JOIN (Jurnal Online Informatika)
p-ISSN: 2528-1682, e-ISSN: 2527-9165
Volume 9 Number 2 | December 2024: 228-237
DOI: 10.15575/join.v9i2.1385

Evaluating Readiness and Acceptance of Artificial Intelligence Adoption Among Elementary School Teachers

Erlan Darmawan[1], Titik Khawa Abdul Rahman[2], Nani Ronsani Thamrin[3]
[1]Department of Information System, Universitas Kuningan, Indonesia
[2]Department of Computer Science, Asia e University, Kuala Lumpur, Malaysia
[3]Department of English Education, Universitas Kuningan, Indonesia

Article Info

Article history:

Received June 08, 2024
Revised August 06, 2024
Accepted August 26, 2024
Published December 27, 2024

Keywords:

Artificial Intelligence
Elementary School Teachers
Integration Model
Readiness Factors
Technology Adoption

ABSTRACT

Artificial Intelligence (AI) is a computer system that mimics the human brain's ability to process information and make decisions. AI technology is used to learn patterns in data and make predictions or decisions based on that learning. Despite the potential benefits of AI in education, elementary school teachers face significant challenges in adopting AI technology due to limited training, lack of resources, and resistance to change. This research aims to identify the factors influencing the adoption of AI technology among primary school teachers in West Java, Indonesia. The study involved 384 participants and employed a quantitative approach. Specific factors influencing AI adoption were identified by developing a model for AI-based teaching and learning and assessing readiness factors. The results identified optimism, innovativeness, insecurity, discomfort, perceived validity, trust, usefulness, and ease of use as critical factors for successful AI adoption among primary school teachers in West Java. The customized adoption model provides a practical roadmap for integrating AI into teaching and learning processes, addressing regional specificities while remaining relevant to similar educational challenges worldwide. The assessment of readiness factors offers actionable insights for fostering a supportive environment for technology integration. The study concludes with recommendations for future research and implications for educators, administrators, and policymakers.

Corresponding Author:

Erlan Darmawan,
Department of Information System, Universitas Kuningan
Jl. Cut Nyak Dhien No.36A, Cijoho, Kec. Kuningan, Kabupaten Kuningan, Jawa Barat, Indonesia. 45513
Email: erlan.darmawan@uniku.ac.id

1. INTRODUCTION

Education is a fundamental aspect of a nation's development. With the rapid advancement of information and communication technology, integrating technology into learning has become a priority to enhance education quality. One technology gaining significant attention is Artificial Intelligence (AI). AI is a computer system designed to mimic the human brain's ability to process information and make decisions by learning patterns in data and making predictions or decisions based on that learning [1]. AI has the potential to transform traditional learning paradigms into adaptive, interactive, and personalized learning experiences [2].

Despite the promise of AI, its adoption in education, particularly in Indonesia, still needs improvement[3], [4]. AI-based teaching and learning involve using algorithms and computer systems to collect, analyze, and process data, providing students with personalized and engaging learning experiences [5]. This approach is expected to enhance the quality of instruction, offer timely feedback, and facilitate interaction and collaboration between students and teachers [6].

In Indonesia, especially in West Java, educational development focuses on improving quality at all levels. However, the adoption of AI technology among primary school teachers remains limited due to factors such as insufficient digital literacy, inadequate resources, and resistance to change [7], [8]. Enhancing digital literacy among educators and students is crucial to optimize AI use in the learning process [9]. To harness AI's potential in West Java's education, it is essential to understand the factors influencing teachers' willingness and acceptance to adopt this technology. Critical factors include information literacy, availability of facilities, and infrastructure [10]. Challenges such as inadequate technological support, insufficient training, and lack of recognition from school leadership must be addressed [11]. The Indonesian curriculum, "Merdeka Belajar" (Freedom to Learn), also faces challenges in the technology accessibility required for online learning [12].

