INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN BUSINESS & SOCIAL SCIENCES
Vol 15, Issue 11, (2025) E-ISSN: 2222-6990

Artificial Intelligence Acceptance in Science Teaching: A Path Analysis Using the UTAUT Model

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DOI Link: http://dx.doi.org/10.6007/IJARBSS/v15-i11/26928

Published Date: 10 November 2025

Abstract
The study aimed to examine the acceptance of artificial intelligence (AI) in science teaching using Unified Theory of Acceptance and Use of Technology (UTAUT) model. This study used a quantitative, non-experimental survey design and involved 345 secondary teacher who were teaching science across Sabah. The structural model elucidated that independent variable—namely, perfomance expectancy, effort expectancy, social influences, facilities condition—exerted a statistically significant and positive influence on intention to use AI in science teaching. The results indicated that facilities condition is the dominant predictive factor. Collectively, this model effectively accounted for 78.9% of the variance in the intention of science teachers in Sabah to adopt AI. The study offers insights to enhance AI acceptance among science teachers in Sabah, fostering innovation in education.
Keywords: Science Teaching, Artificial Intelligence (AI), UTAUT, Facilities Condition, AI Adoption

Introduction

Alam et al. (2025) emphasizes that artificial intelligence (AI) has enormous potential in transforming science education. Therefore, the trend of using AI in STEM and science teaching demands that the educational community transform conventional teaching methods into more innovative teaching methods (Bello et al., 2023). In general, the application of AI in Malaysia is still in its early stages (Ghoni, 2025). However, the use of this technology has been identified as having great potential, especially in STEM education. On this basis, the Ministry of Education has formulated and planned various strategies such as the implementation of the Digital Education Policy (DPD) which aims to introduce this technology to students, thus opening up a new dimension to the implementation of more efficient learning. In the context of science education in Malaysia, the use of AI supports reflective learning, which is learning that involves the process of acquiring and mastering scientific skills through inquiry approaches, constructivism, contextual learning and mastery learning.

According to Huang et al. (2022), AI has great potential in providing an effective student-centered teaching approach such as inquiry-based teaching. Since mastery of scientific skills is the main goal in science teaching (KPM, 2019), teachers need to use strategies that can trigger students' willingness or desire to answer a question scientifically. Xie et al. (2023) reported that through the use of Chatbot, for example, students can develop ideas, find and compare answers, and begin investigations. In addition, Lee et al. (2021) through the use of AI, game-based learning provides a new dimension in learning where students can experience building a science concept. Darayseh (2023) also believes that an interactive learning environment with the help of artificial intelligence can offer a more enjoyable science learning experience.However, past surveys have shown that the level of AI adoption in science teaching is generally lower than in language subject (Collie and Martin, 2024). This finding is in line with the findings of Oyeronke (2025) where the researcher found that the level of AI usage among science teachers was very minimal.

Theoretical Background

Unified Theory of Acceptance and Use of Technology (UTAUT)

The model developed by Venkatesh et al. (2003) this includes four constructs that determine technology acceptance, namely (i) performance expectations (ii) effort expectations, (iii) social influence and (iv) facility conditions. Through this theory, actual usage behavior refers to the actual use of any technology or information system that implicitly exists due to the intention to use it. In general, the use of a technology depends on the user's trust factor, while the continuity and continued use of the technology is influenced by the user's satisfaction factor.UTAUT is used as the main reference source because according to Venkatesh et al. (2003) the UTAUT model is a technology acceptance model that has been proven to explain the variance of behavioral intentions more accurately compared to other models and theories such as TAM and TPB that can only explain 17% to 53% of the variance of behavioral intentions in using a new technology.

In addition, this model is identified to be able to discuss the aspects of an individual's technology acceptance clearly because the factors or dimensions of the study and behavioral intentions are connected in a simple way compared to other acceptance models (Jose & Jose, 2024). The selection of this model is very much in line with today's educational landscape, where the use of technology is constantly evolving, from time to time. Based on UTAUT, there are four dimensions that have an influence on behavioral intentions and acceptance of generative artificial intelligence among science teachers, namely performance expectations, effort expectations, social influence and convenience conditions.

