Journal of Pedagogical Research
Volume 9, Issue 2, 2025
https://doi.org/10.33902/JPR.202531937

Research Article

Harnessing self-efficacy: Mediating the connection between TPACK and AI intentions among teachers

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This study quantitatively identifies the mediating aspect of self-efficacy in the connection between technological pedagogical content knowledge (TPACK) and artificial intelligence (AI) adoption intention towards educators in Indonesia. Data were collected via online surveys using adapted questionnaires, and respondents were selected using stratified random sampling method to ensure the diverse representation of respondent based on their teaching background in Indonesia. Constructs were described by descriptive statistics, and the hypothesized model was tested through mediation analysis of SmartPLS 4.0's bootstrapping algorithm. Findings showed that the constructs of the study have good validity and reliability, the created model was fit, while educators possess high TPACK and self-efficacy levels and a moderate intention to adopt AI. The mediation analysis indicated that self-efficacy significantly serves as a mediator of the relationship between TPACK and intention to adopt AI, demonstrating that the self-efficacy plays an essential role in encouraging educators' readiness to adopt AI in educational environments.

Keywords: AI intention; AI self-efficacy; Teachers; SEM; TPACK

Article History: Submitted 1 November 2024; Revised 20 January 2025; Published online 17 March 2025

1. Introduction

The integration of technology and artificial intelligence [AI] in education has become a crucial matter in the current educational context, demanding greater knowledge of the determining factors of educators' intention to embrace this innovations. A key aspect of this investigation is related to the notion of self-efficacy, defined as the individual's belief in the capabilities to organize and execute the courses of action required to attain certain types of performance. Notably, self-efficacy also mediates the relationship between other constructs in education, including the integration of technology and academic performance (Mokhtar et al., 2021; Osman, 2018). Self-efficacy has been found to be a significant factor in learning environments across the board; for teachers, self-efficacy has been shown to influence their instruction, as well as their willingness to adopt new technologies and pedagogical frameworks such as the Technological Pedagogical Content Knowledge [TPACK] framework (Artino, 2012; Dikmen & Demirer, 2022; Kıray, 2016).

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How to cite: Ismaniati, C., Khairaty, N. I., Yusuf, N., & Supramono, A. (2025). Harnessing self-efficacy: Mediating the connection between TPACK and AI intentions among teachers. *Journal of Pedagogical Research*, *9*(2), 109-126. https://doi.org/10.33902/JPR.202531937

This relationship highlights the importance of fostering self-efficacy among educators, especially as they struggle to implement the complexities of technology into their pedagogical models.

1.1. Technological Pedagogical Content Knowledge Framework

The Technological Pedagogical Content Knowledge framework is an essential model for understanding the complex interplay between technology, pedagogy, and content knowledge in educational settings. TPACK is a framework developed by Mishra and Koehler (2006) to expand on Shulman's original idea of Pedagogical Content Knowledge [PCK] by integrating technology into the way we teach, allowing for a holistic continuum of effective instructional practices that incorporate technology Elmaadaway and Abouelenein (2022). TPACK is the petal arrangement of three liquids: CK (Content Knowledge), PK (Pedagogical Knowledge), and TK (Technological Knowledge) (Chen & Jang, 2018). This framework highlights that knowing alone>(in these areas it is insufficient; it is important to recognize how such domains also work in synchrony to enhance student learning (Redmond & Lock, 2019).

Many studies have employed the TPACK framework to analyze teacher education and professional development. Research investigating TPACK levels of ITE students and its effect on teaching practices (Kim, 2024) Research by Graham et al. (2012) stress the significance of how teacher candidates develop their decisions for technology integration, which leads them to conclude that TPACK is an important framework for understanding these decision-making processes. Furthermore, the model has been utilized for evaluating teachers' technological pedagogical content knowledge in varied educational scenarios emphasizing its adaptability and relevance (Busono et al., 2021). Ultimately, the TPACK framework offers a strong theoretical basis for comprehending how technology can be integrated into education. TPACK is crucial for enhancing teachers' instructional practices and student learning outcomes as they manage the challenges of teaching in the digital age (Mishra & Koehler, 2006). The evolution of TPACK, and especially the implications it must have in relation to emerging technologies such as AI, suggests that research and professional development need continuously updating if we want educators to be able to succeed in educational contexts that are governed by an increasing amount of technology.

The framework suggests that educators should not only know their subject content but also the pedagogical methods and the technological tools that can help improve student learning. This is why TPACK is comprehensive: it represents many of the competencies necessary for the successful integration of technology in education. Recent studies revealed that TPACK competence of educators strongly affects the effectiveness of their teaching practices and conduction of learning processes (Setiawan et al., 2018). Productive engagement with TPACK is rooted in educators' capabilities for efficacy in those technology use and pedagogical strategies (Liang et al., 2013). According to Chen and Jang (2018), teachers' self-efficacy in technology integration is closely associated with their TPACK levels, and improving TPACK can confirm teachers' confidence in technology integration within the classroom.

1.2. The Mediating Role of Self-Efficacy in TPACK and AI Intentions

In the context of artificial intelligence in education, the intersection of TPACK and self-efficacy becomes particularly salient. As educators increasingly confront the integration of AI tools into their teaching practices, their self-efficacy beliefs can significantly influence their intentions to adopt these technologies. Studies have shown that self-efficacy is a strong predictor of technology use, suggesting that educators who feel confident in their technological abilities are more likely to embrace AI tools in their instructional practices (Abbitt, 2011; Agyei & Voogt, 2011; Benson & Ward, 2013).