Strengthening teachers' roles through training and skills development is necessary to support Merdeka Belajar [13]. Readiness to adopt information technology innovations remains low due to limited access to technology, lack of training, and low motivation [14]. Effective integration of AI in learning requires overcoming challenges such as high implementation costs and providing adequate training for educators [15]

This study aims to identify the factors influencing AI technology adoption among primary school teachers in West Java, providing a roadmap for integrating AI into educational practices. The results of this research are expected to contribute to the development of educational policies focused on using AI technology in learning. This research is also expected to guide curriculum development and training programs to increase the readiness and competence of elementary school teachers in West Java to use AI technology. [16] explain the need for a child-centered approach to the use of AI in education, which means ensuring that this technology does not replace the role of teachers but remains a supportive tool that helps teachers facilitate better and personalized learning for each child. [17] explain that AI can significantly contribute to African education. Implementable solutions include developing integrated ICT systems, teacher and student training, flexible and inclusive curriculum development, and increased ICT resources and infrastructure access. Successful implementation of AI in education in Africa will require strong collaboration among all stakeholders and a sustainable and inclusive approach.

According to a study conducted by [18], several situations can be identified in implementing artificial intelligence (AI) in Indonesia's education sector. These include:(1) Indonesia has great potential for implementing AI in the education sector. This is due to the rapid development of information and communication technology and the development of digital infrastructure in the country. (2) Despite the great potential, the implementation of AI in Indonesia's education sector needs more resources. There are constraints related to technology infrastructure, availability of adequate hardware and software, and limited Internet access in specific areas;(3) The implementation of AI in the education sector also needs to improve the understanding and sufficient skills to use this technology. Teachers and educators need adequate training and support to use AI in the learning process effectively;(4) In the context of AI implementation in education, there is a need for mature regulations and policies to govern the use and protection of data, as well as to address privacy and ethical issues. This is critical to ensure security and trust in the application of AI technology in the educational environment. (5) Despite the significant potential benefits, the adoption and acceptance of AI in education still need to be improved. There is resistance to change and concerns about replacing the role of teachers. Therefore, there is a need for appropriate approaches to socialize and engage stakeholders in the implementation of AI in education. By understanding these situations, strategic steps can be designed to address challenges and effectively leverage the potential of AI to improve the quality of education in Indonesia. The several issues can be summarized as follows:

1. Lack of technological readiness: Elementary school teachers in West Java, Indonesia, face challenges in adopting artificial intelligence (AI) technology in learning. Many teachers still have limitations in using AI technology and need to understand its potential and benefits. This hinders the adoption of AI technology [19],[20]
2. Low information literacy: The need for more information literacy about AI technology is a barrier to effectively utilizing it in learning. Teachers need to have a sufficient understanding of AI technology and how to use it effectively and integrate it into the curriculum. This lack of understanding hinders elementary school teachers' adoption of AI technology in West Java. [19].[21]
3. Facility and infrastructure constraints: Facility and infrastructure issues also affect the adoption of AI technology among elementary school teachers. The lack of access to necessary hardware and software, such as computers, unstable internet connections, and limited access to AI devices, poses natural barriers to effectively adopting AI technology in learning [19].[20],[21]

This research aims to identify the factors that influence the technological readiness and acceptance of AI-based learning among elementary school teachers in West Java, Indonesia. Through a deep understanding of these factors, it is expected that effective and sustainable implementation strategies of AI technology can be developed in the educational context of this region. Thus, this research has high relevance in the educational context of West Java, Indonesia, and can make a real contribution to enhancing the quality of learning by harnessing the potential of AI technology

2. METHOD

This study utilizes the Technology Acceptance Model (TAM) to analyze factors influencing the acceptance of AI-based learning technology among primary school teachers in West Java, Indonesia. The factors include perceived usefulness, perceived ease of use, intention to use, and actual usage behaviour of AI technology.

