JURNAL UPI
Journal of Mechanical Engineering Education
(JURNAL PENDIDIKAN TEKNIK MESIN)
Available online at https://ejournal.upi.edu/index.php/jmee
(e.ISSN: 2715-4734, p.ISSN: 2356-4997)

DEVELOPING AN EVALUATION INSTRUMENT BASED ON THE TECHNOLOGY ACCEPTANCE MODEL FOR TEACHERS' ARTIFICIAL INTELLIGENCE READINESS

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ABTRACT/ABSTRAK

In Indonesia, only 48% of vocational teachers demonstrate limited readiness to integrate Artificial Intelligence into learning. Addressing this issue requires a reliable instrument to evaluate prospective teachers' preparedness. This study developed and validated an instrument based on the Technology Acceptance Model to assess the digital competencies of Mechanical Engineering pre-service teachers in Indonesian vocational education. The research quantitatively evaluated four constructs: Perceived Usefulness, Perceived Ease of Use, Behavioral Intention, and Self-Efficacy. Involving 100 respondents from a community service program, the development followed three stages: preparation, expert content validation using Aiken's V, and construct validation via Exploratory Factor Analysis. Results confirmed unidimensional structures for all constructs. Perceived Usefulness and Perceived Ease of Use showed strong validity with high eigenvalues (4.984 and 5.063) and explained variance (49.8% and 50.6%). The Kaiser-Meyer-Olkin measure confirmed sampling adequacy (0.833–0.909). Aiken's V analysis indicated high content (0.83), construct (0.81), and linguistic validity (0.85). Key findings highlight deficiencies in Artificial Intelligence tool proficiency, emphasizing the need for curriculum alignment with Industry 4.0 demands. This study provides a validated tool to guide teacher training and policy, effectively addressing the digital divide in vocational education and bridging a critical gap between theory and practice.

ARTICLE INFO

Article History:

Submitted/Received
07 August 2025

First Revised
11 September 2025

Accepted
01 October 2025

Online Date
09 October 2025

Publication Date
01 December 2025

Keywords:

Instrument; Technology Acceptance Model (TAM); Exploratory Factor Analysis (EFA).

1. PENDAHULUAN

Vocational education in the field of Mechanical Engineering is currently encountering significant challenges in integrating technology into the learning process. One of the main issues is the readiness of the teaching staff. A report by the United Nations Development Programme (UNDP, 2023) highlights that in developing countries, including Indonesia, the use of technology by educators remains suboptimal due to limited infrastructure, insufficient training, and low levels of digital literacy.

This challenge becomes even more complex when observing the readiness level of prospective vocational teachers in Mechanical Engineering, which remains suboptimal in mastering or applying technology in the process of teaching and learning (Hartono et al., 2021). However, the vocational education curriculum has been directed to align with the demands of the Industrial Revolution 4.0 (World Economic Forum, 2020), in reality, many students in the Mechanical Engineering Education program still lack adequate digital skills, whether in mastering engineering software, digital simulations, or the use of technology-based instructional media (Sahputra et al., 2023). This indicates a discrepancy between the ideal competencies that graduates are expected to possess and the actual competencies they acquire during their studies. According to Lase et al. (2022), the limited practical experience of prospective vocational teachers and the inadequate use of technology during lectures along with insufficient supporting facilities on campus, are major factors that hinder the development of these competencies. This situation poses a potential threat to the quality of learning in vocational schools, which require productive teachers who are adaptable to technological advancements.

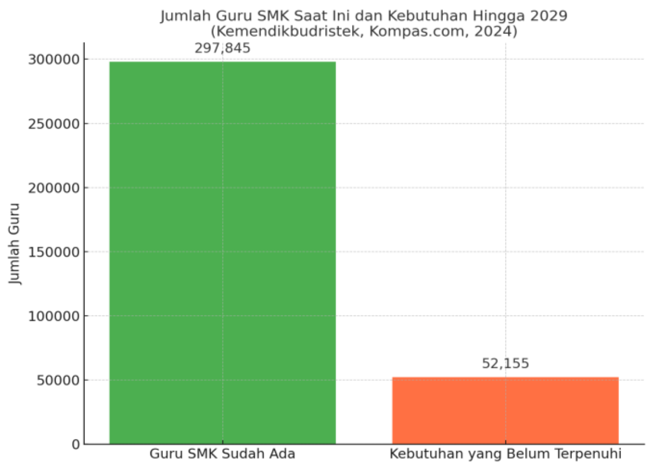

Figure 1. BPS Statistical Data on Vocational High School Teachers in Indonesia and Unmet Demand Quantification

