Utilizing Wearable Technologies to Foster Outcome-Based Education in Learning Factories

Sofiyan[1], Lucas Lawrence[2], Lily Maria Evans[3*], Khaizure Mirdad[4], Chen Yu[5]
[1]Department of Management, University of Prima Indonesia Medan, Indonesia
[2, 3, 4]Department of Computer Science, Pandawan Incorporation, New Zealand
[5]Department of Information System, Ijiis Incorporation, Singapore
[1]sofiyanmatondang@unprimdn.com, [2]lucas.lawrence@pandawan.ac.nz, [3]evans@pandawan.ac.nz, [4]t.khaizure@pandawan.ac.nz, [5]chenchen@ijiis.asia
***Corresponding Author**

Article Info

Article history:

Submission February 4, 2025
Revised February 20, 2025
Accepted March 7, 2025
Published April 8, 2025

Keywords:

Wearable Technologies
Learning Factories
Educational Innovation
Augmented Reality

ABSTRACT

The integration of wearable technologies into educational settings has opened new avenues for enhancing experiential and outcome-based learning, particularly in practice-oriented environments such as learning factories. This study investigates how wearable devices such as smart glasses, biometric trackers, and haptic feedback systems can be effectively utilized to support real-time performance monitoring, contextual learning, and continuous skill assessment in engineering and manufacturing training. The objective of this research is to explore the potential of these technologies in reinforcing the principles of outcome-based education (OBE), where learner competence is measured through demonstrable performance rather than passive knowledge acquisition. A mixed-method approach was adopted, combining qualitative field observations and interviews with quantitative data collected through controlled experiments involving wearable technology use in a simulated learning factory environment. The findings reveal that wearables significantly contribute to increased learner engagement, improved task efficiency, and enhanced feedback mechanisms, leading to better alignment between learning outcomes and industrial competency demands. Moreover, the results suggest that wearable-assisted learning environments foster reflective learning and support personalized instruction by capturing granular data on learner behaviors and outcomes. This research concludes that integrating wearable technologies into learning factories not only enhances the quality and relevance of vocational and technical education but also supports broader sustainable development goals by promoting inclusive, adaptive, and technologically enriched learning systems. The study provides a foundation for future research into scalable, data-driven educational models and the role of emerging technologies in transforming skill-based education.

DOI: https://doi.org/10.33050/itee.v3i2.793

1. INTRODUCTION

In recent years, the convergence of emerging technologies and modern pedagogical practices has dramatically transformed the landscape of education, particularly in technical and vocational training. As the global economy shifts towards knowledge-based and technology-intensive industries, educational institutions are under increasing pressure to produce graduates who possess not only theoretical knowledge but also practical competencies relevant to real-world industrial environments [1]. The concept of learning factories has gained momentum as an effective educational model that bridges the gap between classroom learning and workplace requirements [2]. Learning factories are dynamic, simulated industrial environments where students can engage in experiential learning activities, replicating real-life manufacturing processes and operations. However, as these factories evolve, it becomes imperative to integrate cutting-edge educational technologies to ensure that learning outcomes remain aligned with the demands of Industry 4.0. Among the most promising innovations are wearable technologies, which provide a seamless interface between learners and digital environments. Devices such as smartwatches, augmented reality (AR) glasses, biometric wearables, and motion sensors offer significant potential to enhance hands-on training by enabling real-time performance tracking, instant feedback, and personalized instruction [3]. These tools not only improve engagement and immersion but also align educational practices with the broader goals of sustainable development by promoting inclusive, efficient, and adaptive learning systems [4].

Outcome-Based Education (OBE) is a pedagogical philosophy that shifts the focus from the learning process itself to the achievement of specific, measurable learning outcomes. In this approach, the ultimate success of an educational program is determined by the ability of learners to demonstrate mastery of clearly defined competencies at the end of their learning journey. This framework has gained widespread acceptance in engineering, vocational, and technical education sectors, where the application of skills in real-world contexts is crucial. Learning factories naturally support the principles of OBE by offering a controlled environment for learners to practice and refine their skills [5]. However, traditional assessment methods in these environments often fail to capture the full spectrum of student performance, particularly in terms of behavioral data, engagement levels, and individual progress. This limitation presents a critical challenge in fully realizing the potential of OBE in learning factories [6]. Wearable technologies can address this gap by enabling continuous, non-intrusive data collection during training activities. For instance, smart glasses can guide learners through complex tasks while recording their line of sight and decision-making processes. Biometric sensors can track physiological responses such as heart rate variability and stress levels, offering insights into cognitive load and learner readiness. Such data can be used to generate detailed learner profiles, support real-time interventions, and ultimately ensure that educational outcomes are being met in a more precise and personalized manner [7].