Below are the stages of the theoretical model that cover the factors influencing technology readiness, acceptance and adoption of technology in the research "Factors Influencing Technologies Readiness and Acceptance of adoption model Among Elementary School Teachers in West Java, Indonesia":

a. Technology Readiness
   Identifying Factors: The study identifies factors influencing technology readiness among primary school teachers. These factors include technological knowledge, skills in using technology, self-confidence in adopting technology, and perceptions of the benefits of AI technology in learning.
b. Technology Acceptance:
   Analyzing Factors: The research analyzes factors influencing teachers' acceptance of AI-based learning technology. These factors include perceptions of AI technology's benefits, ease of use, individuals' confidence in using AI technology, and social influence from colleagues or the school environment.
c. Technology Adoption:
   Studying Factors: The study examines factors influencing primary school teachers' adoption of AI-based learning technology. These factors include institutional support, accessibility and availability of resources, and policies and regulations related to technology adoption in education.

The research aims to understand the technology readiness of primary school teachers, their acceptance of AI-based learning technology, and the factors influencing AI technology adoption in education. By comprehending this theoretical model, the study will identify key factors to promote AI technology acceptance and adoption among primary school teachers in West Java, Indonesia. Figure 1 presents the model that is proposed in this research. The formulation of the model draws from various theoretical models. The theories utilized include the information processing theory by [22], the Technology Readiness Model by [23], the Technology Acceptance Model by [24], as well as the Perception theory of truth and belief suggested by [25]

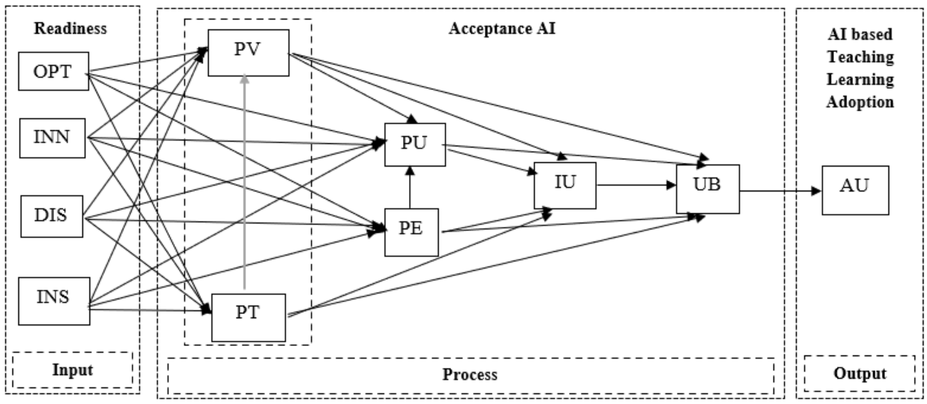

Figure 1. The conceptual model of the study

2.1 Research Hypothesis

Based on Figure 1, The researcher hypothesized the following :
H1: Optimism (OPT) has a significant effect on perceived validity (PV)

H2: Optimism (OPT) has a significant effect on perceived usefulness (PU).
H3: Optimism (OPT) has a significant effect on perceived ease of use (PE)
H4: Optimism (OPT) has a significant effect on perceived trust (PT)
H5: Innovation (INN) has a significant influence on perceived validity (PV).
H6: Innovation (INN) has a significant influence on perceived usefulness (PU)
H7: Innovation (INN) has a significant influence on perceived ease of use (PE)
H8: Innovation (INN) has a significant influence on perceived trust (PT)
H9: Discomfort (DIS) has a significant influence on perceived validity (PV).
H10: Discomfort (DIS) has a significant influence on perceived usefulness (PU)
H11: Discomfort (DIS) has a significant influence on perceived ease of use (PE)
H12: Discomfort (DIS) has a significant influence on perceived trust (PT)
H13: Insecurity (INS) has a significant influence on perceived validity (PV)
H14: Insecurity (INS) has a significant influence on perceived usefulness (PU)
H15: Insecurity (INS) has a significant influence on perceived ease of use (PE)
H16: Insecurity (INS) has a significant influence on perceived trust (PT)
H17: Perceived validity (PV) has a significant influence on perceived usefulness (PU)
H18: Perceived validity (PV) has a significant influence on intention to use (IU)
H19: Perceived validity (PV) has a significant influence on usage behavior (UB)
H20: Perceived trust (PT) has a significant influence on perceived validity (PV)
H21: Perceived trust (PT) has a significant influence on intention to use (IU)
H22: Perceived trust (PT) has a significant influence on usage behavior (UB)
H23: Perceived usefulness (PU) has a significant influence on intention to use (IU)
H24: Perceived ease of use (PE) has a significant influence on perceived usefulness (PU)
H25: Perceived ease of use (PE) has a significant influence on intention to use (IU)
H26: Intention to use (IU) has a significant influence on usage behavior (UB)
H27: Usage behavior (UB) has a significant influence on actual usage (AU).