The role of self-efficacy as a mediator in this dynamic is particularly pertinent, as it can bridge the gap between educators' theoretical knowledge of technology integration and their practical application in the classroom. Studies have shown that enhancing self-efficacy through targeted professional development can lead to improved technology integration behaviors among teachers

(Keser et al., 2015; Şen & Durak, 2022). Self-efficacy has been shown to impact teachers' motivation, instructional practices, and ultimately, student outcomes. Şimşek and Yazar (2019) found a significant positive relationship between training for technological integration and TPACK self-efficacy among prospective teachers, suggesting that experiences in technology integration enhance self-efficacy beliefs, which in turn, support the development of TPACK. This relationship underscores the importance of targeted professional development in fostering educators' confidence in their technological capabilities. Moreover, the literature suggests that self-efficacy not only influences the acquisition of TPACK but also serves as a motivational factor for educators pursuing careers in teaching. Adalar's (2021) study highlights that self-efficacy beliefs for TPACK positively impact teacher candidates' self-efficacy in material design, indicating that confidence in TPACK can enhance overall teaching effectiveness.

Similarly, research by Shahzad and Naureen (2017) emphasizes the correlation between teacher self-efficacy and students' academic achievement, reinforcing the notion that confident educators are more effective in their teaching practices. These findings suggest that enhancing self-efficacy can lead to improved educational outcomes, particularly when integrating AI technologies. The relationship between self-efficacy and TPACK is further supported by studies examining pre-service teachers' self-efficacy regarding online teaching. Naz et al. found that pre-service teachers exhibited high levels of self-efficacy in utilizing the TPACK framework effectively, which is crucial for adapting to modern educational demands (Naz et al., 2021). This aligns with Hatlevik and Hatlevik's (2018) findings, which demonstrate that teachers' ICT self-efficacy is positively associated with their instructional practices, indicating that domain-specific self-efficacy beliefs are essential for effective technology integration.

As educators develop confidence in their technological abilities, they are more likely to explore and implement AI tools in their teaching. Furthermore, the role of self-efficacy as a mediator in the relationship between teacher experience and TPACK has been explored in various studies. For instance, Qiong and Zhao (2021) found that ICT self-efficacy mediates the effects of university support on pre-service teachers' TPACK, highlighting the importance of institutional support in fostering self-efficacy. Such findings emphasize the need for educational institutions to provide robust support systems that enhance teachers' self-efficacy, thereby facilitating the effective integration of AI technologies. In conclusion, the literature illustrates that self-efficacy plays a pivotal role in mediating the relationship between TPACK and educators' intentions to adopt AI in their teaching practices. By fostering self-efficacy through targeted training and support, educational institutions can empower teachers to integrate technology effectively, ultimately enhancing educational outcomes. As the landscape of education continues to evolve with the advent of AI, understanding the dynamics of self-efficacy, TPACK, and technology integration will be crucial for preparing educators to meet the challenges of the digital age.

2. Method

2.1 Research Design

This study was quantitative research design and non-experimental correlative design, which was to analyze the relationship between the variables and to test the mediator effect of self-efficacy on the relationship between TPACK and AI adoption intention among the teachers. The quantitative approach is a scientific approach to data collection; Creswell and Creswell (2023) define the quantitative approach as one that collects, verifies, and interprets data in a systematic way and relies more often on surveys or experimental methods to test a scientific hypothesis. Quantitative research methods are methodical and experimental to explore the relationship between variables in order to prove testable hypotheses; this leads to the collection of numerical data, which can be statistically analyzed and result in quantifiable findings.

Specifically, mediation analysis by self-efficacy as an intervening variable between TPACK and the intention to adopt artificial intelligence was applied. The mediating variable approach has become widely adopted in both educational and psychological research for assessing indirect effects in complex relationships (MacKinnon et al., 2007), in which a mediating variable is introduced to the analysis to test for its impact on the direct relationship of interest. Participants were selected through random sampling from the population, independent from teaching background.

2.2 Participants

This study involved 200 teachers from various educational backgrounds in Indonesia which is collected through online survey (Google Forms). Respondents were selected using a stratified random sampling approach where the students were grouped by the level of teaching experience and by the subjects they specialize in. This technique includes stratification of the underlying population and then select participants with simple random sampling from each stratum (Iliyasu & Etikan, 2021).

2.3 Instruments

Instruments measuring aspect of their research were adapted from validated instruments: TPACK measurement was based on Schmidt et al. (2009), the items for measuring self-efficacy on AI in present study were adapted from Bandura's (1997) general self-efficacy scale, and those for measuring AI adoption intention in present study were developed based on Venkatesh et al. (2003). The same 5-point Likert scale was used for all constructs in these instruments.

2.4 Data Analysis

To analyze the data, this study used the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, utilizing SmartPLS 4.0 software, as it is suitable for examining complex relationships and predictive models (Hair et al., 2021). Measurement model evaluation included tests for reliability and validity, assessed through Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) to ensure internal consistency and convergent validity. Discriminant validity was evaluated using the Heterotrait-Monotrait Ratio (HTMT) criteria (Henseler et al., 2015). To assess the overall fit of the model, Standardized Root Mean Square Residual (SRMR) was examined as an indicator of model fit (Henseler et al., 2014).

Thus, this analytical approach ensures a rigorous assessment of the hypothesized relationships and the mediating role of self-efficacy in linking teachers' TPACK and their intentions to adopt AI in teaching practices.

3. Results

3.1. Measurement Model Analysis

Based on indicator loading factors, the measurement model analysis (see Table 1) demonstrates that the observed indicators accurately reflect each variable at both the first-order and second-order levels. According to Hair et al. (2021), a minimum loading factor of 0.70 is recommended as the threshold for establishing convergent validity. The loading factor results presented in the table confirm that each indicator meets or exceeds this threshold, thereby substantiating the validity of the model's constructs.

In the first-order analysis, individual items for each variable exhibit strong loadings, indicating that each item consistently represents its designated construct. Similarly, in the second-order analysis, the grouping of items into broader aspects (Technology, Pedagogy, Content, Integrated TPACK, Self-Efficacy in Understanding AI, Self-Efficacy in Using AI, Self-Efficacy in Facing AI Challenges, Self-Efficacy to Innovate with AI, Intention to Adopt AI, Intention to AI Skills, Openness to Using AI, and Commitment to Use AI) shows that these overarching constructs are accurately measured by their constituent indicators.