According to data from the Badan Pusat Statistik (BPS, 2024), the current number of vocational high school (SMK) teachers in Indonesia stands at 297,845. Figure 1 reveals a critical deficit of 52,155 teachers against the national requirement. Therefore, an estimated shortage of 52,155 teachers must be resolved in order to support the sustainable advancement of vocational education on a national scale.

However, despite their educational background, many graduates in mechanical engineering education prefer to enter the industrial workforce, driven by the prospect of higher salaries compared to careers in vocational education. A study by Sufa and Yunus (2023) revealed that only about 19% of Mechanical Engineering Education graduates from Universitas Negeri Surabaya pursued careers as teachers, while the majority chose to work in the industrial sector. This situation is further compounded by the low level of student interest in becoming vocational teachers, which is influenced by both internal and external factors.

The Technology Acceptance Model (TAM) is widely utilized in vocational education research to evaluate teachers' perception, perceive and adopt the Technology Acceptance Model to analyze behavioral and actual usage patterns (Huang et al., 2022). Research on Technology Acceptance Model (TAM) confirms that vocational teachers' adoption of educational technology is primarily driven by their perception of its ease of use and perceived usefulness (Sobandi et al., 2022). However, this study is limited to teachers of the Mechanical Engineering expertise program in West Java and has not yet encompassed teachers in the field of Mechanical Engineering. Yuara et al. (2019) investigated the readiness of vocational teachers as a challenge to SMKN 1 West Sumatra, precisely related to the Industrial Revolution 4.0. Results show communication skills, collaborative practices, creative pedagogy, and innovative methods all contribute meaningfully to teaching preparedness. However, this study does not specifically address the integration of learning technologies or employ the Technology Acceptance Model (TAM) framework. Wahyuni et al. (2022), in their literature review, highlight that while technology-based learning demonstrates effectiveness and appeal, many educators still encounter difficulties in utilizing these technologies. Their research emphasizes the need to enhance teachers' competencies in implementing technology-based instruction, though it does not incorporate the TAM framework in its analysis. Similarly, Ambarwati et al. (2023), through community service activities at SMK Bhinneka Karawang, identified that teachers possess low ICT competencies and show reluctance to develop skills related to educational technology usage. Their study aims to strengthen teachers' professional capacity regarding educational technology implementation, yet it does not apply the TAM approach in its evaluation process.

Based on the literature synthesis, it is evident that while numerous studies have examined teachers' readiness in integrating learning technologies, certain gaps remain, particularly among vocational high school teachers specializing in Mechanical Engineering. First, this analytical model, Technology Acceptance Model (TAM) approach has rarely been applied specifically to prospective or in-service mechanical engineering teachers, leaving the influence of factors. These factors include two constructs (Davis, 1989), which identifies perceived usefulness as core determinants of technology adoption and perceived ease of use on their readiness largely unexplored in existing literature. Second, despite adjustments in the Mechanical Engineering Education curriculum to meet Industry 4.0 demands, graduates' digital competencies remain underdeveloped due to inadequate facilities and limited hands-on experience during their studies. Third, the majority of Mechanical Engineering graduates prefer pursuing industrial careers over teaching, resulting in a shortage of qualified instructors in Vocational High Schools with expertise (82%) in technology-integrated education (Paryanto et al., 2022). These findings align with Davis (1989), the Technology Acceptance Model (TAM), which states that users' acceptance of technology is greatly influenced by how easy they perceive the technology to be to use (ease of use) and how useful they perceive it to be (usefulness).

