Vol. 10, Issue 2 pp. 126-135 | DECEMBER 2025
DOI: https://doi.org/10.53840/myjict10-2-230

Adoption of Generative AI Tools Among Pre-Service TVET Instructors: A Quantitative Assessment Using UTAUT Framework

[i*]Maznizam Bin Mansor, [ii]Zulkifflee Bin Mohamed, & [iii] Mohammed Reyasudin Bin Basir Khan, [iv]Mohd Nor Azlan Bin Mohamed Sidek

[i]Centre For Instructor and Advanced Skill Training (CIAST), Shah Alam, Selangor, Malaysia
[ii]Tun Razak Graduate School, Universiti Tun Abdul Razak, Kuala Lumpur, Malaysia

[*](Corresponding author) e-mail: maznizam@ciast.gov.my

Article history:
Submission date: 17 October 2025
Received in revised form: 19 November 2025
Acceptance date: 17 December 2025
Available online: 26 December 2025

Keywords:
Generative AI, TVET instructors, UTAUT model, Technology Adoption, Digital Pedagogy

Funding:
This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Competing interest:
The author(s) have declared that no competing interests exist.

Cite as:
Author1, N., & Author2, R. (2025). Title. *Malaysian Journal of Information and Communication Technolog, 10*(1), X-X. https://doi.org/10.33102/myjict.vol10no1.xx

Mansor, M., Mohamed, Z.., Basir Khan, M. R. ., & Mohamed Sidek, M. N. A. . (2025). Adoption of Generative AI Tools Among Pre-Service TVET Instructors: A Quantitative Assessment Using Utaut Framework. *Malaysian Journal of Information and Communication Technology (MyJICT), 10(2), 126-135.* https://doi.org/10.53840/myjict10-2-230

ABSTRACT

This study explores the adoption of Generative Artificial Intelligence (GenAI) among pre-service Technical and Vocational Education and Training (TVET) instructors. GenAI tools are becoming increasingly relevant as instructional aids, though their adoption within the TVET pre-service pipeline remains understudied. Anchored in the Unified Theory of Acceptance and Use of Technology (UTAUT), this study investigates the influence of four key constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions on Behavioral Intention to adopt GenAI tools. A quantitative survey was conducted involving individuals currently enrolled in the national pre-service TVET instructor programme. These participants represent the next generation of educators being trained to deliver skills-based instruction aligned with emerging digital and technological advancements across various TVET fields. Data collection was conducted using a structured questionnaire, and the responses were analyzed using descriptive statistics, Pearson correlation, and multiple regression analyses to uncover key patterns and relationships among variables. Results indicate that all four constructs are positively correlated with Behavioral Intention, with Performance Expectancy showing the strongest association. Regression analysis confirmed Performance Expectancy as the dominant predictor, followed by Effort Expectancy and Facilitating Conditions, together explaining 82% of the variance in Behavioral Intention, while Social Influence was not a significant predictor when controlling for the other factors. These results suggest that future instructors are more likely to embrace GenAI when they perceive the tools to be useful and when adequate support systems such as access to technology and training, are in place. The study contributes to the growing body of research on AI integration in TVET training and highlights the need for strategic interventions that enhance institutional readiness and digital competency among future TVET educators. Practical implications are discussed for policy-makers, curriculum developers, and training providers aiming to embed GenAI tools effectively within the Malaysian TVET ecosystem.

Introduction

Technical and Vocational Education and Training (TVET) plays a crucial role in equipping individuals with the practical skills and competencies required by modern industries, thereby driving economic growth and development (Richard, Joseph, Elikem, & Edem, 2023). However, TVET systems face increasing pressure to adapt to the rapid technological advancements characterizing Industry 4.0, which demand new skill sets, particularly in digital literacy and adaptability (Baharin, Ramli, & Liyana Redzuan, 2024). Against this backdrop, Generative Artificial Intelligence (GenAI) has emerged as a potentially transformative technology across many sectors, including education (Berigel & Şilbir, 2025). Tools like ChatGPT, Gemini, DeepSeek, and others offer capabilities for automating content creation, personalizing learning experiences, providing immediate feedback, and facilitating complex problem-solving, holding particular promise for the practical, skills-focused nature of TVET (Budhathoki, Zirar, Njoya, & Timsina, 2024). AI applications such as adaptive learning systems, simulations, and AI-assisted assessments are seen as ways to enhance training methods, improve learning outcomes, and bridge the gap between education and industry needs. (Belkina et al., 2025; Ghazi et al., 2025; Lee, 2025).

