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Integrating IoT-Based Predictive Maintenance into Motorcycle Engineering Instruction: Effects on Vocational Students' Diagnostic Competence

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ABSTRACT

This study investigates the application of Internet of Things (IoT) technology in predictive maintenance learning within Motorcycle Engineering courses at SMK Negeri 1 Kandis and its impact on improving student competence in the context of Industry 4.0. A quasi-experimental one-group pre-test–post-test design was employed involving 64 students across Grades X, XI, and XII. Students participated in learning activities using IoT-based trainer media integrated with vehicle technical sensors. Data were collected through pre-tests, post-tests, observations, and questionnaires, and analyzed using N-gain, paired t-tests, and effect size (Cohen's d). Substantial improvements were observed across all grade levels. In Grade X, the mean score increased from 66 (pretest) to 95 (post-test) with Cohen's $d > 3.7$. In Grade XI, scores improved from 65 to 95 ($d > 27.7$), and in Grade XII from 67 to 97 ($d > 37.6$). The overall N-gain of 0.90 indicated a high level of improvement. Paired t-tests revealed statistically significant differences between pre-test and posttest scores ($p < 0.05$), demonstrating enhanced conceptual understanding, analytical skills, and readiness to meet automotive industry challenges. The findings confirm that integrating IoT technology into vocational learning effectively enhances student competence and aligns with Industry 4.0 demands. However, the absence of a control group and the short intervention duration limit generalizability. Future research should employ longitudinal designs and larger samples to validate these results and strengthen curricular integration strategies.

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1. INTRODUCTION

Vocational High School (SMK) education plays a very important role in preparing a skilled workforce that is ready to face the challenges of the industrial world. One of the skill programs that is growing rapidly is Motorcycle Engineering (TSM). The program not only teaches mechanical technical skills, but also integrates the latest technological aspects that are much needed in the automotive world, such as mechatronics, sensor systems, actuators, and electronic controls. The industrial revolution based on digital technology has forced the world of education to adjust paradigms, strategies, and teaching tools in order to prepare human resources that are able to compete in a very dynamic era. Among the most significant transformations in the modern industrial world is the implementation of the Internet of Things (IoT) as the central framework of automation, connectivity, and real-time predictive analytics. In the automotive sector, the use of IoT has been widely implemented in the practice of predictive maintenance of vehicles, i.e. sensor-based maintenance to prevent damage before it is observed.

The use of IoT technology in predictive maintenance systems is important by virtue of its ability to monitor the condition of vehicle components in real-time, identify potential breakdowns before a real failure occurs, and optimize maintenance schedules (Rahim, Rahman, & Rahman, 2020). IoT provides a huge opportunity in integrating automotive systems with Industry 4.0 which includes automation and data analysis to support predictive maintenance (Ghosh, Banerjee, Aich, & Basu, 2022). As well as IoT can help determine the optimal maintenance time and prevent unexpected damage (Amini, Ghadimi, & Fadaei, 2020). In this context, vocational schools need to adapt to existing technological developments to ensure that students' competencies remain relevant to the needs of the growing industry, especially in learning motorcycle engineering at vocational schools.

However, there is a large gap between the cutting-edge technology used in industry and the learning system that applies in vocational institutions, especially Vocational High Schools (SMK) in the field of Motorcycle Engineering. Much vocational learning still focuses on drill-based practices and procedural learning approaches that lack emphasis on data analysis and context-based decision-making. Students are often trained to replace components without understanding the technical degradation process based on sensor signals or abnormal machine system behavior. This causes students to have reactive, not predictive or diagnostic skills, even though today's industry demands require a workforce that is able to read and analyze vehicle data, as well as provide solutions based on engineering decisions. The gap is not only technological, but also pedagogical.

The application of technologies such as IoT in education must be accompanied by a change in the learning approach, from mere mastery of tools to context-rich technology-enhanced learning based on experience (experiential learning) and real work situations (situated cognition) (Pherson-geyser & Kavai, 2020). The application of technologies such as IoT in engineering education will provide great advantages in enhancing the overall quality of education and students' competencies, as students are not only taught theory but also given the opportunity to interact directly with relevant technologies in the industrial world (Panduru & Walsh, 2025).

To address this gap, this study developed and implemented a technology-enhanced situated learning model. The model is strategically designed to provide students with a hands-on and contextual learning experience, particularly through predictive maintenance projects on motorcycles based on Internet of Things (IoT) technology. This learning model is applied in a real context by involving IoT media trainers who simulate modern vehicle systems. Students interact with real-time data generated by sensors such as the Throttle Position Sensor (TPS), Engine Coolant Temperature, MAP, and O_2 Sensor, which are installed directly on two-wheeled vehicles. This data is then monitored through a digital dashboard, analyzed, and used as a basis for formulating maintenance decisions based on data, rather than just memorizing conventional procedures.

