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Evaluation of Readiness among Prospective Mechanical Engineering Vocational Teachers to Apply Generative AI in Education Using Technology Acceptance Model (TAM)

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Abstract: This study evaluates the readiness of prospective vocational school teachers in integrating Generative Artificial Intelligence (GenAI) into learning using the Technology Acceptance Model (TAM) framework, which includes Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioral Intention (BI), and Self-Efficacy (SE). The research employs a descriptive quantitative design with 100 respondents who are prospective vocational high school mechanical engineering teachers. The instrument consists of 30 items (Likert scale 1–5) and was validated by three validators using Aiken's V (content = 0.90; construct = 0.88; language = 0.89; > 0.75). The results showed that PU (mean = 4.01; SD = 0.77) was the highest, followed by BI (mean = 3.93; SD = 0.92) and PEOU (mean = 3.89; SD = 0.82), while SE (mean = 3.66; SD = 0.95) was the lowest but relatively. Item-level analysis indicated strengths in perceptions of industry relevance and AI-assisted learning planning, as well as the need for strengthening technical skills and troubleshooting. These findings support the urgency for vocational curriculum development emphasizing AI literacy, pedagogical-technological training, and industry collaboration.

Keywords: GenAI; Vocational Teacher Readiness; Mechanical Engineering Education

Abstrak: Studi ini mengevaluasi kesiapan calon guru SMK Teknik Mesin dalam mengintegrasikan *Generative Artificial Intelligence* (GenAI) ke dalam pembelajaran dengan kerangka *Technology Acceptance Model* (TAM) yang mencakup *Perceived Usefulness* (PU), *Perceived Ease of Use* (PEOU), *Behavioral Intention* (BI), dan *Self-Efficacy* (SE). Penelitian menggunakan desain kuantitatif deskriptif dengan 100 responden calon guru SMK teknik mesin. Instrumen disusun dari 30 butir (Likert 1–5) dan divalidasi oleh tiga validator melalui Aiken's V (materi = 0,90; konstruk = 0,88; bahasa = 0,89; > 0,75). Hasil menunjukkan PU (rata-rata = 4,01; SD = 0,77) tertinggi, diikuti BI (rata-rata = 3,93; SD = 0,92) dan PEOU (rata-rata = 3,89; SD = 0,82), sementara SE (rata-rata = 3,66; SD = 0,95) terendah namun relatif. Analisis setiap butir mengindikasikan kekuatan pada persepsi relevansi industri dan perencanaan pembelajaran berbantuan AI, serta kebutuhan penguatan pada keterampilan teknis dan *troubleshooting*. Temuan ini mendukung urgensi untuk pengembangan kurikulum vokasi yang menekankan literasi AI, pelatihan pedagogik-tekno, dan kolaborasi industri.

Kata Kunci: GenAI; kesiapan guru vokasi; Pendidikan Teknik Mesin

INTRODUCTION

The development of Generative AI (GenAI) ranging from large language models (LLMs) to multimodal models has increasingly accelerated the transformation of teaching and learning practices; in the context of technical and vocational education, this technology provides support for lesson planning, the provision of industry-contextualized materials, and more precise automated feedback, as widely documented in recent higher-education reviews (Crompton, 2023). Put differently, GenAI not only expands access to learning resources and the automation of routine tasks, but also creates opportunities to design learning experiences that are more authentic and aligned with the evolving needs of the workforce.

In line with this, systematic reviews quantify the surge: a PRISMA review of AI in higher education identified 138 peer-reviewed articles (2016–2022) and reported that output in 2021–2022 was nearly two to three times higher than in prior years (Crompton, 2023). Moreover, recent systematic reviews underscore the breadth of topics but also point to underexplored areas in educators' adoption of AI particularly readiness, instructional workflows, and institutional support (Wang, 2024). an earlier review covering 2007–2018 screened 2,656 records and synthesized 146 articles, likewise highlighting opportunities and implementation challenges from pedagogical alignment to ethical governance (Zawacki-Richter et al., 2019). Accordingly, further investigation is warranted.