2.2 Development Of Instrument

The instrument consists of a request letter to complete the questionnaire and the research question items. The questions consist of 51 statements divided into ten groups, representing each variable to be analyzed. The scale used for the research questions is a 5-point Likert scale: 1. Strongly Disagree, 2. Disagree, 3. Neutral, 4. Agree, and 5. Strongly Agree [26]. The indicators and questions refer to TRI 2.0 [23] and TAM [24], used in similar studies. The questionnaire was distributed directly and indirectly through face-to-face interaction, email, and WhatsApp messages using Google Forms.

2.3 Population And Sampling

The study includes West Java elementary school teachers actively implementing the AI-based teaching and learning adoption model. The population comprises 139,373 teachers, with a sample size of 384 considered appropriate for this study, ensuring a representative sample. The sampling process used a purposive sampling technique, focusing on respondents' profiles, including their practical experience with AI-based methodologies.

2.4 Analysis Of Data

Data analysis employed the Partial Least Squares Structural Equation Modeling (PLS-SEM) method using SmartPLS version 3.0 software. The analysis consisted of two stages: measurement model analysis and structural model analysis. The first stage assessed the reliability and validity of the measurement instruments, and the second stage examined the relationships among the identified constructs, exploring the factors contributing to the acceptance and readiness for AI-based teaching and learning models. This rigorous analysis provides a nuanced understanding of factors influencing the adoption of AI technology among primary school teachers in West Java, Indonesia.

p-ISSN: 2528-1682
e-ISSN: 2527-9165

3. RESULT AND DISCUSSION

In this research, the data collection involves obtaining relevant information through a structured questionnaire. Subsequent steps, such as data screening and cleaning, are critical to ensuring the collected data's quality, accuracy, and integrity. These steps are fundamental to sound research methodology, as they contribute to the reliability of findings and the validity of conclusions drawn from the dataset. From the results of the questionnaire distribution, we obtained completed responses that met the minimum sample size requirement of 384 respondents. Therefore, the subsequent research is based on this collected sample.

3.1. Evaluation of Measurement Model

The main objective of evaluating this study's measurement model, or outer model, is to verify that all the study variables meet the prescribed standards for reliability and validity thresholds. This evaluation includes examining the outer loadings of the variables, assessing their reliability and validity, and assessing the discriminant validity among them. Based on the data processing results from the 384 questionnaires distributed to elementary school teachers, Cronbach's Alpha results are shown in Table 1.

Table 1. Cronbach's Alpha Value

Optimisme (OPT)	0.677
Innovativeness (INN)	0.684
Discomfort (DIS)	0.778
Insecurity (INS)	0.889
Perceived Validity (PV)	0.770
Perceived Trust (PT)	0.814
Perceived Easy of Used (PE)	0.814
Perceived Usefull (PU)	0.809
Intension To Uses (IU)	0.731
Usage Behaviour (UB)	0.768
Actual Used (AU)	0.788

Almost all the variables measured in this study have Cronbach's Alpha values in the high-reliability range of 0.7 to 0.8 or higher. This indicates that the instruments used in this research are consistent and reliable for measuring these variables. Optimism (OPT) and innovativeness (INN) have values slightly below 0.7 but are still within the acceptable range. These values indicate that the data collected are reliable and suitable for further analysis. Therefore, to achieve a threshold above 0.5, indicators with lower outer loading values were removed from these variables. Figure 2 shows the structural model after removing these indicators.