Motivation of Variables

Performance expectancy (PE) refer to the extent to which an individual believes that the use of a technology or system will improve their task performance (Al-Hattami, 2024). In general, performance expectations have a positive impact on the productivity, effectiveness and quality of a given job or task. To date, based on current research, performance expectations remain the main predictor of determining behavioral intentions based on various technology acceptance models (Li & Zhang, 2024). Therefore, in the context of this study, performance expectations for the use of artificial intelligence refer to teachers' perceptions or assumptions regarding the benefits of using such technology in increasing teacher productivity and efficiency, especially in teaching tasks**.**

Effort expectancy (EE) is defined as the extent to which an individual believes that the use of a particular technology does not require a great deal of effort (Lee & Davis, 2024; Perrotta & Selwyn, 2020). Previous research has confirmed that effort expectancy is a key predictor of behavioral intentions to use artificial intelligence (Li & Zhang, 2024). Therefore, in the context of this study, effort expectancy refers to teachers' perceptions or beliefs about whether the use of generative artificial intelligence in science teaching is easy to use and understand, without requiring maximum guidance or intensive training (Chatterjee & Bhattacharjee, 2020). In addition, the assessment of this construct also includes positive experiences experienced while using the technology.

Venkatesh et al. (2003) stated social influence (SI) as a perception related to the extent to which an individual feels that influential or important people around the individual have the belief that they should use a technology. Xu et al.(2024) reported that influential people may consist of superiors, colleagues, close family or close friends. In addition, the assessment of social influence also includes teacher compliance in the implementation of a new educational policy or policy Xie et al., 2021). Therefore, in the context of this study, social influence refers to teachers' perceptions related to the extent to which colleagues, superiors and educational policies influence the desire and acceptance of generative artificial intelligence in science teaching.

According to Venkatesh et al. (2003), the condition of facilities (FC) is referred to as the extent to which the availability of facilities and technical support is able to support the use of a technology. The condition of the facilities is provided either by the individual himself or by an organization. Therefore, in the context of this study, the condition of facilities refers to the teacher's perception regarding the level of adequacy or readiness of facilities which includes two components, namely the infrastructure and infostructure components. In this study, the infrastructure facilities assessed include the provision of conducive usage spaces, stable internet access and the readiness of devices to access the technology. Meanwhile, the infostructure facility component involves the readiness of a digital platform or ecosystem, the support of a consultant or mentor teacher and a training program to improve professionalism related to the use of the technology.

In general, there are various interpretations of the concept of behavioral intention (BI) in technology acceptance (Chen et al., 2024). According to Jose and Jose (2024), behavioral intention is often referred to as the probability for an individual to perform a behavior. Chatterjee and Bhattacharjee (2020), explain that behavioral intention of use is often associated with the individual's ability to try something. Behavioral intention demonstrates the strength of desire to perform an action. According to Hoareau et al. (2021) behavioral intention influences the actual use of a technology. Therefore, in the context of this study, behavioral intention refers to teachers' perceptions regarding the desire to try generative artificial intelligence in science teaching.

Therefore, the following hypotheses are developed based on the above independent variables (PE, EE, SI, FC) toward the behavioural intention (dependent variable) to use or accept AI

Hypothesis 1: Performance expectancy positively affects AI acceptance among science teachers.
Hypothesis 2: Effort expectancy positively affects AI acceptance among science teachers.
Hypothesis 3: Social influence positively affects AI acceptance among science teachers.
Hypothesis 4: Facilitating condition positively affects AI acceptance among science teachers

Research Findings

This research was conducted to obtain a more holystic analysis of AI acceptance among science teachers. The demographic profile of the respondents is presented in Table 1.