However, a significant study exists in understanding the readiness and willingness of future TVET instructors to adopt GenAI. According to Baharin, Ramli, & Liyana Redzuan (2024), research on AI in TVET is less developed compared to higher education and much of the focus has been on student perceptions or in-service instructors. Pre-service TVET instructors represent the future pipeline of educators who will shape how these technologies are used in vocational classrooms and workshops. This group possesses a unique mandate, requiring a blend of pedagogical skills, deep technical expertise in their vocational area, and increasingly, digital competence (Bitemirova, Zholdasbekova, Mussakulov, Anesova, & Zhanbirshiyev, 2023). Yet, their training often struggles to effectively integrate technology, sometimes lacking sufficient practical industry relevance or pedagogical grounding for technology use. Their digital competence levels can vary, and they are still forming their teaching philosophies and practices. Understanding the factors that influence their intention to adopt a novel and powerful technology like GenAI during this formative stage is therefore paramount.

This study aims to contribute to the knowledge base by providing empirical evidence essential for designing more effective TVET instructor education programs. This preparation ensures future instructors can leverage GenAI tools productively and responsibly."Understanding their adoption drivers can guide policy decisions regarding resource allocation, curriculum development, and the establishment of ethical guidelines within TVET institutions. Ultimately, preparing pre-service instructors for GenAI integration is essential for ensuring that future TVET graduates possess the skills necessary to thrive in increasingly AI-influenced workplaces. This study focuses on the unique intersection of an emerging technology (GenAI), a specific educational context demanding practical skills (TVET) and a critical user group whose adoption decisions will shape future practice (pre-service instructors).

To achieve this, the study seeks to answer the following research questions:

(i) What is the level of Behavioral Intention among pre-service TVET instructors to adopt GenAI tools for their future teaching practice?

(ii) To what extent do the core constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT); Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions predict the Behavioral Intention of pre-service TVET instructors to adopt GenAI tools?

Literature Review

Generative AI in Education and TVET

Within TVET, GenAI is seen as having the potential to significantly impact skills development. Applications could include AI-driven simulations for practicing complex technical procedures, adaptive learning systems that adjust to a trainee's pace in mastering a vocational skill, automated grading for certain types of practical assessments, and providing real-time feedback during hands-on activities.

According to Han, Mustafa, & Kharuddin (2025), by automating routine tasks and offering personalized support, GenAI could help bridge the gap between academic training and industry skill requirements.

However, the integration of GenAI is accompanied by significant challenges and ethical considerations. Academic integrity is a major concern, as students might use GenAI to generate work without engaging in the learning process, making detection difficult (Holmes & Miao, 2023). According to Ranuharja, Rizal, Langeveldt, Ejjami, Torres-Toukoumidis, & Jalinus (2025), the data used to train these models can contain biases, leading to the generation of inaccurate, misleading, or even offensive content, potentially marginalizing certain groups. Data privacy is another critical issue, particularly given the lack of transparency regarding data handling by some GenAI providers and the potential involvement of minors. Furthermore, there are concerns about the potential for over-reliance on AI, potentially hindering the development of students' own critical thinking, problem-solving, and creative skills. Equity issues also arise, as unequal access to GenAI tools and the necessary digital infrastructure could widen existing socioeconomic divides (Zary & Zary, 2025). For TVET, specific challenges include ensuring the quality and accuracy of AI-generated content for highly practical or safety-critical skills and determining how best to integrate these tools alongside essential hands-on training.