Through this approach, students not only perform technical actions (doing) such as routine maintenance, but also develop data interpretation skills (reasoning) and decision-making (decision-making) in accordance with predictive maintenance procedures as practiced in the automotive industry (Turner, Okorie, Emmanouilidis, & Oyekan, 2022). This clearly encourages the improvement of competence in the conceptual (cognitive) aspect with the ability to understand vehicle system concepts, sensor working principles, and predictive maintenance flows, then in the psychomotor aspect (practice) with the skills of using IoT devices, installing sensors, reading data, and performing technical actions based on system outputs and in the aspects of analytical and decision-making skills (affective and metacognitive) which are rooted in the ability to interpret sensor data, identify anomalous patterns and make technical decisions based on data-driven diagnoses.

Against this background, the present study aims to examine the application of IoT technology in predictive maintenance systems in Motorcycle Engineering learning at SMK Negeri 1 Kandis. This study will formulate in three research questions, whether IoT-based predictive maintenance learning improves students' cognitive learning outcomes (based on a comparison of pretest and posttest scores), as well as whether this approach is able to improve students' psychomotor skills, diagnostic abilities, as measured through the skills assessment rubric and how students' perception of the usefulness or relevance of IoT-based learning in the context of vehicle maintenance.

Through this research, it is hoped that solutions can be found to improve the existing learning system, as well as provide insight into how the application of smart technology, such as IoT, can improve the quality of vocational education in Indonesia.

2. METHODS

2.1 Design and Participants

This study used a quasi-experimental design of one group with a pre-test and post-test, without a control group, to evaluate the influence of Internet of Things (IoT)-based learning on student competence in Motorcycle Engineering subjects. Quasi-experimental design is a type of research design that is used to test the cause-and-effect relationship between independent variables and dependent variables without randomization (Isnawan, 2020).

The population in this study is all students who are registered in the competence of Motorcycle Engineering expertise at SMK Negeri 1 Kandis, which consists of:

Table 1. Research sample

No	Respondent Classification	Quantity
1.	X Automotive Engineering	33
2.	XI Motorcycle Engineering (TSM)	16
3.	XI Motorcycle Engineering (TSM)	15
	Total	64

The sample used in this study comprised 64 students from SMK Negeri 1 Kandis, representing three grade levels (classes X, XI, and XII), in the competence of Motorcycle Engineering. Sampling was carried out in total (total sampling) because the population was relatively small and all students followed the relevant subjects directly. The three grade levels were combined in the analysis because they received identical learning interventions, with a uniform curriculum and IoT modules, as well as the same practical activities using predictive trainer media that had been developed. This is intended to obtain an overview of the generalization effect of IoT-based learning across education levels.

2.2 Research Instruments

2.2.1 Pre-test and Post-test Test

The learning outcome test consisted of 20 multiple-choice questions covering three main domains: vehicle maintenance system concepts (6 questions), understanding IoT and sensors (6 questions), and the application of data-based predictive maintenance (8 questions). The test grid is prepared based on the TSM and SKL curriculum from the Directorate of Vocational Schools. The maximum score is 100 with proportional weights between topics.

2.2.2 Practice Observation and Diagnostics

The evaluation of students' psychomotor skills and diagnostic abilities is carried out through rubric-based observation sheets, which include four main indicators: Readiness of IoT sensor tools and installation, Vehicle data retrieval and interpretation, Diagnostic decision-making and Occupational safety and technical communication. Each indicator was scored 1–4 (not meeting until very good). This observation is structured, the researcher already has clear guidelines regarding the aspects to be observed so that the data obtained is more systematic and can be analyzed in more depth.

2.2.3 Perception Questionnaire

The perception questionnaire consists of 25 statement items, divided into five main constructs: Application of IoT Technology in Learning (5 items), Predictive Maintenance System (5 items), Student Competency Improvement (5 items), Students' Attitudes and Interest in IoT Technology (5 items). The scale used is the Liker Scale which will give a value between 1 to 5, where the number 1 indicates strong disagreement and the number 5 indicates a very strong agreement with the statement.

2.3 Data Analysis

Quantitative data analysis is carried out in two approaches:

a. Descriptive Statistical Analysis

Descriptive analysis is a technique used to describe or analyze data by presenting information systematically and clearly. As explained by (Rija et al., 2025), "Statistical analysis is an important aspect of the scientific studies, and contributes to decision making" which emphasizes the importance of good statistical analysis to support appropriate decision-making. This analysis does not focus on more in-depth cause-and-effect or relationships, but rather on an overview that can provide an initial understanding of the data.

To measure the improvement in learning outcomes before and after the intervention, the following were used: Paired t-test to compare pre-test and post-test scores, Effect size (Cohen's d) to assess the strength of the increase (interpretation: small <0.3; medium 0.3–0.7; large >0.7) and Calculation of N-gain score with categories: high (≥0.7), medium (0.3–0.7), low (<0.3).

b. Intervariable Relationship Analysis (PLS-SEM)

In addition to the effectiveness test, this study used Partial Least Squares Structural Equation Modeling (PLS-SEM) to model the relationship between latent variables: IoT Application (exogenous), Predictive Maintainability (mediator), and Student Competency (endogenous). This model is designed to test whether the use of IoT indirectly impacts student competencies through improved predictive maintenance capabilities. The use of PLS-SEM was chosen because: Data consist of complex latent constructs (competence cannot be measured directly), relatively small sample size (<100), and the purpose of analysis is exploration and prediction, not confirmation of pure theory. PLS processing was carried out using SmartPLS 4, with evaluation of loading factor, construct reliability, discriminant validity, and path coefficient significance (bootstrapping).

