https://research.adra.ac.id /index.php/ijen/
P - ISSN: 2988-1579
E - ISSN: 2988-0092

Constructing Industry-Ready Identities: A Narrative Study of TVET Students in Production Engineering Project-Based Learning Models

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ABSTRACT

Background. The blistering working development of intelligent manufacturing technologies due to the Industry 4.0 level achievements has had a considerable impact on industrial practice, which generates an urgent demand among vocational graduates who can not only be highly qualified in their technical skills but also adapt to the new digital tools. Traditional methods of teaching Production Engineering and NC (Numerical Control) Programming also favor theory rather than practice leading to a disconnect between the theoretical content of classroom study and practical needs in the industry.

Purpose. This research aims on creating and executing a Smart Manufacturing-Oriented Project-Based Learning (PBL) Model that will help to combine the real-world industrial problems with the latest technologies CNC simulation software and digital manufacturing instruments.

Method. This study employs a Research and Developmet (R&D), with 68 students of vocational higher education who were taking Production Engineering and NC Programming courses as sample. Performance assessments, observational analysis, and feedback surveys were used to collect the data.

Results. Findings indicate that the suggested model significantly enhanced the proficiency of students to learn and master NC programming, optimization of production workflow, and solve problems in the technology-saturated settings. There was also an improvement in collaboration, project management, and adaptation of smart manufacturing tools by students. The model ensures a closer alignment between student learning outcomes and industry performance requirement through smart technnology integration. To sum up, the Smart Manufacturing-Oriented PBL Model is an effective approach that helps to bridge the gap between the academic and the industrial community and develop industry-oriented skills and equip graduates with the requirements of digitalized manufacturing industries.

Conclusion. This study provides a flexible and generalizable model of applying smart manufacturing concepts to the technical education in order to make graduates more employable in the dynamic industrial environment.

KEYWORDS

Industry-Oriented Education, NC Programming, Production Engineering, Project-Based Learning, TVET Education

Citation: Indrawan, E., Rahim, B., Jasman, Jasman., Sakti, H. R., Wulansari, E. R,. & Jalil, S. A. (2026). Constructing Industry-Ready Identities: A Narrative Study of TVET Students in Production Engineering Project-Based Learning Models. *International Journal of Educational Narrative*, *4*(3), 1014–1032. https://doi.org/10.70177/ijen.v4i3.3646

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Received: January 18, 2026

Accepted: April 19, 2026

Published: June 28, 2026

INTRODUCTION

The manufacturing sector is experiencing a dramatic shift caused by the high rate of the implementation of Industry 4.0 technologies, including intelligent machines, IoT-based production models, artificial intelligence (AI), and digital twins. Such developments have transformed the skills that the professionals in the field need, not focusing on technical mastery alone but also adapting, solving problems, and working in technologically advanced settings. In vocational higher education, the courses like Production Engineering and NC (Numerical Control) Programming are very instrumental in equipping the students with such problems. Nonetheless, in practice, traditional methods of lectures pay much attention to theoretical knowledge and do not bridge the gap between theoretical training and practical, industry-related skills as required by the modern manufacturing environment. Such a discrepancy causes graduates who might have difficulties coping with real-world production settings that will be based on smart manufacturing systems. To solve this problem, there is a necessity to introduce pedagogical models that would combine practical and project-based learning with exposure to technologies relevant to industry. Project-Based Learning (PBL) is a promising strategy because it actively involves students in the solutions of real problems, organization of real-life projects, and technical knowledge in practice. PBL may be oriented to smart manufacturing, which may allow students to experience the work with digital tools, CNC simulation software, IoT-based monitoring, and other Industry 4.0 applications directly. The study is thus critical towards forming a Smart Manufacturing-Oriented PBL Model that will seal the divide between theory and practice such that those graduating will be able to obtain the competencies, mindset and adaptability needed to succeed in the changing industrial environment.

Project Based Learning (PjBL) is a long recognized pedagogical tool in technical education, and has proven to be a catalyst for improving the technical understanding of introductory CNC courses (Account et al., 2000). The PjBL is a constructivist approach, which works by giving projects as tools that initiate a deep process of knowledge discovery (Magleby & Furse, 2007). This model is not only very effective in motivating students in vocational training but also is vital for developing critical thinking, flexibility and problem solving skills that are essential to the 21st century workplace (Frank et al., 2003; Knight & T., 2017; Lamar et al., 2010). Moreover, the current pedagogical approach has focused on the need to connect the learning experiences in the classroom with real-life challenges in industries so as to ensure that the students can cope a complex professional environment (Jun, 2010).

The need for PjBL is even greater today in the age of Industry 4.0. PjBL is considered as the most appropriate approach to provide the competencies demanded by the current requirements of industry standards (Amamou & Cheniti-Belcadhi, 2018; Syahril et al., 2020). However, traditional PjBL approaches are typically restrictive in that they focus on either teaching abstract concepts or specific technical skills, and do not adequately cover the interdisciplinary digital literacy needed today. Therefore, this study introduces a Smart Manufacturing-Oriented PjBL model to fill the gap. This model extends beyond traditional limits with its advanced capabilities, including CNC simulation, IoT-enabled monitoring, and data-driven production optimization. This integration fosters a high fidelity technological environment, as close as possible to real industrial practices, helping to overcome the gap between the theory and the skills necessary to be ready for the industry.

Conversely, the reasons why it has chosen a Smart Manufacturing-Oriented Project-Based Learning (PBL) Model are based on the necessity to keep pace with the current trends and needs of the manufacturing industry in the times of Industry 4.0. Traditional learning approaches tend to teach abstract concepts and separate technical expertise, which is not enough to train students to work in contemporary production conditions where interdisciplinary understanding and digital literacy, as well as responsiveness to new technologies, are obligatory. Project-Based Learning is a learner centered model that actively involves students in solving real world problems that are authentic and gives them an opportunity to think critically, collaborate and learn independently. Through the inclusion of intelligent features of manufacturing, i.e., CNC simulation, IoT-powered monitoring, and production optimization based on data, into the PBL structure, the students are introduced to the intensive technological setting that is highly similar to the practice in industry. This combination does not only help bridge the gap between theory and practice, but also develops industry-ready competencies and therefore the graduates are prepared to cope with the skills requirements of the complex manufacturing systems. As such, it is the model to be used to develop both technical and soft skills that would enable success in the modern industrial environment.