Table 1
Demographic Profile

Variable	Item	Frequency	Percentage
Gender	Male	163	47
	Female	182	53
Teaching Experience	Less than 3 years	41	12
	3 to 5 years	55	16
	5 to 10 years	86	25
	10 to 15 years	78	23
	More than 15 years	85	24
Location	Urban	160	46
	Rural	185	54

As demonstrated in Table 1, most of the respondents were female which was at 53 percent whereas 47 percent of them were male. As for the teaching experience, the respondents had less than 3 years teaching experience (12 percent), 3-5 years teaching experience (16 percent), 5-10 years teaching experience (25 percent), 10 to 15 years teaching experience (23 percent) and more than 15 years teaching experience (24 percent). In terms of school location, 55 percent of respondents were from urban schools and 45 percent of respondents were from rural schools.

Measurement Model

Internal consistency reliability for a research model refers to the composite reliability (CR) value and Cronbach's alpha. In the context of this study, assessing the level of reliability through the CR value involves reading values in the range of 0 to 1. According to Hair et al. (2017), reliability is at a satisfactory level if the CR value is between 0.600 to 0.700. Therefore, in this study, the CR value accepted refers to the view of Hair et al. (2017) which is ≥0.700. Apart for that, a Cronbach's alpha value > 0.70 is assumed to be sufficient and acceptable. The other important measurement of reliability showed that convergent validity was acceptable because the Average Variance Extracted (AVR) was over 0.5. The results for reliability and validity along with the factors loadings for the items of 5 constructs are presented in Table 2. The results for reliability and validity along with the factors loadings for the items are presented in Table 2.

Table 2
Loadings, Reliability and Validity

Variable	Construct	Loadings	Cronbach's alpha	AVE	CR
Performance Expectancy (PE)	PE1	0.697	0.759	0.508	0.837
	PE2	0.624			
	PE3	0.725			
	PE4	0.759			
	PE5	0.750			
Effort Expectancy (EE)	EE1	0.693	0.796	0.614	0.862
	EE2	0.729			
	EE3	0.753			
	EE4	0.937			
	EE5	0.693			
Social Influences (SI)	SI1	0.708	0.755	0.583	0.845
	SI2	0.628			
	SI3	0.963			
	SI4	0.713			
Facilitating Condition (FC)	FC1	0.792	0.832	0.607	0.883
	FC2	0.965			
	FC3	0.686			
	FC4	0.641			
	FC5	0.773			
Behavioural Intention (BI)	BI1	0.755	0.834	0.608	0.884
	BI2	0.791			
	BI3	0.789			
	BI4	0.920			
	BI5	0.609			

Discriminant validity was assessed by the Fornell-Larcker's criterion (Fornell & Larcker, 1981), the table shows that the square-root of AVE for the construct was greater than the inter-construct correlation (see Table 3). Discriminant validity was also evaluated by the Heterotrait-Monotrait ratio of correlations (Henseler et al., 2015), with values below the threshold of 0.9. as indicated in Table 4.

Table 3
Fornell Larcker's Criterion

	BI	EE	FC	PE	SI
BI	0.779				
EE	0.703	0.784			
FC	0.750	0.496	0.779		
PE	0.501	0.410	0.370	0.713	
SI	0.167	0.222	0.045	0.098	0.763

Table 4
Heterotrait-Monotrait Ratio (HTMT)

	BI	EE	FC	PE	SI
BI					
EE	0.794				
FC	0.817	0.524			
PE	0.612	0.481	0.425		
SI	0.201	0.279	0.089	0.147	

Structural Model
Fig. 1 illustrate the structural model presents the path coefficients among constructs. Meanwhile, Table 5 displays the results of path coefficients in evaluating the hypotheses constructed based on literature.