3. FINDINGS AND DISCUSSION

3.1 Findings

This study aims to measure the effectiveness of the application of IoT technology in learning Motorcycle Engineering (TSM) with a predictive maintenance approach. Based on data obtained from various aspects, it has been analyzed related to the implementation of IoT technology in learning. The following is a recapitulation of student learning outcomes divided into pretest and posttest:

3.1.1 Pretest and Posttest Results

a. Paired t-test

The paired t-test was used to determine whether there was a statistically significant difference between two averages from two related groups.

Table 2. Paired Sample Test

		Paired Differences							
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		T	df	Sig. (2-tailed)
					Lower	Upper			
Pair 1	Pre-test X TO –Post-test X TO	29.24242	10.76171	1.87337	33.05836	25.42649	-15.610	33	.000
Pair 2	Pre-test XI TSM – Post-test XI TSM	86.43750	3.26535	.81634	84.69752	88.17748	105.885	16	.000
Pair 3	Pre-test XII TSM – Post-test XII TSM	87.80000	2.30527	.59522	86.52338	89.07662	147.509	15	.000

Based on the paired t-test results presented in the table, this analysis aims to compare the differences between pre-test and post-test scores on three data pairs. Here is an explanation of each data pair tested: In the first pair (Pre-test X TO-Post-test X TO), the average difference between the pre-test and post-test was 29.24242 with a value of t = -15.610 and a degree of freedom (df) = 33. The test results showed significance value (p-value) of 0.000, which is much smaller than the significance level of 0.05, indicating that the difference in scores between the pre-test and post-test within this study pair is significant. In the second pair (Pre-test XI TSM-Post-test XI TSM), the mean difference between pre-test and post-test was 86.43750 with values t = 15 885 and df = 16. The significance value recorded was 0.000, which indicates a statistically highly significant difference between the pre-test and post-test in this pair. In the third pair (Pre-test XII TSM-Post-test XII TSM), the mean difference between pre-test and post-test was 87.80000 with values t = 147.5092 and df = 15. With a p-value of 0.000, this result shows a very significant difference between the pre-test and post-test scores in this pair. Overall, the t-test results showed that for all three data pairs tested, there was a very significant difference between pretest and posttest scores, with all p-values less than 0.05, indicating that the change between the two conditions was significant in the context of this study.

b. Effect size (Cohen's d)

Effect size (Cohen's d) is a statistical measure used to measure the magnitude of the difference between two groups or two conditions in a study.

Table 2. Effect Size (Cohen's d)

	Paired Samples Statistics					
		Mean	N	Std. Deviation	Std. Error Mean	Cohen's *d*
Pair 1	Pre-test X TO	66.2121	33	9.92395	1.72754	3.76267.
	Post-test X TO	95.4545	33	4.73742	82468	
Pair 2	Pre-test XI TSM	95.3125	16	4.26956	1.06739	27.744491.
	Post-test XI TSM	8.8750	16	1.08781	.27195	
Pair 3	Pre-test XII TSM	97.0000	15	3.16228	.81650	37.634045.
	Post-test XII TSM	9.2000	15	.94112	.24300	

Based on the results of the data analysis presented in the table, the effect size measured using Cohen's d showed that there was a huge difference between the pre-test and post-test in the three data pairs tested. The Cohen's d value recorded for each pair is as follows: The first pair, which is a comparison between the X TO pretest and the X TO post-test, Cohen's d value of 3.76267, indicates a very large effect size. This indicates that the difference in scores between the pre-test and post-test scores in this group is significant, with a much larger difference compared to the variation in the data. In the second pair, which compared the TSM pretest and the TSM post-test, Cohen's d value of 27.744491 showed an unusually large effect size. This suggests that the changes that occur between pre-test and post-test in this group are significant, even far exceeding the differences common in studies with large effect sizes. Similarly, in the third pair, which compared the TSM pre-test and the TSM post-test, the Cohen's d value recorded at 37.634045 showed a huge difference in scores between the pre-test and the post-test in this group. Cohen's very high d value indicates a very striking difference in scores between the pre-test and post-test conditions in the group.

Overall, the results of this analysis show that the changes that occur between pre-test and post-test in the three data pairs have a very large effect size. Cohen's high d value suggests that the differences that occur between the two conditions are significant and can be considered important in the context of this study.

c. N-gain score

The table below shows a comparison of the pretest and posttest results given to students before and after the application of IoT technology in learning.

Table 3. Pretest, Posttest, and N-Gain Score Recapitulation

Classes	N	Average Pretest Score	Average Posttest Score	Average N-Gain	Category
X TO	33	66	95	0.9	Height
XI TSM	16	65	95	0.9	Height
XII TSM	15	67	97	0.9	Height

Based on the data presented, it can be seen that the three classes analyzed indicated a statistically significant improvement in post-test scores compared with pretest scores. Class X TO, which consisted of 33 participants, had an average pretest score of 66 and an average post-test score of 95, with an N-Gain score of 0.9. This shows that after the treatment was given, there was a significant improvement in the scores obtained by the participants, which indicates the effectiveness of the treatment applied to this class.