To explain and predict technology adoption, the Technology Acceptance Model (TAM) posits that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) shape intentions and subsequent behaviors (Davis, 1989) (Venkatesh & Bala, 2008). A growing body of education research including meta-analyses confirms TAM's relevance for understanding teachers' and students' uptake of digital tools (Scherer et al., 2019) (Al-Emran et al., 2018). In vocational contexts, however, task technology fit, workflow orchestration, and industry alignment are crucial to meaningful integration.

Problem gap. Despite burgeoning interest in GenAI for teaching, empirical evidence on the readiness of Mechanical Engineering prospective teachers broken down by TAM's dimensions and detailed to the item level remains limited. There is also a practical need to link readiness profiles to curricular recommendations (e.g., AI literacy outcomes, micro-credentials) and to industry collaboration characteristic of vocational education.

This study advances the literature by: (1) operationalizing a TAM-based readiness instrument specifically tailored to Mechanical Engineering vocational teaching; (2) establishing high expert-judged content validity using Aiken's V across material, construct, and language criteria; and (3) providing dimension and item level diagnostics to guide targeted interventions in curricula, professional development, and industry university partnerships.

The study aims to evaluate the readiness of prospective Mechanical Engineering vocational teachers to integrate Generative AI into teaching using the TAM framework examining Perceived Usefulness, Perceived Ease of Use, Behavioral Intention, and Self-Efficacy and to identify specific strengths and gaps at the item level that can inform program design, training priorities, and collaboration strategies

METHOD

A descriptive quantitative design was used. We employed a total population (census) sampling of the accessible population at the study site: all undergraduates enrolled in the Mechanical Engineering Education program (i.e., prospective Mechanical Engineering vocational teachers) were invited to complete the online questionnaire during the data-collection window. A total of 100 complete responses met the inclusion criteria and were analyzed.

The instrument comprised 30 items on a 5-point Likert scale mapped to four TAM dimensions. The instrument was structured around four TAM dimensions. Perceived Usefulness (PU) comprised 10 items assessing perceived gains in instructional effectiveness, preparedness for teaching, overall quality of learning, alignment with industry relevance, and development of professional competence. Perceived Ease of Use (PEOU) was operationalized through 10 items capturing learnability, day-to-day operability, flexibility or adaptability to instructional contexts, compatibility with existing knowledge and pedagogical approaches, and support for evaluation design. Behavioral Intention (BI) included 6 items reflecting intentions to use AI in future teaching, engage in continuous skill development, and pursue industry collaboration and certification. Finally, Self-Efficacy (SE) was measured with 4 items focusing on AI knowledge and the technical/troubleshooting skills required for classroom implementation. Indicators and item stems followed the questionnaire blueprint tailored to Mechanical Engineering vocational contexts.

Three experts (subject-matter, vocational pedagogy in Mechanical Engineering, and educational evaluation) evaluated the items using Aiken’s V. Average indices met high criteria: Material = 0.90, Construct = 0.88, Language = 0.89 all above the 0.75 threshold for acceptable content validity (Rozo-García et al., 2024).

Data were collected via an online survey. The analytic strategy comprised (a) descriptive statistics to characterize respondent demographics, (b) computation of dimension-level means and standard deviations for the four TAM constructs Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioral Intention (BI), and Self-Efficacy (SE) and (c) item-level descriptive analyses to identify specific strengths and areas requiring improvement. Participation was voluntary; no identifying information was recorded or reported; and all data were analyzed solely for academic purposes.

RESULTS AND DISCUSSIONS

Results

There were 100 respondents were undergraduate students in Mechanical Engineering Education at Jakarta State University. The profile is:

1. Gender: Male 76% (n = 76), Female 24% (n = 24).
2. Age: 20–22 years 89% (n = 89); < 20 years 6% (n = 6); 23–25 years 5% (n = 5).
3. Semester: 4th 41% (n = 41); 6th 41% (n = 41); 8th 14% (n = 14); > 8th 2% (n = 2); 2nd 2% (n = 2).

This composition indicates most participants are in the mid stage of their program, which is pedagogically relevant for assessing early to intermediate readiness to incorporate GenAI into future teaching.

Readiness by TAM Dimensions

Table 1. Perceived Usefulness (PU) aspect analysis results

Aspect of TAM	Mean	Standard Deviation
Perceived Usefulness (PU)	4,01	0,77

Based on the analysis in Table 1, it can be concluded that respondents perceive GenAI as beneficial for improving instructional effectiveness, supporting planningormedia development, aligning with Industry 4.0, and strengthening professional competence.