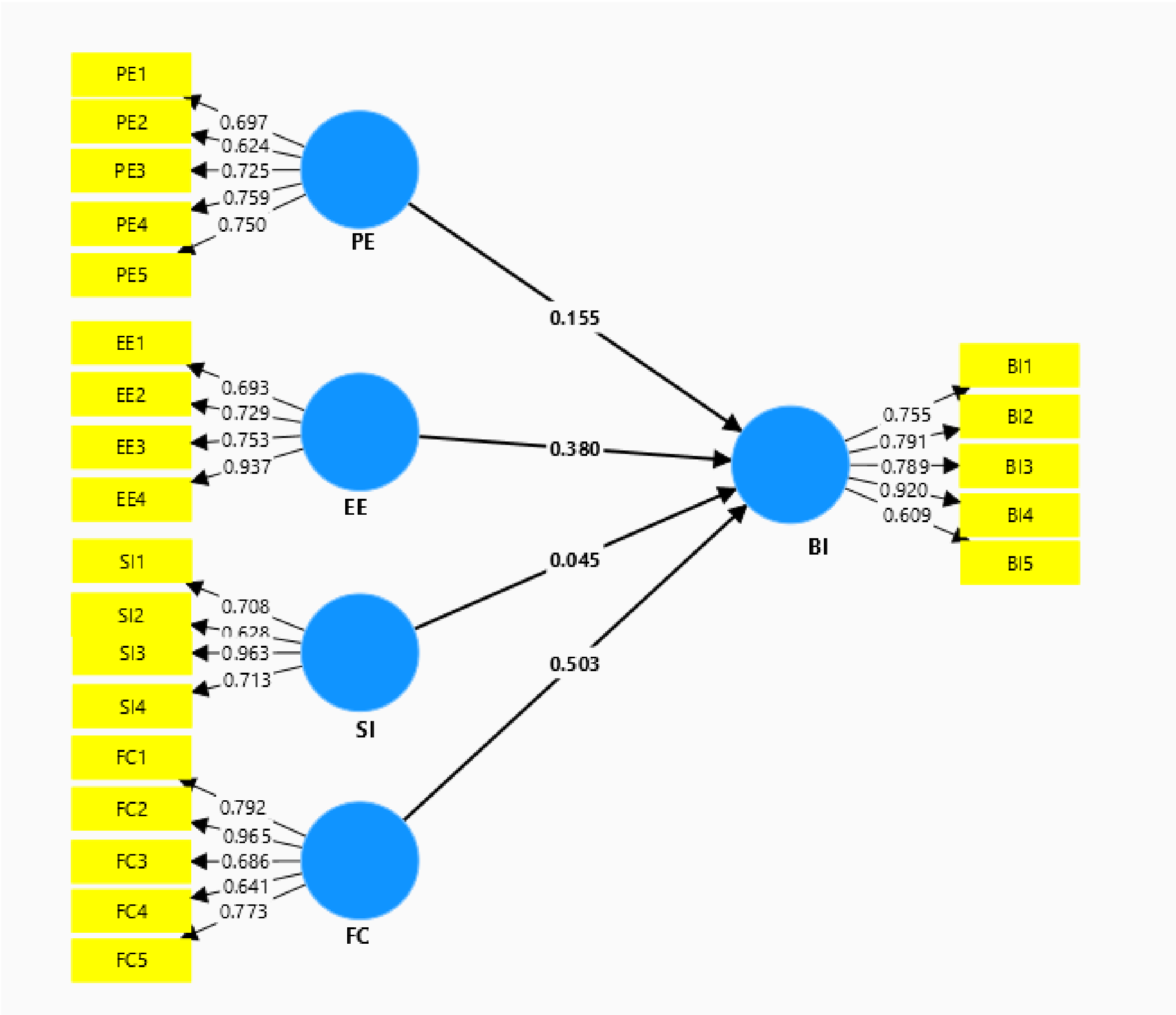

Fig. 1. Structural Model

The test on the significance of the path was conducted using SmartPLS's bootstrap re sampling techniques. It is interesting to note that all independent construct, Perfomance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) indicated a significant relationship to Behavioural Intention (BI). A positive correlation is found between BI and PE (0.155), BI and EE (0.380), BI and SI (0.045) as well as BI and FC

(0.503) at the significance level of 0.05 and 0.001. Therefore, these findings support H1,H2, H3 and H4.