Table 1
Model analysis based on indicator loading factor

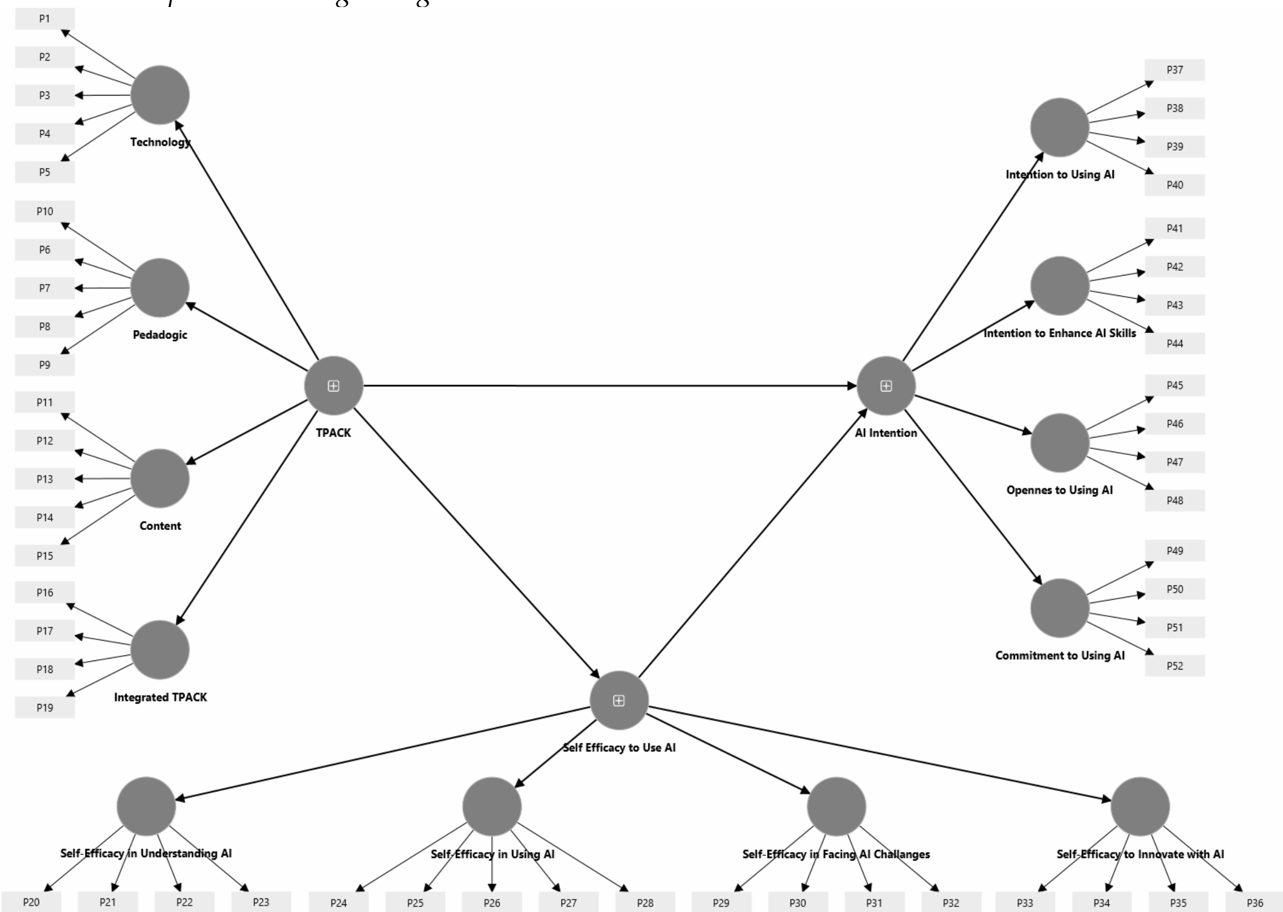
Aspect and item	First Order	Second Order
	Loading Factor	Loading Factor
Technology		0.935
P1	0.867	
P2	0.779	
P3	0.890	
P4	0.858	
P5	0.842	
Pedagogy		0.957
P6	0.885	
P7	0.875	
P8	0.882	
P9	0.879	
P10	0.881	
Content		0.944
P11	0.864	
P12	0.870	
P13	0.908	
P14	0.910	
P15	0.880	
Integrated TPACK		0.929
P16	0.859	
P17	0.920	
P18	0.912	
P19	0.828	
Self-Efficacy in Understanding AI		0.918
P20	0.828	
P21	0.880	
P22	0.903	
P23	0.917	
Self-Efficacy in Using AI		0.955
P20	0.828	
P21	0.880	
P22	0.903	
P23	0.917	
Self-Efficacy in Facing AI Challenges		0.908
P29	0.890	
P30	0.898	
P31	0.876	
P32	0.887	
Self-Efficacy to Innovate with AI		0.952
P33	0.903	
P34	0.892	
P35	0.910	
P36	0.917	
Intention to Adopt AI		0.919
P37	0.907	
P38	0.939	
P39	0.914	
P40	0.913	

Table 1 continued

Aspect and item	*First Order*	*Second Order*
	Loading Factor	*Loading Factor*
Intention to Enhance AI		0.931
P41	0.940	
P42	0.953	
P43	0.938	
P44	0.930	
Openness to Using AI		0.962
P45	0.918	
P46	0.950	
P47	0.934	
P48	0.940	
Commitment to Using AI		0.927
P49	0.897	
P50	0.911	
P51	0.925	
P52	0.881	

This robust validity across both levels of the measurement model strengthens the model's reliability and underscores its suitability for capturing complex constructs within this structural equation modeling framework (see Figure 1). The findings support the use of these indicators as reflective measures of each underlying variable, providing a reliable basis for subsequent analyses within this study.