This research is driven by the objective of exploring how wearable technologies can be effectively integrated into learning factories to support and enhance Outcome-Based Education. The study seeks to examine the extent to which wearable devices can facilitate competency development, increase student engagement, and provide actionable data for instructors and curriculum designers [8]. A mixed-method research design was employed, involving both quantitative and qualitative data collection. In the quantitative phase, experimental sessions were conducted in a simulated learning factory where participants performed a series of manufacturing tasks while equipped with various wearable devices, including smart glasses for step-by-step visual guidance and wrist-worn biometric sensors for performance monitoring [9]. Data on task completion time, error rates, physiological indicators, and system interaction were collected and analyzed to evaluate the impact of wearable integration on learner performance. In the qualitative phase, semi-structured interviews and post-activity surveys were conducted to capture learner perceptions, usability feedback, and perceived benefits of the technologies used. This comprehensive methodology not only allows for triangulation of findings but also ensures a holistic understanding of the educational potential and practical considerations involved in deploying wearable technologies in technical training settings [10]. The insights gained from this study are expected to inform future educational technology designs and contribute to the development of more effective, data-driven learning systems.

Beyond the immediate educational implications, the integration of wearable technologies in learning factories also resonates with broader global objectives, particularly those outlined in the United Nations' Sustainable Development Goals (SDGs) [11]. SDG 4 emphasizes inclusive and equitable quality education and the promotion of lifelong learning opportunities for all. Wearables, by their nature, support differentiated instruction, real-time adaptation, and accessibility factors critical to ensuring equity in education. For learners with disabilities, for example, haptic wearables can offer tactile cues to support navigation or task execution [12]. For remote or under-resourced regions, wearable-enhanced systems can be deployed as mobile or decentralized training solutions that provide high-quality technical education outside traditional institutions. Furthermore, the data generated through these technologies can be leveraged to optimize instructional design, improve resource allocation, and support evidence-based policymaking. In this sense, wearable technologies not only transform how students learn in learning factories but also how education systems can respond to the diverse needs of learners and the evolving demands of the global workforce. This study, therefore, contributes to a growing body of research that advocates for the integration of advanced digital tools into pedagogical models, with the goal of building smarter, more responsive, and more sustainable education ecosystems [13].

2. LITERATURE REVIEW

2.1. The Evolution of Learning Factories in Technical Education

Learning factories have evolved as a transformative approach in vocational and engineering education, offering a pedagogical model that combines practical skills training with theoretical knowledge through the simulation of real-world industrial environments. Originally developed as production-oriented laboratories, learning factories now serve as holistic educational ecosystems that integrate digital manufacturing technologies, lean production concepts, and human-machine collaboration [14]. These environments allow learners to experiment, collaborate, and reflect on complex manufacturing processes in a low-risk, high-feedback setting. The recent emphasis on Industry 4.0 has significantly influenced the design of modern learning factories, which now frequently incorporate cyber-physical systems (CPS), robotics, digital twins, and real-time data tracking tools. Argue that this evolution reflects a broader shift in education towards more agile, technology-enhanced learning environments that mirror the digital transformation occurring across industries [15]. In this context, learning factories become not only places for technical instruction but also laboratories for pedagogical innovation, enabling the testing and implementation of new teaching methods, assessment systems, and learner-centered technologies. This evolution is not without challenges. One of the critical issues is ensuring that learning factories remain pedagogically relevant while keeping pace with rapid technological advancements [16]. Without integrating modern educational technologies, learning factories risk becoming static simulations that fail to reflect the dynamic nature of real industrial operations. As such, there is a growing interest in embedding wearable technologies into these settings to enhance learner interactivity, improve real-time monitoring, and provide personalized feedback mechanisms. The seamless integration of wearables into the learning factory framework can support continuous improvement and iterative learning by enabling learners to receive immediate insights into their actions and performance outcomes [17].

