and contextual depth, enabling a robust interpretation of the STF's pedagogical impact.

RESULTS

This section presents the findings from both quantitative and qualitative data sources to evaluate the Smart Teaching Factory (STF) implementation. The results are organized into four subsections: learning effectiveness, system usability, student behavioral observation, and interaction tracking. Each subsection integrates relevant visuals to support clarity and interpretation.

Quantitative Results

Learning Effectiveness

The effectiveness of the Smart Teaching Factory (STF) implementation was evaluated using standardized pre- and post-test assessments consisting of 30 multiple-choice items, aligned with national vocational curriculum competencies. Both groups—control and experimental—completed the same test at the beginning and end of the intervention period. Table 3 presents the comparative results.

Table 3. Comparison of Pre- and Post-Test Scores Between Groups

Group	Pre-test Mean ± SD	Post-test Mean ± SD	Gain Score
Control	63,2 ± 7,5	70,1 ± 6,9	6,9
Experimental	62,9 ± 7,2	83,4 ± 6,1	20,5

The experimental group, which engaged with STF modules integrating XR, AI, and animated simulations, demonstrated a significantly higher gain score compared to the control group receiving traditional instruction. These results suggest that the STF model fosters substantially improved learning outcomes in vocational education settings.

System Usability Evaluation (SUS)

Usability of the STF platform was assessed through a standardized 10-item usability scale administered to the experimental group (N = 31) following the intervention. The items measured user perceptions regarding system learnability, efficiency, intuitiveness, and overall satisfaction. Each item was rated on a 5-point Likert scale, and a composite score was calculated to represent overall usability.

Table 4. SUS Score Summary

Item	Mean Score (1-5)
"I think that I would like to use this system frequently"	4,2
"I found the system unnecessarily complex" (reversed)	1,8
... (8 other items summarized)	-
Total SUS Score	82,5 / 100

The composite score of 82,5 reflects a high level of perceived usability, indicating that the STF system is not only functionally sound but also well-received by learners. This score places the platform in the "excellent" usability category based on widely accepted benchmarks. Students reported ease of navigation, confidence in use, and appreciation of the system's intuitiveness—factors that contribute to higher engagement and sustained usage.

Qualitative Results

Behavioral Observation Results

Behavioral engagement was evaluated through structured classroom observations using a 10-item checklist developed to capture key learning behaviors, including sustained focus, peer collaboration, active inquiry, and task engagement. Observations were conducted across three sessions by a team of three trained evaluators using standardized rubrics to ensure consistency and inter-rater reliability.

Table 5. Observation Checklist Summary

Behavioral Indicator	% Observed in Experimental Group	% in Control Group
Sustained Focus	88 %	61 %
Peer Collaboration	85 %	58 %
Question Asking	76 %	42 %
Engagement with Tasks	92 %	65 %

The experimental group exhibited significantly stronger engagement across all observed indicators. These results indicate that learning environments enhanced with immersive technologies promote higher levels of attention, interactivity, and peer communication compared to traditional instruction. Observers also noted that students in the STF group showed greater self-initiation and reduced dependence on direct teacher instruction.

Interaction Tracking

Interaction data were captured automatically by the STF platform, which records user activity at a granular level. Logs included metrics such as session duration, time-on-task per activity, sequence of content accessed, and accuracy of responses in simulations and quizzes. These data were used to assess engagement and provide real-time feedback for instructors and learners. The findings indicate that learners actively explored and interacted with STF content in a non-linear, personalized manner, with high engagement in animated simulation zones and AI-based feedback prompts, consistent with adaptive learning models.

Table 6. Summary of Interaction Metrics for Experimental Group

Metric	Average Value	Description
Session Duration	42,5 min	Average time per session spent on the STF platform.
Time-on-Task (Simulations)	8,7 min	Average time spent on animated simulation activities.
Time-on-Task (Quizzes)	4,3 min	Average time spent on quiz activities.

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Response Accuracy (Simulations)	87 %	Average accuracy in simulation tasks.
Response Accuracy (Quizzes)	82 %	Average accuracy in quiz responses.
Content Sequence Variability	78 %	Percentage of learners following non-linear paths.

DISCUSSION

This study investigated the design, implementation, and outcomes of the Smart Teaching Factory (STF) model as a digitally integrated solution for vocational education. By embedding Extended Reality (XR), Artificial Intelligence (AI), animated simulations, and real-time learning analytics into a centralized platform, the STF model offers a transformative learning environment aligned with Industry 4.0 demands.

