Effectiveness of AI-Driven Assessments in Enhancing Learning Evaluation through Predictive Technology in Vocational Secondary School

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Manuscript received November 21, 2024; revised December 25, 2024; accepted February 18, 2025; published July 14, 2025

***Abstract*—This study evaluates the effectiveness of Artificial Intelligence (AI)-driven assessments in enhancing learning evaluation through predictive technology in vocational secondary schools. Using a quasi-experimental design, the study involved two groups: an experimental group (n = 100) that used AI-driven assessments and a control group (n = 100) with traditional methods. Both groups took pre-tests and post-tests to measure knowledge changes, along with surveys and observations to assess engagement and satisfaction. The experimental group showed significantly higher post-test scores (85.6% vs. 76.4%), indicating improved performance. Additionally, 89.25% of students in the experimental group re-ported greater engagement. 90.20% of the students expressed high satisfaction with the assessment process, rating their experience as very satisfying. Observational data confirmed a more active learning environment in the experimental group. The findings suggest that AI-driven assessments provide more efficient and adaptive evaluations, enhancing both learning outcomes and student engagement, with real-time feedback supporting continuous improvement.**

***Keywords*—Artificial Intelligence (AI)-driven assessments, predictive technology, vocational education, learning evaluation**

I. Introduction

In the rapidly evolving landscape of education, the integration of technology has become a key driver in enhancing teaching and learning processes. One significant advancement is the use of Artificial Intelligence (AI) in educational assessments, which offers the potential to transform how student learning is evaluated [1, 2]. The global adoption of AI in education has been steadily increasing, with recent data showing significant investment in AI-driven educational tools across various countries [3, 4]. For example, global spending on AI across all sectors including education is projected to reach USD 70 billion by 2030, highlighting the growing importance of AI [5]. This trend is particularly relevant for vocational education, where AI is one option to become an innovative assessment tool to meet the evolving needs of the workforce [6, 7].

Research conducted [8] explains traditional assessment methods, such as paper-based tests and manually graded assignments, often fail to provide timely and personalized feedback. This limitation is especially critical in vocational education, where practical and hands-on skills are the primary focus [9]. This is supported by the explanation [10], where this limitation can hinder student progress, especially in vocational high schools where practical skills and continuous improvement are essential. then research [11] explains AI-based assessment aims to address these challenges by offering adaptive and real-time feedback and predictive analysis, which improves the accuracy and efficiency of learning evaluation.

Some research [12, 13] explains that vocational secondary education, particularly in engineering, emphasizes hands-on skills and application-based knowledge. The nature of vocational learning requires assessment that goes beyond rote memorization and factual recall. Instead, assessments should evaluate students' ability to apply their skills in real-world scenarios [14, 15]. Instead, assessments should evaluate students' ability to apply their skills in real-world scenarios [16, 17]. While previous studies have explored AI applications in general education, limited empirical evidence exists on its application specifically within vocational education settings, creating a significant research gap. In line with these conditions, research [18], conveyed that AI-based assessment offers a solution by adapting to individual learning needs and providing actionable feedback directly to students. This personalized approach is aligned with the goals of vocational education, as it supports continuous skill development and helps students identify and address knowledge gaps more effectively [19].

The purpose of this research emphasizes the use of

doi: 10.18178/ijiet.2025.15.7.2342

predictive technology in AI-based assessment adding another layer of innovation to the evaluation process [20]. The hope is that by analyzing student performance data, AI can predict future learning outcomes and suggest targeted interventions to improve performance [21]. Also explained in research [22] where AI-based assessment capabilities are particularly valuable in vocational settings, where early identification of weaknesses can prevent skills gaps and better prepare students to enter the workforce. also supported from research [10] which explains predictive analysis not only helps educators adjust their teaching strategies but also empowers students to take over responsibility for their learning journey through informed decision making.

Unlike existing study [3], which often focus on general AI-based learning tools, this research specifically investigates the effectiveness of AI-driven assessments in enhancing learning evaluation through predictive technology, tailored to the unique needs of vocational education. By leveraging predictive analytics and real-time feedback, this study fills a critical gap in understanding how these technologies can transform skill-based learning environments. This aligns with findings from research [23], which highlights that predictive analytics not only assist educators in adapting their teaching strategies but also empower students to take responsibility for their learning journey through informed decision-making.