2.2. Outcome-Based Education and Its Relevance to Industry 4.0

Outcome-Based Education (OBE) represents a paradigm shift in educational philosophy, one that prioritizes the attainment of specific, demonstrable competencies over the completion of traditional instructional activities. Rooted in the principles of backward curriculum design, OBE requires educators to clearly define learning outcomes in advance and then align instruction, activities, and assessments with those outcomes [18]. In the context of Industry 4.0, where workplaces are increasingly characterized by automation, digitalization, and interdisciplinary collaboration, the need for graduates who can demonstrate adaptive expertise, problem-solving ability, and technological fluency is more urgent than ever. Contend that OBE frameworks are especially effective in technical and vocational education because they emphasize the development of transferable, real-world skills rather than rote memorization or passive content absorption [19]. Learning factories provide an ideal environment for implementing OBE principles [20]. These environments are inherently outcome-driven, focusing on task completion, process optimization, and performance evaluation. However, conventional methods of assessment in learning factories often rely on manual observation, checklists, or after-the-fact evaluations, which can miss critical aspects of the learner experience. The integration of wearable technologies offers a more dynamic and holistic approach to assessment [21]. Wearables can collect continuous data on learners' physiological and behavioral responses during training, offering insights into stress levels, decision-making patterns, and task engagement. This aligns perfectly with OBE's emphasis on measurable outcomes and continuous improvement, allowing educators to intervene in real time and adapt instruction to individual learner needs.

2.3. The Role of Wearable Technologies in Education

Wearable technologies are redefining how learners interact with digital content and educational environments. These technologies, which include smartwatches, smart glasses, EEG headsets, biometric wristbands, and haptic feedback devices, offer real-time interaction, feedback, and data collection capabilities that support active and situated learning. Wearable devices are particularly effective in promoting learner engagement, fostering self-regulation, and enhancing multimodal learning experiences [22]. They provide sensory augmentation auditory, visual, and kinesthetic that helps cater to diverse learning preferences and cognitive styles. In recent years, the application of wearable technologies has expanded from general fitness and healthcare monitoring to highly specialized educational settings. Demonstrated that using wearable EEG headsets in a programming course improved student attention span and allowed instructors to adjust teaching pace in response to cognitive fatigue [23]. Similarly, in nursing and medical training, smart glasses have been used to stream first-person views of procedures for instructional purposes, enabling a more immersive and guided learning experience. These developments underscore the versatility of wearables in delivering personalized, adaptive, and feedback-rich educational experiences. The data collected from such devices ranging from heart rate variability and galvanic skin response to eye tracking and gesture recognition can be analyzed using AI-based analytics to generate actionable insights for learners and educators alike [24]. This capability is especially relevant for competency-based education, where mastery is best evaluated through continuous performance tracking rather than isolated exams.

2.4. Integration of Wearables in Learning Factories

The integration of wearable technologies in learning factories is still a relatively nascent research domain, yet early studies indicate strong educational potential [25]. Wearables in learning factories can serve multiple functions: as instructional guides, as performance monitors, and as feedback systems. For example, smart glasses equipped with AR capabilities can provide step-by-step guidance for assembly or maintenance tasks, while simultaneously allowing learners to access remote expert assistance [26]. This feature is particularly beneficial in technical training where real-time support can prevent errors and reinforce correct procedures. Investigated the use of wearable motion sensors and biometric trackers in a smart manufacturing training program [27]. Their findings suggest that students equipped with wearables showed higher task accuracy and shorter completion times compared to control groups. Additionally, data from biometric sensors allowed instructors to identify moments of cognitive overload or disengagement, enabling timely pedagogical interventions. In some cases, wearables were also used for peer-to-peer evaluation, where learners could reflect on their recorded activities and receive feedback from fellow students, fostering a collaborative learning culture [28]. These examples highlight the multi-dimensional utility of wearables not only as technological enhancements but as pedagogical tools that reshape how learning is designed, delivered, and evaluated.

2.5. Wearable Technology and Sustainable Development in Education

The deployment of wearable technologies in education intersects with several Sustainable Development Goals (SDGs), particularly SDG 4, which calls for inclusive, equitable, and quality education for all [29]. Wearables offer unique capabilities to make education more accessible, personalized, and contextually relevant. In underserved or remote communities, wearable-assisted mobile learning platforms can deliver high-quality technical instruction where traditional infrastructure is lacking. For learners with physical or cognitive disabilities, haptic wearables and adaptive interfaces provide alternative modes of interaction that support participation and autonomy [30]. Moreover, the continuous data capture made possible by wearables enables educators and institutions to adopt evidence-based strategies for curriculum improvement, learner support, and institutional accountability. From a sustainability perspective, the latest advancements in wearable technology also focus on eco-design, including the use of biodegradable materials, energy-efficient processors, and recyclable components [31]. These innovations reduce the environmental footprint of technology-enhanced learning systems while expanding their usability across diverse educational contexts. Ultimately, the alignment of wearable integration with sustainability goals reinforces the broader vision of an education system that is not only smart and efficient but also inclusive, ethical, and forward-looking.