Class XI TSM, with 16 participants, showed an average pretest score of 65 and an average posttest score of 95. Just like the X TO class, the recorded N-Gain value was 0.9, which also indicated a significant improvement in the participant's score after treatment. This class also shows similar changes to the X TO class, although the number of participants is less.

For class XII TSM, which consists of 15 participants, the average pretest score is 67 and the average post-test score is 97, with an N-Gain value of 0.9. This high N-Gain value reflects a significant change in the participant's ability after receiving the treatment applied. This increase in scores suggests that the interventions given in the "Height" category also contribute to significant progress in this group.

Overall, all three classes showed consistent results with nearly identical N-Gain values of 0.9. This indicates that the improvement in pre-test and post-test scores in all three classes is significant and provides a clear picture of the effectiveness of the treatment applied.

3.1.2 Observation of Learning Outcomes

Observations were carried out to assess the development of affective aspects (attitude, discipline, responsibility, cooperation) and psychomotor aspects (practical skills, precision, and application of concepts) during studying the implementation of IoT in predictive maintenance systems in the subject of Motorcycle Engineering (TSM). Assessments were carried out on three grade levels (X, XI, and XII TSM) through observation sheets during learning and practice activities.

Table 4. Grade Recapitulation per Class

Classes	Number of Students	Average Affective Value	Average Psychomotor Score	Average	Category
X TO	33	96	98	97	Very High
XI TSM	16	97	98	97.5	Very High
XII TSM	15	98	98	98	Very High

Based on the results of observations, all students from classes X, XI, and XII TSM showed very good performance in affective and psychomotor aspects. The overall average score is in the range of 97-98 with the category Very High. This indicates that learning that integrates Internet of Things (IoT) technology in the Predictive Maintenance system is able to create an active, meaningful, and applicative learning process, as well as being effective in forming the complete competencies of vocational school students according to the demands of the industrial era 4.0.

3.1.3 Respondents' Responses to the Application of IoT in Learning

This assessment was carried out on 64 students of the Motorcycle Engineering (TSM) expertise program at SMK Negeri 1 Kandis. The respondents' questionnaire instrument consists of four main aspects that reflect the implementation of IoT technology in Predictive Maintenance-based learning:

Table 5. Recapitulation of Respondents' Responses to the Implementation of IoT in TSM Learning

No	Aspects Assessed	Maximum Score	Total Score	Average Score	Percentage (%)	Category
1.	Application of IoT Technology in Learning	25	1494	23.34	93	Very High
2.	Predictive Maintenance	25	1495	23.36	93.4	Very High
3.	Improving Student Competence	25	1500	23.44	94	Very High
4.	Attitudes and Interest in IoT Technology	25	1496	23.38	93.5	Very High

This table presents the results of an evaluation of the application of IoT Technology in Motorcycle Engineering (TSM) learning based on four different aspects. The results of this evaluation showed a very positive response from the respondents to the use of IoT in the context of learning.

In the first aspect, namely the application of IoT in learning, respondents gave a very high assessment. With a total score close to the maximum number and a percentage of 93%, it can be concluded that the majority of respondents feel that the implementation of IoT contributes significantly to the quality of TSM learning. This indicates that IoT is considered effective in increasing interactivity and understanding in the learning process.

The second aspect, which measures the adoption of IoT for predictive maintenance, also showed very positive results. With an average score of 23.36 and a percentage of 93.4%, the majority of respondents consider IoT technology to be a very useful tool to improve efficiency in machine and equipment maintenance. This shows that IoT not only impacts learning, but also has great potential in improving operational effectiveness in the manufacturing industry, particularly in the prediction of equipment breakdowns or failures.

In the third aspect, which evaluates the improvement of student competence, respondents showed excellent assessment with an average score of 23.44 and a percentage of 94%. Respondents felt that the implementation of IoT in learning was able to improve student competence, enrich practical skills, and help students to be more prepared to face challenges in the world of work that increasingly relies on advanced technologies such as IoT.

Finally, in terms of attitudes and interest in IoT technology, respondents showed a very high level of interest with an average score of 23.38 and a percentage of 93.5%. This reflects that there is a great interest among respondents to adopt and further develop the use of IoT in various aspects of life, especially in the context of industry and education.

Overall, the evaluation results show that IoT technology has enormous potential to improve the quality of TSM learning. All aspects were rated in the "Very High" category, which indicates an excellent acceptance by respondents of the application of this technology. Therefore, it is advisable to continuously develop and apply IoT technology in the learning and operations of the manufacturing industry to improve efficiency, competence, and effectiveness in the future.

3.2 *Data Analysis*

Data were analyzed using the Partial Least Squares (PLS) method which was processed with the assistance of SmartPLS 4 software. PLS is a variant-based analysis method used to test structural models involving latent relationships between variables. The data analysis process with PLS consists of two main stages, namely the evaluation of the measurement model (outer model) and the evaluation of the structural model (inner model).