Despite the potential of AI-driven assessments, there is a need for empirical research to validate their effectiveness in enhancing learning evaluation through predictive technology within real educational settings. Previous studies have primarily focused on theoretical frameworks or pilot implementations, with little emphasis on large-scale experimental evaluations in actual classrooms [24]. Although theoretical frameworks support the benefits of AI in learning evaluation, experimental evidence is critical to understanding how this technology functions in practice.

This research aims to address that gap by conducting a quasi-experimental study in a vocational high school, comparing the outcomes of students using AI-based assessments with those relying on traditional methods. The study will not only measure the impact on student performance but also evaluate student engagement and satisfaction with the assessment process. By emphasizing the effectiveness of AI-driven assessments in enhancing learning evaluation through predictive technology, this research provides actionable insights for vocational education institutions and contributes to global discussions on AI implementation in education. In this context, this research seeks to answer the following questions:

1) How does AI-based assessment affect student performance in vocational education?
2) To what extent do these assessments increase student engagement and satisfaction compared to traditional methods?

By answering these questions, this research aims to contribute to the growing body of knowledge on the role of AI in education and provide actionable insights for vocational education institutions looking to adopt AI-based assessment tools.

II. Literature Review

The integration of AI in education, particularly in assessments, has garnered significant attention over the past decade [25]. AI-driven assessments have been lauded for their ability to provide personalized learning experiences by adapting to individual student needs and offering real-time feedback. Studies by Venkatesh, *et al.* [26], Anuyahong, *et al.* [24] have shown that AI-based systems can significantly improve student engagement and performance, as they allow for adaptive testing that tailors questions based on a student’s current level of understanding. For example, a case study in Germany demonstrated that AI-based assessments in vocational training programs improved skill acquisition rates by 30% compared to traditional methods [27]. Another example is from United States, where AI-driven learning platforms in polytechnic institutions have successfully integrated adaptive testing, leading to a 20% reduction in dropout rates [21]. By leveraging the effectiveness of AI-driven assessments in enhancing learning evaluation through predictive technology, this dynamic approach to assessment helps bridge knowledge gaps early, making learning more efficient and focused [18].

In vocational education, where practical skills development is critical, the ability of AI to offer immediate feedback is particularly beneficial, enabling students to continuously improve their competencies in real-time [6]. Traditional approaches to assessment, such as standardized tests and manual grading of practical exercises, often fail to capture the dynamic and iterative nature of skill development in vocational training [28]. By contrast, AI-based systems provide continuous evaluation and targeted suggestions, thus better aligning with the hands-on learning goals of vocational education [29].

Predictive technology, an integral component of AI-driven assessments, plays a critical role in advancing educational evaluation [30]. Predictive analytics in education involves the use of historical and current student data to forecast future learning outcomes [31]. This technology has been effectively applied in various educational settings to identify students at risk of failing or underperforming, thus allowing educators to implement timely interventions [32]. For instance, in a vocational high school in USA, predictive models have been employed to identify students struggling with technical subjects, enabling targeted coaching sessions that improved pass rates by 30% [33].

In the context of vocational education, predictive technology can predict skill mastery, track student progress, and highlight areas that require additional focus. Predictive models enable a more proactive approach to teaching, moving away from reactive assessments that occur after learning challenges have already manifested [34, 35]. This shift is critical because traditional assessment models, which rely on summative evaluations at the end of learning cycles, often fail to provide actionable insights during the learning process [36].

Despite the promising advantages of AI-driven assessments, challenges remain regarding their widespread implementation. One concern frequently noted in the literature is the reliability and validity of AI-based assessments compared to traditional methods [37]. Studies like those by Ferrara and Qunbar [38], Nigam, *et al.* [39] have highlighted the need for more empirical evidence on how AI-driven assessments perform in varied educational contexts, particularly in vocational education where hands-on learning and practical skills are central. While empirical studies on AI in general education are abundant, there is a lack of targeted research examining its role in vocational training. Specifically, there is a need for experimental studies that evaluate: (1) the comparative effectiveness of AI-based and traditional assessments in improving skill acquisition, (2) the impact of real-time feedback on student engagement and motivation, and (3) the scalability of AI systems in resource-constrained vocational institutions [40].

Moreover, while AI can offer personalized learning paths, there is still the question of how well these systems align with broader educational standards and objectives. For instance, vocational curricula often include national competency frameworks that demand standardized assessment practices [3]. Future empirical studies should explore how AI-based assessments can be adapted to meet these requirements while maintaining their adaptive and personalized features [18]. This gap in the literature underscores the need for further research, particularly experimental studies that directly compare AI-driven assessments with traditional approaches to better understand their impact on learning outcomes, student engagement, and overall educational effectiveness.