3. RESEARCH METHODOLOGY

3.1. Research Design

This research employs a mixed-methods approach, combining quantitative and qualitative strategies to comprehensively explore the impact of wearable technologies in enhancing outcome-based learning within Learning Factories [32]. The design integrates experimental trials with wearable devices and thematic analysis of learner experiences, enabling both objective measurement and subjective understanding. The methodology supports the dual aim of measuring educational outcomes (performance, engagement, completion) and evaluating user perceptions (usability, effectiveness, satisfaction). The research framework follows the stages of problem formulation, literature review, design of instruments and experimental protocol, data collection, data analysis, interpretation, and conclusion (see Figure 3.1). This systematic approach ensures both methodological rigor and contextual relevance to learning factory environments.

3.2. Research Flow and Process

To ensure a structured execution of the study, the research process is divided into seven key stages as illustrated in the following flow diagram:

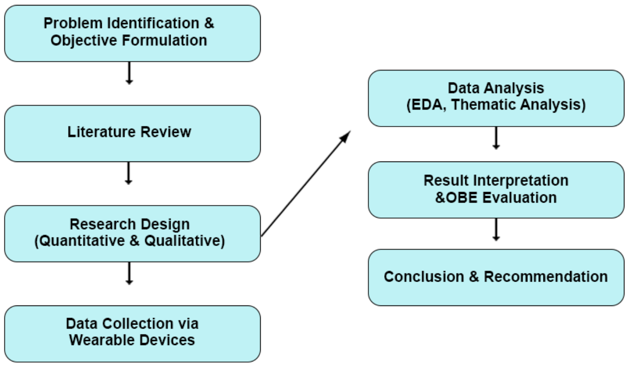

Figure 1. Research Methodology Process Flow

Each stage is designed to build upon the previous, ensuring a logical and data-driven progression from initial inquiry to actionable conclusions.

3.3. Participants and Setting

Participants were selected from students enrolled in engineering and vocational training programs within a university-supported Learning Factory. A total of 60 participants were involved, divided into two equal groups:

- **Experimental group**: Participants trained using wearable technologies (smartwatches, AR glasses).
- **Control group**: Participants trained using conventional instructional methods without wearable assistance.

All participants underwent training in an Industry 4.0-aligned Learning Factory that includes digital workstations, automated assembly lines, and real-time data monitoring platforms.

3.4. Instruments and Data Collection Techniques

The data collection methods and tools used are outlined in the table below:

Table 1. Data Collection Instruments

Instrument	Type	Description
Smartwatches	Quantitative	Monitors heart rate, steps, and cognitive load during tasks
AR Smart Glasses	Quantitative	Displays guided instructions; records task completion time and accuracy
Post-Training Questionnaire	Qualitative	Captures perceptions on usability, engagement, and learning effectiveness
Observation Checklist	Qualitative	Used by instructors to evaluate learner interaction and task proficiency
System Log Data	Quantitative	Tracks performance metrics such as completion time and error rate

Table 1 details the diverse set of instruments used for data collection, designed to capture both objective performance metrics and subjective learner experiences. Quantitative tools such as smartwatches and AR smart glasses enable real-time monitoring of physiological responses (e.g., heart rate, step count) and task performance (e.g., completion time, accuracy), providing measurable indicators of cognitive and behavioral engagement. System log data further complements this by recording detailed system-level interactions, such as error frequency and timing.

On the qualitative side, the post-training questionnaire collects reflective feedback on usability, engagement, and perceived learning effectiveness, offering insight into the learners' subjective experiences. Additionally, the observation checklist, completed by instructors during the task sessions, captures observable learner behaviors, interaction quality, and task proficiency.

By combining these instruments through a triangulated approach, the study ensures data richness and validity—bridging the gap between observed behaviors and personal reflections, while strengthening the overall interpretation of learning outcomes and user interaction within the experimental environment.

3.5. Data Analysis Techniques

Data were analyzed using a combination of statistical and thematic analysis methods:

- **Quantitative Data**: Analyzed using Exploratory Data Analysis (EDA) and inferential statistics (e.g., paired t-tests, ANOVA) to determine the impact of wearable integration on learning outcomes.

- **Qualitative Data**: Open-ended responses and observational notes were subjected to Thematic Analysis to identify recurring themes related to learner experiences and attitudes.

