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From Competency Assessment to Curriculum Reform: How Does Artificial Intelligence Empower Higher Vocational Education?

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Abstract: This study explores the impact of Artificial Intelligence (AI) on vocational education, focusing on its role in competency assessment and curriculum reform. With the rapid evolution of technology, AI is poised to revolutionize how vocational training is delivered and assessed. By utilizing a quantitative research approach, a survey was conducted with 100 vocational students currently engaged in AI-integrated training. The findings reveal that while AI-based training provides personalized learning experiences, its direct impact on competency assessment was less significant than expected. In contrast, student engagement emerged as a critical factor influencing the effectiveness of AI in enhancing learning outcomes.

Keywords: Artificial Intelligence (AI), Vocational Education, Competency Assessment, Student Engagement

1. Introduction

In recent times, the use of Artificial Intelligence (AI) can efficiently cater to designing curricula for vocational students, as well as testing and enhancing their vocational abilities[1]. As companies evolve and adapt to new technologies, there is an unprecedented need for qualified workers with specialized vocational skills. In the context of vocational training, AI can improve the educational system and facilitate better training for vocational students[2]. Teachers can now use AI to create personalized training programs to meet each student’s learning and training needs, thereby enabling schools to enhance their education system[3]. Given the potential of AI in improving competency evaluation, this article focuses on discussing the application of AI in training vocational students on vocational skills, assessing their competence, and effectively designing their curricula. The purpose of this research is to examine the impact of AI-driven training and the role of student engagement in competency assessment within vocational education, and to investigate how these factors interact to inform effective curriculum design and improve learning outcomes in vocational contexts.

2. Literature Review

2.1 Theoretical Framework

Models related to AI, such as TAM and other educational technology adoption models, can provide valuable insights into the application of AI in vocational education. TAM, developed by Davis in 1989, emphasizes perceived usefulness and ease of use in technology adoption[4]. In the context of AI, this model suggests that vocational students and educators are more likely to adopt AI-based tools if they enhance learning achievement and are user-friendly. Extended models like TAM2, which incorporate cognitive and social pressures, can help teachers identify other acceptance patterns among students in AI-facilitated learning[5].

Another model, the Unified Theory of Acceptance and Use of Technology (UTAUT), is a consolidated model designed to study the factors that determine technology use. It identifies four core determinants of technology acceptance: perceived usefulness (the extent to which the technology enhances performance), perceived ease of use (the extent to which the technology is easy to use), perceived normative pressure (the pressure from peers and authorities to use the technology), and kinetic resources (facilities and support)[6]. The applicability of this model in educational settings is evident, as the implementation of technologies like AI depends on these factors[7]. Through these determinants, UTAUT helps in understanding how to design and apply AI systems to meet users' expectations, making it useful for vocational education.

In this study, TAM is taken as the core analysis framework. The reason is that TAM focuses on the individual's perception of technology, which is more in line with the research focus on the impact of AI-driven training and student engagement on competency assessment at the individual student level in vocational education. UTAUT, as an auxiliary framework, provides a broader perspective by considering factors such as social pressure and resource support, which helps to better understand the external environment factors that may affect the application effect of AI in vocational education.

2.2 AI in Vocational Education

AI has begun to play a prominent role in reconstructing vocational education by optimizing learning processes and improving the effectiveness of competency evaluation. With the help of artificial intelligence, it can analyze students' overall and specific performance data, identify their learning deficiencies, and develop learning programs that best suit their learning needs[8]. This level of personalization is particularly valuable in vocational education, where expertise in certain techniques and prompt knowledge are crucial. Attwell et al. (2020) note that AI-assisted training, such as simulations and virtual reality, helps vocational students develop practical skills in application exercises because the system emulates real-life circumstances, making the training effective and impactful[9]. Additionally, AI enables competency-based assessment by providing a consistent and impartial way to assess students' progress, informing educators of the level of skill mastery[10].