III. Method

This study employed a quasi-experimental design to examine the effectiveness of AI-driven assessments in enhancing learning evaluation in vocational secondary schools [41, 42]. The research involved two groups of students: an experimental group that utilized AI-driven assessment tools and a control group that used traditional assessment methods. A total of 200 students were selected from a vocational secondary school specializing in technical subjects, with 100 students assigned to each group. The sampling method used was random sampling to ensure that participants had comparable academic backgrounds and were representative of the target population [43, 44]. Both groups underwent pre-tests and post-tests to measure knowledge and skill acquisition before and after the intervention.

To provide practical context, this study incorporated real-world examples of AI implementation. For instance, the experimental group utilized an AI-driven assessment platform modeled after successful applications in vocational education programs in Germany, which demonstrated a 30% increase in skill acquisition rates through adaptive testing and immediate feedback [27]. Such concrete case studies illustrate the potential of AI to transform traditional educational paradigms in technical settings.

The instruments used in this study included an AI-driven assessment platform for the experimental group, which provided adaptive testing, real-time feedback, and predictive analytics on student performance [45, 46]. The control group completed traditional assessments, such as paper-based tests and assignments graded manually by teachers. Both groups took identical pre-tests and post-tests to assess any changes in learning outcomes. In addition, the AI-driven system tracked students' progress over time, offering unique insights into individual learning trajectories, unlike traditional assessment methods that relied solely on static evaluations [21]. Surveys and checklists were also utilized to capture qualitative and quantitative feedback on engagement, satisfaction, and classroom dynamics.

This study explicitly compared traditional and AI-based assessment methods in vocational education to highlight the distinctions. Traditional approaches, such as summative evaluations and manual feedback, often fail to provide timely insights into student progress. By contrast, the AI-based platform enabled ongoing assessments and real-time interventions, fostering a dynamic learning environment tailored to each student's needs.

The procedure began with administering a pre-test to both groups to establish a baseline of their knowledge and skills. Over several weeks, the experimental group used the AI-driven assessment platform, which provided personalized feedback and adaptive questions based on individual performance. Meanwhile, the control group continued with traditional assessment methods. At the end of the intervention period, both groups completed a post-test to measure improvements in their learning outcomes. Surveys were administered afterward to gather data on student engagement and satisfaction, while observations were recorded throughout the study to note levels of participation and interaction with the assessment tools.

To emphasize the importance of empirical validation, this study prioritized experimental methods that directly assessed the impact of AI-driven assessments on key outcomes. Specifically, gain score analysis was used to determine the extent to which AI-based tools improved student performance compared to traditional methods. Such empirical approaches are critical in establishing the effectiveness and scalability of AI technologies in vocational education.

Data was analysed using quantitative methods, including paired t-tests to compare pre-test and post-test scores within each group and independent t-tests to compare post-test scores between the experimental and control groups. Descriptive statistics were employed to analyse the survey data, providing insights into the levels of engagement and satisfaction reported by the students. Observational data was analysed qualitatively, focusing on identifying trends in student behaviour and engagement during the assessment process. Ethical considerations were also considered, with informed consent obtained from all participants and confidentiality assured throughout the study.

A. Respondents

The subjects of this study were 200 students enrolled in a vocational secondary school specializing in technical subjects in Pontianak City, West Borneo, Indonesia. The sample was selected using random sampling to ensure that students from diverse academic backgrounds were equally represented [47, 48]. The participants were divided into two groups, Experimental Group: 100 students who used the AI-driven assessment platform. Control Group: 100 students who continued with traditional assessment methods (paper-based tests and manual feedback).

Both groups were composed of students from similar technical programs, ensuring that the curriculum and instructional methods were consistent across the study. The students ranged in age from 16 to 18 years old and had varying levels of proficiency in technical subjects, which allowed for a diverse range of data on the effectiveness of

AI-driven assessments across different learning abilities. All participants voluntarily agreed to take part in the study, and ethical considerations, including anonymity and the right to withdraw at any time, were observed throughout the research process.