The overall goal of the proposed study is to create and confirm a Smart Manufacturing-Oriented Project-Based Learning (PBL) Model to be used in Production Engineering and NC Programming classes in vocational higher education. The model will contribute to the development of technical competence, problem-solving skills, teamwork, and flexibility to Industry 4.0 contexts of the students by combining project work with smart manufacturing technologies, such as CNC simulation software, IoT-based monitoring systems, and digital manufacturing tools. The originality of the present work can be explained by its systematic application of Industry 4.0 tools to the PBL framework in order to provide a learning experience that could be similar to the real-life production environment.

RESEARCH METHODOLOGY

Research Approach

The proposed research follows a Research and Development (R&D) design process where a Smart Manufacturing-Oriented Project-Based Learning (PBL) Model of Production Engineering and NC Programming classes in vocational higher education will be designed, developed, and validated (Plomp, 2013).

Research Subjects and Setting

The research was conducted in a vocational higher education institution offering specialized courses in Production Engineering and NC (Numerical Control) Programming. The study involved 68 students enrolled in these courses during the academic semester in which the model was implemented. The participants divided into an experimental group (n=34) and a control group (n=34). Groups were assigned based on existing class section to maintain instructional continuity. Participants were selected using a purposive sampling technique to ensure they possessed basic knowledge of manufacturing processes and CNC operations and with the condition of being limited to the existing institutional class structure, the validation of the homogeneity of the class was carried out by using pre-test assessment on NC programming and pre-test assessment on NC production theory which gives a homogeneous class starting point to minimize the effect of selection bias.

Research Design

This study used a Research and Development (R&D) approach with the Plomp model divided into three systematic phases. The first phase focuses on developing the syntax and learning tools of the Smart Manufacturing-oriented PjBL model. After the model is developed, a validity test (expert judgment) is conducted. This stage is crucial for testing the theoretical and practical feasibility of the model before its implementation in the field. After the model is declared valid by experts, the research continues to the third phase, namely the effectiveness test. In this phase, the model is implemented using a Quasi-Experimental approach with a Non-equivalent Control Group design. This design was chosen because participants were not randomly selected, but rather purposively. The analytical logic is to compare the increase in learning outcomes (gain scores) between the class using the new model (the experimental group) and the control group to determine the effectiveness of the Smart Manufacturing-Oriented PjBL model in improving student competency. The control group used conventional methods, where learning was teacher-centered, using lectures, question-and-answer sessions, and individual assignments from textbooks. Both groups studied the same Learning Outcomes (CP) for the same duration. Both groups underwent the same number of meetings. Both classes were also taught by the same teacher to avoid teaching style bias (teacher effect). Both used the same textbook and basic references, and the post-test to measure final competencies used identical questions for both groups. To establish baseline equivalent between the two groups, a pre-test was administrired. The independent t-test showed no statistically significant difference between the experimentan and control groups prior to the intervention [t(df) = 0.582, p > 0.005), indicationg both groups started with equivalent baseline knowledge.

Table 1. Pretest Analysis

Observations	Groups	N	Paired Sample T-test t	df	P
Pretest-Posttest analysis of Competency Test	Experimental	34	0.581	66	0.238
	Control	34			

Model Development Stages

Development process is based on the Plomp model, which includes the following phases: Preliminary resarch, development or prototyping phase and assessment phase; to guarantee a systematic and iterative improvement of the model. During the initial research phase, the needs assessments, literature-based, and discussions with the manufacturing professionals were used to identify the industry skill requirements and gaps in the curriculum. The second stage of development or the prototyping stage and the third stage of assessment entailed the development of PBL framework incorporating smart manufacturing tools including, and then confirmation of the model by scholarly and industry users. In the assessment period, the model was implemented in a semester long basis with 68 vocational students, with them having to be involved in the group and traditiconal approach projects, which simulated real-life manufacturing challenges. Lastly, measured the effectiveness of the model using competency tests and project performance rubrics. Such guided R&D philosophy makes sure that the learning model derived is pedagogically correct, technologically apt, and in line with the requirements of the contemporary smart manufacturing setting.

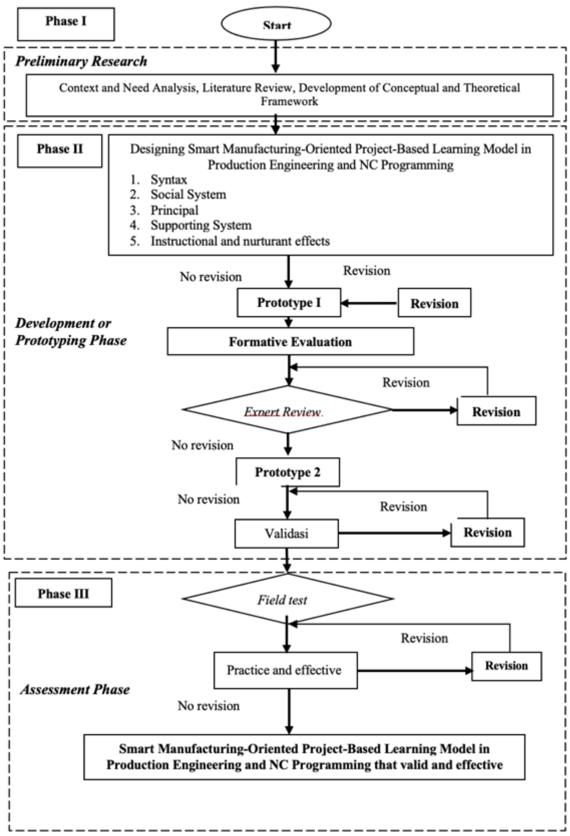

Figure 1. Research Design and Procedures for the Development of Project-Based Learning Models (adapted from Plomp Procedures, 2013)

Research Instruments

Experts who validated were those that had knowledge and competencies pertaining to the development of learning models in the production engineering course and the NC programming course. The validation steps were created with the help of supporting tools with the help of a questionnaire on a Likert-scale. This tool is made of eight aspects of validation which are as follows, 1) Understanding of the theoretical concepts of the course on production engineering and NC programming, 2) Leading and managing students on work groups, 3) Project work drawings design and project proposal preparation, 4) Project assignment presentation, 5) Concept simulation of programs, 6) Project work execution and monitoring of the project work, 7) Project work result asessment 8) evaluation of production engineering and NC programming learning.

