Woody International Publish Limited
An Multidisciplinary Academic Journal Publisher

Journal of Theory and Practice in Education and Innovation, Volume 2, Issue 4, 2025
https://www.woodyinternational.com/

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.

Cited as: Wang, S., & Xu, M. From Competency Assessment to Curriculum Reform: How Does Artificial Intelligence Empower Higher Vocational Education?. *Journal of Theory and Practice in Education and Innovation*, *2*(4), 1–8. Retrieved from https://woodyinternational.com/index.php/jtpei/article/view/256

1. Introduction

Designing curricula for high school students as well as testing and enhancing their vocational abilities in recent times can be catered to efficiently by the use of Artificial Intelligence. (AI) (Nguyen et al., 2023). There is a greater need than ever for qualified workers with specialised vocational skills as companies change and adapt to new technologies, as these AI-learned teachers can improve the educational system and help train high school students better in the context of vocational training (Dahri et al., 2024). In order to satisfy each student's training and learning needs, teachers can now use AI to create personalised training programmes, and thus, schools can improve their education system (Liu and Baucham 2023). Considering the potential of AI to improve competency evaluation, this article will significantly discuss the use of AI to train high school students on vocational skills, assess their competence, and design their curricula effectively. The purpose of this research is to examine the AI-driven training impact and role of student engagement on competency assessment within vocational education, investigating how such factors interact to inform effective curriculum design and improve learning outcomes in vocational contexts.

2. Literature Review

2.1 Theoretical Framework

TAM and other educational technology adoption models that are linked to AI will give better insights on the subject of AI in vocational education. TAM which was developed by Davis in 1989, insists in perceived usefulness and ease of use in the usage of technology (Li et al., 2024). Concerning AI, this model implies that vocational students and educators will more likely adopt the AI-based tools if they improve the learning achievement and are available. However, extended models like TAM2 include cognitive and social pressures, which can be useful to the teachers to recognise other acceptance patterns among the students in learning facilitated by AI technology (Otto et al., 2024).

Another model, Unified Theory of Acceptance and Use of Technology (UTAUT) model is a consolidated model designed for studying factors that define the use of technology. It identifies four core determinants of technology acceptance: The constructs include perceived usefulness (the extent to which the technology will enhance performance), perceived ease of use (the extent to which the technology is easy to use), perceived normative pressure (the pressure exerted by peers and authorities on the use of the technology), and kinetic resources (facilities and support) (Kwak et al., 2022). Thus, the applicability of this model is apparent in educational settings, as the degree of technological implementation like, AI depends on these factors (Strzelecki, 2024). Through these determinants, UTAUT provides understanding of how to design and apply AI systems to meet users' expectation which renders it useful for vocational education.

2.2 AI in Vocational Education

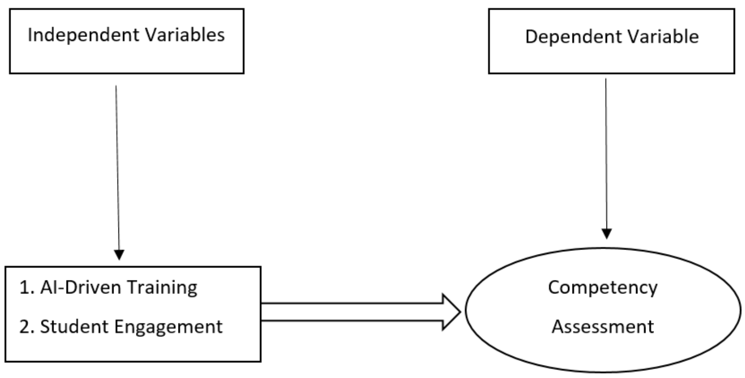
AI has started to have a prominent role to play in the reconstruction of vocational education by optimizing the learning processes and increasing the effectiveness of competency evaluation. With the help of artificial intelligence, gross and specific data of students' performance can be analysed and learning programs can be developed that are best suitable for their learning needs by identifying their learning deficiencies (Bankins et al., 2024). This level of personalisation is especially valuable in the area of vocational education in which expertise in certain techniques alongside prompt knowledge is crucial. Attwell et al. (2020) note that AI-assisted training such as simulations and virtual reality help vocational students to develop practical skills in application exercises since the system emulates real-life circumstances hence effective and impactful. Besides, AI makes competency based assessment possible by providing a constant and impartial way of assessing the progress of a student in order to inform the educators of the level of mastery of skills by the student (Wang et al., 2021).