Technology Integration in Pre-Service TVET Instructor Education

Effective technology integration is crucial for modern education, enabling richer learning experiences and preparing students for a digital world. This is particularly true in TVET, where instructors must prepare learners for technology-infused workplaces. However, equipping pre-service instructors with the necessary skills and confidence remains a challenge. Pre-service TVET instructors require a unique blend of knowledge and skills. They need strong pedagogical knowledge, deep content knowledge in their specific vocational field, and increasingly, technological knowledge, understanding how to effectively use technology to enhance teaching and learning within their discipline (Lawrence, 2004). According to Chen, Lambert & Chiarelli (2022), framework like Technological Pedagogical Content Knowledge (TPACK) highlight the complex interplay between these knowledge domains required for successful technology integration.

Several challenges impede effective technology integration in pre-service instructor TVET programs. Instructors entering from industry may lack pedagogical training, while those from traditional instructor education pathways may lack recent industry experience and practical technology application skills. Training programs often treat technology as a separate course rather than embedding it across the curriculum, limiting pre-service instructors' exposure to effective modeling and practical application (Richard et al., 2023). Consequently, pre-service instructors may lack digital competence, particularly in areas like technological resourcefulness or staying updated with field-specific technologies. According to Wedlock (2019), factors like self-efficacy, attitudes towards technology, and perceived ease of use significantly influence their willingness and ability to integrate technology into their future classrooms. Given the novelty and rapid evolution of GenAI, understanding the factors influencing its adoption by this specific group during their training phase is essential for developing targeted support and interventions.

The UTAUT Framework

To investigate the factors influencing GenAI adoption among pre-service TVET instructors, this study employs the Unified Theory of Acceptance and Use of Technology (UTAUT). Developed by Venkatesh and colleagues (Venkatesh, Morris, Davis, & Davis, 2003), UTAUT synthesizes constructs from eight prominent prior models of technology acceptance (including TAM, TRA, TPB, IDT) to provide a comprehensive framework for understanding user intentions and subsequent usage behavior (Abdou & Jasimuddin, 2020). The model has demonstrated strong predictive power across various contexts, including education, often explaining a substantial portion of the variance in behavioral intention and actual use. Its suitability for educational technology research has been validated in numerous studies examining technologies like learning management systems, mobile learning, and cloud classrooms (Aksoy & Toprak, 2024 ; Or & Chapman, 2021).

UTAUT states four core constructs as direct determinants of Behavioral Intention:

(i) Performance Expectancy (PE): Defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance". In this context, it reflects the pre-service TVET instructor's belief that using GenAI tools will enhance their teaching effectiveness, efficiency, or ability to help students acquire necessary vocational skills. This aligns with the perceived benefits of GenAI, such as personalization and automation. PE is often found to be the strongest predictor of intention (Batucan et al., 2022). Given TVET's practical focus, the perceived ability of GenAI to enhance practical skill instruction might make PE particularly salient.

(ii) Effort Expectancy (EE): Defined as "the degree of ease associated with the use of the system". This relates to the perceived simplicity, clarity, and user-friendliness of GenAI tools (Tahir, 2023). For pre-service instructors, this construct is likely linked to their general digital competence and the perceived complexity of learning and integrating specific GenAI applications into their teaching routines.

(iii) Social Influence (SI): Defined as "the degree to which an individual perceives that important other believe he or she should use the new system". In the pre-service context, influential others could include university faculty, mentor instructors during practicums, peers in the training program, and potentially future employers or industry contacts. The modeling of technology use by faculty and peer norms within the cohort could shape SI (Schretzlmaier, Hecker, & Ammenwerth, 2022).

(iv) Facilitating Conditions (FC): Defined as "the degree to which an individual believes that an organizations and technical infrastructure exists to support the use of the system". For pre-service instructors, this pertains to the availability of necessary resources within their instructor education program and placement schools, including access to GenAI tools, reliable internet, technical support, and relevant training opportunities. FC is often conceptualized as directly influencing use behavior, though some studies also link it to Behavioral Intention (Wedlock & Trahan, 2019). Given potential resource constraints in TVET institutions, FC might be a critical factor.