Table 2. Pilot Study Analysis of Validation Instruments

Indicators	Answer	ICC	Cronbach's Alpha	Item Total
Understanding the theoretical concepts of the production engineering & NC programming course	Likert Scale by Strongly Agree (5) to Strongly Disagree	0.737	0.873	4
Organizing and guiding students in work groups		0.728	0.734	5
Designing/theming project work drawings and preparing project proposals		0.826	0.862	4
Presenting project assignments		0.783	0.726	4
Conceptualizing and simulating programs for project completion		0.834	0.736	4
Project execution and monitoring project work implementation		0.789	0.873	4
Assessing the results of programming and project work		0.724	0.724	4
Conducting Evaluation of Production Engineering and NC Programming Learning		0.764	0.863	5

Data collection was carried out by giving students an initial test (Pretest) and a final test (Posttest) using competency tests and project performance rubrics.

Table 3. Pilot Study Analysis of Effectiveness Instruments

Instrument	Indicators	Type	ICC	Cronbach's Alpha
Competency tests	Accuracy in creating, editing, and optimizing NC programs.	Test	0.787	0.847
	Ability to operate CNC machines following industry-standard procedures.		0.782	0.784
	Minimization of programming errors and operational downtime		0.830	0.748
	Ability to analyze and solve real-world manufacturing problems.		0.863	0.836
Project performance	Quality and completeness of project documentation and reporting	Rubric	0.747	0.864
	Technical Accuracy and Quality of Output		0.846	0.836
	Integration of Smart Manufacturing Technologies		0.879	0.768
	Problem-Solving and Innovation		0.738	0.783
	Team Collaboration and Project Management		0.783	0.738

Validators (Experts) consisted of 5 experts (material, media, language, model, and TVET) for the ICC test, while respondents (Trial Subjects) consisted of 30 students for the Cronbach's Alpha test. ICC is used to measure the extent to which the validators agree with each other (Inter-rater Reliability). The procedure is that the score data from all validators is input into statistical software (SPSS) and the model used is a Two-way mixed effects model. While Cronbach's Alpha is used to measure the internal reliability of statement items in one instrument. The procedure is calculated based on product trial data to respondents. The threshold criteria > 0.70 is considered reliable.

Data Analysis Technique and Hypothesis Development

In the given study, the data analysis adopted the quantitative methods to fully assess the success of the Smart Manufacturing-Oriented Project-Based Learning (PBL) Model. The data analysis can be seen at Table 4 in detail.

Table 4. Data Analysis Technique and Hypothesis Development

Variable	Hypothesis Development	Data Analysis Technique
Validity	Aiken's V Coeffecient, Kaisar Mayer Olkin (KMO) and Barlett Test	
Effectiveness	There was no statistically significant difference in the mean scores of students' competency skills from the pre-test to the post-test	Paired sample t-tests
	There was no statistically significant difference in the mean scores of students' project performance from the pre-test to the post-test	
	There was no statistically significant difference in the mean scores of posttest students' competency skills between control and experimental group	Independet sample t-test
	There was no statistically significant difference in the mean scores of posttest project performance skills between control and experimental group	
	There was no statistically significant difference in the mean scores of posttest competency skills and project performance skills between control and experimental group	ANOVA

RESULT AND DISCUSSION

Preliminary resarch

Industrial Skill Requirement

The initial research phase was initiated with a comprehensive study of the competencies needed in the industry when generating smart manufacturing. The structured interviews and surveys with professionals of the manufacturing industry, CNC operators, production managers, and vocational education experts were also used to collect data. It was found that the new manufacturing sectors require graduates that are well-trained in NC programming, knowledge of CNC machine operation, and knowledge of implementing Industry 4.0 technologies, including IoT-based monitoring, machine-driven decision making, and digital twins. Concurrently, a curriculum gap analysis was performed in the form of reviewing the syllabuses of any current courses on Production Engineering and NC Programming on the vocational higher education level. The analysis showed that the curriculum did not provide enough exposure to actual world project management, integration of smart manufacturing tools and problem solving in technology-heavy settings, although the basic machining theory and basic programming were well covered. Moreover, the existing method of teaching was mostly lecture-based with few chances to provide the students with the opportunity to work on industry simulated practical projects. These gaps indicated that a Smart Manufacturing-Oriented Project-Based Learning Model is required that is not only focused on technical competencies but also improves collaboration, flexibility, and innovativeness to make graduates well-equipped to meet the needs of the manufacturing industry, which is constantly changing.

Table 5. Comparison of Industry Skill Requirements and Current Curriculum

Industry Skill Requirements	Current Curriculum Coverage	Identified Gaps
Advanced NC programming skills including optimization and error troubleshooting	Basic NC programming with limited exposure to optimization techniques	Lack of in-depth training on program optimization, error prevention, and advanced machining strategies
Proficiency in operating CNC machines with industry-standard procedures	CNC machine operation covered at a basic skill level	Limited hands-on practice with complex machining operations and multi-axis CNC
Integration of smart manufacturing tools (CNC simulation, IoT-enabled monitoring, digital twin)	Dedicated modules (limited*) on Industry 4.0 technologies in manufacturing	Absence of practical training on IoT systems, digital manufacturing software, and simulation-based error detection
Real-world project management in manufacturing workflows	Project tasks given but not aligned with industry scenarios	Lack of structured project-based learning that mirrors industry timelines, quality control, and teamwork requirements
Problem-solving and innovation in technology-rich environments	Theoretical problem-solving exercises in classroom	Direct application of problem-solving in real manufacturing challenges with digital integration
Collaboration and communication in cross-functional teams	Group assignments exist but focus mainly on academic tasks	Insufficient emphasis on teamwork, role distribution, and industry-style reporting and documentation

*Modules exist in the curriculum structure but lack practical implementation and advanced technical depth