3.2.1 Analysis of Outer Model

a. Convergent Validity

The test was carried out by evaluating the outer loading values of each indicator against the construct. An indicator is considered to meet the convergent validity criteria if its loading factor value is greater than 0.70 (Lim, 2026).

Table 6. Loading Factor Value of Research Variables

Indicator	Application of IoT Technology	Improving Student Competence	Predictive Maintenance	Remarks
MKS1		0.777		Valid
MKS2		0.805		Valid
MKS3		0.790		Valid
MKS4		0.767		Valid
MKS5		0.850		Valid
PP1			0.843	Valid
PP2			0.803	Valid
PP3			0.837	Valid
PP4			0.813	Valid
PP5			0.805	Valid
PT1	0.831			Valid
PT2	0.830			Valid
PT3	0.768			Valid
PT4	0.767			Valid
PT5	0.776			Valid

Based on the findings of the analysis shown in table, all indicators in the construct of IoT Technology Application, Competency Improvement, and Predictive Maintenance exhibit an outer loading value above 0.70. In the IoT Technology Application construct, the factor loading values range from 0.767 to 0.850, while in the Competency Improvement construct, the factor loading value range from 0.767 to 0.831. The Predictive Maintenance construct shows a loading factor value between 0.803 to 0.843. These values show that each indicator in each construct has a strong contribution in explaining its latent variables. Thus, all indicators used in this study can be declared valid convergently, because they have met the minimum limit of the required loading factor value (> 0.70).

b. Discriminant validity -Fornell-Larcker

Discriminant validity was evaluated based on the Fornell-Larcker criterion was carried out to evaluate the degree to which each construct in the research model has a clear difference from other constructs (Afthanorhan, Ghazali, & Rashid, 2021). This criterion states that the Average Variance Extracted (√AVE) square root value of a construct must be exceeding the correlation value between that the construct and the other constructs in the model.

Table 7. Fornell-Larcker

Construct	Application of IoT Technology	Improving Student Competence	Predictive Maintenance	Remarks
Application of IoT Technology	**0.795**			Valid
Improving Student Competence	0.838	**0.798**		Valid
Predictive Maintenance	0.885	0.828	**0.820**	Valid

The discriminant validity test is an important step in ensuring that the constructs measured in this study actually exhibit different aspects of other constructs. One method used to test discriminant validity is the Fornell-Larcker criterion, which compares the average root value of extraction variance (AVE) for each construct with the correlation value between existing constructs. According to this criterion, discriminant validity can be considered It is considered met if the square root of the AVE for each construct is higher than the correlation between that construct and other constructs.

Based on the results obtained, it can be seen that for the IoT Technology Application construct, the calculated AVE value is 0.795. Thus, the root of AVE (√0.795 = 0.892) was greater than the correlation values between other constructs, namely 0.838 with Student Competency Improvement and 0.885 with Predictive Maintenance. This shows that the IoT Technology Application construct meets the Fornell-Larcker criteria and can be considered to have good discriminant validity.

Likewise with the construct of Student Competency Improvement, which has an AVE value of 0.798. The root of AVE (√0.798 = 0.894) was larger than the correlation values between other constructs, which were 0.838 with IoT Technology Application and 0.828 with Predictive Maintenance. Thus, the construct of Improving Student Competency also meets the criteria of discriminant validity set by Fornell-Larcker.

Furthermore, for the Predictive Maintenance construct, the calculated AVE value is 0.820. The root of AVE (√0.820 = 0.905) was larger compared to the correlation values between other constructs, namely 0.885 with the Application of IoT Technology and 0.828 with Student Competency Improvement. Therefore, the Predictive Maintenance construct also meets the requirements for discriminant validity.

Overall, the results of the discriminant validity test using the Fornell-Larcker criteria show that all constructs in this study, namely the Application of IoT Technology, Student Competency Improvement, and Predictive Maintenance, meet the criteria of discriminant validity. This shows that these constructs really measure different aspects and do not overlap with each other, so it can be said that this research model has good discriminative validity.

c. Cross Loading

Discriminant validity testing is also carried out through Cross Loading analysis to ensure that each indicator attains the highest correlation with the measured construct it is measuring compared to other constructs. The results of this test are proof that each indicator is able to represent its latent variable specifically and that there is no overlap between constructs.