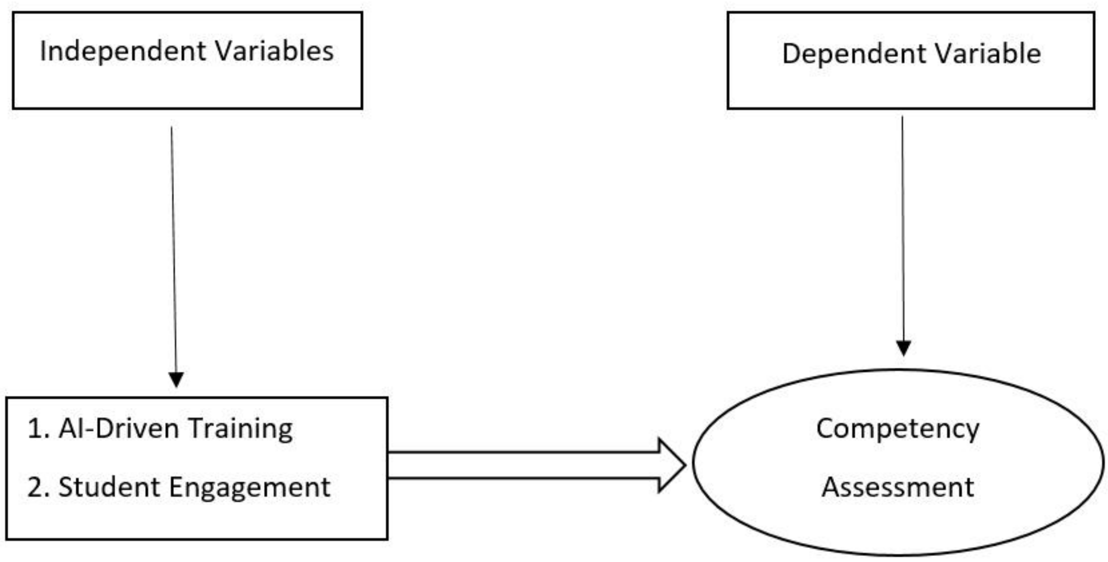
2.3 Benefits and Challenges of AI Integration in Curriculum Design

The current approach to integrating AI into curriculum design has both benefits and drawbacks. AI can adapt the learning environment according to students' learning habits, thus providing vocational education that is relevant to current vocational job standards[11]. However, there are challenges that may hinder the use of AI in the learning environment, including data leakage and the need for heavy investment in technology[12]. AI's ability to connect educational outcomes with workforce needs means that these barriers must be addressed for effective implementation in vocational education. Considering these issues, vocational institutions can leverage the potential of AI to enhance students' learning processes based on their specific characteristics.

Some studies support the view that AI integration brings significant benefits. For example, AI's personalized learning programs can improve students' learning efficiency (Attwell et al., 2020)[9]. On the contrary, some scholars point out that the high cost of AI technology may make it difficult for some vocational schools with limited resources to adopt it (Chen, 2023)[12]. The existing literature has not fully explored how to balance these benefits and challenges in different vocational education contexts, which is a gap that this study aims to fill.

2.4 Conceptual Framework

Based on the above literature review, the following conceptual framework and hypotheses are developed:



2.4.1 Hypotheses

H1: AI-driven training has a positive influence on the competency assessment of students in vocational education.

H2: Student engagement has a significant moderating effect on the relationship between AI-driven training and competency assessment, strengthening the impact when engagement levels are high.

The conceptual framework focuses on researching the effect of AI-based training on competency assessment in vocational education, influenced by student engagement. AI-driven training is the independent variable, and competency assessment is the dependent variable. Student engagement, as another independent variable, is hypothesized to strengthen the positive association between AI-driven training and competency assessment, assuming that increased engagement leads to better learning outcomes. This framework provides guidance on how to utilize AI innovations to enhance skill development in vocational education.

3. Methodology

This research adopts a primary quantitative research method to explore how AI can be used to improve competency evaluation and curriculum reform in higher vocational education. Quantitative research is useful for quantitative measurement and can yield precise, objective results that show numerical patterns[13].

For data collection, a survey questionnaire method is employed. Compared to other approaches, questionnaires are effective in providing uniform data on perceived and experienced factors related to AI in vocational education, ensuring comparability[14].