Methodology

Research Design

This study adopted a quantitative research approach utilizing a cross-sectional survey design. According to Creswell (2014), a quantitative approach is appropriate for testing objective theories by examining the relationship among variables. The cross-sectional design was specifically selected to assess the perceptions, attitudes, and behavioral intentions of the target population regarding technology adoption at a single point in time (Sekaran & Bougie, 2016). This method facilitates the statistical testing of the hypothesized relationships derived from the UTAUT model efficiently. To ensure the research was conducted systematically, the study followed an operational framework divided into four distinct phases. These phases outline the step-by-step process from conceptualization to the final analysis:

Phase 1: Planning and Conceptualization. The initial phase focused on defining the research scope and identifying the problem. A comprehensive review of existing literature was conducted to understand the current landscape of GenAI in TVET education. The Unified Theory of Acceptance and Use of Technology (UTAUT) was identified and selected as the theoretical underpinning to guide the research framework.

Phase 2: Instrument Development. The second phase involved designing the research instrument. A structured questionnaire was developed by adapting validated items from Venkatesh et al. (2003). This phase included refining the items to ensure they were contextually relevant to pre-service TVET instructors, focusing on constructs such as Performance Expectancy, Effort Expectancy, and Social Influence.

Phase 3: Data Collection. In this phase, the sampling strategy was executed. Random sampling was employed to select participants from the Centre for Instructor and Advanced Skill Training (CIAST), Shah Alam. The survey was distributed to the target respondents, and data collection was monitored to ensure a representative sample across various disciplines.

Phase 4: Data Analysis. The final phase involved the screening and analysis of the collected data. The raw data were checked for completeness to filter out unusable responses. Statistical analysis was then performed on the valid data (N=43) to test the research hypotheses and interpret the findings in relation to the study's objectives.

Participants And Sampling

The target population for this study comprised pre-service instructors currently enrolled in TVET instructor training programs across various disciplines under the National Instructor Training Programme. To obtain a representative sample, random sampling was employed among students who were actively participating in the pre-service instructor training program at the Centre for Instructor and Advanced Skill Training (CIAST), Shah Alam campus. This approach ensured that participants reflected a cross-section of different fields of study and training backgrounds, thereby enhancing the generalizability of the findings. The final sample consisted of 43 respondents who voluntarily completed the survey in its entirety and provided usable data for analysis.

Instrument Development

A structured questionnaire was developed based on the UTAUT model. The items measuring the core constructs; Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC) and Behavioral Intention (BI) were adapted from previously validated scales, primarily from Venkatesh et al. (2003). Minor wording adjustments were made to ensure clarity and relevance to the context of pre-service TVET instructors and GenAI tools (e.g., framing PE in terms of teaching effectiveness, FC in terms of institution program support).

Results and Findings

Demographic

A total of 43 pre-service instructors participated in the study, selected through random sampling from students currently enrolled in the pre-service TVET instructor training program at the CIAST, Shah Alam campus. The sample was well-balanced in terms of gender, comprising 53.5% female (n=23) and 46.5% male (n=20) participants. This distribution provides a relatively even representation of perspectives across genders, allowing for more generalizable insights.

In terms of specialization areas, participants represented a diverse range of TVET fields, with Mechanical Engineering Technology (16.3%) recording the highest representation, followed closely by Automotive Technology (14.0%), Electrical Technology (14.0%), Fashion Design (14.0%), Hospitality (14.0%), and Office Management (14.0%). Smaller proportions came from Business/Administration/Finance (7.0%), Arts/Design (2.3%), Manufacturing (2.3%), and other disciplines (2.3%). This spread indicates that the sample captures a broad cross-section of TVET specializations, which strengthens the applicability of findings across various vocational domains.

Regarding digital confidence, the majority of respondents (95.3%) rated themselves at level 4 (high confidence) on a 5-point scale, indicating high confidence in using digital technologies for educational purposes. Only 2.3% rated themselves at level 3 (moderate confidence) and 2.3% at level 5 (very high confidence). This suggests that most pre-service instructors already possess a solid foundation in digital literacy, which is an important precondition for adopting emerging technologies such as Generative AI.

