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Development of Teaching Factory Model-Based Artificial Intelligence: Improving the Quality of Learning Vocational Schools in Indonesia

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ABSTRACT

This study aims to develop an AI-based teaching factory model in Vocational High Schools (SMKs) to improve vocational education quality and align student competencies with Industry 4.0 requirements. Integrating AI is anticipated to enhance students' technical and non-technical skills, including problem-solving, creativity, and technology adaptation. The research utilized a mixed-methods approach, combining quantitative and qualitative techniques. Data were collected through surveys, interviews, and observations from teachers and students in SMKs implementing AI-based teaching factories. Analysis was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM) and in-depth teacher interviews to evaluate readiness and integration challenges. Findings reveal that AI applications in teaching factories significantly enhance students' technological proficiency, learning efficiency, and industry-readiness. Teachers reported improved teaching effectiveness, although they faced obstacles in areas like teacher training and technological infrastructure. The study highlights the potential of AI in elevating vocational education but identifies barriers requiring attention, such as the need for continuous teacher development and robust infrastructure. Recommendations include targeted training programs, increased investment in technology, and curriculum revisions to integrate AI comprehensively. Implementing AI in SMKs presents a promising strategy to address the evolving demands of Industry 4.0, enhancing educational outcomes for students and teaching effectiveness for educators.

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1. INTRODUCTION

Vocational education in Indonesia, particularly at the Vocational High School (SMK) level, aims to equip students with the skills necessary to meet workforce demands and address industry needs.

However, a persistent challenge lies in the gap between the competencies taught in schools and the rapidly evolving requirements of modern industries. Many SMKs rely heavily on theory-based teaching methods, with limited emphasis on practical, contextualized learning experiences. Consequently, graduates often struggle to meet the demands of the workforce, especially in industries that require advanced technical skills and adaptability to emerging technologies (Wahjusaputri & Nastiti, 2022).

Meanwhile, the Teaching Factory model has been introduced as a solution to bridge the gap between education and industry. The Teaching Factory concept integrates a real work environment into schools, so that students can experience the production or service process directly, from design to product completion (Haddad & Hornuf, 2019). This model not only provides practical experience for students but also strengthens their work skills. However, although the Teaching Factory concept is effective in providing practical experience, its application in many vocational schools is still limited to traditional sectors, such as manufacturing or services that have minimal integration of the latest technology (Wahjusaputri & Bunyamin, 2021).

Rapid technological advances, especially artificial intelligence (AI), have fundamentally changed the way industries work. Many jobs that used to be done by humans can now be automated through AI-based systems, which are able to perform certain tasks faster, more efficiently, and with high precision. The Industrial Revolution 4.0 requires graduates who are not only able to use traditional tools and machines, but also understand, operate, and collaborate with advanced technologies such as AI. The biggest challenge here is ensuring that vocational school graduates have the relevant technical and cognitive skills to operate in a world dominated by smart technology. Artificial Intelligence not only replaces routine manual work, but also opens up new job opportunities that require in-depth technical understanding and critical thinking skills. Therefore, vocational high school graduates must have more complex skills, including the ability to analyze data, basic programming, and solve technology-based problems (Teng, Ma, Pahlevansharif, & Turner, 2019). However, many vocational high schools have not been able to provide adequate training to meet these demands. There are still significant gaps in terms of curriculum, teaching methods, and the readiness of teaching staff to integrate AI technology into the learning process. This study aims to address the gap between the skills possessed by vocational high school graduates and the needs of modern industry through the development of an artificial intelligence (AI)-based teaching factory model. The integration of AI into the teaching factory model enables a more realistic and relevant work environment simulation with today's industrial world. With AI, students can be involved in more complex production processes, such as data analysis, production automation, and data-based decision-making that approaches the reality of the future world of work (Kearns, 2012).

Some of the strategies proposed to address this gap include: 1) Technology-Based Curriculum Development: This study will develop a curriculum that focuses on the integration of AI in the vocational learning process, including how AI can be used to support various technical and non-technical tasks that are relevant to industry needs (Glass, Miersch, & Metternich, 2018); 2) Teacher and Student Competency Improvement: By providing intensive training for teachers and students on AI, this study aims to improve technological literacy and problem-solving skills among vocational high school students. Teachers will be trained to use AI as a tool in teaching industry-relevant skills (Wahjusaputri, Bunyamin, & Bakrun, 2021); 3) Technology Infrastructure and Supporting Facilities: This study will also seek to address the infrastructure gap by proposing improvements to technology facilities in vocational high schools, including computers, AI software, and AI-based production simulation devices (Shiohira, 2021). 4) Collaboration between vocational high schools and industry: One focus of this AI-based TEFA model is to build closer collaboration between vocational high schools and industry. By involving industry in the curriculum development and training process, it is hoped that students can gain hands-on experience and skills that are relevant to current industry needs (Teng et al., 2019).