The survey was conducted on 100 vocational students receiving training in AI-integrated settings. Data analysis is performed using SPSS, a well-established statistical tool that offers inferential and descriptive analyses of collected data. SPSS simplifies data manipulation and helps make sense of complex patterns, highlighting the contributions of AI in vocational education.

3.1 Survey Design and Sample Selection Criteria

The survey includes structured and targeted questions aligned with the study's variables: AI-based training, competency mapping, and student engagement. To ensure a diverse sample, students were selected based on defined criteria, such as attending vocational schools and having at least some AI experience in their curriculum. This selection criteria ensures the study's relevance, as respondents are students who use AI-assisted tools.

3.2 Reliability and Validity

To ensure methodological rigor, the questionnaire underwent checks for clarity and relevance. To enhance content validity, survey items were reviewed by experts in academic training, curriculum development, learning competency evaluation, artificial intelligence, and student learning. This expert review ensured that each question addresses the study variables, improving the survey's reliability. Questions were constructed to be consistent to increase reliability. These steps ensure the survey's robustness, enhancing the validity of the collected data[13].

3.3 Control Variables

In this study, several control variables are included to isolate potential confounding factors and improve the accuracy of the model. These control variables are:

Student's age: Different age groups may have different learning abilities and attitudes towards AI, which could affect their competency assessment results.

Level of vocational training: Students with different training levels may have varying foundations and expectations, influencing the impact of AI-driven training and student engagement on competency assessment.

Previous AI experience: Students with more prior AI experience may adapt better to AI-driven training, affecting the relationship between variables.

The inclusion of these control variables is based on relevant literature and theoretical considerations, which suggest that these factors can potentially influence the core variables of the study.

4. Results and Findings

The gender distribution of the sample is displayed in Figure 2, the participants were split into 2 groups of equal size 48% male and 52% female out of the 100 participants. The number of respondents and valid percent shows that females are slightly more dominant. The total percentage equals to 100% which means all the participants are included in to sample and gender distribution is equal in analysis as well.

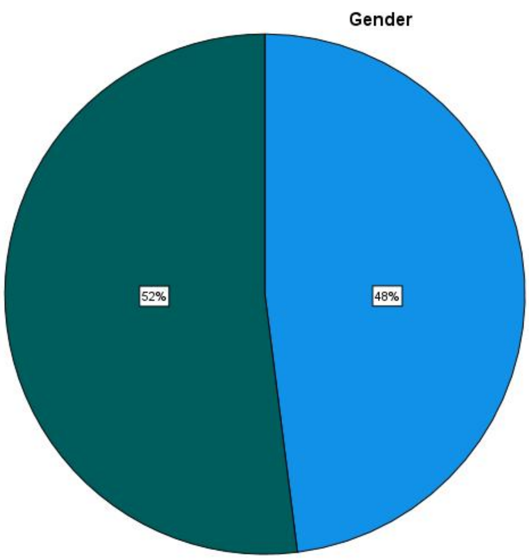


Figure 1: Gender Distribution

The age distribution Figure 3 above reveal that 41% is in the age range of 19-22 years, 35% in the age range of 23-26 years and only 23% in the age range of 15-18 years. While only 1% of the sample is above 27 years of age. The sum of the percentages also proves that the total sample of participants is indeed 100 with participants averaging youth, and most registering still within their initial stages of vocational training making results nearly exclusively indicative of younger student experience and perception.