2.3 Benefits and Challenges of AI Integration in Curriculum Design

The current approach of adopting the integration of AI in curriculum design has it benefits and drawbacks. Thus, AI can adapt the learning setting in accordance to the students' learning habits, and hence provide vocational education that are relevant to the current standards of vocational jobs (Clarke and Braun, 2017). Though there are some challenges which may hinder the use of AI in learning environment, including data leakage and the need to invest heavily in technology (Chen, 2023). AI's ability to help find a connection between educational outcomes and workforce needs means that these barriers have to be addressed in order for AI to be effectively implemented in vocational education. Considering these issues, incumbent vocational institutions can implement the potential of AI to enhance students' learning process based on their peculiarities.

2.4 Conceptual Framework

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



2.4.1 Hypotheses

H1: AI-driven training influence positively on the competency assessment of students within vocational education.

H2: Student engagement has a significant relationship among AI-driven training and competency assessment, reinforcing the impact when the levels of engagement are high.

The conceptual diagram is designed to focus on the research of the effect of AI-based training on competency appraisal in the vocation education context, impacted by students' engagement. AI-driven training as the independent variable used on the dependent variable; competency assessment. Student engagement, as a second independent variable, is postulated to strengthen the positive association between AI in delivering training and competency assessments, provided that increased engagement makes for better learning. This framework will give some direction as to how it is possible to utilise AI innovations and improve skill enhancement in vocation education.

3. Methodology

The current research utilizes a primary quantitative research method to establish how AI can be used to improve competency evaluation and the modification of curriculum in higher vocational education. Therefore, quantitative research is useful in making quantitative measurement and has precision for yielding objective results that show numerical patterns (Fryer et al., 2018).

In terms of data collection, the survey questionnaire method is going to be used. Questionnaires are also effective in providing uniform data on other perceived and experienced factors pertaining to AI in vocational education in comparison to other approaches, hence ensure comparability (Moraga et al., 2020). The survey was conducted on 100 vocational students who are receiving training in AI- integrated settings.

Data analysis shall be done by the use of SPSS, which is a well-established statistical tool that offers inferential and descriptive analyses from data collected. The analysis with the help of SPSS is useful in simplifying data manipulation and in making sense of the complicated patterns asserting the contributions of AI in vocation education.

3.1 Survey Design and Sample Selection Criteria

The survey was designed with both structured and targeted questions that align with the study's variables: Firstly AI-based training, competency mapping and student engagement. In order to achieve the sample that is as diverse as possible, students were selected according to the defined criteria, such as attending vocational schools and having some kind of AI experience at least at the level of their curriculum. This selection criteria makes the study pertinent to the topic as the respondents are students who use AI assisted instruments.

3.2 Reliability and Validity

To maintain methodological rigor, the questionnaire was subjected to crucial check for clarity and relevance. To increase content validity, the survey items were reviewed by experts in the field of academic training, curriculum development, and evaluation of learning competencies, artificial intelligence, and students' learning. This expert review process has ensured that each of the questions addresses the study variables hence enhancing reliability of the survey. To increase reliability, questions were posed constructively to be consistent. Such steps put measure in place to ensure that the survey is stronger and secure thereby improving the validity of the data that is collected (Fryer et al., 2018).