In the context of mechanical engineering vocational education, teachers or teacher candidates who perceive a learning technology as both user-friendly and instructionally beneficial demonstrate higher motivation to adopt it. However, the primary challenge remains enhancing these dual perceptions, given that many mechanical engineering vocational teachers still lack familiarity with digital tools. The primary goal of this study is to develop and design an evaluation instrument grounded in Davis et al. 's (1989) TAM assessment tools.

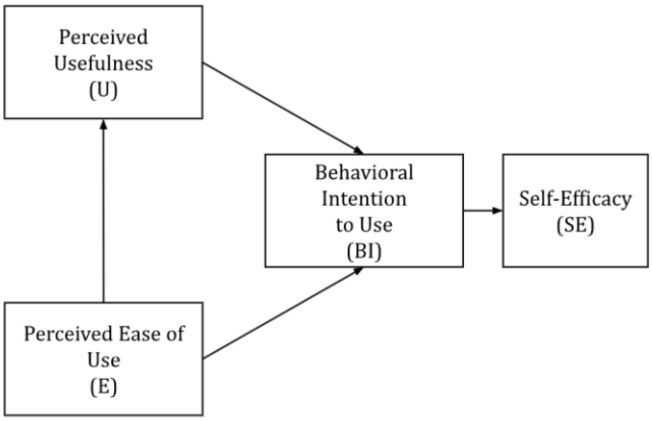

Figure 2. Technology Acceptance Model Davis et al. (1989)

As depicted in Figure 2, the Technology Acceptance Model (TAM) encompasses four fundamental constructs. It's specifically tailored for pre-service teachers in Mechanical Engineering Education programs. The instrument is designed to assess four core constructs of TAM model, which are Perceived Usefulness enhances job performance, Perceived Ease of Use, Behavioral Intention to Use and Self-Efficacy, confidence in executing technology in instructional settings. The strength of this instrument lies in its adaptation to the context of Mechanical Engineering Vocational High School education, an area that has rarely been studied specifically. Furthermore, this research integrates additional indicators based on Industry 4.0 demands and the competency profile of vocational graduates aligned with the Indonesian National Qualifications Framework, enhancing the instrument's relevance to current workforce needs. Thus, the novelty of this study is not only in its application of the TAM approach but also in the development of contextual indicators tailored specifically for prospective Mechanical Engineering teachers, while remaining attuned to technological integration trends in vocational education.

This study holds significant implications for the development of vocational education, particularly within Mechanical Engineering Education programs at Vocational High Schools. First, according to Scherer et al. (2019), developing evaluation instruments based on the Technology Acceptance Model (TAM) can serve as reliable and valid measurement tools for assessing prospective teachers' readiness to integrate learning technologies. Consequently, educational institutions and Vocational High School administrators can conduct more targeted selection and development programs for teacher candidates, grounded in concrete data. Second, this study's findings can accelerate technology adaptation and integration within vocational education. This enables curricula and teaching methodologies to become more responsive to the demands of the Industry 4.0

and 5.0 eras. Third, this research contributes academically by enriching the relatively scarce literature on TAM application within Mechanical Engineering Education. Practically, the instrument can also provide a foundation for designing training programs and enhancing teacher competency development, better equipping educators for the ongoing digital transformation in education. Therefore, this work contributes not only to the advancement of evaluation instruments but also more broadly supports improving human resource quality within the Mechanical Engineering Education field.

2. RESEARCH METHODS

A minimum number of mechanical engineering education students who have participated in the Teaching Skills Practice program contributed to this study is set by 100 respondents. After data cleaning (removal of incomplete/inconsistent responses), 100 valid responses were analyzed. The Demographic details are outlined in Table 1 as can be seen.

Table 1. Demographic Details of Participants with N = 100.