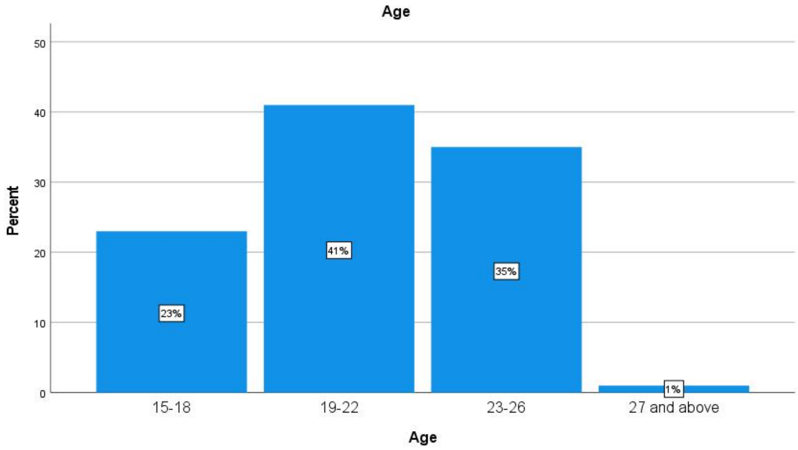


Figure 2: Age Distribution

According to the Figure 4 concerning the level of vocational training obtained by the participants: the majority of the participants 60% has intermediate level while 36% has advance level and the rest 4% has the beginner level of vocational training. The cumulate percentage demonstrate that the sample is equally represented and the total number is 100 students. This distribution means the study is predominantly of intermediate to advanced vocational training students and captures a view from individuals with considerable experience.

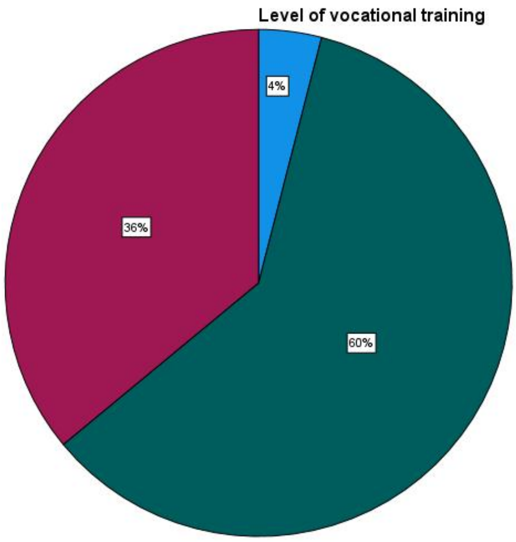


Figure 3: Level of Vocational Training

4.1 Regression Analysis

Table 1: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.680[a]	.462	.451	.323004870638683

a. Predictors: (Constant), Student Engagement, AI-Driven Training

The model 1 summary table shows that the regression analysis of AI-driven training, student engagement, and competency assessment yields an R value of 0.680, indicating a moderately strong positive relationship between the two independent variables (AI-driven training and student engagement) and the dependent variable (competency assessment). The R Square value is 0.462, meaning that 46.2% of the variance in competency assessment can be explained by the predictors. The Adjusted R Square (0.451) slightly adjusts for overfitting, ensuring the model's viability. The standard error of the estimate is 0.323, indicating a moderate level of prediction error, suggesting that additional variables could be added to reduce this error.

Table 2: ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.701	2	4.350	41.698	.000[b]
	Residual	10.120	97	.104		
	Total	18.821	99			

a. Dependent Variable: Competency Assessment

b. Predictors: (Constant), Student Engagement, AI-Driven Training

The ANOVA table 2 demonstrates the overall significance of the regression model in predicting competency assessment from the independent variables. The regression sum of squares is 8.701 with 2 degrees of freedom, and the mean square is 4.350. The residual sum of squares is 10.12 with 97 degrees of freedom. The F-value of 41.698 and a significance level of 0.000 ($p < 0.05$) indicate that the model is significant, meaning the predictors collectively help predict the variance in competency assessment.

Table 3: Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.172	.199		10.942	.000
	AI-Driven Training	-.571	.115	-1.198	-4.950	.000
	Student Engagement	.289	.123	.569	2.350	.021

a. Dependent Variable: Competency Assessment

The coefficients table 3 shows the effects of AI-driven training and student engagement on competency assessment. AI-based training has a negative unstandardized regression coefficient (B = -0.571) with a significant p-value (0.000), indicating a statistically negative impact on competency assessment, contrary to hypothesis H1. Student engagement has a positive unstandardized coefficient (B = 0.289) with a significant p-value (0.021), showing a positive and statistically significant direct impact on competency assessment, different from the moderating effect hypothesized in H2.