Familiarity with GenAI tools, however, was more moderate. The vast majority (90.7%) reported a familiarity level of 3 out of 5, indicating partial awareness but limited depth of experience. Only 7.0% rated their familiarity at level 4, and 2.3% at level 5, suggesting that very few participants consider themselves highly knowledgeable about GenAI tools. When asked about their current usage, 86.0% reported that they use GenAI tools only occasionally, while 14.0% indicated frequent use (several times per week). This reflects a gap between digital readiness and actual integration of GenAI into their learning or teaching-related activities, highlighting a potential area for targeted intervention through training and exposure.

Descriptive Statistics

Descriptive statistics (means, standard deviations) and Cronbach's alpha reliability coefficients for the core UTAUT constructs are presented in Table 1. On average, participants reported. All scales demonstrated acceptable internal consistency, with Cronbach's alpha values exceeding the recommended threshold of 0.80.

Table 1: Descriptive Statistics And Reliability Of Constructs

Construct	No. of Items	Mean	Std. Deviation	Cronbach's Alpha (α)
Performance Expectancy (PE)	4	4.30	0.42	0.939
Effort Expectancy (EE)	4	4.49	0.51	0.950
Social Influence (SI)	4	4.37	0.40	0.856
Facilitating Conditions (FC)	4	4.35	0.42	0.900
Behavioral Intention (BI)	3	4.30	0.43	0.926

Correlation and Regression Analysis

A correlation matrix showing the relationships between the constructs is presented in Table 2.

Table 2: Pearson Correlations Between UTAUT Constructs

Variable	1	2	3	4	5
1. PE	—				
2. EE	.737**	—			
3. SI	.482**	.943**	—		
4. FC	.514**	.854**	.910**	—	
5. BI	.919**	.730**	.550**	.717**	—

Note: *N = 43. Values are Pearson correlation coefficients.* **p** *< .001 for all correlations.* **PE** *= Performance Expectancy,* **EE** *= Effort Expectancy,* **SI** *= Social Influence,* **FC** *= Facilitating Conditions,* **BI** *= Behavioral Intention.* ***p < .05,* ****p < .01 (all here significant at p < .001).*

Table 2 presents the Pearson correlations among the study variables. All constructs were significantly and positively correlated with Behavioral Intention (BI) ($p < .001$). Performance Expectancy (PE) showed the strongest correlation with BI ($r = .919$), underscoring that respondent who perceive GenAI tools as highly useful are the most likely to express intention to adopt them. Effort Expectancy (EE) ($r = .730$) and Facilitating Conditions (FC) ($r = .717$) were also strongly related to BI, suggesting that ease of use and institutional/technical support are critical factors driving adoption.

Social Influence (SI) was moderately correlated with BI ($r = .550$), indicating that encouragement from peers, mentors, and institutional culture plays a meaningful, though relatively smaller, role. Taken together, these findings provide preliminary evidence that all four UTAUT determinants are relevant in predicting the adoption intentions of pre-service TVET instructors, with PE emerging as the most dominant predictor.

Table 3: Multiple Regression Predicting Behavioral Intention (BI)

Predictor	B	SE B	β	t	p	% Variance Explained
(Constant)	0.15	0.20	–	0.75	.458	–
PE (Performance Expectancy)	0.65	0.08	**0.70**	8.12	<.001	**49%**
EE (Effort Expectancy)	0.28	0.09	0.25	3.11	.003	6%
SI (Social Influence)	0.10	0.08	0.09	1.25	.218	1%
FC (Facilitating Conditions)	0.22	0.07	0.20	3.14	.003	4%

Model Summary: *$R^2 = 0.82$, Adjusted $R^2 = 0.80$, $F(4, 38) = 41.70$, $p < .001$, Durbin–Watson = 2.02.*

A multiple regression analysis was conducted to examine the combined effect of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) on Behavioral

Intention (BI) to adopt Generative AI tools. The overall model was statistically significant, $F(4, 38) = 41.70$, $p < .001$, and explained 82% of the variance in BI (Adjusted $R^2 = .80$).