Variable	Value	n	(%)
Gender	Male	76	76.0%
	Female	24	24.0%
Age	<20	6	6.0%
	20-22	90	90.0%
	23-25	4	4.0%
Education Level	Bachelor’s degree	100	100%
Semester	2	2	2.0%
	4	41	41.0%
	6	41	41.0%
	8	14	14.0%
	>8	2	2.0%

The participants are mostly male (76.0%), age range between 20-22 (90%), and the education level of each participant of the survey is 100% from Bachelors’ Degree.

a) Instrument

This instrument was developed using three stages. First, instrument preparation. Second, content validation by experts (is an essential step in the process) and TAM using Aiken’s V. Third, construct validation with Exploratory Factor Analysis to identify latent structures. This instrument is a multiple-choice test instrument. It has four variables and these variables refer to the competencies that teachers must have in order to pursue a career in education as a teacher in the field of mechanical engineering education. As presented in Table 2 the indicators pertaining to the instrument are delineated.

Table 2. Instrument Blueprint for Vocational High School Mechanical Engineering Teachers' Readiness

Variable	Indicator
Perceived Usefulness (PU)	-Enhanced Learning Effectiveness -Improved Teaching Preparedness -Elevated Instructional Quality -Industry Needs Alignment -Professional Competency Development
Perceived Ease of Use (PEU)	-AI Learnability -Operational Simplicity -Usage Flexibility -Prior Knowledge Compatibility -Assessment Design Ease
Behavioral Intention to Use (BI)	-Usage Intention -Professional Development Intention -Industry Collaboration Intention
Self-Efficacy (SE)	-AI Knowledge -Technical Proficiency

The data collection has obtained permission from each respondent in Mechanical Engineering Students. The questionnaire was filled out voluntarily and arranged by the researcher herself. Referring to (Widayanti, 2020), instruments are given using a google form. Each statement was assessed using a five-point Likert scale. This scale ranged from number 1 which means the respondents strongly disagree with the statement to number 5 which means the respondents strongly agree, the teacher fills out the instrument then the data is processed using SPSS.

Validation of the instrument's content with experts is the next step. Then continue with the Aiken's V formula to convert the qualitative data to quantitative. The construct validation was carried out in two stages, first, instruments were given to 150 students, screening the data to get the valid responses, and then analyzing the data using EFA. The data that has been analyzed is then visualized and interpreted into a narrative.

b) Procedure

The factor analysis, Exploratory Factor Analysis (EFA) was conducted (Hair et al., 2019). This was done systematically to examine the underlying measurement of the instrument's structure. As illustrated in Figure 3, the process began with data screening to ensure data quality (Dalawi et al., 2025). Subsequently, this study performed factorability tests to ascertain the suitability of the data for further analysis for Exploratory Factor Analysis to gather perceived scores (raw data). The Kaiser-Meyer-Olkin or KMO measure yielded values between 0.833 and 0.909 across all dimensions (Zhang et al., 2024).

According to (Karimian & Chahartangi, 2024), KMO used to determine which samplings are suitable for factor analysis. For factor extraction, the Maximum Likelihood (ML) method was employed due to its robustness in estimating latent constructs. The eigenvalue threshold was set at ≥1.0 and loading factor >0.5, ensuring that only meaningful factors were retained (Wang, et al., 2024).

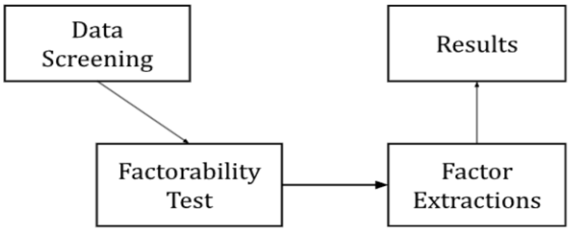

Figure 3. Exploratory Factor Analysis Procedure

3. RESULTS AND DISCUSSION

3.1 RESULTS

a) Material Validity Test

The results of the material validity assessment (Table 3.) indicate that the three expert evaluators (I, II, III) provided scores of 135, 137, and 145, respectively. Meanwhile, the three student assessors (s1, s2, s3) gave scores of 105, 107, and 115. The total score (Σs) reached 327 with a validity coefficient (V) of 0.91, which falls into the “High” category with items 1-30 PU, PEU, BI, dan SE. This shows that the instructional material was judged to be highly valid in terms of its content and alignment with the intended learning objectives

Table 3. Material Validity Test

I	II	III	s1	s2	s3	Σs	V	Desc.
135	137	145	105	107	115	327	0,90833333	High

b) Construct Validity Test

Table 4 presents the construct validity results. The scores from the expert panel (I = 132, II = 126, III = 150) and student assessors (s1 = 102, s2 = 96, s3 = 120) yielded a total score of 318. The validity coefficient was 0.88, categorized as “High.” These findings suggest that the construct of the instrument is well represented by the items, ensuring that the dimensions measured (PU, PEU, BI, and SE) are conceptually sound.