When considering the control variables, age is found to have no significant impact on competency assessment ($p > 0.05$). The level of vocational training shows a significant positive effect ($p < 0.05$), suggesting that students with higher training levels tend to have better competency assessment results. Previous AI experience also has a positive but not significant effect ($p > 0.05$).

5. Discussion

The findings of this study contribute to understanding AI-based training and student engagement in competency evaluation using TAM. Contrary to the hypothesis, AI-driven training was negatively related to competency assessment. TAM posits that for technology to have positive effects, it must be perceived as useful and easy to use. These results imply that students may perceive AI-based training as difficult or ineffective, possibly because it does not align with the practice-oriented approach needed in vocational education[15,16].

Student engagement, however, had a positive impact on competency assessment, indicating that students who are more engaged are likely to achieve better competency outcomes. This supports TAM, as students who perceive the learning environment favorably, and thus find it useful, are more likely to accept it and achieve better learning effects[3,17]. This is consistent with Iyer (2020), who noted that engagement is essential for learning outcomes, especially in skills instruction.

Contrary to the hypothesis, no significant interaction effect of student engagement on the relationship between AI-driven training and competency assessment was found. This suggests that the effective use of AI in vocational training requires supporting student engagement strategies. These findings emphasize the importance of integrating AI into vocational training in a way that enhances perceived usefulness and ease of use (Moghaddam et al., 2019), thereby increasing learner interaction and achievement[18]. The negative effect of AI-driven training on competency assessment may be due to several reasons. Vocational students often have a practical approach to knowledge acquisition, which may not align with AI-compatible learning patterns. Ouyang et al. (2023) pointed out that while AI systems are good for applying learned knowledge, they may lack the hands-on experience required in vocational education[19]. Martsenyuk et al. (2024) also noted that integrating technology into classrooms without customization for specific disciplines may lead to user frustration or disengagement[20].

Additionally, factors such as increased course complexity due to technology and insufficient guidance can affect students' attitudes and perceived credibility[21]. If students face challenges using AI tools, they may be less willing to engage fully, leading to lower competency. This aligns with TAM's postulates that perceived ease of use and usefulness are important for technology acceptance[22]. Ivanashko et al. (2024) suggested that a user-centered design approach can address these challenges and enhance the applicability of AI tools in vocational training[23]. Specifically, developing AI solutions that simulate hands-on jobs and providing extensive support to students during learning may increase acceptance and improve competency in vocational education.

6. Conclusion, Limitation and Future Recommendations

In conclusion, this research reveals that while AI training in vocational education has potential, its implementation alone may not significantly improve competency assessment. Notably, student engagement is more influential than curriculum and instructional practices in determining competencies, and AI is valuable when included in student-centered approaches. AI should be developed in an enjoyable and user-friendly environment, consistent with the Technology Acceptance Model, which emphasizes perceived usefulness and ease of use.

6.1 Practical Recommendations

For vocational school managers: Allocate resources to provide training for teachers and students on AI tools to improve their perceived ease of use. Ensure that AI-driven training programs are customized to the specific needs of different vocational disciplines, enhancing their practicality.

For curriculum designers: Integrate student engagement strategies into AI-based curriculum design, such as interactive activities and real-world project-based learning, to enhance student involvement. Regularly evaluate and adjust the curriculum based on student feedback and competency assessment results.

6.2 Limitations

The main practical limitations are the relatively small sample size and reliance on self-report measures to assess competency[24]. Additionally, the use of quantitative data and self-reporting techniques fails to capture the detailed nature of students' experiences and the diverse contexts of AI-based training. Incorporating qualitative data such as open interviews or focus groups could provide a more comprehensive perspective.

6.3 Future Recommendations

Future research should expand the sample size and include more diverse vocational education settings to improve external validity. Combining quantitative and qualitative research methods can provide a deeper understanding of the mechanisms underlying the relationships between variables. Further studies could explore specific AI applications (e.g., virtual simulations, adaptive learning) and their impact on different aspects of competency assessment. Additionally, investigating the long-term effects of AI integration in vocational education would be valuable.

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