Table 5
Path Coefficient

Dependent variable	Independent Variable	Path	Observed *t*-statistics	*p*-value
Behavioural	PE	0.155	4.485	0.000*
Intention (BI)	EE	0.380	10.197	0.000*
R^2 = 0.789	SI	0.045	1.591	0.000*
	FC	0.503	14.783	0.012**

Perfomance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) indicated a significant relationship to Behavioural Intention (BI), sig level *(0.01) and level **(0.05)

Discussion and Conclusion

Overall, the findings of this study are in line with the basic principles of the UTAUT model where all constructs have a positive and significant direct effect. The findings confirm that FC are the main predictors of AI acceptance among science teachers in Sabah. This finding proves that the acceptance of AI does not only depend on internal factors such as PE and EE, but is instead more influenced by external and technical factors such as FC. In reality, adequate facilities can increase the behavioral intention to use a technology, especially new technology (Venkatesh et al., 2012). Typically, the implementation of any technology requires quality internet access. In this context, the use of AI required stable internet access because most AI system operations and applications require access to data and cloud processing (Liang et al., 2023). In addition, some application involve analyze data in real time, as well as send information or responses quickly and according to user instructions (Xue & Wang, 2022)

On this basis, the availability of internet access influences the formation of user BI.However, in Sabah, geography and topography are major challenges in creating a stable internet network across all schools especially in rural areas. The proof is, based on statistics announced by the Malaysian Communications and Multimedia Commission (MCMC) Sabah is among the states identified as having the lowest fixed broadband penetration rate (24.8%) in 2024. Apart from that, Sabah is the only state that has not yet achieved 100% mobile penetration by 2025. Therefore, if the quality of internet access can be improved throughout Sabah, then teachers' intention to use AI will increase.

Apart form that, EE demonstrated a moderate but statistically significant influence on BI. Thos findings suggests that if science teacher perceive the AI tools to be easier to use, without high technology skill, their intention to accept it increases significantly. In the context of this study, science teacher’s will choose to integrate AI in teaching if the technology is user-friendly, accessible, flexible, and requires minimal effort during the initial phase of using the technology. This finding is consistent with the findings of Li and Zhang (2023) and Acosta-Enriquez et al. (2025).

On the other hand, the findings confirmed that PE has slightly stronger positive influence on BI. According to Wang et al. (2023), an individual's intention to use a innovative technology can be enhanced if there is a belief that will yield results, whether for themselves or for their students. In the context of this study, if teachers believe that the use of AI can improve their efficiency, performance, or the quality of teaching, then those teachers will be more motivated to use AI. In other words, teacher may be more inclined to use AI if they believe this technology will enhance their teaching quality. This finding aligns with the conclusions drawn by Ayenwale et al. (2022) dan Wang et al. (2023). Therefore, EE and PE should be enhanced through continuous training and workshop related to the integration of AI in teaching session.

The investigation also explores the based on the small coefficient value, social influence is not the main factor driving science teachers' intentions to use AI. Such findings resonate with the studies conducted by Li and Zhang (2023) and Pappa et al. (2024). In the context of this study, the social environment exists because all educational institutions in Malaysia are striving to enhance digital education. In this regard, the social organization in schools, is assumed to have cultivated the use of AI. Therefore, teachers will use AI even without social influence**.** Thus, the effect of SI on BI is weak, possibly due to the social environment that encourage all teacher need to integrate AI in their teaching session. Notably, this model accounts for a substantial portion, 78.9%, of the variance in science teachers' behavioural intention to use AI. This outcome indicates the model's effectiveness in explaining the factors driving sciecne teachers' intention to adopt AI.

Implication

This study explores the factors influencing secondary school science teachers' intentions to use AI in Sabah. By using UTAUT model, this study offers a comprehensive understanding of the specific determinants or factor affecting these teachers' behavioral intentions. The empirical results significantly contribute to both practical and theoretical aspects.

In the theoretical aspect, this study lends empirical support to the UTAUT model, affirming the significance of all predictors in shaping behavioral intention to use AI. This study provides solid evidence that secondary school science's teacher intention to adopt AI are well explained through the UTAUT model. Additionally, the findings establishes that facilities condition is key factor influencing these perceptions among science teachers. Furthermore, the study yielded findings that were parallel with some previous studies, making the study significant to be used as a reference in the context of AI adoption in science teaching,

In the practical aspect, the findings suggest several strategies that should be interesting to educational experts, policymakers, instructors and school administrators. For instance, facilities condition especially internet access and access to device should be a priority in strengthening the use of various technologies including AI at the school level. Second, to ensure the use of AI only deal with minimal effort, teachers provided with ongoing microtraining and technical support. Furthermore, to enhance teachers' comprehension and understanding about AI adoption in science teaching, educational experts and policy makers should explain the benefits of using AI through professional development programme such as workshops that link AI tools to science process skill or inquiry-based science teaching.