SMK Negeri 1 Pekanbaru, SMKN 1 Pacet in Cianjur, West Java, and SMKN 11 Bandung, West Java, serve as ideal pilot projects for implementing and testing the AI-based teaching factory model. These schools have advanced infrastructure aligned with industry standards, including AI technology integration, an AI-based curriculum already incorporated into teaching factory activities, and competent teachers trained in AI applications (Suklani, 2023). This combination of resources positions these schools as exemplary environments for evaluating the effectiveness of the AI-based teaching factory approach.

To ensure the development of a robust model, the research employs Aiken's Formula and Partial Least Squares Structural Equation Modeling (PLS-SEM). Aiken's Formula is a crucial tool for assessing the validity of research instruments through expert validation, ensuring that data collection tools yield relevant and high-quality information (Brüggemann, Stempin, & Meier, 2020). Meanwhile, PLS-SEM facilitates the analysis of complex relationships among variables, enabling researchers to explore how AI integration in teaching factories influences student and teacher outcomes. This dual-method strategy not only enhances the reliability of the model but also provides a comprehensive understanding of its impact on vocational education.

By combining validated research instruments with sophisticated analytical methods, the study ensures that the findings contribute significantly to the development of AI-based teaching factories, ultimately addressing the evolving needs of Industry 4.0.

To evaluate the effectiveness of the AI-based Teaching Factory model, this research utilizes Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the structural relationships between latent variables. This approach enables a comprehensive examination of how AI integration enhances vocational education by improving student skill development, aligning curricula with industry needs, and ensuring the relevance of vocational training in response to technological advancements (Imbar, Supangkat, Langi, & Arman, 2022; Zouhri & Mallahi, 2024).

The study addresses key questions regarding the influence of the AI-based Teaching Factory model on students' technical and non-technical skill development, the alignment of vocational school curricula with Industry 4.0 demands, and the challenges and opportunities associated with implementing AI-driven teaching models in vocational education. By exploring these questions, the research aims to develop and validate a model that can significantly enhance vocational education quality. It also seeks to assess the impact of AI on student learning outcomes, curriculum relevance, and industry alignment, while offering actionable recommendations for the effective application of AI in educational settings.

This research holds considerable significance for bridging the gap between vocational education and the demands of the modern job market. By integrating AI into the teaching factory model, the study aspires to prepare vocational high school graduates for the challenges of a rapidly evolving, technology-driven employment landscape. Additionally, it emphasizes strengthening collaboration between educational institutions and industries, ensuring that graduates are equipped with the skills, adaptability, and readiness required to excel in increasingly competitive job markets (Wu, 2021; Wahjusaputri, Nastiti & Sukmawati, 2024; Haji & Azmani, 2020; Mohamed, Alnaqbi, & Yassin, 2021).

2. METHODS

This study employs a Research and Development (R&D) methodology. This approach seeks to establish an AI-driven teaching factory model in Vocational High Schools (SMK) via a sequence of methodical phases encompassing needs analysis, prototype creation, testing, assessment, and model enhancement. (Tanti, Purwanto, Habibi, & Basukiyatno, 2022). This study is an example of development research, which combines theory and practice to come up with new goods for vocational learning (Davy Tsz Kit, Luo, Chan, & Chu, 2022). Model Design encompasses essential elements such as technological infrastructure, curriculum, and learning process. This design aims to include artificial intelligence (AI) in the production and learning process, facilitating personalized learning (Magowan & Stewart, 2021).