Figure 1
Mediator's Impact- Resulting Using Smart PLS 4.0



The reliability analysis results summarized in Table 3 indicate that all variables exhibit acceptable reliability levels, based on composite reliability values exceeding the recommended threshold of 0.70. The average variance extracted values, which are also above the accepted minimum of 0.50, confirm that each variable captures sufficient variance to establish convergent validity.

Table 2
Reliability Analysis

Variable	*Alpha*	*CR*	*AVE*
TPACK	0.973	0.975	0.677
Technology	0.902	0.927	0.719
Pedagogy	0.927	0.945	0.775
Content	0.932	0.948	0.786
Integrated TPACK	0.903	0.932	0.776
Self-Efficacy to Use AI	0.972	0.974	0.690
Self-Efficacy in Understanding AI	0.905	0.934	0.779
Self-Efficacy in Using AI	0.928	0.946	0.777
Self-Efficacy in Facing AI Challenges	0.911	0.937	0.788
Self-Efficacy to Innovate with AI	0.927	0.948	0.820
AI Intention	0.977	0.979	0.747
Intention to Using AI	0.938	0.956	0.843
Intention to Enhance AI Skills	0.956	0.968	0.884
Openness to Using AI	0.953	0.966	0.876
Commitment to Using AI	0.925	0.947	0.817

Specifically, the TPACK construct and its sub-dimensions—Technology, Pedagogy, Content, and Integrated TPACK—show high CR values, with AVE values above 0.67, demonstrating a strong internal consistency. Likewise, the Self-Efficacy to Use AI construct and its dimensions (Self-Efficacy in Understanding AI, Using AI, Facing AI Challenges, and Innovating with AI) also meet the reliability criteria with CR values above 0.90 and AVE values above 0.69, indicating each dimension's robustness. Similarly, the AI Intention construct and its sub-dimensions (Intention to Adopt AI, Intention to Enhance AI Skills, Openness to Using AI, and Commitment to Use AI) demonstrate very high reliability and convergent validity, with CR values around 0.95 and AVE values exceeding 0.74.

In addition to CR and AVE, Cronbach's alpha values for all variables also exceed the 0.70 threshold, further supporting the reliability of these constructs. These findings confirm that the measurement model possesses a high degree of convergent validity, establishing a solid foundation for subsequent structural analysis. This comprehensive reliability across constructs underscores the robustness of the model in accurately representing the intended theoretical constructs.

3.2. Hypothesis Testing

Results from hypothesis testing reveal (see Table 3) unique pathways and effects in the model. First, TPACK significantly relates to Self-Efficacy to Using AI with a high path coefficient (0.835) and high significance level (< .001), thus confirming this hypothesized relationship. Alternatively, the TPACK did not have an impact on AI Intention either (B = 0.018, p = .842), which leads to the rejection of this hypothesis. For AI Intention, Self-Efficacy to Using AI is very strong (B = 0.783, p < .01), which is in line with the hypothesis. Moreover, TPACK indirectly influences AI Intention through Self-Efficacy to Use AI (B = 0.654, p < .01), suggesting that Self-Efficacy to Use AI mediates the relationship between TPACK and AI Intention.

Table 3
The hypothesis testing result

No	*Hypothesis*	*B*	*p*	*Result*
1	TPACK Self-Efficacy to Use AI	0.835	< .01	Accepted
2	TPACK AI Intention	0.018	0.842	Rejected
3	Self-Efficacy to Use AI AI Intention	0.783	< .01	Accepted
4	TPACK Self Efficacy to Use AI AI Intention	0.654	< .01	Accepted

R-square and *F*-square analyses were used to measure the quality and fit of the model. Hair et al. (2019) classifies *R*-square values greater than .75 as high, .50 as moderate, and .25 as low. In this model, AI Intention has *R*-square of .637, which shows that TPACK and Self-Efficacy to Use AI explains a considerable proportion of the variance in AI Intention. The *R*-square value was also high in this model, too high (.697) for Self-Efficacy to Use AI further confirming our original model's power in explaining these effects.

3.3. Quality and Model Fit

3.3.1. R-Square

The *R*-square values derived from the model (see Table 4) provide insights into the extent to which the independent and mediating variables explain the variance in the dependent variables. In this analysis, the *R*-square for *AI Intention* is 0.637, suggesting that *AI Intention* is moderately influenced by both TPACK and Self-Efficacy to Use AI, with a high level of overall predictive power. Similarly, *Self-Efficacy to Use AI* has an *R*-square of 0.697, indicating a substantial proportion of its variance is explained by TPACK, further underscoring the strong effect of TPACK on enhancing self-efficacy in AI contexts. These *R*-square values validate the model's predictive strength, confirming that TPACK and Self-Efficacy to Use AI substantially account for the variance in AI Intention.

Table 4
R-Square values

Variable	*R-square*	*Category*
AI Intention	0.637	High
Self Efficacy to Use AI	0.697	High

3.3.2. F-Square

The *F*-square values in this analysis (see Table 5) provide insight into the magnitude of each variable's influence within the structural model, as outlined by Hair et al. (2021), where *F*-square values of 0.35 indicate a large effect, 0.15 a medium effect, and 0.02 a small effect. The results demonstrate that AI Intention has a strong influence on its subdimensions, with notably high *F*-square values for *Openness to Using AI* (12.533), *Intention to Enhance AI Skills* (6.456), and *Commitment to Use AI* (6.118), indicating these elements significantly contribute to shaping AI Intention. Similarly, *Self-Efficacy to Use AI* strongly impacts *AI Intention* (0.512), reflecting a substantial influence, and also shows high values across its subdimensions, such as *Self-Efficacy to Innovate with AI* (10.378) and *Self-Efficacy in Facing AI Challenges* (4.687).