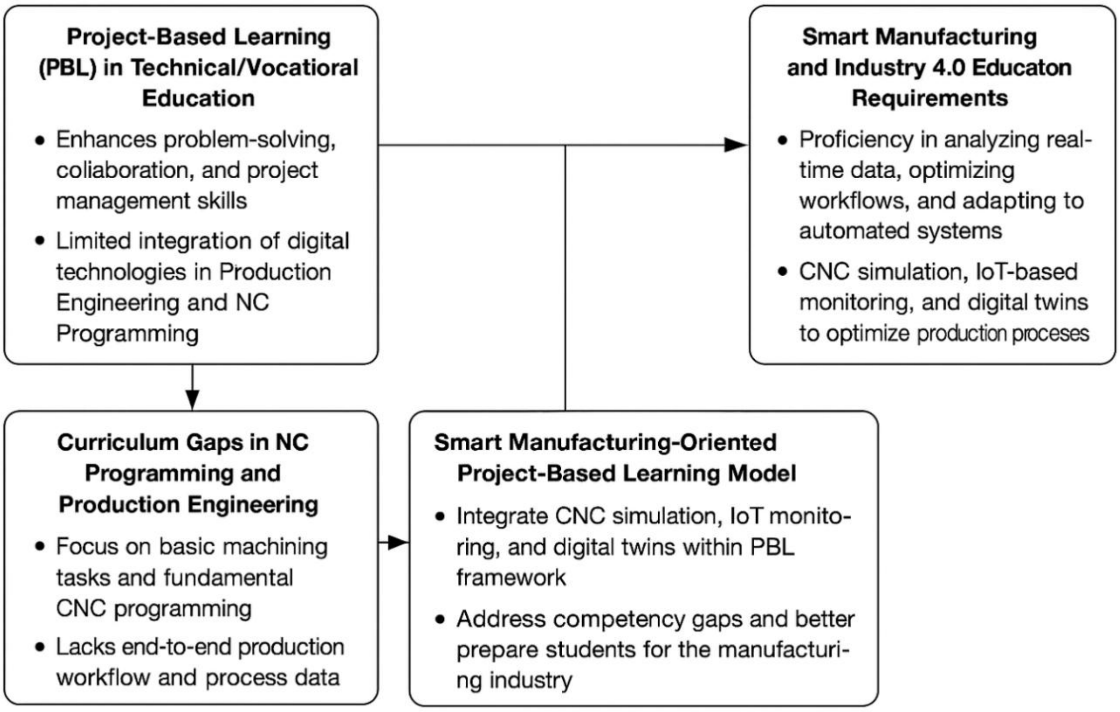

Figure 2. Literature Review Synthesis

The Project Based Learning (PBL) model has been used as an important model in technical and vocational education and training (TVET) for a long time. PBL generates opportunities for students to experience situations that are real in the workplace, allowing students to effectively link theoretical engineering knowledge with the needs of the workplace, especially when it comes to developing the soft skills of collaborative problem solving, teamwork, and project management (Adli & Ambiyar, 2023; Birdman et al., 2022; Martínez et al., 2011). In the context of CNC programming and production engineering, the traditional PBL approach has been effective in improving machining accuracy, programme optimization and students' learning engagement (Dewi & Sutisna, 2019). The literature search, however, shows that there are critical technological limitations: the traditional use of PBL is still in isolated workshops and in basic machining tasks (Gonzalez-Rubio et al., 2016). For example, Chen et al. (2019) showed the efficiency of PBL in CNC programming; however, it was applied in the traditional workshop without the support of modern digital infrastructure. Likewise, the positive effects of project-based manufacturing classes on teamwork were confirmed by Lei et al. (2012) but their pedagogical approach focused on competencies that are not aligned with Industry 4.0 competencies, such as real-time monitoring, and data-driven decision-making. Besides, simulation-based learning in CNC programming has been proven as an alternative to improve error-detection skills, but they are not always presented in a structured, collaborative PBL model similar to actual industrial processes (Alves et al., 2011). Thus there is a significant need to develop pedagogical support in the way it relates to the complex, modern workflow of automated production.

The current manufacturing industry has undergone a paradigm shift to the Industry 4.0, which is built on the foundation of the Internet of Things (IoT) connected monitoring, advanced CNC simulation and visualisation of digital twins (Ahluwalia & Aggrawal, 2010). In today's production engineering, a person's ability to work in such cyber-physical environments demands technical expertise in NC programming, along with real-time data analysis, process integration and collaborative troubleshooting in cloud environment (Hosseinzadeh & Hesamzadeh, 2012). Yet, despite these evident industrial changes, CVET curricula in the HE context continue to be seriously out of step with the demands of today's industry (Fernandes, 2014; Lima et al., 2017). To date, the emphasis of most production engineering courses remains on the operation of individual machines and basic CNC programming as opposed to the total manufacturing process. Only limited project management cycles involving digital design, data-based quality testing and predictive maintenance are presented to students. In smart factories, the misalignment of pedagogy is resulting in graduates who are not prepared for the data-driven decision-making required of them (Zhao & Wang, 2022). The need to bridge this structural gap would call for a redesign of the curriculum that can incorporate advanced technological components into the already established active learning frameworks.

PjBL using technology is a powerful pedagogic approach to address some of the existing challenges in vocational higher education. With high fidelity CNC simulation, students can validate code and optimize toolpaths with no risk, IoT telemetry can provide real time process data streams and digital twin emulations can give students the opportunity to experiment without interrupting production from the real shop floor (Syahril et al., 2024). Such an holistic approach caters for both practical technical skills as well as thinking skills. Although the individual advantages of active learning and the technologies of Industry 4.0 in education are already acknowledged in literature, a systematic integration of these technologies in the field of Production Engineering and NC Programming is lacking. The gap to the above is filled by the proposed Smart Manufacturing-Oriented Project Based Learning Model. This model breaks out of the cocoon of conventional instruction by integrating digital twin visualization, interactive simulators and monitoring embedded in a collaborative PBL matrix. It shifts the learning process from 'know-how' training to a combined and 'smart industry' learning process, and the skills gained by the students are directly applicable to the smart manufacturing industry of today.

Development or prototyping phase

Project-based learning (PjBL) or project-based learning (P. Chen et al., 2015; Jalinus et al., 2020; Syahril et al., 2024) can be considered a learning strategy that is capable of helping students to develop their thinking and problem-solving and interacting skills, as well as help in the investigation that leads to the solutions to the real-life problems. A number of studies have indicated that 90 percent of students that are involved in a learning process through project-based learning are secure and hopeful that they will adopt project-based learning in workplaces and enhance their academic performance (Paugam et al., 2010). According to the study conducted by Kuppuswamy & Mhakure

(2020), 78 out of the 100 students claimed that project-based learning curriculum could be used to help them to enter the workforce because students not only learn theory but also gain practical skills in the area.