The research design employs the ADDIE (Analysis, Design, Development, Implementation, Evaluation) development model, which comprises five primary stages: 1) Analysis, specifically the conduct of a needs analysis in vocational schools to ascertain the skills required for industry 4.0 and the readiness of instructors and students to incorporate AI technology into their learning. 2) Design, specifically the development of an AI-based teaching factory model that encompasses the preparation of AI tools, curriculum development, and the creation of an industrial simulation environment. 3) Development, specifically the creation of a prototype of the AI-based Teaching Factory model that will be evaluated on a limited number of vocational school students; 4) Implementation, specifically the implementation of the prototype that was developed at the vocational school that was chosen as the research subject. 5) Evaluation, which involves assessing the model's efficacy in relation to its implementation outcomes and modifying the model in accordance with the feedback received (Martins, Wagg, & Afonso, 2022; Rahma, 2022; Zouhri & Mallahi, 2024). The research was conducted at two vocational schools in West Java Province, namely SMK Negeri-1 Pacet and SMK Negeri 11 Bandung. These schools have implemented artificial intelligence technology to enhance their teaching factory learning. A total of 100 students were selected as respondents.

In this study, sampling was carried out purposively, namely selecting individuals who were considered most appropriate and had direct relevance to the research topic. This strategy was chosen because it aimed to obtain in-depth perspectives and data from participants who had direct experience related to the teaching and learning process in vocational schools. Through a purposive approach, students and teachers involved in the trial will be selected based on specific criteria tailored to the needs of the study. The selection criteria for students and teachers aim to ensure that the selected sample can provide representative data related to the implementation of AI-based teaching factory. The selected students are those in grades 10-12 at vocational schools with relevant study program backgrounds, such as PPLG Software and Game Development (PPLG), Computer and Network Engineering (TJKT), Multimedia, and DKV (Visual Communication Design), Software Engineering (RPL).

The teachers selected were those who taught subjects relevant to technology or who were directly related to teaching factory activities, such as productive teachers or information technology teachers. Teachers who were actively involved in the trial process and were willing to provide in-depth input on the application of AI in the learning process. Thematic analysis was used to identify key themes from the qualitative data obtained during the trial. The thematic analysis process was carried out through several stages to ensure transparency and accuracy of the results. Qualitative data collected through interviews or focus group discussions with students and teachers were fully transcribed. Through this sampling strategy and thematic analysis process, the study aims to gain a comprehensive understanding of the application of AI-based teaching factories in vocational schools, which can be the basis for developing models that are more in line with learning and industry needs (Wahjusaputri et al., 2024). The data were analysed using Aiken's V approach and Partial Least Squares Structural Equation Modelling (PLS-SEM), which is a statistical analytic technique employed to simulate intricate interactions between latent variables (variables that cannot be directly measured) and indicators that quantify these variables (Davy Tsz Kit, Luo, Chan, & Chu, 2022). Partial Least Squares Structural Equation Modelling (PLS-SEM) is commonly employed in research that focuses on structural models, particularly when the data exhibits specific features such as limited sample sizes, non-normal data distribution, or a complex model structure (Shamala, Ahmad, Zolait, & Sedek, 2017; Suyatno et al., 2023).

Validation is conducted to assess the findings of the study by utilizing the output in the form of constructing a teaching factory model that relies on artificial intelligence (AI). The questionnaires are distributed to respondents who are deemed capable of completing the Smart Mobile Application Assessment Model (SMAPA) questionnaire via Google Form. The questions are formulated to represent each characteristic being tested. Subsequently, a readability test is conducted on each question to ensure that it can be easily comprehended by the respondent and does not possess any ambiguous interpretations. The user's text consists of two references, (Moalosi, Molokwane, & Mothibedi, 2012) and (Brynjolfsson, Rock, & Syverson, 2017). Student participation is highly beneficial for evaluating the content of the instrument that includes 25 success factor items. The evaluation is done using a Likert scale and is distributed to 100 students specializing in Software Engineering, Visual Communication Design, TJKT, Hospitality, and Agribusiness Processing of Agricultural Products. The questionnaire employs a Likert scale ranging from 1 to 5, with 1 representing "very inappropriate," 2 representing "not appropriate," 3 representing "less appropriate," 4 representing "appropriate," and 5 representing "very appropriate." To analyse the data collected from the questionnaire, it is necessary to test the results. Convergent validity was enhanced through the application of Partial Least Squares Structural Equation Modelling (PLS-SEM), a statistical analysis method used to model intricate relationships between latent variables (variables that cannot be directly measured) and the indicators that assess these variables. The analysis focused on measuring and reassessing indicators related to teaching, student, and technology factors in order to improve their accuracy. The user's text is "(Mavrikios, Sipsas, Smparounis, & Rentzos, 2017). This is an experimental calculation of the teaching factory model utilizing artificial intelligence, namely the PLS-SEM method. The calculation considers several indicators, including students, technology, learning, and teaching (Reisinger et al., 2019)".