As presented in Table 3, PE emerged as the most powerful predictor ($\beta = .70$, $p < .001$), uniquely accounting for approximately 49% of the variance in BI. EE contributed an additional 6%, and FC accounted for about 4%. SI, while positively related, explained only 1% of the variance and was not statistically significant ($\beta = .09$, $p = .218$). These findings indicate that perceptions of how GenAI enhances teaching performance (PE) are the dominant driver of adoption intention, whereas ease of use (EE) and access to support (FC) play smaller but still meaningful roles. Peer and institutional influence (SI) appear to have relatively minor impact once other factors are considered. Collinearity diagnostics (all VIF < 4) confirmed that multicollinearity was not a concern, supporting the validity of the model estimates.

Discussion

The results of this study provide strong empirical support for the UTAUT model in explaining the Behavioral Intention of pre-service TVET instructors to adopt Generative AI (GenAI) tools. Descriptive analysis indicated that participants reported high levels of agreement across all four core constructs; Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) with EE recording the highest mean, suggesting that participants generally perceive GenAI as easy to learn and use. This is encouraging because ease of use is often cited as a major barrier in the adoption of emerging technologies (Aksoy & Toprak, 2024).

Key Predictors Of Adoption

The correlation analysis further demonstrated that all four constructs were positively and significantly related to Behavioral Intention (BI), with PE showing the strongest relationship ($r = .919$, $p < .001$). This underscores the centrality of Performance Expectancy (PE) in driving adoption, consistent with previous UTAUT (Aksoy & Toprak, 2024; Baharin et al., 2024; Han et al., 2025) which found PE to be the strongest predictor of intention across multiple technology contexts. EE and FC also showed strong positive correlations, suggesting that participants value not only ease of use but also the presence of institutional and technical support when deciding whether to adopt GenAI tools.

The multiple regression results reinforce these findings, revealing that PE is the most influential predictor ($\beta = .70$), uniquely explaining 49% of the variance in BI. EE and FC contributed an additional 6% and 4% respectively, indicating that these factors remain significant even when controlling for PE. Interestingly, SI did not significantly predict BI once other factors were controlled, despite its significant bivariate correlation. This suggests that while social and organizational encouragement may help raise awareness, individual perceptions of usefulness and system readiness (PE, EE, FC) are ultimately more decisive in shaping adoption intentions.

These findings align with earlier research in educational technology adoption, which consistently highlights PE as the primary driver of behavioral intention, followed by EE and FC, with SI often exhibiting weaker or context-dependent effects (Tahir, 2023; Budhathoki, 2024). In the context of TVET, this indicates that pre-service instructors are more motivated by the tangible benefits GenAI brings to teaching and learning (e.g., realistic simulations, automated feedback, resource generation) than by social pressure or institutional mandates.

Practical Implications

From a practical standpoint, these results suggest that TVET instructor education programs should prioritize interventions that demonstrate the practical value of GenAI in authentic teaching contexts. This can be achieved through case studies, project-based assignments, and live demonstrations that clearly show how GenAI can enhance pedagogical practice. Furthermore, training must extend beyond technical proficiency to encompass comprehensive AI literacy and ethical reasoning. It is crucial that instructors are equipped not only with the skills to operate these tools but also with the critical ability to evaluate the accuracy of AI-generated content, address data privacy concerns and navigate issues related to academic

integrity. Programs should integrate these ethical competencies across multiple courses rather than isolating them in a single module, ensuring that GenAI is positioned as a scaffold for learning rather than a replacement for critical thinking.

At the policy level, stakeholders should invest in equipping TVET institutions with the necessary infrastructure to support GenAI adoption. These initiatives align directly with the strategic goals of the Malaysia Artificial Intelligence Roadmap 2021-2025, which emphasizes the cultivation of AI-ready talent for the digital economy. Additionally, integrating GenAI into the curriculum supports the National TVET Policy 2030's objective of producing a future-proof workforce capable of meeting Industry 4.0 demands. To realize this, policymakers must develop specific national guidelines for responsible AI use in TVET. This will help ensure that the adoption of GenAI is not just technically feasible but also pedagogically meaningful and ethically grounded, empowering Malaysian TVET instructors to genuinely enhance TVET outcomes.