Table 4. Construct Validity Test

I	II	III	s1	s2	s3	Σs	V	Desc.
132	126	150	102	96	120	318	0,88333333	High

c) Language Validity Test

As shown in Table 5, language validity was also rated highly. The expert scores (128, 139, 144) and student assessments (98, 109, 114) produced a total of 321, with a validity coefficient of 0.89. This coefficient is classified as "High," indicating that the instrument's language use is clear, consistent, and easily understandable by the target respondents.

Table 5. Language Validity Test

I	II	III	s1	s2	s3	Σs	V	Desc.
128	139	144	98	109	114	321	0,89166667	High

A. Perceived Usefulness

The Kaiser-Meyer-Olkin or KMO measure of Sampling Adequacy in PU is 0.909. This number indicates excellent sample adequacy, while the significant Bartlett's Test of Sphericity result ($\chi^2 = 488.984$, $p < 0.001$). Based on the result of the goodness-of-fit test of PU, a chi-square value of 59.301, indicated that degrees of freedom or df is 35, with a significance level of 0.006. The significant value is $p = 0.006$, which is below 0.05 indicates that the model is not perfect, but this is a common phenomenon in medium-sized samples (N=100). This finding underscores that the PU instrument is valid and reliable for measuring the perceived usefulness of AI, particularly in the aspects of lesson planning and providing feedback to students. The Total Variance Explained table for PU shows that there is only one dominant factor that has been extracted with an eigenvalue of 4.984, which is able to explain 49.835% of the total data variance. The range of extraction communalities for all items is 0.445 to 0.584. This number indicates that approximately 44.5% to 58.4% of the variance for each item could be accounted for by the common factor.

B. Perceived Ease of Use

The analysis using EFA in PEU dimension, showed a KMO's value of 0.903, which exceeded the minimum limit of 0.6. A significant Bartlett's Test of Sphericity with a value of $\chi^2 = 525.439$ with a number of p less than 0.001, this $p < 0.001$ confirmed that the data was eligible for factor analysis with EFA. The Goodness-of-fit Test value of PEU shows a Chi-Square with a ratio of $\chi^2/df = 2.07$ (72.462/35). It is evident that the value remains within the minimum value (threshold) of the acceptance criteria. Which is set at 0.30. The results also indicate a p value of 0.000. This value is statistically significant, where the model is imperfect as it is below the minimum value of 0.05. For PEU, the eigenvalue is 5.063 which explains 50.635% of the total variance, with communalities ranging between 0.389–.707. The extracted communality values ranged from 0.389-0.707. The value range indicates that 38.9% to 70.7% of each item of variance could be explainable by a shared factor, with the same factor.

C. Behavioral Intention to Use

In this BI dimension, based on the KMO and Bartlett's Test above, the KMO measurement shows that the value is 0.893, exceeding the minimum value of 0.6, so that the sample size is ideal for factor analysis. The number 494.041, with df 15, and $p < 0.001$ indicates the feasibility of factor analysis using EFA because the correlation matrix is not identical. Although the goodness-of-fit test of BI showed statistical discrepancy (χ^2=31.376, $p<0.001$), the ratio $\chi^2/df = 3.49$. The goodness-of-fit test results of SE shows $\chi^2/df = 2.83$ with $p = 0.059$. This indicated a good fit of the model as a unidimensional construct. For BI, the eigenvalue of factor 1 is 4.248, more than >1.0, which explains 70.799% of the total variance. The communalities ranged between 0.666-0883 so each item of communalities could be explained by the same factor.