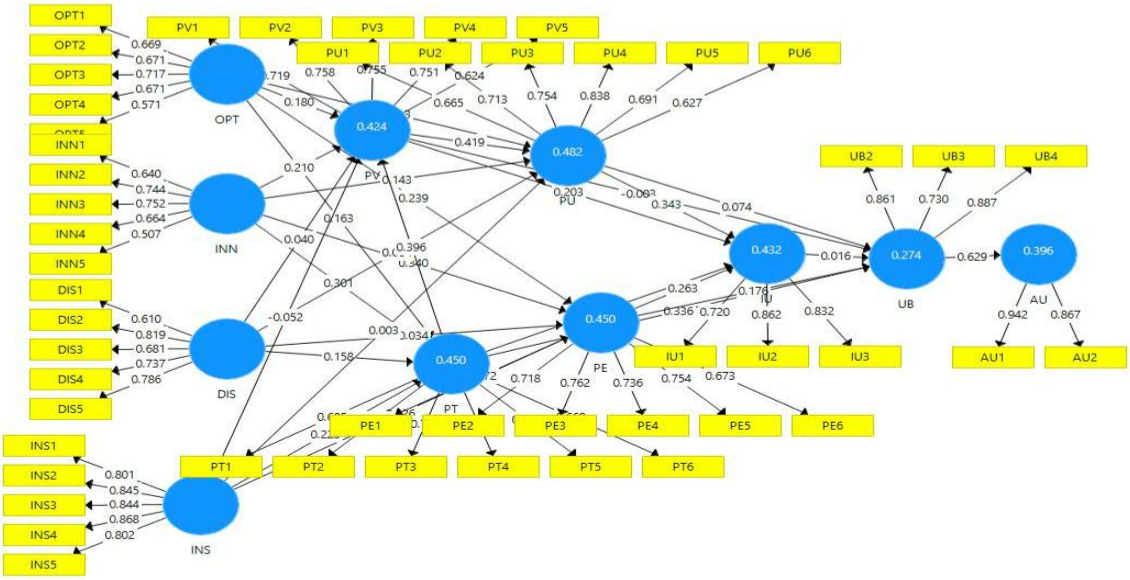

Figure 2. Loading of Outer Model

3.2. Construct Reliability and Validity

Construct reliability and validity are critical concepts in research and measurement. Construct reliability ensures that the measurement consistently captures the underlying construct, while construct validity ensures that the measurement accurately reflects the intended theoretical concept. The results from the SmartPLS analysis, showing construct reliability and validity for all study variables, are presented in Table 2.

Table 2. Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
OPT	0.677	0.680	0.795	0.538
INN	0.684	0.702	0.798	0.545
DIS	0.778	0.778	0.850	0.533
INS	0.889	0.892	0.919	0.693
PV	0.770	0.771	0.845	0.523
PT	0.814	0.817	0.866	0.518
PE	0.814	0.816	0.866	0.518
PU	0.809	0.822	0.863	0.515
IU	0.731	0.748	0.848	0.651
UB	0.768	0.775	0.868	0.687
AU	0.788	0.877	0.901	0.820

The results derived from the SmartPLS analysis show that all variables meet the criteria for construct reliability, as evidenced by Cronbach's Alpha values that exceed the minimum threshold of 0.50. In addition, the rho_A value, which indicates composite reliability, exceeds the acceptable minimum of 0.50 with a minimum value of 0.680. Similarly, the CR values meet the established standards, with minimum values exceeding 0.795 and maximum values reaching 0.919. In terms of construct validity, as assessed by AVE values, it was found that all variables met the minimum acceptable threshold of 0.50.