For the TPACK variable, the *F*-square analysis reveals a significant effect on several subdimensions, including *Pedagogy* (10.856), *Content* (8.125), and *Technology* (6.937), suggesting TPACK plays a critical role in enhancing these specific aspects. However, TPACK's direct effect on AI Intention is negligible, with an *F*-square of 0.000, indicating no direct predictive power on AI Intention in the model.

Table 5
F-square values

Item	*F-Square*	*Level*
AI Intention → Intention to Using AI	5.425	High
AI Intention → Intention to Enhance AI Skills	6.456	High
AI Intention → Opennes to Using AI	12.533	High
AI Intention → Commitment to Using AI	6.118	High
Self-Efficacy to Use AI → AI Intention	0.512	High
Self-Efficacy to Use AI → Self-Efficacy to Innovate with AI	9.717	High
Self-Efficacy to Use AI → Self-Efficacty to Face AI Challenges	4.687	High
Self-Efficacy to Use AI → Self-Efficacy to Understand AI	5.330	High
Self-Efficacy to Use AI → Self Efficacy in Using AI	10.378	High
TPACK → AI Intention	0.000	Very Low
TPACK →Content	8.125	High
TPACK→ Pedadogy	10.856	High
TPACK → Self-Efficacy to Use AI	2.303	High
TPACK → TPACK1	6.351	High
TPACK → Technology	6.937	High

Overall, the high *F*-square values across various constructs highlight the model's structural strength, particularly in showing how *AI Intention* and *Self-Efficacy to Use AI* are effectively explained by their respective subdimensions, supporting the robustness of the model's hypothesized relationships.

3.3.3. Model fit

The model's fit was further evaluated using the Standardized Root Mean Square Residual (SRMR), which was found to be 0.070—below the recommended threshold of 0.080 (Hair et al., 2021) indicating an acceptable model fit. This alignment suggests that the predicted structure of the model is consistent with the observed data. Together, these findings highlight the model's reliability, validity, and strong predictive quality. The indirect pathway from TPACK to AI Intention via Self-Efficacy to Use AI enhances the model's explanatory strength by illustrating how TPACK influences teachers' intentions to adopt AI through elevated self-efficacy.

4. Discussion

This research employed Structural Equation Modeling analysis to examine the relationships between teachers' TPACK (Technological, Pedagogical, and Content Knowledge), their self-efficacy in using AI, and their intentions to adopt AI. The findings provide valuable insights into the interactions between these constructs and highlight factors that significantly influence teachers' readiness and motivation to integrate AI tools in educational settings.

4.1. The Relationship between TPACK and Self-Efficacy to Use AI

The first hypothesis posited a positive relationship between TPACK and self-efficacy to use AI, which was supported. This finding demonstrates that TPACK, as a multidimensional framework, strengthens teachers' self-efficacy in AI usage by providing them with an integrated understanding of content, pedagogy, and technology. Mishra and Koehler (2006) initially conceptualized TPACK as the intersection of these three domains, enabling teachers to effectively combine subject knowledge with pedagogical techniques and technological tools. Our study shows that TPACK's comprehensive structure not only builds understanding but also enhances confidence in AI integration, aligning with previous research on TPACK's positive impact on teacher self-efficacy (Abbitt, 2011; Chai et al., 2023; Şimşek & Sarsar, 2019).

TPACK primarily contributes to self-efficacy by helping teachers align AI tools with their pedagogical goals and content requirements. For instance, TPACK enables teachers to adapt AI applications across various learning objectives, from personalized instruction to collaborative learning environments (Thibaut et al., 2018). As teachers develop expertise in these areas, their confidence in leveraging AI for customized instruction grows, enhancing their self-efficacy as described in Bandura's (1986) Social Cognitive Theory [SCT]. SCT suggests that individuals' beliefs in their capabilities are crucial for engaging with complex tasks. In the context of AI-based education, TPACK serves as the mechanism that builds these efficacy beliefs, enabling teachers to master AI tools for various instructional needs.

Previous studies highlighted the role of TPACK in improving teachers' understanding and comfort with advanced technologies and the findings of this study are also consistent with these studies. Similarly, Şimşek and Sarsar (2019) showed that well-build TPACK helped teachers more efficiently adapt to rising technologies, indicating that TPACK offers teachers a necessary set of skills and confidence to work with new digital technologies. Moreover, during their study Elmaadaway and Abouelenein (2022) noticed that TPACK-oriented professional development programmes sharply increase teachers' self-efficacy by providing them with the decision-making needed to effectively integrate technologies, such as AI. Well if teachers learn how to integrate AI with pedagogical practice and content, they may be able to create a plan of action to unleash the power of AI and improve their output and self-efficacy.

The relationship between TPACK and self-efficacy is also supported by the Unified Theory of Acceptance and Use of Technology [UTAUT], which describes self-efficacy as a key factor influencing the acceptance and use of technology (Venkatesh et al., 2003). According to UTAUT, people are more inclined to accept new technologies when they are convinced that they can successfully use them. TPACK helps scaffold this sense of capability by providing teachers with a structured knowledge framework, which in turn, enables teachers to approach AI adoption more confidently. As teachers hear that AI is not only manageable, but an enhancement of their practice, they are more willing to play around with tools, and ultimately see a place for them in their teaching. Angeli and Valanides (2009) study corroborates this idea; they suggest that as teachers' advanced TPACK develops, their self-efficacy and comfort with technology also increase, which alleviates the concern related to the use of this new technology.

In addition, TPACK equips teachers with the confidence to frame the integration of AI as a design process where both their pedagogical knowledge and their learning of technology come together to solve problems in their classroom. The support provided by TPACK frameworks grants teachers the confidence they need to experiment with novel technologies by empowering them through a structured method for approaching the multifaceted design of any digital integration. This incremental approach not only builds teachers’ technical confidence, but also reinforces SCT evidence that showing teachers that they can actually work with AI tools leads them to believe they can, a key factor in self-efficacy (Bandura, 1986). And, as teachers have confidence in their ability to adopt this technology effectively, they are much more likely to stick with the challenges and try new ways to use the technology, creating a virtuous cycle between confidence and competence.