D. Self-Efficacy

The KMO Measure value of SE is 0.833 exceeds Kaiser's minimum value of 0.6, it is evident that Bartlett's Test results are statistically significant (332.286). The p value was less than 0.001 ($p < 0.001$), which indicates that there is a correlation between the items. For SE, the eigenvalues is 3.101, which explains 77.514% of the total variance. The communalities range from 0.666-0.883, indicating that between 66.6% and 88.3%, are indicated by the fact that each item's variance variability can be attributed to a shared underlying factor.

3.2 DISCUSSIONS

The results of validity test using Aiken’s V demonstrate that the tested instrument (instrument evaluation) meets the criteria for validity. These numbers indicate a consensus among the three experts that the instrument is relevant, has clear concepts, and uses appropriate language. Thus, the instrument is reliable for further data collection. This outcome echoes findings from prior research on instrument validation in educational technology contexts, where expert judgments have similarly validated tools for assessing technology integration in vocational training (Widodo et al., 2022). Nonetheless, instances of marginally lower validity scores for select indicators highlight potential areas for refinement, such as enhancing item wording to bolster uniformity and precision.However, if there are certain indicators that have lower individual validity scores, it is recommended that revisions be made to improve the consistency and accuracy of the instrument. Such revisions are crucial to mitigate measurement errors, particularly in dynamic fields like mechanical engineering education, where technological tools like AI must accurately reflect pedagogical needs (UNESCO, 2023).

Results of the Exploratory Factor Analysis (EFA) for the Perceived Usefulness (PU) dimension confirm that the research instrument meets all validity and reliability requirements. The KMO and Bartlett's results verify that the data correlation matrix is appropriate for factor analysis. The significance level below 0.05 confirms that the correlation matrix is non-identical, thus validating the data's suitability for EFA. With an eigenvalue of 4.984 PU dimension, this value is in the adequate category for research in the field of social science, where according to Hair et al. (2019), a variance value explained above 40% is acceptable. Only one factor has an eigenvalue above 1.0 (Kaiser Criterion), while other factors show much smaller eigenvalues (ranging from 0.275 to 0.799). This indicates that the measured constructs are unidimensional, where all items measure the same aspect of the latent variable. These results of the validity test confirm the validity of using this instrument evaluation, to measure the usability of AI technology in the context of mechanical engineering education. The items developed have successfully captured the essence of the latent variable to be measured.

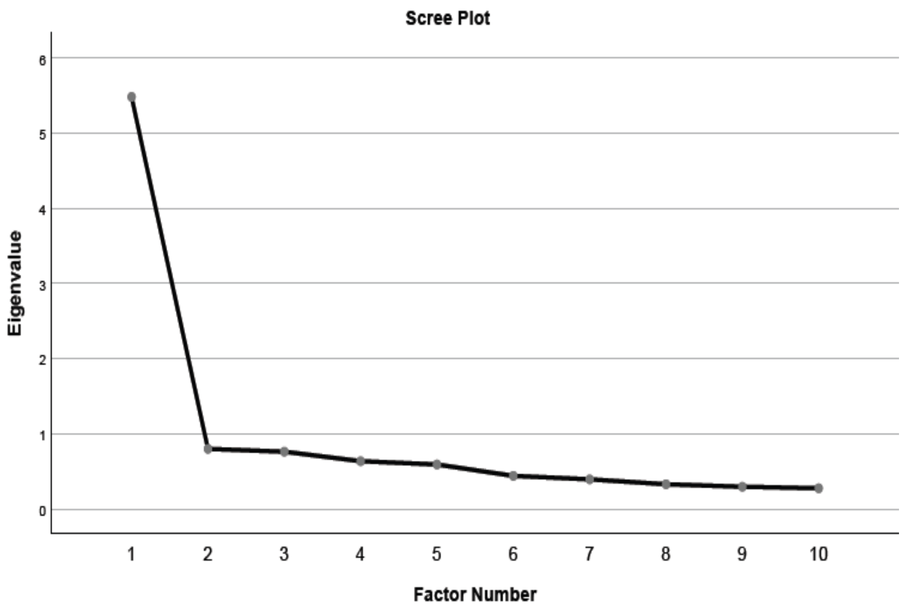

Figure 4. Scree Plot between Factor Number and The Eigenvalue of Perceived Usefulness