In conclusion, this study has not only successfully established the reliability and validity of the constructs but has also met all three criteria for convergent validity. All indicator loadings are greater than 0.50, thus meeting the three conditions. The observed construct reliability (CR) values range from 0.795 to 0.919, indicating high internal consistency reliability. In addition, the average variance extracted (AVE) values range from 0.515 to 0.820, exceeding the recommended threshold of 0.50..

3.3. Evaluation of Structural Model

The internal or structural model was examined, including the study variables and their relationships. These relationships are derived from the proposed model. The effectiveness of the proposed model in explaining and predicting one or more target variables was verified through the results obtained from the structural model analysis. As recommended, a systematic approach is essential to evaluate the structural model of a study. This methodology includes various statistical techniques such as multicollinearity assessment, coefficient of determination (R^2), f^2 effect sizes, blindfold-based cross-validated redundancy measure (Q^2), and hypothesis testing to establish the statistical significance and relevance of the path coefficients for the relationships between the variables under study. In addition, the ability of the structural model to predict out-of-sample data (q^2) is assessed using the PLSpredict technique.

The evaluation of the structural model revealed several key findings. First, the multicollinearity assessment showed no significant issues, as all VIF values were below the recommended threshold of 3, ensuring the reliability of the regression results. Second, the coefficient of determination (R^2) values indicated that the model's explanatory power was moderate for most constructs, explaining between 26.4% and 48.2% of the variance in the dependent variables. Third, the f^2 effect size analysis demonstrated that most relationships between variables had small to moderate effect sizes, with the relationship between Usage Behavior (UB) and Actual Use (AU) showing a large effect size. Fourth, the predictive relevance (Q^2) values confirmed that the model had adequate predictive power, with all Q^2 values above 0. Finally, the q^2 effect size analysis showed small effect sizes for the predictive relevance of the variables, indicating that the predictor variables made modest contributions to the explanatory power of the endogenous constructs. Overall, these results suggest that the structural model is robust and capable of explaining a significant portion of the variance in the variables related to AI-based teaching and learning adoption among elementary school teachers in West Java, Indonesia.

3.4. Direct Relationship Analysis

Examining the direct relationships provides deep insights into the dynamics between different variables in the structural model in the context of this research. Of the 27 hypotheses tested, 21 received substantial support, indicating a statistically significant direct relationship between the predictor and response variables. These supported hypotheses (H1, H2, H3, H4, H5, H6, H7, H8, H10, H12, H15, H16, H17, H18, H20, H22, H23, H24, H25, H26, and H27) highlight the importance of specific factors such as optimism (OPT), innovativeness (INN), discomfort (DIS), insecurity (INS), perceived validity (PV), perceived trust (PT), perceived usefulness (PU), perceived ease of use (PE), intention to use (IU), usage behaviour (UB), and actual use (AU).

However, six hypotheses (H9, H11, H13, H14, H19, and H21) were rejected, indicating that certain expected direct relationships did not show statistical significance in the study context. These rejections point to the nuanced nature of factors such as optimism (OPT), perceived trust (PT), discomfort (DIS), and intention to use (IU), indicating that their direct effects on certain response variables may not be statistically significant among elementary school teachers in West Java.

3.5. Mediating Relationship Analysis

The mediating relationship analysis provides crucial insights into the indirect effects of the structural model of AI-based teaching and learning adoption among elementary school teachers in West Java, Indonesia. The analysis reveals that specific variables such as perceived ease of use, perceived trust, and perceived usefulness significantly mediate the relationships between innovativeness, insecurity, and perceived value on teachers' intention to use, usage behaviour, and actual use of AI technology. Notably, hypotheses involving pathways like innovativeness through perceived ease of use and perceived value through perceived usefulness were supported, indicating significant indirect effects. In contrast, other pathways, such as perceived ease of use through intention to use, were not supported. These findings highlight the complex interplay of factors influencing AI adoption, providing valuable insights for educational policymakers and administrators to enhance strategies for improving the readiness and acceptance of AI-based teaching and learning models among teachers in this region.