The construction of the PjBL model of the course on the production engineering and NC programming course was conducted based on the implementation of the PjBL model offered by Kerdpo (2015), Jalinus (2017; 2019) with 9 (nine) steps of PjBL. The production engineering and NC programming course project-based learning model yields a new model named Smart Manufacturing-Oriented Project-Based Learning Model comprising of 8 (syntax), which are: (a) Understanding the theoretical concepts of the production engineering and NC programming course, (b) Organizing and guiding students in work groups, (c) Designing/theming project work drawings and preparing project proposals, (d) Presenting project assignments, (e) Conceptualizing and simulating programs to complete a project, (f) Project execution and monitoring project work implementation, (g) Assessing the results of programming and project work, and (h) Conducting Evaluation of Production Engineering and NC Programming Learning.

The integration of Smart Manufacturing technology fundamentally redefines the learning trajectory in TVET education. In traditional PjBL, the learning cycle is often linear and reactive; students identify errors only after physical production occurs (e.g., a broken tool or a damaged workpiece). In contrast, Smart Manufacturing-Oriented PjBL introduces a proactive feedback loop through two key pillars: CNC Simulation as Virtual Commissioning: High-fidelity simulation transforms the learning process from trial and error on physical machines to predictive analysis. Students learn to anticipate failures in a virtual environment, fostering higher-order thinking skills (analysis and evaluation) before physical resources are consumed. IoT-Based Real-Time Reflection: While traditional PjBL relies on post-project evaluation, IoT integration enables in-process reflection. By monitoring data in real time, students no longer act as mere machine operators but instead evolve into systems analysts who make decisions based on live data streams.

The implementation of smart technology in this PjBL model brings fundamental changes to four key aspects of learning. First, in terms of error handling, traditional PjBL tends to be reactive, where students only become aware of errors after the physical machining process has been performed, often resulting in damage to the workpiece or cutting tool. In contrast, Smart Manufacturing-Oriented PjBL is predictive; through high-fidelity simulations (digital twins), students can mitigate risks and refine programming logic before touching the physical machine. Second, regarding feedback sources, whereas in the traditional model, students relied heavily on manual inspection and subjective instructions from instructors, this Smart model provides real-time IoT data and digital sensors that provide objective and instant feedback. This directly impacts the third aspect, decision-making. Students no longer make decisions based on intuition or limited manual experience, but instead shift to data-driven decision-making by monitoring digital analytics throughout the production process. Finally, this technology integration significantly changes the role of students. In conventional PjBL, students tend to assume the role of operators or skilled craftspeople focused on technical execution. However, in the Smart Manufacturing ecosystem, their roles have evolved into process engineers or systems analysts. They are required to possess managerial skills in cyber-physical system integration, a core competency required by today’s modern manufacturing industry.

Table 6. Validity Analysis of Smart Manufacturing-Oriented Project-Based Learning Model

Indicators	∑s	V Coefficient	Category
Understanding the theoretical concepts of the production engineering & NC programming course	17	0,87	Valid
Organizing and guiding students in work groups	17	0,83	Valid
Designing/theming project work drawings and preparing project proposals	18.6	0,83	Valid
Presenting project assignments	17	0,89	Valid

Conceptualizing and simulating programs for project completion	18	0,90	Valid
Project execution and monitoring project work implementation	17.8	0,88	Valid
Assessing the results of programming and project work	17.2	0,81	Valid
Conducting Evaluation of Production Engineering and NC Programming Learning	17.4	0,84	Valid

The model validity was calculated using Aiken's V coefficient, involving five validators. The experts provided assessments on a scale of 1 to 5. Based on Aiken's formula, the V value is calculated by dividing the sum of the lowest score differences by the product of the number of experts and the scale range. The findings of the model validity test yields an average value of V coefficient of close to 1 with a valid category. According to the findings of Table 7. The validation analysis to examine whether or not the syntax is valid was tested using Confirmatory Factor Analysis, and the objective is to test whether the developed phases can affirm the general constructs of the models that have been developed. Evaluation of the variables to be analyzed and conduct a determination on whether the variables can be used as factors. The analysis of the research variables given by the KMO Test and Barlett test has the following results.

Table 7. Variable Feasibility Analysis Results

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.890**
Bartlett's Test of Sphericity	Approx. Chi-Square	188.727
	Df	28
	Sig.	.000

Based on the results in Table 7 the Kaiser Mayer Olkin (KMO) score shows a score of 0.890 > 0.600, thus stating that all variables are worthy of further analysis. The factoring process aims to determine the number of factors formed from the factor analysis that has been carried out. The principal component analysis method is used. Based on the analysis of the eight phases, 1 formed variable is known which is a new construct from the phases that have been formed in one learning model. To find out the contribution of each component to the formed factors.

Table 8. Communalities Analysis Results

	Initial	**Extraction**
Phases1	1.000	.578
Phases2	1.000	.854
Phases3	1.000	.799
Phases4	1.000	.895
Phases5	1.000	.744
Phases6	1.000	.963
Phases7	1.000	.824
Phases8	1.000	.705

Based on Table 8, it is described that phase 1 can explain 57.8% of the model formed, phase 2 can explain 85.4% of the model, phase 3 can explain 79.9% of the model, phase 4 can explain 89.5% of the model, phase 5 can explain 74.4% of the model, phase 6 can explain 96.3% of the model, phase 7 can explain 82.4% of the model, and phase 8 can explain 70.5% of the model. The results of the total variance explained analysis determine the number of factors formed from the factor analysis that has been carried out.

Table 9. Total Factor Score

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.362	79.529	79.529	6.362	79.529	79.529
2	.970	12.130	91.659			
3	.501	6.268	97.926			
4	.166	2.074	100.000			
5	0.000	0.000	100.000			
6	0.000	0.000	100.000			
7	0.000	0.000	100.000			
8	0.000	0.000	100.000			

Extraction Method: Principal Component Analysis.

Based on Table 9, it is explained that the formed factor is only 1 factor that has an Eigenvalues number > 1, it can be observed that the formed factor has 6,362 eigenvalues, with the ability to explain the model of 79.52% overall. Based on the formation of factors in the Total Variance Explained that has been carried out, it is stated that a learning model has been formed that has 8 phases, thus, no factor rotation is carried out because there is only 1 formed component, for proof.

Table 10. Total Componen Matrix

Component Matrix[a]	Component
	1
Phases 1	-.760
Phases 2	.924
Phases 3	.894
Phases 4	.946
Phases 5	.863
Phases 6	.981
Phases 7	.908
Phases 8	.839

Based on Table 10, the Component Matrix above states that there is only one group of factors that encompasses all the components that have been analyzed. This means that all phases are declared valid to form a project-based learning model in the Production Engineering and NC Programming course. For a more concise result of the formation of the phases into a model, see Figure 4 Scree Plot.