The results of the EFA analysis of Perceived Usefulness, with the Maximum Likelihood extraction method, revealed a clear factor structure with one dominant dimension capable of explaining 50.625% of the total data variance. This finding suggests that the measured construct is unidimensional, where all items tend to measure the same fundamental aspects. According to the Figure 4, the dominance of the first factor (eigenvalue = 5.063) which is much greater than the next factor (eigenvalue of the 2nd factor) reinforces this conclusion. The percentage of variance explained is adequate for social science research, although ideally above 60% (Hair et al., 2019). This value recommended by Kaiser indicates excellent sample adequacy. The single strong solution for PE shows that students view the usefulness of AI as a holistic concept, similar to the findings by Mutambara & Bayaga (2021) in their study on the acceptance of mobile learning by prospective teachers.

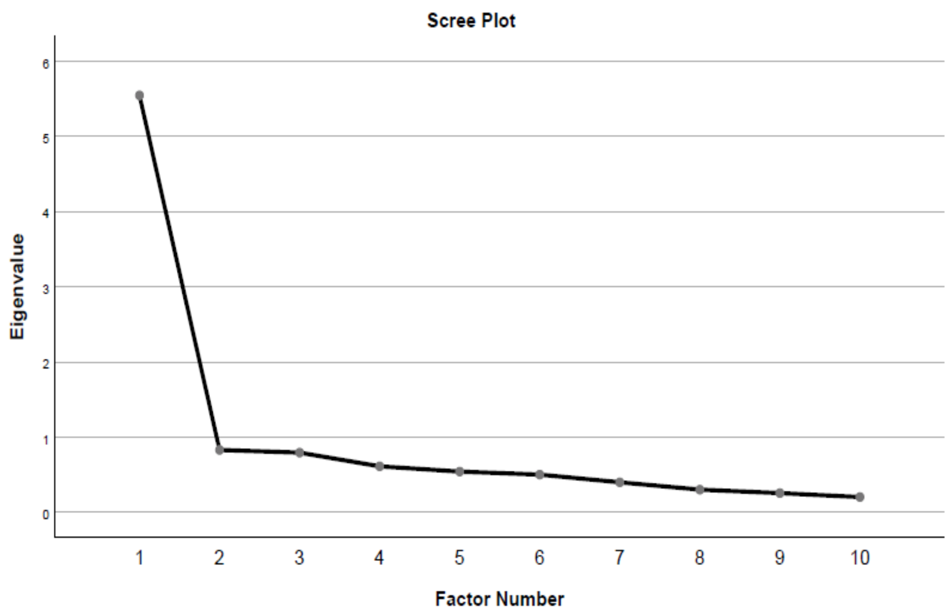

Figure 5. Scree Plot of Perceived Ease of Use

Based on the Figure 5, the scree plot above for the PEU dimension shows a very clear pattern with a decrease in the eigenvalue after the first factor. The elbow criterion visually indicates that only one dominant factor needs to be retained in the measurement structure. These findings are consistent with the research by Almaiah et al. (2022), which also validates the unidimensional structure of PU and PEU in the context of AI acceptance in higher education. Between factors 1 and 2, it is followed by a relatively flat line for subsequent factors. Thus, the subsequent factors do not contribute to explaining the variance. This result is also consistent with the previous analysis of variance explained values. The analysis also identified relative weaknesses in certain items, such as ‘The use of AI does not disrupt the learning flow,' which had the lowest communality (0.389) in PEU, as well as relatively lower confidence in 'overcoming technical problems' in SE.

The KMO value for Behavioral Intention to Use is more than the minimum, which indicates good sample adequacy for factor analysis. The amount of variance explained provides strong support for construct validity. The number is more than >1.0, so this factor value is very strong for social research.