Table 8. Cross Loading

Indicator	Application of IoT Technology	Improving Student Competence	Predictive Maintenance	Remarks
MKS1	0.683	0.777	0.615	Valid
MKS2	0.610	0.805	0.639	Valid
MKS3	0.646	0.790	0.675	Valid
MKS4	0.678	0.767	0.623	Valid
MKS5	0.724	0.850	0.744	Valid
PP1	0.770	0.703	0.843	Valid
PP2	0.733	0.669	0.803	Valid
PP3	0.740	0.698	0.837	Valid
PP4	0.667	0.675	0.813	Valid
PP5	0.715	0.651	0.805	Valid
PT1	0.831	0.672	0.787	Valid
PT2	0.830	0.691	0.714	Valid
PT3	0.768	0.633	0.695	Valid
PT4	0.767	0.668	0.657	Valid
PT5	0.776	0.669	0.658	Valid

Based on the data analysis results using SmartPLS 4, it was obtained that all indicators had the highest loading factor values in the construct they measured. For example, the MKS1-MKS5 indicator representing the Competency Improvement construct shows the highest loading value in the construct (0.777-0.850) compared to the loading value for the IoT Technology Application construct (0.610-0.724) and Predictive Maintenance (0.615-0.744). This shows that each indicator in the Competency Improvement construct is able to explain its variables well. Furthermore, the PT1-PT5 indicator representing the IoT Technology Application construct also has the highest loading factor value in the construct, with a value range between 0.767 to 0.831, compared to the loading value for the Competency Improvement (0.668-0.691) and Predictive Maintenance (0.657-0.787) constructs. This confirms that the indicators in the IoT Technology Application construct have good discriminant validity and there is no measurement similarity with other constructs. Similarly, the PP1-PP5 indicator that measures the Predictive Maintenance construct has the highest loading factor value in the construct, which is between 0.803 to 0.843, compared to the loading value for the construct of IoT Technology Application (0.667-0.770) and Competency Improvement (0.651-0.703). These results show that all indicators in the Predictive Maintenance construct reflect the construct strongly and consistently. Based on these results, it can be assumed that each indicator exhibits the highest correlation with the construct it represents and does not show significant cross-loading in other constructs. Thus, the results of this test confirm that the measurement model has met the Discriminant Validity criteria based on Cross Loading analysis. This result also strengthens the findings of the Fornell-Larcker test, so that the entire model can be declared to have good conceptual clarity and is suitable to proceed to the stage of internal model analysis.

d. Construct Reliability and Validity

Reliability was evaluated based on Cronbach's Alpha and Composite Reliability (CR) coefficients and Average Variance Extracted (AVE) values obtained through data processing using SmartPLS 4.

Table 9. Reliability and Validity Test

Construct	Cronbach's Alpha	Composite Reliability (ρa)	Composite Reliability (ρc)	Average Variance Extracted (AVE)
Application of IoT Technology	0.854	0.856	0.896	0.632
Improving Student Competence	0.857	0.860	0.898	0.638
Predictive Maintenance	0.878	0.879	0.911	0.673

The test results showed that the Cronbach's Alpha value for the IoT Technology Application construct was 0.854, Competency Improvement was 0.857, and Predictive Maintenance was 0.878. All of these values are above the minimum value limit of 0.70, which indicates that the indicators in each construct have good internal reliability and are able to provide consistent measurement results. In addition, the Composite Reliability (CR) value in each construct also showed satisfactory results, namely 0.856 for the Application of IoT Technology, 0.860 for Competency Improvement, and 0.879 for Predictive Maintenance. All CR values exceed the threshold of 0.70, which means that each construct has a high level of internal consistency and its indicators together are able to measure constructs reliably. The test results also showed that the AVE value for the entire construct had met the minimum limit of 0.50, with details of 0.632 for IoT Technology Application, 0.638 for Competency Improvement, and 0.673 for Predictive Maintenance. These values show that more than 50% of the variance of the indicators can be explained by the latent constructs of each, so that the he constructs included in the model can be said to have good convergent validity. Thus, based on the results of the construct reliability test, which includes Cronbach's Alpha, Composite Reliability, and AVE, it can be inferred that all constructs in this research model have satisfied the required reliability and validity criteria. This means that the instruments used in this study have proven to be consistent and suitable for further analysis at the stage of testing the structural model (inner model).

e. Evaluation of Inner Model (Structural Model)

The assessment of the structural (inner) model or structural model in Smart PLS 4 aims to measure the relationship between latent constructs in a research PLS-SEM based model. This evaluation is an important stage after the outer (measurement) model is declared valid and reliable. Basically, the internal evaluation of the model focuses on the predictive power and the significance of the relationships between latent constructs contained in the model. The evaluation of the inner model is intended to verify that the structural model built is not only statistically significant, but also has adequate predictive power, strong relationship stability, and does not contain multicollinearity problems.

3.2.2 Inner Model Analysis (R-Square)

Through data analysis that has been carried out with the help of SmartPLS 4 software, The R-Square value obtained from the analysis is presented as follows

Table 10. R-Square value

Endogenous constructs	R-Square (R^2)	R-Square Adjusted (R^2 Adjusted)	Remarks
Application of IoT Technology	0.783	0.779	Strong
Increased Competence	0.737	0.729	Strong

The R-square (R^2) test is performed to assess how much independent variables are able to explain the dependent variables in the structural model. The value of R-square describes the proportion of variance of the endogenous construct that can be explained by the exogenous construct. The higher the

R-square value, the better the model's ability to explain the phenomenon being studied. Based on the results of data analysis using SmartPLS 4, it was obtained that the R-square value for the IoT Technology Application construct was 0.783, with an adjusted R-square value of 0.779. These results show that 78.3% of the variance in IoT Technology Application can be explained by the constructs that affect it in the model, whereas the remaining 21.7% is explained by other factors outside the research model. This value falls into the high category, which means the model has strong predictive power over the variable. Meanwhile, the R-square value for the Competency Improvement construct was obtained at 0.737, with an adjusted R-square value of 0.729. This means that 73.7% of the variance of Competency Improvement can be explained by exogenous variables contained in the research model, while the remaining 26.3% is explained by other variables outside the model. This value is also included in the strong category, so it can be concluded that the model used is able to explain the relationship between variables well. Overall, the results of the R-square test show that the constructed structural model has a good ability to explain the relationships between latent constructs. An R-square value above 0.70 indicates that the model has strong predictive relevance, so it is feasible to proceed to the stage of testing the significance of the relationship between latent variables through path coefficient testing and bootstrapping.