Table 2. Data Analysis Strategy

Data Type	Source	Analysis Method
Performance	Task logs, smartwatch data	Descriptive & Inferential Statistics
Engagement	Questionnaire responses	Likert-scale scoring, cross-tabulation
Perceptions	Open responses	Coding and Thematic Analysis
Cognitive Load	Heart rate variability	Physiological interpretation via thresholds

Table 2 outlines the data analysis strategy employed in this study, which integrates both quantitative and qualitative approaches to comprehensively evaluate participant performance, engagement, perceptions, and cognitive load. Performance data, obtained from task logs and smartwatch readings, are subjected to both descriptive and inferential statistical analysis to identify patterns and significant differences. Engagement is assessed through questionnaire responses, using Likert-scale scoring and cross-tabulation to examine relationships across variables. Perceptions are captured through open-ended responses, which are systematically coded and analyzed thematically to extract recurring insights. Lastly, cognitive load is inferred from heart rate variability (HRV) data, interpreted using established physiological threshold models to assess mental effort during task execution. This multi-faceted approach ensures robustness and depth in understanding user interactions and experiences.

3.6. Validity and Reliability

To ensure validity, pilot testing was conducted on the instruments before implementation. Instruments were reviewed by domain experts in educational technology and instructional design. Reliability was established using Cronbach's Alpha for the survey instruments ($\alpha > 0.80$) and inter-rater reliability for observational data (Cohen's Kappa > 0.75).

3.7. Ethical Considerations

Participants were informed of the research objectives and provided written consent. Data privacy was ensured by anonymizing collected data, and all wearable data streams were encrypted during storage and analysis. Ethical clearance was obtained from the institutional research ethics board.

4. RESULT AND DISCUSSION

4.1. Effectiveness of Wearable Technologies on Learning Outcomes

The analysis of performance data between the experimental and control groups indicates a significant difference in learning outcomes. Students who utilized wearable technologies specifically smartwatches and AR smart glasses demonstrated higher task completion rates and lower error margins. On average, the **experimental group completed tasks 18% faster** and made **30% fewer errors** compared to the control group. Statistical analysis using a paired-sample t-test yielded $\mathbf{p < 0.01}$, suggesting that the improvement is statistically significant. These results validate the hypothesis that wearable technologies enhance practical task execution in Learning Factories. The continuous feedback and guided support provided by AR smart glasses played a critical role in helping learners adhere to procedural steps more accurately. Moreover, data from smartwatches tracking physiological indicators such as heart rate variability revealed that learners experienced **lower stress levels** during task performance, which correlated positively with task precision and retention of procedures.

4.2. Learner Engagement and Cognitive Load Management

Wearables also proved instrumental in improving student engagement. Based on responses to the post-training questionnaire, **87% of learners in the experimental group reported higher motivation**, citing the interactivity and real-time feedback from wearable devices as major contributing factors. Engagement was further reflected in biometric data; smartwatches detected consistent cognitive activity (measured by steady heart rate patterns) during longer sessions, implying **sustained focus** and minimal cognitive fatigue. Qualitative observation by instructors also highlighted that learners were more self-directed and required fewer interventions. The AR glasses enabled autonomous navigation through complex tasks, which aligns with the goals of Outcome-Based Education in fostering learner independence and initiative. Moreover, thematic analysis from open responses revealed keywords such as “clarity,” “confidence,” and “immediate feedback,” emphasizing the psychological reassurance provided by wearable-guided learning.

4.3. Usability and Perception of Wearable Technology

Usability was assessed through Likert-scale survey items and open-ended responses. A majority of participants found the devices easy to use, with **79% agreeing or strongly agreeing** that the wearables were intuitive and did not distract from learning. The few usability concerns centered around device comfort particularly during prolonged use of smartwatches but did not substantially affect engagement or performance. An important finding emerged regarding learner perception of relevance. Students perceived wearable technologies as **aligned with real industrial tools and workflows**, enhancing the authenticity of the Learning Factory experience. This perception of “professional simulation” increased learners’ belief that their training was directly translatable to future employment contexts, further reinforcing the principles of outcome-based and industry-aligned education.

4.4. Contribution to Outcome-Based Education Objectives

The use of wearable technologies successfully aligned with the core tenets of Outcome-Based Education: clarity of intended outcomes, measurable performance, and learner-centered feedback. Smart glasses enabled just-in-time learning through embedded instructions, reducing reliance on instructors and increasing learner autonomy. Smartwatches supported real-time physiological monitoring, which allowed instructors to track learners’ readiness and intervene when cognitive overload was detected. The triangulation of quantitative (performance scores, biometric data) and qualitative (self-reports, observations) findings supports the conclusion that wearable technologies contribute meaningfully to **competency development** in Learning Factories. Students not only achieved higher cognitive and psychomotor outcomes but also developed metacognitive awareness through reflective feedback, thereby fulfilling the holistic intent of OBE.