Table 2. Perceived Ease of Use (PEOU) aspect analysis results

Aspect of TAM	Mean	Standard Deviation
Perceived Ease of Use (PEOU)	3.89	0.82

Based on the analysis in Table 2, it can be concluded that genAI is rated as relatively learnable and operable and compatible with existing knowledge; however, some respondents are cautious about potential workflow disruptions to established lesson flows.

Table 3. Behavioral Intention (BI) aspect analysis results

Aspect of TAM	Mean	Standard Deviation
Behavioral Intention (BI)	3.93	0.92

Based on the analysis in Table 3, it can be concluded that intentions are positive regarding future use, continuous AI skill development, and industry collaboration for project-based learning; certification intentions are somewhat less strong but still favorable.

Table 4. Self-Efficacy (SE) aspect analysis results

Aspect of TAM	Mean	Standard Deviation
Behavioral Intention (BI)	3.66	0.95

Based on the analysis in Table 4, it can be concluded that this is comparatively the lowest dimension. Knowledge-based confidence outpaces technicalortroubleshooting efficacy, signaling a need for hands-on training and mentoring.

Item-Level Highlights

Table 5. level items of Perceived Usefulness (PU) aspect analysis results

Level	Items	Mean
Top Items	AI helps me understand the latest industrial technologies so instruction matches industry needs	4.22
	AI helps me prepare better lesson plans	4.14
Lower items	Integrating AI helps me provide more precise feedback to students	3.83
	AI helps me develop technical competence as a prospective teacher	3.81

Based on the analysis in Table 5, it can be concluded that strongest readiness relates to industry relevance and lesson-planning support; opportunities exist to deepen analytics-informed feedback and technical competence.

Table 6. level items of Perceived Ease of Use (PEOU) aspect analysis results

	Items	Mean
Top Items	I can quickly understand AI features relevant for teaching	4.03
	I can easily integrate AI into the instructional methods I have learned	4.03
Lower items	AI integration aligns with pedagogical approaches I have learned	3.78
	Using AI does not disrupt my planned lesson flow	3.62

Based on the analysis in Table 6, it can be concluded that learnability or operability are favorable; pedagogical alignment and non-disruptive workflow require attention

Table 7. level items of Behavioral Intention (BI) aspect analysis results

	Items	Mean
Top Items	I intend to continually develop my AI skills	4.08
	I intend to collaborate with industry to use AI platforms for project-based learning	4.01
Lower items	I intend to obtain certification as an AI practitioner for teaching	3.82
	I intend to use AI when I become a teacher	3.79

Based on the analysis in Table 7, it can be concluded that strong growth mindset and collaboration intent; certification and routine usage commitments can be strengthened

Table 8. level items of Self-Efficacy (SE) aspect analysis results

	Items	Mean
Top Items	I have sufficient basic knowledge about AI and its applications	3.72
	I understand various types of AI applicable to Mechanical Engineering teaching	3.66
Lower items	I possess the necessary technical skills to use AI	3.63
	I can handle basic technical issues when using AI	3.61

Based on the analysis in Table 8, it can be concluded that knowledge efficacy exceeds technical efficacy; targeted practice is needed for setup, integration, and troubleshooting.

Discussions

The finding that PU obtained the highest score reinforces TAM's central proposition that perceived usefulness is a primary determinant of intention and technology-use behavior (Davis, 1989) (Venkatesh & Bala, 2008) (Scherer et al., 2019). In the context of vocational mechanical engineering education, the perception that GenAI clarifies learning objectives, accelerates lesson and material preparation, and enhances industry relevance directly strengthens adoption readiness among prospective teachers. Recent international literature likewise shows that when AI technologies are integrated for lesson planning, formative feedback, and the contextualization of industry cases, perceived usefulness increases and positively affects sustained usage intentions (Crompton, 2023) (Zawacki-Richter et al., 2019)

Beside that, studies involving students and vocational ecosystems indicate that the use of Technology improves learning effectiveness and the learner experience, thereby being perceived as beneficial (Erliana, 2021). In terms of teacher performance, technology use correlates with improvements in instructional outcomes, reinforcing the usefulness construct in practice (Haeranah et al., 2023). With respect to GenAI which can be translated into lesson planning (RPP), contextualized materials, and assessment in technical education (Pratiwi et al., 2024) (Andriyanti et al., 2023). Accordingly, interventions that foreground concrete GenAI use cases (e.g., a lesson-planning assistant, feedback generator, and industry-case creator) are likely to strengthen PU and, in turn, bolster BI.