Quantitative results indicate that the STF model significantly improves learning performance. The experimental group outperformed the control group in knowledge gains, as evidenced by pre- and post-test score differentials. These results affirm the pedagogical value of XR for experiential learning, AI for real-time adaptation, and animation for visualizing complex technical concepts—when used not in isolation, but in a synergistic ecosystem. This supports the initial research assumption that STF enables transformative, student-centered learning experiences beyond traditional lecture-based methods.[42]

Usability analysis yielded a SUS score exceeding 80, placing STF in the "excellent" category of digital learning systems. High scores on learnability, efficiency, and satisfaction indicate that the platform was well-received by students. This reinforces the necessity of designing educational technologies with user experience at the core, especially in vocational settings where tool familiarity and ease of use are essential for adoption.[43,44]

Qualitative findings from behavioral observations and interaction tracking reveal a marked increase in student engagement, collaboration, and focus within the STF environment. Interaction logs demonstrate active exploration across learning modules, with learners spending significant time on animated simulations and responding accurately to AI-driven feedback prompts, supporting the interpretation that immersive technologies foster deeper cognitive and emotional involvement. This is particularly valuable in vocational education, where learning is often practice-based and spatially contextual.

Crucially, the STF model was adapted to the Indonesian vocational school context, ensuring alignment with national curriculum standards and student readiness levels. This contextualization strengthens the model's relevance and applicability in under-resourced or transitioning educational environments. It addresses the critique often leveled at global EdTech solutions: a lack of cultural and curricular fit.

Despite the positive outcomes, several implementation barriers were identified. These include technological complexity, onboarding difficulties for educators, and infrastructure variability among schools.[45,46,51] Such challenges are common in EdTech rollouts in developing regions and underscore the importance of sustained teacher training, phased implementation, and institutional readiness. Additionally, the study's duration (four weeks) and sample size (N = 62) limit the generalizability of the findings. Longer-term studies across diverse institutions are required to validate broader impacts on learning retention, employability, and industry readiness.

The STF framework contributes substantively to both vocational pedagogy and digital education policy. It bridges theory and practice by aligning experiential learning with real-time analytics, thereby operationalizing concepts from constructivism, connectivism, and heutagogy in a digitally mediated environment.[47,48,49,50]

From a practical standpoint, STF equips students with context-relevant, industry-aligned competencies through immersive, personalized, and feedback-rich instruction. For institutions and policymakers, STF presents a scalable model that integrates high-impact technologies within existing vocational curricula, offering a blueprint for smart education systems in developing nations.

To further enhance the Smart Teaching Factory (STF) model, future research should focus on several key directions. First, longitudinal studies are essential to assess the long-term impact of STF on students' workplace readiness, skill retention, and career progression beyond the classroom. Second, there is significant potential for cross-disciplinary expansion, where the STF framework can be adapted and applied to other vocational fields such as healthcare, agriculture, hospitality, and creative industries, thereby broadening its relevance and scalability. Third, refining the AI-driven personalization features of the platform can deepen the individualization of learning experiences, allowing the system to adapt more precisely to students' unique progress and behavioral data. Fourth, cloud-based deployment should be prioritized to enable remote access in rural and underserved regions, particularly where infrastructure and bandwidth are limited. Lastly, integrating STF with digital credentialing systems—such as micro-credentials or blockchain-based certifications—can help validate learning outcomes and support lifelong learning pathways aligned with industry standards. These directions collectively aim to strengthen the STF model's adaptability, sustainability, and impact across diverse educational contexts.

In summary, the Smart Teaching Factory stands as a scalable, replicable, and pedagogically robust solution for advancing vocational education. It invites further innovation and cross-sector collaboration to ensure that digital transformation in education is inclusive, context-aware, and future-ready.

CONCLUSION

This study designed, implemented, and rigorously evaluated the Smart Teaching Factory (STF), an integrative instructional framework that leverages Extended Reality (XR), Artificial Intelligence (AI), and animated simulations to modernize vocational education. Situated in an Indonesian vocational high school context, the STF model was examined through a mixed-methods quasi-experimental approach to assess its impact on student learning, engagement, and usability.

The findings affirm that the STF model significantly enhances vocational learning outcomes. Quantitative analyses demonstrated substantial improvements in knowledge acquisition, as indicated by the higher post-test scores in the experimental group compared to the control group. Complementary qualitative data, including structured behavioral observations and real-time interaction tracking via platform logs, further revealed elevated levels of student focus, collaboration, and engagement within STF-based environments. Specifically, interaction data showed active exploration of animated simulation zones and AI-based feedback prompts, consistent with adaptive learning models. Additionally, the high System Usability Scale (SUS) score underscores the platform's functionality, user-friendliness, and acceptance among learners.

The STF model contributes to educational practice by addressing persistent gaps in traditional vocational training—namely, the disconnect between theoretical instruction and practical application. It offers a cohesive, technology-enriched learning environment that aligns with Industry 4.0 demands and supports the development of job-ready skills. The model also provides a replicable and scalable blueprint for integrating immersive technologies in resource-constrained settings, supported by real-time analytics and adaptive feedback mechanisms.

By synthesizing multiple technologies into a unified pedagogical model, STF advances the discourse in vocational education innovation. It invites further empirical exploration, particularly in longitudinal studies and across broader vocational domains. The model also holds potential for integration with credentialing systems, AI-based personalization, and remote learning deployments. Ultimately, this study positions the STF as both a research-based framework and a practical, future-facing solution for transforming vocational education in the digital era.

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