Limitation

However, it is essential to acknowledge the inherent limitations of this study. Firstly, the research scope is restricted to explore the factors influencing AI adoption among secondary school science teachers in Sabah. Notably, due to location and demographic factors, teachers' response to the facilities condition may be far different from schools in other states. Furthermore, the study's findings are specific to the perceptions of science teachers at the secondary school in Sabah. Next, generalizing these results to include science teachers in school settings with adequate facilities may be inaccurate. Additionally, the study's participants were exclusively involved science teacher. Although the findings of the survey method with longitudinal format are more accurate and precise, due to the location of the study, the researcher chose the cross-sectional survey method, which means that data collection only occurs once. Therefore, the collected data cannot be generalized if there are any drastic changes in the future.

Co-Author Contribution

The first author conceptualised the study, conducted data collection and analysis, and wrote the initial manuscript. The second author, provided feedback on the statistical analyses, ensured data reliability, and contributed to the writing of the results section. The third author playing a crucial role in both revising and finalising the overall organisation and writen content of the manuscript

References

Acosta-Enriquez, B. G., Ballesteros, M. A., Vilcapoma Pérez, C. R., Jordan, O. H., Vergara, J. A. M., Acosta, R. M., Perez Vargas, C. G. A., & Castillo, J. C. A. (2025). AI in academia: How do social influence, self-efficacy, and integrity influence researchers' use of AI models? Social Sciences & Humanities Open, 11, 101274. https://doi.org/10.1016/j.ssaho.2025.101274

Al-Hattami, H. M. (2024). What factors influence the intention to adopt blockchain technology in accounting education? Humanities and Social Sciences Communications, 11, 787–798. https://doi.org/10.1057/s41599-024-02678-2

Alam, M., Sk, M. M., & Sain, S. K. (2025). Utilizing artificial intelligent to transform rural communities: Difficulties and way outs. International Journal of Creative Research Thoughts (IJCRT), 13(7), 1–15. https://ijcrt.org/papers/IJCRT2507092.pdf

Ayanwale, M., Sanusi, I. T., Adelana, O. P., Aruleba, K. D., & Oyelere, S. S. (2022). Teachers' readiness and intention to teach artificial intelligence in schools. Computers and Education: Artificial Intelligence, 3, Article 100099. https://doi.org/10.1016/j.caeai.2022.100099

Bello, J., Concon, L., Polache, M. C. C., Ayaton, M. J., Manlicayan, R., Campomanes, J., & Saro, J. (2023). Contextualized and localized science teaching and learning materials and its characteristics to improve students' learning performance. Psychology and Education: A Multidisciplinary Journal, 7(1), 77–84. https://doi.org/10.5281/zenodo.7607686.

Chatterjee, S. & Bhattacharjee, K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. Education and Information Technologies, 25. https://doi.org/10.1007/s10639-020-10159-7

Collie, R. J., & Martin, A. J. (2024). Teachers' motivation and engagement to harness generative AI for teaching and learning: The role of contextual, occupational, and background factors. Computers and Education: Artificial Intelligence, 6, Article 100224.

https://doi.org/10.1016/j.caeai.2024.100224

Darayseh, A. S. (2023). Acceptance of artificial intelligence in teaching science: Science teachers' perspective. Computers and Education: Artificial Intelligence, 4, Article 100132. https://doi.org/10.1016/j.caeai.2023.100132

Ghoni, R. (2025). AI dalam pendidikan: Transformasi dan masa hadapan. Dewan Masyarakat, 02/2025. Dewan Bahasa dan Pustaka

Hoareau, L., Thomas, A., Tazouti, Y., Dinet, J., Luxembourger, C., & Jarlégan, A. (2021). Beliefs about digital technologies and teachers' acceptance of an educational app for preschoolers. Computers & Education, 172, Article 104264. https://doi.org/10.1016/j.compedu.2021.104264

Huang, W., Hew, K. F., & Fryer, L. K. (2022). Chatbots for language learning—Are they really useful? A systematic review of chatbot-supported language learning. Journal of Computer Assisted Learning, 38(1), 237–257. https://doi.org/10.1111/jcal.12610.