The relatively high PEOU score indicates that respondents regard GenAI as easy to learn and operate, although concerns remain about possible disruptions to lesson flow. Theoretically, PEOU enhances both PU and BI the easier a system is to use, the more useful it is perceived to be and the stronger the intention to adopt (Davis, 1989) (Venkatesh & Bala, 2008) (Scherer et al., 2019). International reviews also emphasize that successful classroom integration of AI critically depends on task–technology fit and the orchestration of instructional workflows AI needs to be woven into teaching sequences rather than becoming an additional burden (Crompton, 2023) (Zawacki-Richter et al., 2019).

TAM-based research in organizational and educational settings shows that ease of use is a consistent determinant of acceptance (Cahyaning, 2021) (Handayani & Harsono, 2016). In vocational learning contexts, perceptions of ease are likewise reflected in online learning experiences: when systems and learning resources are easy to access and operate, attitudes toward using technology become more positive (Erliana, 2021). Therefore, strategies to improve PEOU for GenAI should target workflow design and concrete operational support.

The finding that BI falls in the positive range aligns with meta-analytic evidence showing that perceived usefulness (PU) and perceived ease of use (PEOU) are primary predictors of teachers' intention to adopt educational technologies; when the benefits of GenAI are salient (e.g., planning, feedback, industry relevance) and its use feels straightforward, intention to adopt typically rises (Scherer et al., 2019). This pattern is consistent with studies of in-service and pre-service teachers in which the PU or PEOU to BI pathway is robust across settings (Teo, 2011) (Scherer et al., 2019). Focusing specifically on Generative AI, recent work in school contexts similarly indicates that intention to use GenAI is shaped by perceived benefits, ease, and considerations of fairness or ethics suggesting that capacity-building and clear policies can help convert intention into routine practice (Kong et al., 2024) (Lu et al., 2024). In vocational contexts comparable to our sample, research with Indonesian VET teachers also identifies determinants of intention to use web-based learning, reinforcing the relevance of the PU or PEOU to BI route in vocational ecosystems (Sawiji, 2024).

The comparatively lower SE, especially for technical operation and troubleshooting mirrors literature positioning self-efficacy as a prerequisite for perceived ease and intention: when teachers feel technically capable, PEOU tends to increase and BI strengthens (Igbaria & Iivari, 1995). In pre- or in-service teacher studies, digital pedagogical self-efficacy and technology competence exert direct and indirect effects on intention via improvements in PEOU or PU, implying that hands-on training and mentoring are effective levers for raising SE and stabilizing BI (Antonietti, 2022) (Yang & Appleget, 2024). Extending to GenAI, emerging findings indicate that bolstering confidence in operating core features and embedding GenAI into lesson workflows is associated with greater acceptance and planned classroom use underscoring targeted SE development as a strategic pathway to sustainable adoption.

Validity supports inference. High Aiken's V indices across material, construct, and language validate the instrument's appropriateness for the target population, supporting the accuracy of dimension and item level interpretations. The implications for vocational curriculum and policy point to an integrated, multi-level strategy. First, curricular embedding should explicitly incorporate AI literacy outcomes and concrete GenAI applications such as lesson planning, media development, formative feedback, and authentic assessment within course syllabi or Rencana Pembelajaran Semester (RPS) in Mechanical Engineering Education. Second, tiered professional development is needed in the form of short, practice-oriented bootcamps on AI pedagogy and technical operations, culminating in micro-credentials that elevate self-efficacy (SE) and consolidate behavioral intention (BI) to use GenAI. Third, industry collaboration ought to structure project-based learning through industry platforms and teaching-factory models so that students and pre-service teachers engage in authentic tasks that heighten perceived usefulness (PU). Finally, robust ethics and governance frameworks encompassing academic integrity, data privacy, and responsible AI use at both class and program levels are essential to ensure trust, accountability, and long-term sustainability of GenAI integration

CONCLUSION

Prospective Mechanical Engineering vocational teachers exhibit moderate-to-high readiness to integrate GenAI, strongly driven by perceived usefulness and supported by generally positive ease-of-use perceptions and behavioral intentions. The main developmental need lies in self-efficacy, particularly technical operation and troubleshooting, to ensure smooth, non-disruptive classroom integration. Validity evidence (Aiken's V) supports the instrument's suitability for this context. Practical recommendations include curricular embedding of AI literacy, tiered PD with micro-credentials, industry-linked projects, and explicit ethicsorgovernance mechanisms.