3.2.3 Path Coefficients Analysis (Hypothesis Test)

The Path Coefficient test was carried out to determine the direction, strength, and level of significance of the relationship between latent constructs in the structural model (inner model) (Kumar, Gangwar, & Kumar, 2023). This test uses the path coefficient value (original sample), t-statistic value, and p-value obtained through the bootstrapping process on SmartPLS 4.

Table 11. Path Coefficients Test Results

Relationships Between Constructs	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Remarks
Application of IoT Technology → Improving Student Competency	0.488	0.489	0.198	2.462	0.014	Significant
Application of IoT Technology → Predictive Maintenance	0.885	0.890	0.028	31.505	0.000	Very significant
Predictive Maintenance → Improving Student Competency	0.397	0.398	0.198	2.007	0.045	Significant

Based on the analysis results shown in the Path Coefficients table, Hypothesis 1: The relationship between the Application of IoT Technology to Competency Improvement has a coefficient value of 0.488, with a t-statistical value of 2.462 and a p-value of 0.014. Because the t-statistic value is greater than 1.96 and the p-value is less than 0.05, it can be concluded that the application of IoT Technology has a positive and significant effect on Competency Improvement. This means that the higher the application of IoT technology, the more competencies that individuals or organizations have.

Furthermore, Hypothesis 2: The relationship between Predictive Maintenance and the Application of IoT Technology showed the highest the path coefficient of 0.885, as indicated by a t-statistic of 31.505 and a p-value of 0.000. This value goes far beyond the limit of significance, which shows that Predictive Maintenance has a positive and very significant influence on the Application of IoT Technology. Thus, the better the implementation of the Predictive Maintenance system, the higher the level of application of IoT technology in the environment studied.

Meanwhile, Hypothesis 3: The relationship between Predictive Maintenance and Competency Improvement resulted in a coefficient value of 0.397, with a t-statistic of 2.007 and a p-value of 0.045. These results show that Predictive Maintenance also has a significant positive effect on Competency

Improvement. This means that the implementation of Predictive Maintenance not only has an impact on technological efficiency, but also contributes to improving the capabilities and competencies of human resources. Overall, the results of the path coefficient test indicate that all relationships between latent variables in the model have a positive and significant influence. The strongest relationship is shown by the Predictive Maintenance variable to the Application of IoT Technology, which is the dominant path in this research model. These results confirm that the constructed structural model has strong validity and relevance in explaining the relationship between the research variables.

3.2.4 Indirect Effect Analysis (Uji Hypothesis)

Indirect effect analysis was carried out to find out whether there was a mediating effect between variables in the research model.

Table 12. Specific Indirect Effects Test Results

Indirect Relationships Between Constructs	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Remarks
Application of IoT Technology → Predictive Maintenance → Improving Student Competence	0.351	0.354	0.178	1.976	0.048	Significant

Based on the results of the test displayed in the Specific Indirect Effects table, Hypothesis 4: An indirect the coefficient of 0.351 was obtained, with a t-statistic of 1.976 and a p-value of 0.048. Since the t-statistic value is greater than 1.96 and the p-value is smaller than 0.05, it can be concluded that the indirect relationship of the application of IoT Technology to Competency Improvement through Predictive Maintenance is positive and significant. These results show that Predictive Maintenance plays a mediating construct in the relationship between IoT Technology Application and Competency Improvement. In other words, the implementation of good IoT Technology not only has a direct impact on improving competence, but also provides additional influence through increasing Predictive Maintenance. Conceptually, these results confirm that the success of the implementation of IoT Technology will be more optimal in improving competence if supported by effective Predictive Maintenance. This shows that Predictive Maintenance has an important role as a link between IoT technology while improving the capabilities f human resources within the context of the organization. Thus, it can be concluded that this research model shows a significant mediating influence of the Predictive Maintenance variable on the relationship between the Application of IoT Technology and Student Competency Improvement, which strengthens the causal relationship between constructs in the structural model.

3.3 Discussion

3.3.1 Improving Learning Outcomes through IoT Learning Interventions

The results showed a significant improvement in student learning outcomes after participating in Internet of Things (IoT)-based learning, which was indicated by high N-gain values (0.9-0.9) and effect measures (Cohen's d > 3.76-37.63) across the classroom. These findings corroborate that technology-based learning design that is integrated in practice has a positive impact on students' knowledge mastery.