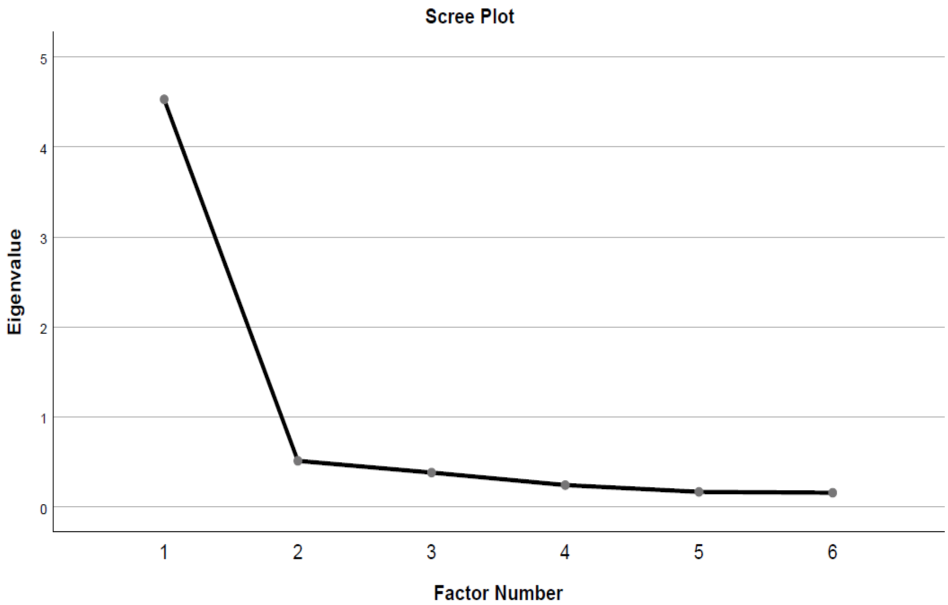

Figure 6. Scree Plot of Behavioral Intention to Use

The scree plot shows an elbow pattern after the first factor (4.530) to (0.514), thus finding unidimensionality in this construct. This is followed by a stable sloping line, so this pattern is consistent with the variance explained value of 70.799% and the KMO result (0.893). The scree plot pattern showing a sharp 'elbow' after the first factor indicates that no other factors need to be retained in the EFA analysis. The limitations of this single dimension reflect that TAM validation in educational technology, as seen in the research by Ifinedo & Kankaanranta (2023), where this BIU construct often appears as a predictor with high variance on adoption intentions among educators.

The strength of these findings is demonstrated by the variance explained value, which is adequate for social sciences, especially in BIU, which reached 70.799%. Items with the strongest contributions consistently reflect specific contexts, such as 'AI is compatible with mechanical engineering knowledge' (0.707) in PEU. This indicates that for mechanical engineering students, perceived ease of use is strongly related to the relevance and integration of this technology with their core disciplinary knowledge.

The strongest item in the Self-Efficacy construct was “I understand the different types of AI that can be used in learning mechanical engineering” (0.883). The weakest item is “I am able to overcome basic technical problems that may arise when using AI” (0.666), but this value still meets the minimum criteria of 0.40 according to Hair et al., 2019. This shows that for engineering students, smooth flow and basic technical skills may not be the most central aspects in assessing the ease of use and self-efficacy of AI, in contrast to the emphasis in research in more general contexts. Thus, these EFA results successfully validate the instrument while revealing the uniqueness of perceptions in the context of mechanical engineering education.

4. CONCLUSION

This study successfully establishes a robust methodological foundation for assessing Artificial Intelligence’ Readiness among pre-service Mechanical Engineering teachers by developing and validating a specialized Technology Acceptance Model (TAM) instrument. The research makes a significant methodological contribution through its psychometrically-validated tool, which is specifically contextualized for technical vocational education while incorporating Industry 4.0 competency requirements. The findings underscore the critical need to embed TAM-based evaluation frameworks into vocational teacher education curricula, practical utility in evaluating how vocational teachers perceive and adopt digital learning tools, while highlighting the necessity of integrating such assessment frameworks into teacher education curricula to better align pedagogical approaches with Industry 4.0 competencies. Although currently limited to mechanical engineering contexts, this validated tool provides a foundational benchmark for future research to explore its predictive validity in real educational settings and its applicability across broader vocational disciplines. Subsequent research should therefore investigate its predictive validity regarding actual user behavior in authentic learning scenarios and explore its application across diverse vocational disciplines to enhance external validity.

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