The findings also emphasize the importance of TPACK-based professional development programs in supporting AI adoption. Chai et al. (2023) note that such programs are crucial in helping teachers understand technology integration within specific pedagogical contexts. These programs build familiarity and competence, addressing the "technology anxiety" often associated with AI implementation (Teo, 2009).

In conclusion, our supported hypothesis reinforces TPACK's critical role in enhancing teachers' self-efficacy with AI by providing a structured, adaptable framework for technology integration. This combination of content, pedagogical, and technological knowledge enables teacher experimentation with AI tools, aligning with both SCT and UTAUT models. TPACK serves as both a knowledge foundation and confidence-building framework, supporting teachers in meaningfully incorporating AI into modern education.

4.2. The Relationship between TPACK and AI Intention

The second hypothesis, which proposed a direct effect of TPACK on AI intention, was not supported. While TPACK does improve teachers' technological knowledge and ability to integrate AI into their (teaching) practices, it has no direct impact on their intention to adopt AI technologies, which is mediated by self-efficacy. This result suggests a crucial role for self-efficacy as a mediator between knowledge of theory and action. Knowledge and intention are not as directly related; as illustrated in Ajzen's (1991) Theory of Planned Behavior [TPB], perceived behavioral control akin to self-efficacy often becomes an essential predictor in determining if individuals take action with the knowledge and skills they possess. In other words, no amount of TPACK foundation will push teachers towards using AI if teachers aren't confident that they can use AI.

This observation aligns with previous research that has documented similar patterns. For example, Qiong and Zhao (2021) found that while TPACK is a necessary component for technology adoption, it is often insufficient on its own. Their study emphasizes that additional factors such as institutional support, administrative encouragement, and individual intrinsic motivation significantly influence teachers' intentions to adopt new technologies. Baran and Uygun (2016) echo this sentiment, highlighting that teachers' intentions to incorporate technology are often more heavily influenced by their confidence and the resources available to them, rather than by their knowledge alone. This indicates that while knowledge frameworks like TPACK are essential, they must be supplemented with the right motivational and contextual elements to foster meaningful engagement with technology.

In other words, as noted by Inan and Lowther (2010), motivation and self-efficacy play important roles in technology adoption. They imply that if TPACK does not easily lead to immediate, practical applications — as with the implementation of AI in the classroom — then teachers will be incapable of translating their knowledge into action and will not feel confident enough to do so. This highlights the need for education professional development and support structures to address both knowledge and self-efficacy.

Thus, this result reinforces the idea that TPACK is a base knowledge construct for technology integration in higher education, and translating the knowledge is a need for additional contextual settings or motivation for adoption of AI. As teachers grapple with this shift, they may require strong support systems in place, including ongoing professional development workshops that go beyond the TPACK framework to include self-efficacy and practical experiences with AI technologies in the classroom. What's more, these peer opportunities for collaboration can build confidence as educators exchange tips and experience with actualizing AI in their respective classrooms.

Recent literature reinforces the importance of such interventions. Venkatesh et al. (2023) argue that comprehensive professional development programs that enhance both self-efficacy and situational factors such as supportive infrastructure and strong leadership are crucial for motivating educators to translate their theoretical knowledge into actionable intentions. The authors advocate for creating an environment where teachers feel supported and empowered, thus increasing the likelihood that they will commit to adopting AI technologies in their instructional practices.

Moreover, given that TPACK was originally developed to help teachers facilitate ICT integration in their pedagogy and subsequent frameworks that supported technology integration in classroom practice, the divide between TPACK and AI intention, or ICT, could potentially also be the result of a lack of clear pedagogy around how to implement AI in practice. If educators don't find AI tools immediately relevant or applicable to their context, they may not have the motivation to adopt such technologies. As such, education structures must engage in linking TPACK preparation expertise to announce world implementations of AI devices so educators can take risks on AI inside the structures where they may be equipped with you to test and fail within the frame of TPACK.

Overall, the results from this research suggest that, although definite important groundwork for AI integrative knowledge can be established through TPACK, this is fell short on its own to enable teachers' intentions towards the integration of AI technologies within their classrooms. The interaction of self-efficacy, context, and professional development proves to be essential elements that shape teachers choices. To do so, Educational leaders and policymakers can ensure that these are present as these would facilitate the process of technology adoption and ultimately AI integration in teaching and learning.

4.3. The Relationship between Self-Efficacy to Use AI and AI Intention

The third hypothesis which studies the relationship between self-efficacy in using AI and intention to adopt AI was strongly supported. The finding reinforces the role of self-efficacy as a key antecedent to the adoption of technology, consistent with the classic technology adoption and self-efficacy (Bandura, 1986; Venkatesh et al., 2003). These results indicate that self-efficacy is a key factor in stimulating behavioral intentions, where individuals who have confidence in their ability to use AI well are significantly more likely to turn it into their teaching process. This interaction plays an important role in fostering positive technology-related habits and improving educational outcomes via AI (Ertmer et al., 2012; Morales-García, 2024).

Self-efficacy is well recognized for predicting technology uptake in many fields. For instance, Ho et al. (2022) did a similar study in organizational settings and found that those with high self-efficacy were more pressed to adopt the AI technology. The significance of this finding is that it shows how self-efficacy acts as a driving factor for individuals to adopt AI, moving from a theoretical context, to application in the real world. Additionally, when it comes to educational dimensions, this notion is also supported by Kim (2021) who reported that teachers possessing higher levels of self-efficacy in digital competencies exhibited greater intentions to adopt and use various technologies, including AI, in their classrooms. This relationship highlights that teachers who are confident in their technology knowledge will be more likely to utilize new tools and strategies.