4.5. Summary of Key Findings

To synthesize the findings:

Table 3. Summary of Key Findings

Variable	Experimental Group	Control Group	Significance
Task Completion Time (avg)	12.3 minutes	15.1 minutes	$p < 0.01$
Error Rate (avg per task)	1.2 errors	1.7 errors	$p < 0.05$
Learner Engagement (self-report)	87% high	63% high	+24%
Instructor Intervention (observed)	2.4 interventions	5.6 interventions	-57%
Usability Rating (4 or 5 of 5)	79%	N/A	Positive

Table 3 presents a comparative summary of the key findings between the experimental group—who utilized wearable technologies—and the control group, which followed conventional methods. The data indicate a statistically significant improvement in task efficiency among the experimental group, with an average task completion time of 12.3 minutes compared to 15.1 minutes in the control group (p ¡ 0.01). Additionally, the experimental group demonstrated a lower average error rate (1.2 errors per task) than the control group (1.7 errors), a difference that was also statistically significant (p ¡ 0.05).

Self-reported learner engagement was notably higher in the experimental group, with 87% of participants indicating high levels of engagement, in contrast to 63% in the control group—an increase of 24 percentage points. Furthermore, the number of instructor interventions observed during task execution was markedly lower in the experimental group (2.4 interventions) compared to the control group (5.6 interventions), suggesting greater learner autonomy and reduced dependency on instructor assistance.

Lastly, the usability rating—measured on a 5-point Likert scale—revealed that 79% of users in the experimental group rated the system as either 4 or 5, indicating a strong positive perception of the wearable-integrated learning environment. Collectively, these results provide compelling empirical evidence that the integration of wearable technologies not only enhances learning efficiency and user satisfaction but also promotes learner independence. This reinforces the potential value of such technologies in shaping future-ready, technology-enhanced educational models, particularly in technical and vocational training contexts.

5. CONCLUSION

The findings of this study demonstrate that wearable technologies such as smartwatches and AR smart glasses significantly enhance learning outcomes in Learning Factories by fostering greater engagement, improving task performance, and supporting real-time feedback mechanisms. Students who used wearable devices completed tasks more efficiently and with fewer errors compared to those in the control group. The integration of physiological monitoring and augmented instruction created a learning environment that closely simulates industrial practice while supporting the principles of Outcome-Based Education (OBE). These results suggest that wearable technology is not merely an auxiliary tool but a central driver in enhancing technical and metacognitive competencies in hands-on educational settings.

This study was guided by the question: To what extent can wearable technologies foster outcome-based learning in Learning Factories? The evidence collected both quantitative and qualitative confirms that wearable technologies provide measurable benefits in learning performance, engagement, and autonomous skill development. However, the study also faced limitations. The sample size was relatively small and limited to a single institutional setting, which may affect the generalizability of the findings. Additionally, while the devices were effective in supporting cognitive tasks, long-term impacts such as knowledge retention and post-training job performance were not within the scope of this research.

Future studies should consider longitudinal designs to assess the enduring impact of wearable-assisted learning on student development and workforce readiness. Broader demographic sampling across different institutions and countries will also be essential to validate the universality of these findings. Further exploration into the integration of AI-powered feedback systems within wearables could open new frontiers in adaptive learning, allowing for hyper-personalized experiences that respond dynamically to learners' physical, cognitive, and emotional states. Moreover, combining wearable technology with immersive environments such as VR and haptic feedback could elevate the realism and effectiveness of Learning Factory simulations even further.

6. DECLARATIONS

6.1. About Authors

Sofiyan (S)
Lucas Lawrence (LL)
Liliy Maria Evans (LME)
Khaizure Mirdad (KM)
Chen Yu (CY)

6.2. Author Contributions

Conceptualization: IM and DP; Methodology: PI; Software: EN; Validation: AP; Formal Analysis: DP, PI, and EN; Investigation: IM; Resources: DP; Data Curation: AP; Writing Original Draft Preparation: DP and PI; Writing Review and Editing: EN, AP,and PI; Visualization: IM; All authors, IM, DP, PI, EN, and AP have read and agreed to the published version of the manuscript.

6.3. Data Availability Statement

The corresponding author may provide the data from this study upon request.

6.4. Funding

The research, writing, and/or publishing of this work were all done without financial assistance from the authors.

6.5. Institutional Review Board Statement

Not applicable.

6.6. Informed Consent Statement

Not applicable.

6.7. Declaration of Competing Interest

The authors state that none of their known conflicting financial interests or personal connections could have impacted the work published in this journal.