3. FINDINGS AND DISCUSSION

3.1. AI Impact on Skills and Learning Efficiency in SMKs

PLS-SEM can also be utilized to assess the excellence of structural models and measurements using diverse metrics such as Average Variance Extracted (AVE), Composite Reliability (CR), and R-squared (R^2). This contributes to the assurance of the accuracy and dependability of the proposed model. AVE is an indicator that shows how much proportion of the variance of the indicators is explained by the latent construct compared to the variance caused by measurement error. An AVE value greater than 0.50 indicates that the construct has good convergent validity. AVE value > 0.50: The construct explains more than 50% of the variance of its indicators, which means that the convergent validity of the construct is considered adequate. AVE value < 0.50: The construct is not strong enough in explaining its indicators, so the model can be considered to have convergent validity problems

Table 1. Quality Evaluation of the AI-Based Teaching Factory Model

	Cronbach's alpha	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
Learning	0.751	0.746	0.829	0.493
Teaching	0.707	0.774	0.801	0.455
Students	0.765	0.784	0.826	0.329
Technology	0.806	0.813	0.847	0.361

The findings indicate that indicators with low outer loadings (<0.40) or those between 0.40 and 0.70 that are not theoretically significant can be removed to enhance construct validity. The data processing results show that Cronbach's Alpha values exceeding 0.70 indicate good internal reliability, while Composite Reliability (CR) values above 0.70 confirm adequate overall reliability for the construct.

For the Average Variance Extracted (AVE), low values suggest the need for improvement. Researchers should take steps such as evaluating indicators with low factor loadings (<0.70) and removing those deemed theoretically insignificant. Additionally, the reliability of the construct should be reassessed through the CR value, as low AVE might signify that the variance explained by the construct is suboptimal, even if the CR value is adequate. To address this, researchers can consider refining the measurement by reformulating items or introducing more relevant indicators to better capture the construct's variance.

Therefore, the data shows that it has good validity and reliability, so it can be used to predict the effectiveness of teaching factory-based learning with high accuracy at SMK Negeri 1 Pacet Cianjur and SMK Negeri 11 Bandung as follows:

1. Improvement of Students' Technical Skills.
   The implementation of AI-based Teaching Factory showed a significant increase in students' technical skills, especially in mastering the latest technologies relevant to Industry 4.0. Students who use this model are able to understand and operate AI-based tools in realistic industrial simulations. For example, students can utilize AI algorithms to optimize production processes, automatically detect product defects, and perform predictive analysis on production data.
2. Improvement of Non-Technical Skills (Soft Skills). In addition to technical skills, students also show improvements in non-technical skills, such as problem-solving, teamwork, and communication. The AI-based Teaching Factory model places students in industrial simulation situations where they must work together to complete assigned tasks, face technological challenges, and adapt to dynamic workflows. This supports the development of critical and innovative thinking skills, which are key needs in today's workforce.
3. Teacher Acceptance and Readiness.
   From the teacher perspective, the pilot showed that while most teachers responded positively to the integration of AI into the learning process, there is an urgent need for more intensive training. Many teachers admitted that they felt less confident in operating AI technology optimally and in guiding students to use AI-based tools efficiently. Therefore, ongoing training for teachers is one of the pilot's main recommendations.
4. Technology Infrastructure Gap.
   The trial also revealed that not all vocational schools have adequate technology infrastructure to support optimal AI implementation. Some schools experience limitations in the hardware and software needed to run AI-based simulations. This highlights the importance of investing in technology infrastructure as part of efforts to ensure equitable AI adoption across vocational schools
5. Increasing Student Learning Motivation.
   The use of AI technology in Teaching Factory has been proven to increase student learning motivation. They feel that learning is more relevant and interesting because it is based on real situations that they will face in the world of work. Students feel that the skills they learn through this model are more in line with industry needs, which encourages them to be more serious in learning.