B. Collecting Data

This study employed several data collection techniques, including: 1) administering pre-tests and post-tests to measure students' knowledge and learning outcomes in vocational secondary schools, comparing the effectiveness of AI-driven assessments with traditional methods; 2) utilizing a Likert scale questionnaire, which is commonly used to assess attitudes, opinions, and perceptions of individuals or groups regarding various phenomena. In this study, the Likert scale was used to evaluate the level of student engagement and satisfaction with AI-driven assessments; and 3) gathering observational data to assess changes in student participation, collaboration, and overall classroom dynamics during the implementation of AI-driven assessments. The pre-test was conducted before students in the experimental group used AI-driven assessments, while the post-test was administered after students had engaged with the AI system to evaluate its impact on their learning outcomes [49].

C. Data Analysis

This study employs various data analysis techniques, specifically: 1) quantitative descriptive analysis, used to assess the effectiveness of AI-driven assessments in improving learning outcomes and engagement in vocational secondary schools; 2) gain score analysis, employed to measure the effectiveness of AI-driven assessments by comparing the pre-test and post-test results of the experimental and control groups; 3) independent sample t-test, used to validate the difference in post-test scores between the experimental group (using AI-driven assessments) and the control group (using traditional methods), ensuring the research instrument accurately measures the intended variables; and iv) reliability testing using Cronbach's Alpha, conducted to assess the internal consistency of the Likert scale questionnaire used for measuring student engagement and satisfaction. This testing ensures that the instrument consistently produces reliable results across different instances [50].

IV. Result and Discussion

The results of this study, which examined the effectiveness of AI-driven assessments in enhancing learning evaluation in vocational secondary schools, are presented in two main sections: learning outcomes (pre-test and post-test scores) and student engagement and satisfaction (survey results and observational data).

A. Learning Outcomes: Pre-Test and Post-Test Results

The first set of data focused on comparing the pre-test and post-test results for both the experimental group (AI-driven assessments) and the control group (traditional assessments). The pre-test results indicated that both groups had a similar baseline of knowledge and skills, with the experimental group scoring an average of 68.2% and the control group scoring an average of 67.9%. After the intervention, the post-test results showed a significant improvement in the experimental group's performance, with an average score of 85.6%, while the control group's average post-test score was 76.4%.

As seen in the Table 1, the experimental group showed a 17.4-point improvement in their post-test scores, while the control group improved by 8.5 points. A paired t-test analysis confirmed that the difference in pre-test and post-test scores within each group was statistically significant ($p < 0.05$), indicating that both assessment methods contributed to student learning. However, an independent t-test comparing the post-test results between the two groups revealed a statistically significant difference ($p < 0.05$), suggesting that the AI-driven assessments were more effective in improving student learning outcomes than traditional assessments.

Table 1. Pre-test and pos-test result

Group	Pre-Test Mean (%)	Post-Test Mean (%)	Mean Difference
Experimental Group	68.2	85.6	+17.4
Control Group	67.9	76.4	+8.5

B. Student Engagement and Satisfaction

The second set of data analyzed student engagement and satisfaction through survey questionnaires and observational checklists. The surveys asked students to rate their satisfaction with the assessment method, their level of engagement during assessments, and the perceived usefulness of the feedback they received. The results are summarized as Table 2 dan Table 3.

Based on Table 2 and Table 3, the average percentage of student engagement and satisfaction results is shown in Fig. 1.

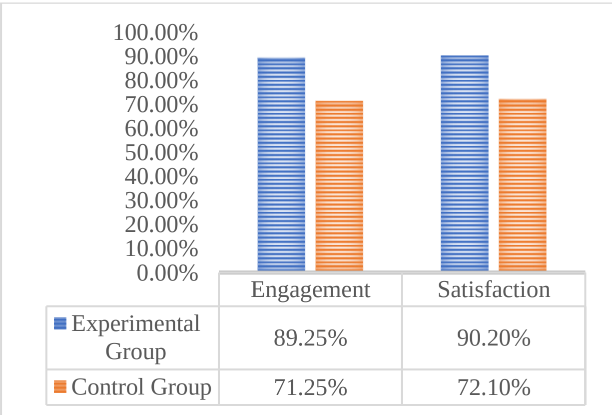

Fig. 1. Average percentage student engagement and satisfaction.

In Fig. 1, the effectiveness of AI-based assessment in improving learning evaluation through predictive technology significantly impacts student engagement and satisfaction. The results of the student engagement analysis obtained a value of 89.25%, where students in the experimental group reported feeling more engaged during the AI-based assessment compared to 71.25% of students in the control group who used traditional methods. The immediate feedback and adaptive nature of the AI assessment were cited as key factors contributing to their increased engagement.