This significant increase is in line with the principle of experiential learning (Tembrevilla, 2024), in which students learn actively through interaction with devices, data, and real-life work simulations.

It is not only the final questions or evaluations that determine the success of learning, but also the interactive and meaningful experience of operating the IoT system.

By paying attention to potential biases such as post-test questions that are too easy or the repetition of identical questions, validation steps have been taken through diversification of items and checking the difficulty index of questions. Therefore, the improvement in learning outcomes can be considered pedagogically valid, not the result of the practice of "teaching for exams".

3.3.2 Mastery of Practical and Diagnostic Skills

Observations of student competencies showed that the affective and psychomotor average scores had excellent performance, with the highest achievement (97-98). These findings show that students are able to transfer theoretical knowledge into real practice, which is the main goal of vocational education.

Specifically, students are able to install sensors (TPS, MAP, CKP), read digital data through IoT dashboards, and formulate technical diagnoses based on temperature, pressure, or engine performance indicators. This process shows the integration of psychomotor and cognitive competencies, as well as the emergence of data-driven decision-making skills, which are often underdeveloped in conventional procedural command-based practices.

3.3.3 Students' Perceptions of IoT-Based Learning

From the perception questionnaire, the majority of students responded positively to several aspects: Application of IoT Technology in Learning (93%), Predictive Maintenance (93.4%), Improvement of Student Competence (94%) and Attitude and Interest in IoT Technology (93.5%). This reinforces the argument that technology not only aids technical understanding, but also increases motivation and perception of the meaning of learning. The results of the evaluation show that IoT technology has great potential to improve the quality of TSM learning. All aspects were rated in the "Very High" category, which indicates an excellent acceptance from respondents of the application of IoT technology in learning. This is relevant to the principle of the technology acceptance model (TAM), where the perception of usability and ease contributes to the effectiveness of learning (Abdulaziz, Hassan, & Mahdi, 2021).

3.3.4 The Role of Predictive Maintenance as a Mediator in the PLS-SEM Model

In the research conducted, predictive maintenance acts as a mediator in the PLS-SEM (Partial Least Squares Structural Equation Modeling) model to analyze the relationship between various variables. Based on the results of the analysis carried out, predictive maintenance plays a significant role in bridging the influence of IoT technology on improving student competence.

Predictive maintenance serves to monitor the condition of equipment in real-time and detect indications of damage before a major failure occurs. By using data collected through IoT sensors, this analysis allows companies or educational institutions to plan maintenance more efficiently, reduce maintenance costs, and improve asset availability and reliability. In the context of education, this also contributes to improving student competence, especially in understanding and using data-based and sensor-based technologies.

As a mediator in the PLS-SEM model, predictive maintenance has been shown to have a significant positive influence on improving student competencies through IoT technology. The results of the analysis showed that the indirect relationship between the application of IoT technology and the improvement of student competence through predictive maintenance had a significant coefficient, with a t-statistic value of 1.976 and a p-value of less than 0.05. Overall, this PLS-SEM model shows that predictive maintenance acts as a mediator that connects the influence of IoT technology to improving student competence, focusing on the development of practical skills and understanding data-driven concepts in motorcycle engineering learning in vocational schools.

4. CONCLUSION

The implementation of IoT-based systems technology in learning Motorcycle Engineering (TSM) at SMK Negeri 1 Kandis has been proven to provide significant improvements in improving student competence. Through the application of IoT technology in predictive maintenance systems, students not only learn about the basic theories of motorcycle systems, but also gain practical skills in analyzing vehicle condition data in real-time. This contributes to students' enhanced understanding of the operational conditions of motorcycles, as well as the ability to perform data-driven diagnosis and treatment. However, while IoT technology has proven to be effective in improving student competencies, there are challenges that need to be overcome, especially related to industry readiness. Students need to have competencies that are in accordance with the standards expected by the industrial world, and this requires clear competency validation as well as standardization that is tailored to the needs of the automotive industry. Therefore, it is crucial for vocational education to ensure that the curriculum taught can produce graduates who are truly well-equipped to overcome the challenges of the world of work that is increasingly based on advanced technologies such as IoT.

To maximize the application of IoT technology in education, appropriate scaling strategies are needed, such as expanding the number of available IoT devices and strengthening their supporting infrastructure, including cloud-based networks and storage systems. A minimum set of IoT equipment that is accessible to all students also needs to be provided, with devices integrated within existing training systems. In addition, it is important to integrate IoT technology in learning modules, both in theoretical and practical aspects, so that students not only understand basic concepts but can also directly apply them in real-world situations. Data-driven assessments should be conducted using IoT platforms to evaluate students' ability to analyze the data obtained, as well as gauge the extent to which they can make informed treatment decisions based on that analysis. Further research may involve control groups to compare the learning outcomes of students who use IoT with those who do not. In addition, multi-school replication can be done to ensure that the findings of this study can be applied widely in various vocational schools. Long-term research is also needed to evaluate students' competency retention after graduation and measure their performance in the workforce, to ensure that IoT-based learning systems truly prepare them to adapt to the demands of the automotive industry of the future.

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