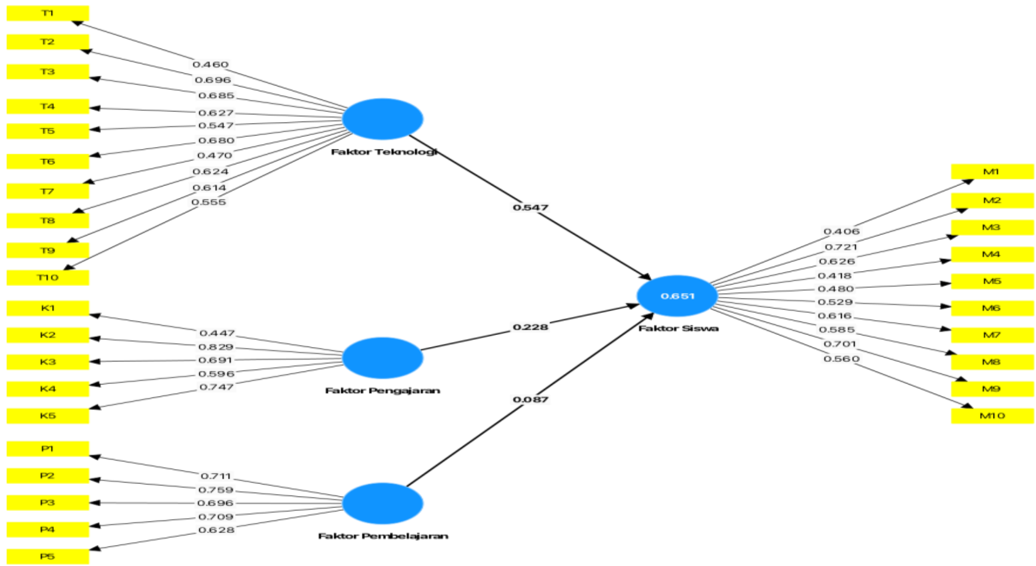

Figure 1. Implementation of the Artificial Intelligence-Based Teaching Factory Model Using PLS-SEM

The teaching factor yielded a score of 0.447, indicating that pupils have not comprehended the instructional content of the artificial intelligence-based teaching factory. The learning factor demonstrates a highly favourable outcome of 0.759, indicating that the utilization of artificial intelligence technology in education has the potential to enhance student motivation to study. Within the realm of student performance, the results remain subpar, specifically measuring at 0.406, 0.418, and 0.480. This can be attributed to the absence of guidance or support from teachers or industry stakeholders, resulting in students encountering challenges when attempting to grasp and implement the concepts and applications of artificial intelligence in educational settings. Conversely, artificial intelligence has the potential to enhance both soft skills and hard skills, as well as boost students' capacities to successfully complete learning activities, resulting in a score of 0.721. In order to foster motivation and student engagement, it is imperative for schools to offer recognition through rewards for projects cantered around artificial intelligence at SMKN-1 Pacet and SMKN-11 Bandung. Within the realm of artificial intelligence technology, its efficiency remains suboptimal with a value of 0.460.

3.2. *Limitations of the AI-Based Teaching Factory Study*

The trial study of teaching factory based on artificial intelligence (AI) in vocational high schools has made a significant contribution to the development of innovative learning models. However, like other studies, this study has several limitations that need to be considered. Here are some of the main limitations:

1) Potential Bias in the Study
   a) Selection Bias: The purposive selection of students and teachers as participants has the potential to create selection bias. Only students who are interested in technology or who are more skilled in a particular area may be more active in the trial, so the results of the study tend to ignore the challenges faced by students with lower skills (Samala, Sokolova, Grassini, & Rawas, 2024).
   b) Response Bias: Teachers and students involved may give answers or responses that tend to be positive because they feel involved in the research, known as social desirability bias. This can affect the objectivity of the data collected. (Rakhmetov, Sadvakassova, Saltanova, & Yessekenova, 2022);