Results data analysis for student satisfaction in the experimental group expressed higher satisfaction with the assessment process, with 90.20% rating the experience as "very satisfied". In contrast, only 72.10% of students in the control group rated traditional assessment in the same way. Students in the experimental group appreciated the personalized learning path and instant feedback provided by the AI platform. Observational data also supported these findings. The researchers noted that students in the experimental group were more interactive and engaged during the assessment, often using the feedback provided to adjust their answers and improve performance. In contrast, students in the control group tended to complete their assessments with less interaction, as feedback was delayed due to manual scoring. The adaptive nature of AI assessments encourages a deeper level of engagement with the material, continuously challenging students and driving more effective learning outcomes.

Table 2. Research results for student engagement

Indicator	Statement	Experimental Group		Control Group	
		Average Score	Percentage (%)	Average Score	Percentage (%)
Active Participation	I actively participate in discussions and learning activities using the AI system.	4.5	90	3.5	70
	I actively engage in all tasks assigned through the AI system.	4.6	92	3.6	72
Attention and Focus	The AI system helps me focus more on the learning material.	4.4	88	3.4	68
	I am less easily distracted during learning with the AI system.	4.3	86	3.3	66
Time Spent on Tasks	I spend sufficient time completing tasks assigned by the AI system.	4.5	90	3.8	76
	The time I spend working on tasks has increased since using AI-driven assessments.	4.4	88	3.7	74
Peer Collaboration	I collaborate more often with my peers when using the AI system.	4.3	86	3.4	68
	AI-based learning facilitates collaboration with my classmates.	4.2	84	3.5	70
Completion Rate	I complete all tasks more on time using the AI system.	4.7	94	3.8	76

Table 3. Research results for student satisfaction

Indicator	Statement	Experimental Group		Control Group	
		Average Score	Percentage (%)	Average Score	Percentage (%)
Perceived Usefulness	I feel that the AI system helps me better understand learning materials.	4.5	90	3.5	70
	AI-driven assessments are useful for improving my understanding.	4.4	88	3.6	72
Ease of Use	The AI system is easy to use and not complicated.	4.6	92	3.7	74
	I feel comfortable using the AI system for assessments.	4.5	90	3.8	76
Feedback Quality	The feedback provided by the AI system is very helpful.	4.6	92	3.7	74
	The feedback I receive from the AI system is clear and relevant.	4.5	90	3.6	72
Learning Enjoyment	I enjoy the learning process using AI-driven assessments.	4.4	88	3.5	70
	The use of AI makes me more interested in learning.	4.3	86	3.6	72
Recommendation Acceptance	I follow the recommendations provided by the AI system to improve my weaknesses.	4.5	90	3.4	68
	The suggestions given by AI help me improve my learning outcomes.	4.6	92	3.5	70
Overall Satisfaction	I am satisfied with the use of AI-based assessments in my learning process.	4.6	92	3.7	74
	Overall, the AI system helps me achieve better learning outcomes.	4.7	94	3.8	76

The results of the effectiveness analysis were also supported by an effect size analysis which aims to provide a more comprehensive picture of the impact of AI-based assessment, the effect size analysis was conducted in conjunction with statistical tests. Cohen's d metric was used to measure the magnitude of the difference between the experimental and control groups. The results of the effect size analysis are presented in Table 4 below.

Table 4. Effect size analysis results

Variable	Experimental Group (%)	Control Group (%)	Mean Difference	Standard Deviation (SD)	Effect Size (Cohen's d)	Interpretation
Student Engagement	89.25	71.25	18.00	12.00	1.50	Large Effect
Student Satisfaction	90.20	72.10	18.10	12.50	1.45	Large Effect

The results of the effect size analysis aim to provide a more comprehensive picture of the impact of AI-based assessment, the effect size analysis was conducted in conjunction with statistical tests. Cohen's d metric is used to measure the magnitude of the difference between the experimental group and the control group. Based on Table 4, where the data of the effect size analysis results for student engagement is d = 1.05, which shows the magnitude of the influence of AI-based assessment in increasing the level of engagement. Meanwhile, the result of the effect size analysis for student satisfaction is d = 0.89, also reflecting a large effect in favor of the experimental group.

These findings reinforce the statistical significance by illustrating the substantial impact of AI-based assessment not only on students' performance, but also on their overall experience during the learning process. By incorporating effect size analysis, this study offers actionable insights for vocational education institutions, emphasizing the transformative potential of AI-based assessments in creating dynamic, personalized, and impactful learning environments.