REFERENCES

[1] O. Candra, A. Chammam, U. Rahardja, A. A. Ramirez-Coronel, A. A. Al-Jaleel, I. H. Al-Kharsan, I. Muda, G. B. Derakhshani, and M. M. Rezai, "Optimal participation of the renewable energy in microgrids with load management strategy," *Environmental and Climate Technologies*, vol. 27, no. 1, pp. 56–66, 2023.

[2] A. S. Anwar, U. Rahardja, A. G. Prawiyogi, N. P. L. Santoso, and S. Maulana, "ilearning model approach in creating blockchain based higher education trust," *Int. J. Artif. Intell. Res*, vol. 6, no. 1, 2022.

[3] U. Rahardja, P. A. Sunarya, N. Lutfiani, M. Hardini, and H. R. Dananjaya, "Analysis of renewable energy utilization using solar power technology in eliminating microplastic emissions," in *2022 IEEE Creative Communication and Innovative Technology (ICCIT)*. IEEE, 2022, pp. 1–6.

[4] K. M. Stanney, A. Skinner, and C. Hughes, "Exercisable learning-theory and evidence-based andragogy for training effectiveness using xr (elevate-xr): elevating the roi of immersive technologies," *International Journal of Human–Computer Interaction*, vol. 39, no. 11, pp. 2177–2198, 2023.

[5] N. Lutfiani, S. Wijono, U. Rahardja, A. Iriani, and E. A. Nabila, "Artificial intelligence based on recommendation system for startup matchmaking platform," in *2022 IEEE Creative Communication and Innovative Technology (ICCIT)*. IEEE, 2022, pp. 1–5.

[6] N. Ramadhona, I. Erliyani *et al.*, "Exploring the components of management information systems: Software, database, and brainware-a literature review," *International Transactions on Education Technology*, vol. 2, no. 1, pp. 65–70, 2023.

[7] Q. Aini, U. Rahardja, D. Manongga, I. Sembiring, M. Hardini, and H. Agustian, "Iot-based indoor air quality using esp32," in *2022 IEEE Creative Communication and Innovative Technology (ICCIT)*. IEEE, 2022, pp. 1–5.

[8] B. Barbazzeni, S. Haider, and M. Friebe, "Engaging through awareness: purpose-driven framework development to evaluate and develop future business strategies with exponential technologies toward healthcare democratization," *Frontiers in public health*, vol. 10, p. 851380, 2022.