2) Contextual Nature of the Study
   a) Limited Scope: This study was conducted in a specific vocational school with specific environmental conditions, including supporting facilities, teacher readiness, and student interest in AI technology. The results obtained reflect the local context that may not be fully relevant to vocational schools in other regions with different characteristics.
   b) Model Scalability: This study tested the model on a small or limited scale, making it difficult to determine the effectiveness of the model in wider implementation or in schools with a larger number of students and teaches artificial intelligence aids in the enhancement of not only technical skills, but also soft skills like communication, teamwork, and time management. AI can be employed in collaborative platforms to oversee students' participation to team projects, offer feedback on their duties, and enhance their communication skills (Vergaray, Cruz, & Flores, 2023).
3) Challenges in Implementation in Resource-Constrained Areas
   a) Limited Technology Infrastructure: Many vocational education institutions experience limitations in providing adequate AI infrastructure, such as access to sophisticated software and hardware, such as servers for big data processing or fast internet connections.
   b) Teaching Staff Skills: Teachers or trainers often need additional training to be able to teach AI-based skills effectively. For example, a teacher in the tourism sector needs to understand AI-based CRM tools, while an agribusiness teacher must be able to use AI devices to analyze agricultural products.
   c) Practical Learning (Pedagogical) Approach: The use of AI shifts pedagogy towards "learning through practice," where students can conduct simulations and experiments with the support of AI tools, thereby encouraging critical thinking and problem-solving skills.
   d) Collaborative Learning: AI technology encourages teamwork and collaboration between students and teachers, especially in projects that require data analysis and solution design based on data provided by AI tools.
   e) Collaboration with Technology and Industry Companies: In the tourism sector, for example, partnerships with hospitality companies allow educational institutions to use real customer service data to analyze patterns using AI. In the agribusiness sector, partnerships with agritech companies give students access to crop or weather monitoring tools.
   f) AI-Based Internships: In software, industry partnerships allow students to work directly with AI-focused development teams, providing practical experience in AI programming, automation, and machine learning.
   g) Policy Implications: Technology Infrastructure Investment, AI-Based Curriculum Development, Certification Standardization

3.3. *Further Research Development*

To address the limitations and strengthen the findings of this study, future research can explore several key areas. Expanding the scope of trials to include vocational schools across diverse regions, including remote areas or schools with limited technological infrastructure, would provide a more comprehensive understanding of the model's applicability. Comparative studies between urban and rural vocational schools could offer valuable insights into the factors influencing the success of implementation and highlight contextual challenges.

Simplifying the AI-based teaching factory model is another area worth exploring. Developing a version that relies less on expensive hardware would make it more accessible to schools with limited budgets. Additionally, integrating alternative technologies such as open-source software or cloud-based solutions could reduce costs and promote scalability. To ensure effective implementation, future research should also focus on designing teacher training programs and practical implementation guides tailored to their needs. Engaging teachers from diverse backgrounds could help identify specific challenges and refine the training process.

Long-term evaluations of the model are crucial for assessing its sustained impact on students' skill development and workforce readiness. Longitudinal studies could provide deeper insights into the model's effectiveness over time and inform strategies for adapting it to evolving industry requirements. Addressing research bias is equally important. Ensuring inclusive sample selection that represents students with varying abilities and utilizing data triangulation methods would enhance the robustness of the findings. Independent evaluations by external observers could further improve objectivity and validate the results. These strategies would collectively strengthen the AI-based teaching factory model and its potential to transform vocational education.

4. CONCLUSION

To measure the long-term effectiveness of the AI-based teaching factory model, future research can focus on the following areas aimed at understanding the sustainable impact of this educational innovation, namely: 1) Tracking Graduate Employment Outcomes. The AI-based teaching factory model affects the employment opportunities of vocational high school graduates in the industrial world, especially in sectors that utilize AI-based technology. The approach taken is to track the career path of graduates for 3-5 years after they complete their education. In addition, collecting data related to unemployment rates, types of jobs obtained, starting salaries, and the relevance of jobs to skills acquired from the teaching factory model. The Success Indicator is the proportion of graduates working in the technology sector or other sectors that utilize AI-based skills. The level of employer satisfaction with graduates from the teaching factory program; 2) Retention and Skills Development, the aim is to evaluate the extent to which skills taught in the AI-based teaching factory are maintained and developed by students after graduation. The Success Indicator is the Retention Rate of technical skills learned and the Ability of graduates to adapt to new technologies that are developing in the world of work; 3) Social and Economic Impact Analysis, which measures the contribution of this model to improving the standard of living of students and their families, as well as its impact on the local economy; 4) Inter-Regional Comparative Study, Objective: Identify variations in the effectiveness of this model in vocational schools located in various regions, including urban, rural, and resource-limited areas; 5) Integration with Future Technologies, Objective: Assess the ability of the AI-based teaching factory model to adapt to future technologies, such as advanced machine learning, the Internet of Things (IoT), or robotics; 6) Balance Between Technology Education and Soft Skills, Objective: Evaluate whether the AI-based teaching factory model also supports the development of soft skills, such as communication skills, teamwork, and problem solving, which are important in the world of work; 7) Model Development for Schools with Limited Resources, Objective: Refine the AI-based teaching factory model to be more inclusive and applicable to schools with limited infrastructure and funding.