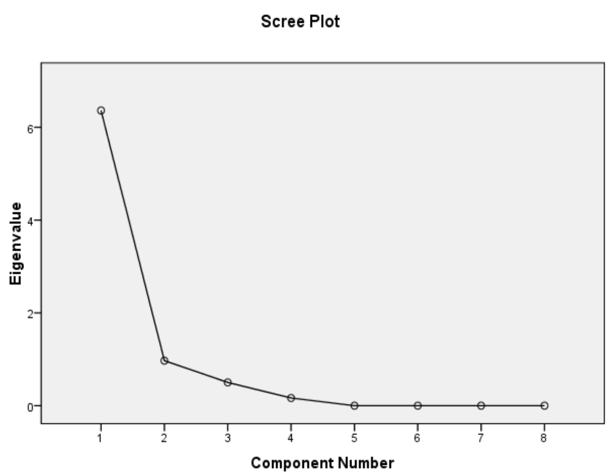

Figure 3. Scree Plot of the Formation of Phases into a Model

Based on Figure 3, it can be explained that of the 8 components tested, only one component has an Eigenvalue of more than 1. Thus, it is stated that the 8 existing components have formed one factor. If it is related to the formation of syntax in the trial of this learning model, it can be concluded that the eight phases tested have formed a complete model unit, thus this learning model is declared valid based on factor analysis.

Smart manufacturing is the process of using sophisticated digital technologies, data analysis, and connected systems to optimize the manufacturing process, enhance the efficiency of it, and allow making adaptive and real-time decisions. Smart manufacturing is based on the concepts of Industry 4.0 and uses tools to generate smart manufacturing facilities. Another application of smart manufacturing in the context of Production Engineering and NC Programming is that it changes the prevailing CNC operations by facilitating remote monitoring, predictive maintenance, real-time optimization of processes, and data-driven quality control. This paradigm shift shifts the production process beyond the manual and sequential production processes to structured, automated and highly flexible production systems. Students in education can be taught skills pertinent to the industry by integrating smart manufacturing into Project-Based Learning (PBL) which is relevant to the modern factory setting. Students not only learn to master core machining and programming skills, but also data interpretation, integration of systems and innovation of processes- skills which are now being more and more required by the highly technological manufacturing sectors. Integrating intelligent manufacturing components into curriculum enables the trainees to take end-to-end production projects that simulate the industrial environment. This method will match university learning outputs with the changing industry competence demands so that graduates are saved to be in digitalized, connected and flexible manufacturing ecosystems.

A number of the past studies investigated the validation of instructional models in technical and vocational education, especially the ones that include the elements of Project-Based Learning (PBL) or Industry 4.0 technologies. As an example, a PBL framework of mechanical engineering courses was validated by Account et al. (2000) with the help of expert assessment and measuring student performance with the Content Validity Index (CVI), where the latter was reported to be 0.87, with the significant enhancement of the practical skills of the students. Their model, however, was not applied to more sophisticated digital manufacturing technologies so that it will be restricted to the modern-day smart manufacturing conditions. Amamou & Cheniti-Belcadhi (2018) evaluated an Industry 4.0-driven curriculum module by means of expert judgment and pilot deployment with an average level of expert agreement of over 85%. Although the validation made the module relevant to the modern industry needs, there was no well-defined PBL model that can be used to systematically develop teamwork, problem-solving, and project management competencies.

Conversely, Magleby & Furse (2007) have created a blended learning model of CNC simulation and IoT-based monitoring that is confirmed by the expert (CVI = 0.92) review as well as the quasi-experimental implementation. The findings showed enhanced data-driven decision-making ability amongst the students. However, this was limited to particular machining processes and not the entire production process of designing through quality control. The current study builds on these previous validation studies by merging PBL with an overarching smart manufacturing ecosystem, such as CNC simulation, IoT-based monitoring, and digital twins applications, to address the whole production process. The validation will be carried out using mixed methods, whereby expert judgment is used in content validity, pilot implementation will be used in practicality, and post-test and pre-test competencies will be used in the determination of effectiveness. This multi-dimensional validation approach ensures that the proposed model is pedagogically sound, technologically relevant, and aligned with industry skill requirements.

Assessment phase

The assessment is conducted on the revised prototype. The assessment is an effectiveness test. The activities in this stage are focused on field trials aimed at determining whether the developed model is effective. The effectiveness test assessed the effectiveness of the project-based learning model for the Production Engineering & NC Programming course applied to students. Students implemented the learning process by forming four small groups, and assessments were conducted using pretest and posttest techniques.

Table 11. Descriptive Analysis of Competency

		Competency			
		Experimental Group		Control Group	
		Posttest	Pretest	Posttest	Pretest
N	Valid	34	34	34	34
	Missing	0	0	0	0
Mean		87.47	61.64	66.64	60.29
Median		88	56	68	56
Mode		76	56	74	56
Std. Deviation		7.72	10.08	9.49	9.09
Variance		59.711	101.690	90.114	82.699
Range		22	38	34	32
Minimum		76	40	44	46
Maximum		98	78	78	78
Sum		2974	2096	2266	2050

Based on Table 11 above, it is explained that during the pretest, students in the experimental class achieved an average learning outcome of 61.64 and 87.47 in the posttest. Meanwhile, in the contorol class, students achieved an average competency score of 60.29 in the pretest and 66.64 in the posttest. The analysis of the obtained data also showed that most students performed very well but some of the students showed lower results with minimum score of 76. When the project is investigated more, these lower results are related to the cognitive and technical barriers that were revealed in the project execution. In particular, students who scored 76 had a great problem with the need to convert the complex digital twin simulations into actual CNC operations, known as the 'abstraction gap'. This indicates that although the Smart Manufacturing-Oriented PjBL model is effective, further scaffolding for students with higher cognitive loads in managing the integrated cyber-physical systems is needed.

There were some challenges during the integration of Smart Manufacturing into PjBL. On a technical level, there were challenges with data interoperability, in that isochore and NC code execution would be able to be synchronized with the sensor feedback from an IoT device. A key challenge in terms of cognition was the 'systemic shift': students' difficulty in moving from linear manufacturing processes to a data-driven world. This made the cognitive load greater because students had to keep track of both physical machining process parameters and digital data streams. It is crucial to understand and overcome these barriers to ensure that TVET curricula can be continually enhanced to produce a work-ready student. Meanwhile, the effectiveness of the project-based learning model for the production engineering & NC programming course on the project performance aspect is as follows.