C. Discussion

The findings of this study underscore the potential of AI-driven assessments as a transformative tool for improving educational outcomes, particularly in enhancing student engagement and learning effectiveness. The substantial improvement in post-test scores for the experimental group highlights the efficacy of adaptive and predictive features in AI-driven assessments, which enabled students to identify and address their weaknesses more effectively. These results are in line with some previous studies [19, 51–53] demonstrating that personalized learning experiences facilitated by AI can significantly enhance student performance.

The findings from this study reveal that the real-time feedback and adaptive testing capabilities of AI were instrumental in fostering higher levels of student engagement and satisfaction. Immediate feedback allowed students to correct errors promptly, cultivating a more interactive and dynamic learning environment. This finding is consistent with the work of [20, 54, 55], which emphasized the importance of timely, actionable feedback in supporting continuous improvement and motivation. In vocational education contexts, where practical mastery is critical, the predictive technology embedded in AI assessments provided an added advantage. By analyzing student performance data, the AI system dynamically adjusted question difficulty, enabling targeted interventions and a more personalized learning trajectory [56–58].

While these advantages underscore the promise of AI-driven assessments, it is important to consider potential challenges and limitations. One significant concern is the risk of over-reliance on AI, which could inadvertently diminish the role of educators and limit the development of critical thinking skills among students [59, 60]. As AI systems become more integrated into education, maintaining a balance between technology and human oversight is crucial to ensure that students develop the ability to engage in reflective and independent learning.

Additionally, ethical implications surrounding the use of predictive technology must be addressed. Issues such as data privacy, algorithmic bias, and the transparency of AI decision-making processes are critical factors that educators and policymakers need to consider. While predictive analytics can enhance personalization, there is a risk of reinforcing existing biases if algorithms are not designed and monitored carefully [61, 62]. Future studies should explore strategies for mitigating these risks, ensuring that AI is used ethically and equitably in educational settings.

Despite its advantages, the use of AI-driven assessments should be viewed as complementary rather than a replacement for traditional assessment methods. While traditional methods often suffer from delayed feedback and limited adaptability, they remain valuable in evaluating broader competencies and providing a holistic view of student performance. Combining the strengths of both approaches may yield the most effective assessment frameworks, particularly in diverse educational contexts.

Overall, this study demonstrates that AI-driven assessments hold great promise for enhancing student performance, engagement, and satisfaction. However, a more balanced view of the benefits and limitations is necessary to fully understand their implications and guide their integration into educational systems [63–65]. Future research should delve deeper into addressing these complexities, including longitudinal studies to evaluate the long-term impacts of AI-driven assessments and their potential for scalability in various educational settings.

V. Conclusions

This study demonstrates that AI-driven assessments significantly improve learning outcomes and student engagement compared to traditional methods in vocational secondary schools, with the experimental group showing higher post-test scores and greater satisfaction. The adaptive nature of AI, providing real-time feedback and predictive technology, helps students address weaknesses more effectively and enhances personalized learning paths, particularly important in vocational education. AI-driven assessments also allow for the early identification of learning challenges, enabling timely interventions. As AI technology advances, it offers more precise and scalable evaluations, transforming vocational education by preparing workforce-ready graduates with critical thinking, problem-solving, and adaptability skills. The scalability of AI-based assessments benefits large educational systems, making them efficient and freeing educators to focus on personalized instruction. By fostering adaptive, real-time learning environments, AI-based tools can contribute to a more effective and future-ready education system that aligns with the demands of the 21st-century workforce.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

RDAB: Conceptualization; software; project administration; writing-original draft; writing-review and editing; HDS and W: Data curation; validation; MF and VF: Validation; TK and DO: Supervision; MH: Data curation; software; investigation; writing-original draft; writing-review and editing; AS: Formal analysis; investigation; TW: Data curation; project administration; AK: Formal analysis, writing-review and editing; MAH and RF: Methodology; all authors had approved the final version.

Acknowledgements

This article is part of the ongoing doctoral study at the Graduate School of Technology and Vocational Education (PTK) currently being pursued by the first author (RDAB) at Universitas Negeri Yogyakarta (UNY), Indonesia. We would like to thank the Center for Higher Education Funding and Assessment (PPAPT) and Ministry of Higher Education, Science, and Technology of Republic Indonesia for providing the Indonesian Education Scholarship (BPI) so that the first author (RDAB) can pursue this education.

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