REFERENCES

Brüggemann, H., Stempin, S., & Meier, J. M. (2020). Consideration of digitalization for the purpose of resource efficiency in a learning factory. *Procedia Manufacturing*, *45*(2019), 140–145. https://doi.org/10.1016/j.promfg.2020.04.085

Brynjolfsson, E., Rock, D., & Syverson, C. (2017). Artificial intellegience and the modern productivty paradox. In *Nber Working Paper Series* (Vol. 24001). Retrieved from http://www.nber.org/papers/w24001

Davy Tsz Kit, N. G., Luo, W., Chan, H. M. Y., & Chu, S. K. W. (2022). Using digital story writing as a pedagogy to develop AI literacy among primary students. *Computers and Education: Artificial Intelligence*, *3*, 100054. https://doi.org/10.1016/j.caeai.2022.100054

Glass, R., Miersch, P., & Metternich, J. (2018). Influence of learning factories on students' success - A case study. *Procedia CIRP*, *78*, 155–160. https://doi.org/10.1016/j.procir.2018.08.307

Haddad, C., & Hornuf, L. (2019). The emergence of the global fintech market: economic and technological determinants. *Small Business Economics*, *53*. https://doi.org/10.1007/s11187-018-9991-x

Haji, E. El, & Azmani, A. (2020). Proposal of a digital ecosystem based on big data and artificial intelligence to support educational and vocational guidance. *International Journal of Modern Education and Computer Science*, *12*(4), 1–11. https://doi.org/10.5815/ijmecs.2020.04.01

Imbar, V. R., Supangkat, H. S., Langi, A., & Arman, A. A. (2022). Digital transformation readiness in Indonesian institutions of higher education. *World Transactions on Engineering and Technology Education*, *20*(2), 52–57. https://doi.org/10.1016/j.ifacol.2019.12.445

Kearns, L. R. (2012). Student Assessment in Online Learning: Challenges and Effective Practices. *MERLOT Journal of Online Learning and Teaching*, *8*(3), 198–208. Retrieved from http://jolt.merlot.org/vol8no3/kearns_0912.htm

Magowan, S., & Stewart, M. (2021). A mixed methods study to evaluate physiotherapy student preferences in digital teaching for achieving effective learning of practical skills. *Physiotherapy*, *114*, e73–e74. https://doi.org/10.1016/j.physio.2021.12.010

Martins, K., Wagg, A., & Afonso, E. (2022). Heliyon Gaining supervision skills in pre-registration nursing through peer teaching : An evaluative survey. *Heliyon*, *8*(October), e11398. https://doi.org/10.1016/j.heliyon.2022.e11398

Mavrikios, D., Sipsas, K., Smparounis, K., & Rentzos, L. (2017). A Web-based Application for Classifying Teaching and Learning Factories. *7th Conference on Learning Factories, CLF 2017*, *9*, 222–228. The Author(s). https://doi.org/10.1016/j.promfg.2017.04.002

Miranda, P., Isaias, P., & Costa, C. J. (2014). From Information Systems to e-Learning 3 . 0 Systems ' s Critical Success Factors : A Framework Proposal. *International Conference on Learning and Collaboration Technologies*. https://doi.org/10.1007/978-3-319-07482-5_18

Moalosi, R., Molokwane, S., & Mothibedi, G. (2012). Using a Design-Orientated Project to Attain Graduate Attributes. *Design and Technology Education*, *17*(1), 30–43. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=EJ968209&login.asp&lang=es&site=ehost-live

Mohamed, A., Alnaqbi, A., & Yassin, A. (2021). Evaluation of Success Factors in Adopting Artificial Intelligence in E-Learning Environment. *International Journal of Sustainable Construction Engineering and Technology (IJSCET)*, *12*(3), 362–369.

Rahma, A. (2022). Ecoliteracy assessment using Q-methodology : Indonesian high school students ' views on disaster and ecology. *Issues in Educational Research*, *32*(2), 701–720.

Rakhmetov, M., Sadvakassova, A., Saltanova, G., & Yessekenova, A. (2022). Usage and effectiveness of educational platforms in Kazakhstan during the Covid-19 pandemic. *World Transactions on Engineering and Technology Education*, *20*(3), 226–231.