Table 12. Percentage of Experimental and Control Groups' Project Performance

Aspects	Experimental Group				Control Group			
	Group 1	Group 2	Group 3	Group 4	Group 1	Group 2	Group 3	Group 4
Project Assignment Assessment	10 (67%)	12 (80%)	13 (87%)	12 (80%)	5 (33%)	9 (60%)	8 (53%)	9 (60%)
Project Assignment Competence	11 (73%)	12 (80%)	14 (93%)	13 (87%)	8 (53%)	9 (60%)	7 (47%)	8 (53%)

Aspects	Experimental Group				Control Group			
	Group 1	Group 2	Group 3	Group 4	Group 1	Group 2	Group 3	Group 4
Programming Competencies (Work Process)	31 (69%)	39 (87%)	39 (87%)	36 (80%)	19 (42%)	24 (53%)	24 (53%)	26 (58%)
Product Result Assessment	7 (70%)	9 (90%)	9 (90%)	8 (80%)	4 (40%)	5 (50%)	5 (50%)	6 (60%)
Timeline	4 (80%)	4 (80%)	5 (100%)	4 (80%)	3 (60%)	3 (60%)	2 (40%)	3 (60%)
Work Attitude	17 (68%)	22 (88%)	23 (92%)	22 (88%)	10 (40%)	14 (56%)	12 (48%)	13 (52%)
Report	9 (60%)	13 (87%)	13 (87%)	11 (73%)	9 (60%)	8 (53%)	8 (53%)	9 (60%)

Based on Table 12, it can be explained that the average group of students in experimental group had a large percentage of the four work groups, namely group three had the highest average project performance. In order to proceed with hypothesis testing, prerequisite analysis tests will be carried out first, including normality and linearity tests as follows.

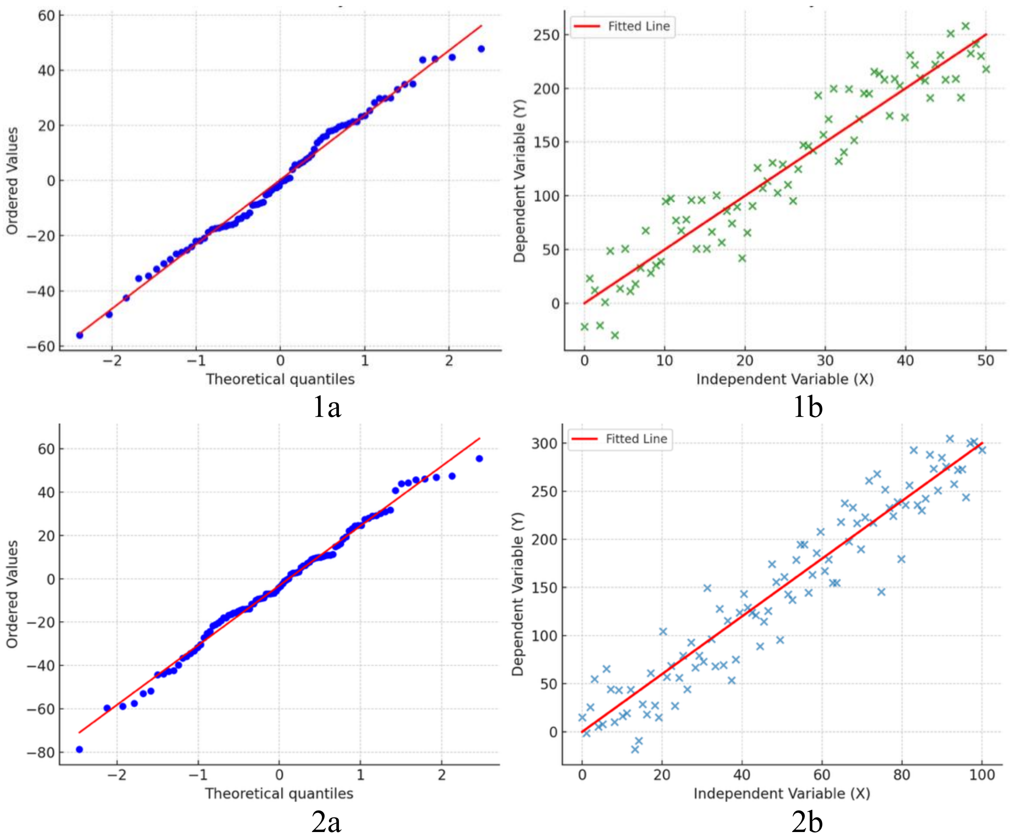

Figure 4. QQ Plots of Normality Test (a) and Scatter Plot of Linearity Test (b)

Table 13. T-Test Analysis

Observations	Groups	N	Paired Sample T-test		
			t	df	P
Pretest-Posttest analysis of Competency Test	Experimental	34	14.863	33	0.000
	Control	34	1.423	33	0.310
			Independent Sample T-test		
			T	**df**	**P**

Post-test comparison analysis of Competency Test	Experimental Control	34 34	16.331	66	0.000
Observations	**Paired Sample T-test**				
	Groups	**N**	**T**	**df**	**P**
Pretest-Posttest analysis of Project Performance Rubric	Experimental Control	34 34	13.667 1.423	33 33	0.001 0.251
			Independent Sample T-test		
			t	**df**	**P**
Post-test comparison analysis of Project Performance Rubric	Experimental Control	34 34	16.382	66	0.000

Table 13 shows a significant difference in competency between the two groups [df=66, t=16.331, p-value=0.00, p<0.05]. The experimental group showed a better increase in competency than the control group. Consequently, the treatment effect was seen in the post-test scores after implementing the Smart Manufacturing-Oriented Project-Based Learning Model in the experimental group. The p-value indicates this effect; a p-value smaller than 0.05 rejects the null hypothesis. Based on this statistic, H0 is rejected, which indicates a difference in post-test scores between the two groups. This finding indicates that the implementation of the Smart Manufacturing-Oriented Project-Based Learning Model in learning has a positive effect on students' competency skills.