4. Results and Findings

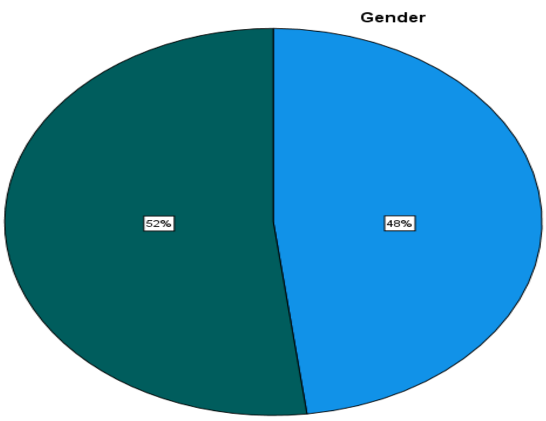


Figure 1: Gender Distribution

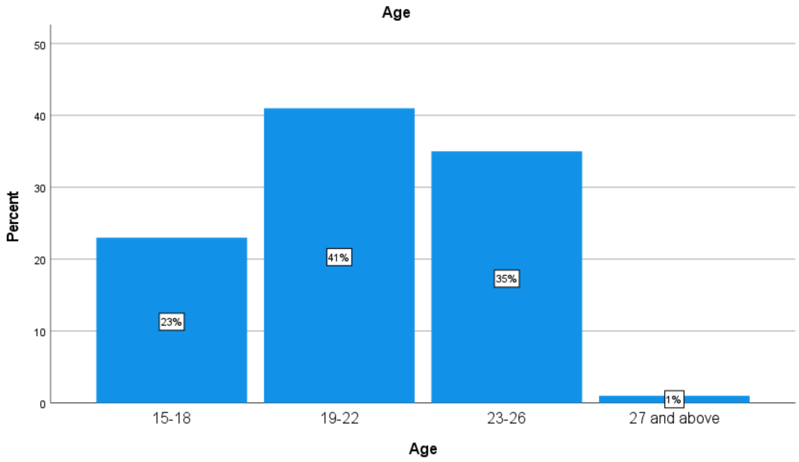


Figure 2: Age Distribution

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.

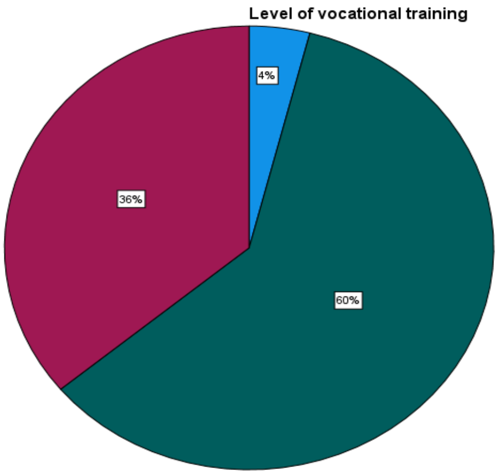


Figure 3: Level of Vocational Training

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.

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.

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 summary table 1 is evidenced by the following: Regression analysis results of AI-driven training, student engagement, and competency assessment. The result shows that the value of R is 0.680, which means that the positive relationship of the two independent variables; AI-driven training and student engagement is moderately strong with the dependent variable; competency assessment. The actual R Square value of the current model stands at 0.462, meaning that 46.2% of variance in independent variable (competency assessment) can be attributed to the said predictors, in terms of the model's explanatory power. The Adjusted R Square (0.451) reduces this slightly of course, providing compensation for overfitting, giving assurance of the model's viability. The standard error of the estimate is equal to 0.323 which means moderate level of prediction error in the chosen model and there is a space to add the variables further to decrease that level of 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 shows the overall significance of the regression model in predicting competency assessment arising from the independent variables. Total regression sum of squares is 8.701 with total df=2, mean square is 4.350, while residual sum of squares is 10.12 with residual df=97. As presented, the F-value of 41.698 and with a significance level of 0.000 means the model indeed has a reasonable significance ($p < 0.05$) which also implies that overall, all the predictors significantly help to predict the variance in competency assessment. This suggests that computer based training and student interaction affect competency assessment results rooted in artificial intelligence.

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 effect of AI-driven training and student level of engagement on their competency assessment.

The coefficient results in table 3 show that the AI-based training has a negative unstandardized regression coefficient estimate (B = -0.571) which is significant p-value with Sig value of 0.000; thus meaning the training had a statistically negative impact on competency assessment. This is noted as contrary to the hypothesis H1 which postulated that AI driven training has a positive relationship with competency assessment.

The analyses further reveal that students' engagement has a positive unstandardised coefficient (B = 0.289), (Sig value of 0.021); thus having a positive and statistically significant impact on competency assessment. In contrast with the H2 hypothesis that positioned student engagement as a moderating variable which strengthens the impact of the AI-driven training on competency assessment, the results reveal that student engagement has a positive direct effect on competency assessment.