Conclusion

This study provides empirical evidence that the UTAUT framework is highly effective in explaining the intention of pre-service TVET instructors to adopt Generative AI (GenAI) tools. The model explained 82% of the variance in Behavioral Intention (BI), with Performance Expectancy (PE) emerging as the most influential determinant, followed by Effort Expectancy (EE) and Facilitating Conditions (FC). Social Influence (SI) was not a significant predictor when controlling for other variables, highlighting those personal beliefs about usefulness, ease of use, and availability of support systems are more critical than peer or institutional pressure. These results underscore the need to prioritize strategies that enhance the perceived pedagogical value and practical applicability of GenAI for future instructors.

These findings provide valuable insight for shaping TVET instructor training program. They show that adoption of GenAI depends not only on its usefulness and ease of use but also on access to proper training, resources, and institutional support. This study emphasizes the need for training program to demonstrate the practical value of GenAI, ensure user-friendliness, and build robust support systems, while also developing AI literacy and ethical awareness. A human-centered approach is essential to ensure GenAI enhances teaching and learning rather than creating new challenges.

While this study offers significant insights into GenAI adoption among pre-service TVET instructors, it is subject to certain limitations regarding sample size and generalizability. Specifically, the reliance on a relatively small sample (N=43) from a single training institution limits the extent to which findings can be extrapolated to the broader TVET population. To address this, future research should prioritize expanding the scope by recruiting a larger, more diverse cohort from multiple TVET institutions across Malaysia, ensuring a more comprehensive representation of the instructor community.

Furthermore, the use of a cross-sectional design captures data at only a single point in time, which restricts the ability to observe how user perceptions evolve as they gain experience with the technology. As GenAI adoption is a dynamic process, future scholars are encouraged to adopt a longitudinal approach to track changes in behavioral intention over time. Additionally, incorporating qualitative methods such as in-depth interviews could complement survey data by uncovering specific challenges and motivations that quantitative analysis alone may not fully capture.

Acknowledgement

This paper is the result of a collaborative effort between the Centre for Instructor and Advanced Skill Training (CIAST) and Universiti Tun Abdul Razak (UNIRAZAK).

References

Abdou, D., & Jasimuddin, S. M. (2020). The use of the UTAUT model in the adoption of e-learning technologies: An empirical study in France-based banks. *Journal of Global Information Management, 28*(4), 38–51. https://doi.org/10.4018/JGIM.2020100103

Aksoy, I. G., & Toprak, E. (2024). AI adoption in accounting education: A UTAUT-based analysis of mediating and moderating mechanisms. *Journal of Pedagogical Research, 8*(1), 381–408.

Baharin, A. T., Sahadun, N. A., Ramli, S., & Liyana Redzuan, N. A. (2024). Exploring the adoption of Generative Artificial Intelligence by TVET students: A UTAUT analysis of perceptions, benefits, and implementation challenges. *Behaviour & Information Technology, 43*(6), 941–957.

Batucan, G. B., Gonzales, G. G., Balbuena, M. G., Pasaol, K. R. B., Seno, D. N., & Gonzales, R. R. (2022). An extended UTAUT model to explain factors affecting online learning system amidst COVID-19 pandemic: The case of a developing economy. *Frontiers in Artificial Intelligence, 5*, 768831. https://doi.org/10.3389/frai.2022.768831

Belkina, M., Daniel, S., Nikolic, S., Haque, R., Lyden, S., Neal, P., ... & Hassan, G. M. (2025). Implementing generative AI (GenAI) in higher education: A systematic review of case studies. *Computers and Education: Artificial Intelligence*, 100407.

Berigel, D. S., Şilbir, L., & Şilbir, G. M. (2025). Integrating artificial intelligence (AI) into technical and vocational education and training (TVET): A PRISMA-based systematic review. *Calitatea Vieții, 36*(1), 1–27.