Table 14. Effect Size

				95% Confidence Interval	
		Standardizer[a]	Point Estimate	Lower	Upper
nilai	Cohen's d	8.65521	2.406	1.773	3.028
	Hedges' correction	8.75514	2.378	1.753	2.993
	Glass's delta	9.49284	2.194	1.476	2.896

Table 14 also shows a significant difference in project performance between the two groups with a remarkably large effect size [Cohen's d = 2.41]. According to Cohen's (1988) guidelines, an effect size greater than 0.8 is considered large. Therefore, the obtained Cohen's d of 2.41 indicates an exceptionally strong practical impact of the developed model, demonstrating that the integration of IoT and digital twin simulations moves the students' performance by more than two standard deviations ahead of the traditional learning approach. The experimental group showed a better improvement in project performance than the control group [df=66, t=16.382, p-value<0.001, p<0.05]. Consequently, the treatment effect was seen in the post-test scores after implementing the Smart Manufacturing-Oriented Project-Based Learning Model in the experimental group. The p-value indicates this effect; a p-value smaller than 0.05 rejects the null hypothesis. Based on this statistic, H0 is rejected, indicating a difference in post-test scores between the two groups. This finding indicates that the implementation of the Smart Manufacturing-Oriented Project-Based Learning Model in learning has a positive effect on students' project performance.

The finding that the Smart Manufacturing-Oriented Project-Based Learning (PBL) Model enhances students' project performance reflects and expands upon earlier research in technical and engineering education. Jun (2010) demonstrated that PBL implementation improved students' ability to deliver projects on schedule and meet basic quality criteria, while Frank et al. (2003) showed that incorporating CNC programming into collaborative projects increased precision in final outputs. However, these studies often focused on either project management or technical execution as separate elements. In contrast, the present research adopts a fully integrated approach where smart manufacturing tools are embedded throughout the entire project lifecycle. This approach not only improves technical accuracy but also fosters innovation, optimizes resource utilization, and strengthens teamwork coordination. The result is a significant improvement in project deliverables' quality, adherence to industrial standards, and efficiency, demonstrating a broader and more holistic effect than those reported in prior studies.

Table 15. ANOVA Analysis

Source of Variation	Sum of Squares (SS)	df	Mean Square (MS)	F-value	p-value	Decision
Between Groups	1450.32	1	1450.32	37.68	0.000	Significant
Within Groups	2540.68	66	38.49			
Total	3991.00	67				

The outcome of one-way ANOVA analysis shows that the mean scores of competency skills in the posttest and project performance skill between the experimental group and the control group were statistically significantly different. This result implies that the introduction of the Smart Manufacturing-Oriented Project-Based Learning (PBL) Model positively and significantly influenced students in relation to the traditional instructional practices. In terms of competency skills, the posttest mean scores in the experimental group were dramatically higher which implies that in the conditions of the practice of the Smart Manufacturing-Oriented PBL Model, the students presented became more competent in terms of technical knowledge, problem-solving skills, and readiness to handle the industry-oriented tasks. In the case of project performance skills, the analysis also showed that the students in the experimental group had a significant improvement. This shows that the inclusion of smart manufacturing components in PBL would not only increase the technical implementation, but also teamwork, innovation and the quality of the project deliverables that would have met the industrial standards. In general, the findings of the ANOVA can be discussed as finding in favor of the research hypothesis, which said that the implementation of the Smart Manufacturing-Oriented PBL Model results in the significant improvement of the competency skills, as well as, project performance skills, which indicate the potential effectiveness of the model as the means of equipping students with the abilities relevant to the industry.

The results of this research that demonstrate the important rise in both competency skills and project performance of students in the experimental group that underwent the Smart Manufacturing-Oriented PBL Model are aligned with a number of the previous researches in the engineering and vocational education. Indicatively, Chen et al. (2019) discovered that project-based learning combined with the use of digital technologies has led to substantially greater improvement in the technical skills and critical thinking of students in contrast to the lecture-based teaching. Equally, Lei et al. (2012) emphasized that the smart manufacturing assimilation into education leads to increasing adaptability and problem-solving ability, which is comparable to the competency skills enhancement identified in this research.

In terms of performance on the project, Alves et al. (2011) established that students engaged in industry oriented PBL projects had better collaboration and innovations in the projects results than their control groups. This is similar to the findings of the present study whereby the experimental group presented better project deliverables, in accordance to industry standards. Nonetheless, in contrast to a part of previous literature, which examined either the technical competency or the team performance, this study is novel in its own way in that it authenticated the enhancement in both competency skills and the project performance skills in the framework of smart manufacturing education. This two-fold improvement points to the distinctiveness of the combination of Smart Manufacturing ideas and PBL to bridge the curriculum divide and satisfy the industry requirement of skills as a more holistic approach.

CONCLUSION

This study provide emperical evidence that the Smart Manufacturing-Oriented Project-Based Learning (PBL) Model is a suitable approach for improving competency skills and project performance in Production Engineering and NC Programming within the studied TVET environment. The model incorporates smart manufacturing concepts in real project-based activities and thus, thereby alignment academic study with contemporary industrial practices and skills requirements. The significant variations witnessed between the experimental and control group demnstrated the ability of the model to develop industry ready skills such as technical expertise, problem solving, teamwork, and project management within this specific context. However, there are also some limitations to this study. Since the research was conducted in a single institutuin with a limited sample size, the conclusions emphasize contextual applicability rather than broad generalization. Moreover, this study shows immediate improvements in technical skills and industry readiness, the lack of longitudinal data warrants future studies to follow graduates over time to assess skills retention and career path within the Smart Manufacturing industry. While the findings suggest the potential of the Smart Manufacturing-Oriented PBL as a curriculum transformation framework applicable on a large scale in TVET education, such generalization requires further validation. As a practical implication, TVET institutions are advised to begin transforming towards a cyber-physical learning environment by investing in hybrid infrastructure and enhancing faculty competencies. Furthermore, industry collaboration should be expanded into integrated co-creation, such as through real-world production data sharing agreements and cloud-based mentoring, to ensure graduates possess competencies relevant to future manufacturing needs. The model also offers viable advice to those educators and policymakers who want to incorporate Industry 4.0-linked learning strategies in the engineering curriculum. Consequently, future studies should validate this model accross different institutional settings to confirm its long-term effectiveness. The additional study of such modern technologies such as digital twins and artificial intelligence is also recommended to enhance the role of the smart manufacturing in the vocational and engineering education.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work the author(s) used ChatGPT in order to improve the clarity, grammar, and academic language of the manuscript. After using this tool, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

AUTHORS' CONTRIBUTION

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; Investigation.

Author 3: Data curation; Investigation.

Author 4: Formal analysis; Methodology; Writing - original draft.

Author 5: Supervision; Validation.

Author 6: Supervision; Validation.

DECLARATION OF COMPETING INTEREST

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

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