REFERENCES

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018). Technology Acceptance Model in M-learning context: A systematic review. *Computers & Education*, *125*, 389–412. https://doi.org/10.1016/j.compedu.2018.06.008

Andriyanti, E., Sudartinah, T., & Setiawan, B. (2023). Menulis buku ajar di tengah perkembangan artificial intelligence (ai). *Humanika*, *23*(2), 167–174. https://doi.org/10.21831/hum.v23i2.66386

Antonietti, C. (2022). Can teachers' digital competence influence technology acceptance? Testing TAM in vocational education. *Computers in Human Behavior*, *129*, 107137.

Cahyaning, E. K. (2021). Evaluasi penerimaan sistem TI Branch Delivery System (TAM). *ABIS: Jurnal Administrasi Bisnis*.

Crompton, H. (2023). Artificial intelligence in higher education: The state of the field (2016–2022). *International Journal of Educational Technology in Higher Education*, *20*(1).

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340.

Erliana, E. (2021). Vocational students' perception of online learning during the Covid-19 pandemic. *Jurnal Pendidikan Teknologi Dan Kejuruan*.

Haeranah, H., Firman, A., & Oktaviani, A. R. (2023). Pengaruh Pendidikan, Pelatihan, dan Teknologi Terhadap Peningkatan Kinerja. *Paradoks : Jurnal Ilmu Ekonomi*, *6*(1), 57–70. https://doi.org/10.57178/paradoks.v6i1.602

Handayani, W. P. P., & Harsono, M. (2016). APLIKASI TECHNOLOGY ACCEPTANCE MODEL (TAM) PADA KOMPUTERISASI KEGIATAN PERTANAHAN. *Jurnal Economia*, *12*(1), 13. https://doi.org/10.21831/economia.v12i1.8415

Igbaria, M., & Iivari, J. (1995). The effects of self-efficacy on computer usage. *Omega*, *23*(6), 587–605.

Kong, S. C., Yang, Y., & Hou, C. (2024). Examining teachers' behavioural intention of using generative artificial intelligence tools for teaching and learning based on the extended technology acceptance model. *Computers and Education: Artificial Intelligence*, *7*, 100328. https://doi.org/10.1016/j.caeai.2024.100328

Lu, H., He, L., Yu, H., Pan, T., & Fu, K. (2024). A Study on Teachers' Willingness to Use Generative AI Technology and Its Influencing Factors: Based on an Integrated Model. *Sustainability*, *16*(16), 7216. https://doi.org/10.3390/su16167216

Pratiwi, N. K., Yulianto, B., Mintowati, M., & Sodiq, S. (2024). Optimizing ChatGPT for scientific writing in the digital age. *LITERA*, *23*(2). https://doi.org/10.21831/ltr.v23i2.72979

Rozo-García, H., Alcantar-Nieblas, C., & Soledad Ramirez-Montoya, M. (2024). *Scale to measure student perception in collaborative online international learning experiences: design and validation*.

Sawiji, H. (2024). Determining factors influencing vocational high school teachers' intention to use web-based e-learning. *Cogent Education*, *11*(1), 2355830.

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The Technology Acceptance Model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology. *Computers & Education*, *128*, 13–35.

Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. *Computers & Education*, *57*(4), 2432–2440. https://doi.org/10.1016/j.compedu.2011.06.008

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273–315.

Wang, S. (2024). Artificial intelligence in education: A systematic literature review. *Expert Systems with Applications*, *238*, 122297.

Yang, S., & Appleget, C. (2024). An exploration of preservice teachers' perceptions of Generative AI: Applying the technological Acceptance Model. *Journal of Digital Learning in Teacher Education*, *40*(3), 159–172.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1), 39. https://doi.org/10.1186/s41239-019-0171-0