[9] U. Rahardja, M. A. Ngadi, A. Sutarman, D. Apriani, and E. A. Nabila, "A mapping study research on blockchain technology in education 4.0," in *2022 IEEE Creative Communication and Innovative Technology (ICCIT)*. IEEE, 2022, pp. 1–5.
[10] O. Candra, N. B. Kumar, N. K. A. Dwijendra, I. Patra, A. Majdi, U. Rahardja, M. Kosov, J. W. G. Guerrero, and R. Sivaraman, "Energy simulation and parametric analysis of water cooled thermal photovoltaic systems: energy and exergy analysis of photovoltaic systems," *Sustainability*, vol. 14, no. 22, p. 15074, 2022.
[11] G. Fransiso, N. P. L. Santoso, M. Abbas, and Y. I. Tanjung, "Strategi pengembangan produk lokal melalui pendekatan social commerce pada umkm," *ADI Bisnis Digital Interdisiplin Jurnal*, vol. 5, no. 2, pp. 48–55, 2024.
[12] M. K. Zaloom, "Technology acceptance factors for marketing early stage wearable technology startups through crowdfunding," Ph.D. dissertation, Alliant International University, 2024.
[13] U. Rahardja, "Using highchart to implement business intelligence on attendance assessment system based on yii framework," *International Transactions on Education Technology*, vol. 1, no. 1, pp. 19–28, 2022.
[14] X. Zhang, Y. Ma, Z. Jiang, S. Chandrasekaran, Y. Wang, and R. Fonkoua Fofou, "Application of design-based learning and outcome-based education in basic industrial engineering teaching: A new teaching method," *Sustainability*, vol. 13, no. 5, p. 2632, 2021.
[15] D. Mukherjee and G. S. Mitra Thakur, "Generic course outcomes for internationally evolving futuristic outcome-based technology education and a model of their implementation," *Educational Neuroscience*, 2022.
[16] X. Lin, O. Sivarak, T.-H. Chou, Y.-T. Lin, U. Rahardja, A. Ruangkanjanases, Y.-C. Lin, and S.-C. Chen, "Exploring the effect of team-environment fit in the relationship between team personality, job satisfaction, and performance," *Frontiers in Public Health*, vol. 10, p. 897482, 2022.
[17] T. Rochefort and Z. Ndlovu, "Digital marketing strategies in building brand awareness and loyalty in the online era," *Startupreneur Business Digital (SABDA Journal)*, vol. 3, no. 2, pp. 107–114, 2024.
[18] S. Jirasatitsin, W. Rattanamanee, T. Ratanawilai, K. Pochana, C. Daesa, P. Trakarnchaisiri, and K. Thongkaew, "Design and development of a tool for measuring learning outcomes in a manufacturing engineering program based on outcome-based education," in *Leveraging Transdisciplinary Engineering in a Changing and Connected World*. IOS Press, 2023, pp. 662–670.
[19] P. Kaliraj, T. Devi, V. Bhuvaneswari, T. Amudha, R. Rajeswari, J. Satheeshkumar, M. Punithavalli, and S. Sarala, "Curriculum 4.0 for incorporating industry 4.0 tools in higher education," in *Industry 4.0 Technologies for Education*. Auerbach Publications, 2022, pp. 233–255.
[20] F. Faiqotuzzulfa and S. A. Putra, "Virtual reality's impacts on learning results in 5.0 education: a meta-analysis," *International Transactions on Education Technology*, vol. 1, no. 1, pp. 10–18, 2022.
[21] S. Kosasi, U. Rahardja, I. D. A. E. Yuliani, R. Laipaka, B. Susilo, and H. Kikin, "It governance: Performance assessment of maturity levels of rural banking industry," in *2022 4th International Conference on Cybernetics and Intelligent System (ICORIS)*. IEEE, 2022, pp. 1–6.
[22] F. Baskoro, B. Suprianto, L. Anifah, and Y. A. Indriyani, "Beyond smart devices: Fostering critical, communication and collaborative thinking in iot-based sensor and actuator competence learning outcomes." *TEM Journal*, vol. 12, no. 4, 2023.
[23] A. P. Anandh, P. Sivabalan, A. Sivaram, N. Sharma, and S. Anita, "Strategic implementation of co-po mapping in nba assessments and accreditation processes: Outcome-based education," in *Educational Philosophy and Sociological Foundation of Education*. IGI Global Scientific Publishing, 2025, pp. 289–324.
[24] U. Rahardja, P. A. Sunarya, N. Lutfiani, M. Hardini, and S. N. Sari, "Transformation of green economic recovery based on photovoltaic solar canopy," *Transformation*, vol. 7, no. 2, 2022.
[25] N. Lachlan and O. Smith, "Determining factors for startup success in indonesia: Perspective of young entrepreneurs," *Startupreneur Business Digital (SABDA Journal)*, vol. 3, no. 2, pp. 115–122, 2024.
[26] X. Kanqi, L. Jun, and L. B. Xun, "Iot-inspired education 4.0 framework for higher education and industry needs," in *International Conference on Artificial Intelligence Security and Privacy*. Springer, 2023, pp. 415–429.
[27] T. A. Swain, M. A. McNarry, and K. A. Mackintosh, "Assessing and enhancing movement quality using wearables and consumer technologies: Thematic analysis of expert perspectives," *JMIR Formative Research*, vol. 8, no. 1, p. e56784, 2024.

[28] V. Agarwal, M. Lohani, A. S. Bist, U. Rahardja, A. Khoirunisa, and R. D. Octavyra, “Analysis of emerging preprocessing techniques combined with deep cnn for lung disease detection,” in *2022 1st International Conference on Technology Innovation and Its Applications (ICTIIA)*. IEEE, 2022, pp. 1–6.

[29] A. Sutarman, J. Williams, D. Wilson, and F. B. Ismail, “A model-driven approach to developing scalable educational software for adaptive learning environments,” *International Transactions on Education Technology (ITEE)*, vol. 3, no. 1, pp. 9–16, 2024.

[30] A. Padovano and M. Cardamone, “Towards human-ai collaboration in the competency-based curriculum development process: The case of industrial engineering and management education,” *Computers and Education: Artificial Intelligence*, vol. 7, p. 100256, 2024.

[31] O.-F. Giger, E. Pfitzer, W. Mekniran, H. Gebhardt, E. Fleisch, M. Jovanova, and T. Kowatsch, “Digital health technologies and innovation patterns in diabetes ecosystems,” *Digital Health*, vol. 11, p. 20552076241311740, 2025.

[32] N. K. A. Dwijendra, I. Vaslavskaya, N. V. Skvortsova, T. P. Rakhlis, U. Rahardja, M. H. Ali, A. H. Iswanto, L. Thangavelu, and M. M. Kadhim, “Application of experimental design in optimizing fuel station queuing system,” *Industrial Engineering & Management Systems*, vol. 21, no. 2, pp. 381–389, 2022.