Similarly, Kwak et al. (2022) provided further support for the role of self-efficacy in technology adoption through their research with nursing students. They discovered that students with heightened self-efficacy toward AI usage demonstrated stronger behavioral intentions to incorporate AI technologies into their learning and practice. This finding highlights the critical role of confidence as a significant predictor of technology acceptance and usage across diverse fields, suggesting that fostering self-efficacy can lead to increased adoption rates of AI and other technological innovations.

The theoretical foundation for these findings is grounded in Bandura's (1986) Social Cognitive Theory, which posits that self-efficacy is a key determinant of individuals' motivation and behavior. According to this theory, individuals with higher levels of self-efficacy are more likely to undertake challenging tasks and persist in the face of difficulties, which is essential for integrating new technologies such as AI into educational practice. Bandura's framework suggests that enhancing self-efficacy can lead to greater engagement with technology, as teachers who feel capable are more willing to explore AI applications in their teaching.

Moreover, Venkatesh et al. (2003) expand on this idea through the Unified Theory of Acceptance and Use of Technology, which identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as key constructs influencing technology adoption. Self-efficacy can be viewed as an integral part of effort expectancy, where individuals' perceptions of their ability to use technology effectively influence their intention to adopt it. The intersection of these theories provides a robust framework for understanding the dynamics between self-efficacy and technology adoption in educational settings.

In practical terms, the findings of this study have significant implications for professional development programs aimed at enhancing educators' capabilities in using AI. By focusing on building self-efficacy through targeted training and support, educational institutions can foster a more confident teaching workforce that is more willing to embrace AI technologies. For example, providing opportunities for hands-on practice, mentorship, and collaborative learning can empower educators, helping them to develop the necessary skills and confidence to integrate AI effectively into their classrooms.

Furthermore, these findings highlight the importance of creating a supportive environment that encourages experimentation with AI tools. Institutional support, such as access to resources, technical assistance, and encouragement from leadership, can bolster educators' self-efficacy, ultimately leading to greater adoption of AI technologies. As educators gain confidence in their abilities to utilize AI, they are more likely to explore its potential benefits, thereby enhancing student learning experiences and outcomes.

In conclusion, the strong relationship between self-efficacy in using AI and the intention to adopt AI reinforces the need to prioritize self-efficacy enhancement in educational contexts. By understanding the critical role that self-efficacy plays in technology adoption, educational leaders and policymakers can implement strategies that not only improve teachers' technological competencies but also empower them to embrace AI as a transformative tool in their teaching practices.

4.4. The Mediating Role of Self-Efficacy in the Relationship between TPACK and AI Intention

The fourth hypothesis examined the mediating role of self-efficacy in the relationship between TPACK and AI intention, which was supported. Supporting the fourth hypothesis, it showed that self-efficacy had a significant mediating role in the association between TPACK and AI intention. While TPACK provides a framework of sources of knowledge, self-efficacy may be needed to transform that documentation into behavioral intentions and thus occupy a key place in understanding the gap between knowledge and intention, this study found. That is to say, even when teachers know exactly what it would take for them to successfully incorporate the tool into their classroom, whether or not they actually do so often depends on how confident they feel in their ability to use the technology well.

Emerging studies have suggested that self-efficacy plays a mediating role in technology adoption. Teachers with high level of TPACK are frequently hesitant to switch to new technologies especially under high pressure situations like the COVID-19 pandemic, where having confidence in one's own capacity is paramount (Musthofa, 2024). This insight implies that merely having theoretical knowledge is not enough; teachers need to have faith in their own ability to enact that knowledge. Drawing on the same idea, Kim (2024) points out that while TPACK training that provides teachers with the technical knowledge they need to use AI tools is important, self-efficacy is also critical to technology adoption, which is why TPACK training should also focus on developing teachers' confidence to use AI tools. Providing opportunities to implement techniques in actual integrated community practice with ongoing coaching and trajectory support will greatly increase the chances that teachers will utilize AI in their instruction.

The results align with the Unified Theory of Acceptance and Use of Technology proposed by Venkatesh et al. It is different from the model of Davis et al.(2003), which sees self-efficacy as a significant factor affecting the intention to use technology. In essence, this theory relays that although TPACK involves knowledge on how to integrate technology in the class room, self-efficacy is what pushes teachers to employ their knowledge in real-life settings. When combined, these two approaches provide a holistic structure for encouraging AI implementation in schools. Already armed with theory, educators can then engage with the practical application of AI — the real world.

Additionally, Bandura's (1986) Social Cognitive Theory serves as a theoretical framework to explore the importance of self-efficacy in this context. Self-efficacy affects a person's choices, persistence, and effort when they face challenges, Bandura said. For educators, when individuals have a sense of capability, they will be more willing to experiment with new technologies such as AI, to learn constantly and to refine their skills in line with educational evolution. This interaction suggests the importance of training not just informing teachers about AI, but making them confident enough to use it.

Ultimately, although not conclusive, our findings support the interlink between TPACK and self-efficacy towards AI use integration in educational practice. While TPACK offers educators the knowledge framework necessary to comprehend how they can integrate AI, self-efficacy is crucial in transferring this knowledge into intentional practices to implement AI. In order for schools to drive up the adoption of AI in education, professional development programs that promote both knowledge acquisition and confidence should be enacted.

Future studies could address further contextual elements that might shape the association of TPACK, self-efficacy and intentions to adopt AI. Factors including peer support, availability of resources, and leadership styles may play a key role in the confidence of educators that integrates into the adoption of AI into the instruction process.

4.5. Model Evaluation and Practical Implications

The evaluation for the structural model indicates that the model has a good fit. These R-squared figures point to a considerable amount of variance accounted for by the model and that, collectively, TPACK and self-efficacy explain a significant amount of teachers' intention to use AI in instruction. The respective constructs account for the majority of variation in educational factors that impact AI adoption and, hence, are statistically significant.