Jose, J., & Jose, B. (2024). Educators' academic insights on artificial intelligence: Challenges and opportunities. Electronic Journal of E-Learning, 22(2), 59–77. https://doi.org/10.34190/ejel.21.5.3272

Kementerian Pelajaran Malaysia. (2019). Buku panduan pentaksiran. Kementerian Pendidikan Malaysia.

Lee, S. Y., Mott, B. W., Ottenbreit-Leftwich, A., Scribner, A., Taylor, S., Park, K., Rowe, J., Glazewski, K., Hmelo-Silver, C. E., & Lester, J. C. (2021). AI-infused collaborative inquiry in upper elementary school: A game-based learning approach. Proceedings of the AAAI Conference on Artificial Intelligence, 35(17), 15591–15599. https://doi.org/10.1609/aaai.v35i17.17836

Lee, Y. J., & Davis, R. (2024). Korean in-service teachers' perceptions of implementing artificial intelligence (AI) education for teaching in schools and their AI teacher training programs. International Journal of Information and Communication Technology Education, 14(2), 214–219. https://doi.org/10.18178/ijiet.2024.14.2.2042

Li, M., & Zhang, H. (2024). A study on the behavioral intention of primary and secondary school teachers using generative artificial intelligence in teaching. In 2024 the 9th International Conference on Distance Education and Learning (ICDEL 2024) (pp. 1–7). ACM. https://doi.org/10.1145/3675812.3675870

Pappa, C. I., Georgiou, D., & Pittich, D. (2024). Technology education in primary schools: Addressing teachers' perceptions, perceived barriers, and needs. International Journal of Technology and Design Education, 34, 485–503. https://doi.org/10.1007/s10798-023-09785-2

Oyeronke, A. (2025). Overcoming infrastructural and pedagogical barriers to AI adoption in rural vs. urban CLT classrooms. Proceedings of the AAAI Conference on Artificial Intelligence, 35(17), 15591–15599. https://www.researchgate.net/publication/39448

Perrotta, C., & Selwyn, N. (2020). Deep learning goes to school: Toward a relational understanding of AI in education. Learning, Media and Technology, 45(3), 251–269. https://doi.org/10.1080/17439884.2020.1686017

Suruhanjaya Komunikasi dan Multimedia Malaysia. (2024). Communications and multimedia: Facts and figures, 3Q 2024. Malaysian Communications and Multimedia Commission. https://www.mcmc.gov.my/en/resources/statistics/communications-and-multimedia-pocket-book-of-stati

Wang, X., Li, L., Tan, C. S., Yang, L., & Lei, J. (2023). Preparing for AI-enhanced education: Conceptualizing and empirically examining teachers' AI readiness. Computers in Human Behavior, 146, Article 107751. https://doi.org/10.1016/j.chb.2023.107751

Xie, J., Rice, M. F., & Griswold, D. E. (2021). Instructional designers' shifting thinking about supporting teaching during post Covid-19. Distance Education, 42(3), 331–351. https://doi.org/10.1080/01587919.2021.1956303

Xue, Y., & Wang, Y. (2022). Artificial intelligence for education and teaching. Wireless Communications and Mobile Computing, 2022(Article ID 1234567), 1–10. https://doi.org/10.1155/2022/1234567

Xu, S., Chen, P., & Zhang, G. (2024). Exploring Chinese University Educators' Acceptance and Intention to Use AI Tools: An Application of the UTAUT2 Model. SAGE Open, 14(4). https://doi.org/10.1177/21582440241290013

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