Reisinger, G., Trautner, T., Hennig, M., Alexandra, G. R., Mazak, T., Hold, P., … Mazak, A. (2019). TU Wien Pilot Factory Industry 4.0. *9th Conference on Learning Factories 2019*, *31*, 200–205. Elsevier B.V. https://doi.org/10.1016/j.promfg.2019.03.032

Samala, A. D., Sokolova, E. V., Grassini, S., & Rawas, S. (2024). ChatGPT: a bibliometric analysis and visualization of emerging educational trends, challenges, and applications. *International Journal of Evaluation and Research in Education (IJERE)*, *13*(4), 2374. https://doi.org/10.11591/ijere.v13i4.28119

Shamala, P., Ahmad, R., Zolait, A., & Sedek, M. (2017). Integrating information quality dimensions into information security risk management (ISRM). *Journal of Information Security and Applications*, *36*, 1–10. https://doi.org/10.1016/j.jisa.2017.07.004

Shiohira, K. (2021). Understanding the Impact of Artificial Intelligence on Skills Development. Education 2030. In *UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training*. Retrieved from https://www.proquest.com/reports/understanding-impact-artificial-intelligence-on/docview/2540428113/se-2?accountid=13637

Suklani, S. (2023). Evaluation model and its urgency on elementary education programs. *Jurnal Obsesi : Jurnal Pendidikan Anak Usia Dini*, *7*(2), 1639–1650. https://doi.org/10.31004/obsesi.v7i2.4201

Suyatno, S., Istiningsih, E., Wantini, W., Hidayati, D., Fajria, A., & Zulaiha, S. (2023). Contribution of academic supervision to vocational students' learning readiness. *International Journal of Evaluation and Research in Education*, *12*(2), 710–719. https://doi.org/10.11591/ijere.v12i2.24422

Tanti, T., Purwanto, B., Habibi, B., & Basukiyatno, B. (2022). Developing Project-Based Learning for Social & Sciences Teaching Modules to Increase Learning Motivation at Smk Center of Excellence. *Proceedings of the 1st International Conference on Law, Social Science, Economics, and Education, MALAPY 2022*. https://doi.org/10.4108/eai.28-5-2022.2320490

Teng, W., Ma, C., Pahlevansharif, S., & Turner, J. J. (2019). Graduate readiness for the employment market of the 4th industrial revolution. *Education + Training*, *61*(5), 590–604. https://doi.org/10.1108/ET-07-2018-0154

Vergaray, J. M., Cruz, C. M. C., & Flores, E. (2023). Teaching competency in virtual education : Systematic review. *International Journal of Evaluation and Research in Education*, *12*(3), 1429–1439. https://doi.org/10.11591/ijere.v12i3.24430

Wahjusaputri, S., & Bunyamin. (2021). Challenge of Teaching Factory Based on School's Potentials in West Java during Covid-19 Pandemic. *Turkish Journal of Computer and Mathematics Education*, *12*(7), 2209–2217.

Wahjusaputri, S., Bunyamin, B., & Bakrun. (2021). Critical Success Factors in Implementing Teaching Factory- Based Competency for Vocational High School Students. *Cakrawala Pendidikan*, *40*(3). https://doi.org/http://doi:10.21831/cp. v40i3.2887

Wahjusaputri, S., & Nastiti, T. I. (2022). Digital literacy competency indicator for Indonesian high vocational education needs. *Journal of Education and Learning (EduLearn)*, *16*(1), 85–91. https://doi.org/10.11591/edulearn.v16i1.20390

Wahjusaputri, S., Nastiti, T. I., & Sukmawati, W. (2024). *Development of artificial intelligence-based teaching factory in vocational high schools in Central Java Province*. *18*(4), 1234–1245. https://doi.org/10.11591/edulearn.v18i4.21422

Wu, X. (2021). Application of Artificial Intelligence in Modern Vocational Education Technology. *Journal of Physics: Conference Series*, *1881*(3). https://doi.org/10.1088/1742-6596/1881/3/032074

Zouhri, A., & Mallahi, M. El. (2024). Improving Teaching Using Artificial Intelligence And Augmented Reality. *Journal OfAutomation, Mobile Robotics and Intelligent Systems*, *18*(2), 57–61. https://doi.org/10.14313/JAMRIS/2