Bitemirova, S., Zholdasbekova, S., Mussakulov, K., Anesova, A., & Zhanbirshiyev, S. (2023). Pre-service TVET teachers' digital competence: Evidence from survey data. *TEM Journal, 12*(2).

Budhathoki, T., Zirar, A., Njoya, E. T., & Timsina, A. (2024). ChatGPT adoption and anxiety: A cross-country analysis utilising the unified theory of acceptance and use of technology (UTAUT). *Studies in Higher Education, 49*(5), 831–846. https://doi.org/10.1080/03075079.2023.2171901

Chen, P. D., Lambert, R., & Chiarelli, S. (2022). Effect of a science-based TPACK program for elementary preservice teachers according to their gender. *Contemporary Issues in Technology and Teacher Education, 22*(3).

Creswell, J. W. (2014). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches (4th ed.). SAGE Publications.

Ghazi, F., Chong, G., Juhdiy, F., Khalid, A., Mazlan, M., & Ali, W. N. H. W. (2025). Adoption and Usage of Generative Artificial Intelligence (GenAI) Tools Among Bandar Penawar MARA Professional College Students. *Innovative Teaching and Learning Journal*, *9*(1), 247-257.

Han, M., Mustafa, H., & Kharuddin, S. (2025). AI adoption in accounting education: A UTAUT-based analysis of mediating and moderating mechanisms. *Journal of Pedagogical Research, 9*(2), 191–205.

Holmes, W., & Miao, F. (2023). Guidance for generative AI in education and research. UNESCO Publishing.

Lawrence, E. M. (2004). Technology integration and pre-service teacher training: The effectiveness of embedding technology use in three pre-methods courses (Doctoral dissertation). Nova Southeastern University. https://nsuworks.nova.edu/gscis_etd/659/

Lee, A. H. C. (2025). Use of Generative Artificial Intelligence among Selected Pre-University Business Students at a Private University in Malaysia. *Asia-Pacific Journal of Futures in Education and Society*, *4*(1), 1-20.

Or, C., & Chapman, E. (2021). An extended Unified Theory of Acceptance and Use of Technology model for education contexts. *Journal of Applied Learning and Teaching, 4*(2), 98–109. https://doi.org/10.37074/jalt.2021.4.2.16

Ranuharja, F., Rizal, F., Langeveldt, D., Ejjami, R., Torres-Toukoumidis, A., & Jalinus, N. (2025). Relevance and impact of generative AI in vocational instructional material design: A systematic literature review. *Salud, Ciencia y Tecnología, 5*, 1336.

Richard, G. S., Joseph, A., Elikem, K., & Edem, B. K. (2023). Technology integration in technical and vocational education and training (TVET): The role of the art teacher. *Journal of Technical Education and Training, 15*(4), 73–88. https://doi.org/10.30880/jtet.2023.15.04.007

Sekaran, U., & Bougie, R. (2016). Research Methods for Business: A Skill-Building Approach (7th ed.). Wiley.

Schretzlmaier, P., Hecker, A., & Ammenwerth, E. (2022). Suitability of the Unified Theory of Acceptance and Use of Technology Two (UTAUT2) model for predicting mHealth acceptance using diabetes as an example: Qualitative methods triangulation study. *JMIR Human Factors, 9*(1), e34918. https://doi.org/10.2196/34918

Tahir, M. M. (2023). Students' behavioural intention towards adoption of online education: A study of the extended UTAUT model. *Journal of Learning for Development, 10*(3), 392–410.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Wedlock, B. C., & Trahan, M. P. (2019). Revisiting the Unified Theory of Acceptance and Use of Technology (UTAUT) model and scale: An empirical evolution of educational technology. *Research Issues in Contemporary Education, 4*(1), 6–20.

Zary, A., & Zary, N. (2025). Artificial intelligence in technical and vocational education and training: Empirical evidence, implementation challenges, and future directions [Preprint]. https://doi.org/10.20944/preprints202504.2173.v1