5. Discussion

The findings of the present study contribute to a better understanding of the AI-based training and student involvement in competency evaluation with the help of the TAM. The actual training, in this case, facilitated by AI, was negatively related to competency assessment, thereby disputing the hypothesis that AI foster positive impact on competency student outcomes. TAM posits that for technology to help enhance positive results, the technology has to be perceptions and easy to use by the users. These results imply that students may consider AI-based training as difficult or not very effective, at least because it does not correlate enough with the practice-oriented approach to knowledge necessary in vocational education (Hamilton, 2020; Goel et al., 2024).

However, student engagement was found to have a positive impact on competency assessment carrying a message that students who pay attention are likely to learn competencies as intended. In support with TAM, students who perceive the learning environment as favourable probably perceive it as helpful, resulting in higher acceptance and learning effects (Luckin and Holmes, 2016; Liu and Baucham, 2023). This concurs with Iyer (2020) who pointed out that engagement is essential for learning outcomes; particularly where skills instruction is involved.

As it was hypothesised, there would be a significant role of the students' engagement in the AI-facilitated training; however, no such interaction was revealed, so it is argued that the usage of AI yields the best outcomes if supported by student engagement strategies. The replication of these findings highlights the importance of embedding AI into vocational training in a manner that will lead to its perceived usefulness and ease of use Moghaddam et al. (2019) thereby increasing the learners' interaction and achievement.

In light of the emergent negative effect of the AI-trained model in competency assessment, understanding the possibilities of challenges that students experience in using AI-based tools in vocational contexts would be useful. One probability is that vocational students have field practical approaches towards knowledge acquisition and not AI compatible learning patterns. Ouyang et al. (2023), the AI systems is good for applying what has been learned in a program but may not offer the practical hands-on feel required especially when learning in vocational institutions. Martsenyuk et al. (2024), also support the same assertion by suggesting that integration of the technology in classrooms without proper customization to suit for specific discipline may simply result in user's frustration or disengagement.

Moreover, it is noteworthy that factors like technological enhanced course complexity and insufficient guidance can influence the attitude and perceived credibility (Mutambik, 2024). Incompetency does occur if students are less eager to interact fully because they face challenges while using a range of AI tools. This is in consonance with TAM's postulates that perceived ease of use and perceived usefulness are two important variables to influence the acceptance and efficiency of technology among the targeted population (Strielkowski et al., 2024). According to Ivanashko et al. (2024) implementing the user-centred design approach, challenges observed today can be overcome, and applicability of AI tools to vocational training enhanced. Precisely delivering AI solutions to realize hand-on jobs and incorporating extensive support for students while learning may increase the reception and competency for vocational education.

6. Conclusion, Limitation and Future Recommendations

In conclusion, this research revealed that the application of the AI training in the vocational education is promising, at least where and when the, competency assessment is concerned, the AI implementation alone may not yield significant advantage. Notably, student engagement is more influential than curriculum and instructional practices in determining competencies while AI, if included in student-centred approaches is valuable. AI is ought to be generated within a context of an enjoyable, understandable user environment compatible with the Technology Acceptance Model that highlights perceived usefulness and ease of use.

The major practical limitation is a relatively small sample size and the necessity to rely on self-report measures to assess competency (Ruggiano and Perry, 2019). Furthermore, this research has some limitations potential to the use of quantitative data and self-reporting techniques among the respondents; thereby failing to cover up the detailed character of the experiences of the students and the diverse contexts of the AI-based training. Adding qualitative data like open interviews or focus groups might have given all-embracing perception and views among students using AI instruments alongside its barriers and advantages in vocational environments.

Also, the study involved a single education setting, which might not capture the various vocational settings. The current study should be expanded by including a larger and more heterogeneous number of samples across various vocational areas to increase external validity. The analysis of particular applications of AI methods, for example, virtual simulations or adaptive learning could provide more detailed information about the possible improvements regarding the use of AI in vocational training (Nguyen et al., 2023; Suparyati et al., 2023). Moreover, the use of leisure time and student engagement data collected from both quantitative and qualitative methods might give a comprehensive view of interest and feelings levels of the students. Finally, the framework of the implementation of AI has to incorporate it into an environment that provides models of competence development which are student-centred.

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