In addition, the model fit indices indicate the robustness of the structural model. Relationship between the variables was statistically significant, as was predicted by the model. Further support for the model's integrity comes from the results of multicollinearity tests, which indicate that all VIF (Variance Inflation Factor) scores fall below the critical threshold of 5. Furthermore, Furthermore, these results indicate that the different constructs in the model are separate and provide unique insights into the explanation of teachers' intentions to adopt AI.

This evidence has important implications for educational policymakers and trainers, from a practical point of view. Recognising that supporting the development of teachers' TPACK is needed also means that supporting their confidence to use AI for their learners is needed too. As self-efficacy plays a solid role in mediating these three relationships, managers leading AI adoption initiatives should, therefore, include activities to foster self-efficacy as part of the AI adoption activities. Training opportunities might range from interactive workshops to hands-on practice sessions to incremental challenges designed to build teachers' comfort and confidence with using AI tools. These kinds of approaches can help build supportive learning environments that enable teachers to thrive in their roles, promoting a culture of innovation and experimentation with AI tools in the classroom. This focused approach may allow educational stakeholders to better promote and utilize TPACK and self-efficacy development, which together may improve the integration of AI, ultimately leading to more favourable teaching and learning experiences.

5. Conclusion

This study investigated the relationships among Technological Pedagogical Content Knowledge, self-efficacy in using artificial intelligence, and intention to adopt AI in the educational context. These findings specify the essential Accessibility Principal Model framework of TPACK in university classes and how important TPACK is when it comes to participating in the public. Yet, the findings also indicate that simply possessing knowledge does not guarantee adoption intentions; in fact, self-efficacy is an important mediating factor that determines whether TPACK translates to intent for action or not.

Additionally, results underscore the importance of professional development experiences that grow TPACK through a focus on self-efficacy, but practical application in a friendly climate. This dual interplay enables educators to utilize AI more seamlessly in their practices, putting them in a better position to enhance educational experiences and outcomes in the digital era. This adds empirical evidence to the discussion around technology in education while adding depth to our understanding of this process and how the interplay of knowledge, confidence, and intention affects technology adoption in education.

6. Limitations

While the study provides valuable insights, it is important to critically examine its limitations. The cross-sectional design, capturing data at a single point in time, restricts the ability to draw causal inferences between TPACK, self-efficacy, and AI intention. This limitation raises questions about the stability of these constructs over time. Longitudinal studies could provide deeper insights into how these relationships evolve, offering a clearer picture of the dynamics involved in technology adoption.

Moreover, using self-reported measures for measuring TPACK and self-efficacy may lead to patient bias and experience but it can also impact the quality of the findings. Self-report data is susceptible to social desirability bias and respondents may exaggerate their ability. Future research should integrate objective assessments or observational methods, to triangulate self-reported data and improve the strength of the findings.

The results are not generalizable as the study is limited to one particular educational context. These settings may also offer different levels of support, resources, and challenges that affect the relationships between TPACK, self-efficacy, and AI adoption. Increasing the data set with regards to different types of education such as in urban vs rural communities and different economic environments would further the research to understand this dynamic.

Moreover, though the present study highlights self-efficacy as the primary mediator, it does not explore other moderating variables that may affect an individual's intention to adopt AI. Such perceptions and interactions can thus be heavily influenced by sociotechnical factors, including institutional policies, access to technology, and teacher workload. Other variables should be studied in future research to build a more multidimensional picture of the complex terrain of education technology adoption.

7. Educational Implications

The findings of this research have significant implications specifically for the education system, mainly the incorporation of AI in education. The significant correlation found between TPACK and self-efficacy highlights the importance of comprehensive training programs that not only improve teachers' knowledge in technology but also increase their confidence in the effective use of AI. This dual focus is essential since self-efficacy is a key predictor of technology adoption (Bandura, 1986; Venkatesh et al., 2003).

Self-efficacy as a mediating factor in this regard backbone to stake the movement the importance cannot be exaggerated. It also indicates that teachers may avoid even professionally appropriate AI tools if their confidence in their ability to implement them successfully is low, even if they have the necessary knowledge. This indicates the importance of the design of initiatives for educational policy-makers and professionals so as to pave a supportive environment for teachers. Examples of such initiatives are mentorship programs, collaborative workshops, and peer-to-peer learning opportunities that contribute to the nurturing of self-efficacy. With this focus on confidence as well as knowledge, these programs have the potential to significantly improve teachers' preparedness to adopt AI in their classrooms.

Furthermore, the study calls for a more nuanced understanding of the AI adoption-driving forces. Although TPACK and self-efficacy are essential, this study emphasizes pervasive need to investigate more into contextual factors such as institutional support, teaching experience, and technological infrastructure. In doing so, they must also acknowledge that teaching is a contextually complex undertaking; multiple and intertwining factors affect teachers' intentions and behaviours towards technology integration. Such an approach is necessary to design interventions that can specifically target the challenges teachers are experiencing in unique environment.

Author contributions: Christina Ismaniati: Contributed to the conceptual framework of the study, developed the research design, and was responsible for the data collection process. Ismaniati also conducted the initial analysis and interpretation of the data. Nurul Inayah Khairaty: Played a key role in the literature review, providing critical insights into the theoretical background of the study. Khairaty also assisted in drafting the manuscript, ensuring clarity and coherence in presenting the findings. Nuraini Yusuf: Conducted the statistical analysis using advanced modeling techniques and interpreted the results in the context of existing research. Yusuf also contributed to the discussion section, integrating findings with practical implications. Agus Supramono: Oversaw the overall project management, coordinated between team members, and contributed to revisions of the manuscript. Supramono ensured compliance with ethical standards and facilitated the submission process.

Declaration of interest: The authors declare that no competing interests exist.

Data availability: Data generated or analyzed during this study are available from the authors on request.

Ethical declaration: The authors declare that this research adheres to ethical standards, including participant consent, confidentiality, and accurate reporting of findings without plagiarism or data manipulation.

Funding: The authors stated that they received no financial support for their study.

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