DISCUSSION

The discussion section contextualizes the results within the broader literature and explores their implications for theory, practice, and future research.

Comparison with Previous Studies

The findings of this study align with previous research on the Technology Acceptance Model (TAM) and its extensions, demonstrating that perceived ease of use, perceived usefulness, and perceived trust are critical factors in adopting AI-based teaching and learning technologies. For instance, the strong direct effect of perceived usefulness on both intention to use and actual use is consistent with the foundational principles of TAM, which posits that users are more likely to adopt a technology if they perceive it to be useful in achieving their tasks.

However, the study also reveals unique insights specific to the context of elementary school teachers in West Java, Indonesia. The rejection of certain hypotheses, such as the non-significant direct relationship between perceived ease of use and intention to use, suggests that cultural or contextual factors may influence the adoption process differently than in other settings. This points to the necessity of tailoring adoption models to local contexts, considering the specific needs and perceptions of the target population.

Practical Implications

For practitioners, these findings underscore the importance of addressing technological and psychological factors when implementing AI-based educational tools. Training programs that enhance teachers' perceived ease of use and usefulness of AI technologies can significantly impact their readiness and acceptance. Building trust through transparent communication about the benefits and potential challenges of AI integration is crucial for fostering a positive attitude toward these technologies.

Educational policymakers should consider developing comprehensive support systems that include continuous professional development, technical support, and resources to assist teachers in integrating AI into their teaching practices. Moreover, involving teachers in the decision-making process regarding AI adoption can enhance their sense of ownership and acceptance of the technology.

Future Research Directions

This study opens several avenues for future research. First, exploring the impact of cultural factors on the adoption of AI in education could provide deeper insights into the variations observed in different contexts. Comparative studies between regions or countries could help identify universal versus context-specific determinants of AI adoption.

Second, longitudinal studies that track the adoption process over time would be valuable in understanding how teachers' perceptions and usage behaviors evolve. Such studies could also assess the long-term impacts of AI integration on educational outcomes and teacher efficacy.

Expanding the research to include qualitative methods, such as interviews or focus groups, could provide a richer, more nuanced understanding of teachers' experiences and challenges with AI adoption. This mixed-methods approach could complement the quantitative findings and offer a more comprehensive picture of the factors influencing AI adoption in education.

4. CONCLUSION

This comprehensive study explored the adoption of AI technology among primary school teachers in West Java, Indonesia, successfully achieving its primary objectives. The research identified critical factors influencing AI adoption, such as optimism, innovativeness, discomfort, insecurity, perceived validity, perceived trust, perceived usefulness, and perceived ease of use. These insights contribute to the local understanding of AI adoption, offering practical implications for educators, administrators, and policymakers.

One of the unique contributions of this study is the development of a tailored adoption model specifically designed for the educational landscape of West Java. This model, which provides a roadmap for effective AI integration in teaching and learning processes, is a significant practical contribution. It addresses the specific needs and challenges teachers in this region face, making it a valuable reference for other regions grappling with similar challenges in adopting educational technology.

The study also assessed readiness factors, revealing insights into teachers' intention to use AI, usage behavior, and the mediating roles of perceived ease of use and perceived usefulness. These findings offer actionable information for designing interventions to foster a supportive environment for technology integration, such as professional development programs and infrastructure enhancements.

Despite the study's successes, certain limitations should be acknowledged. The reliance on self-reported data introduces potential inaccuracies, as participants' responses may only partially reflect their experiences or behaviors. Additionally, the study's focus on a specific regional context limits the generalizability of its findings to other geographic areas or educational levels. The cross-sectional design also presents limitations in establishing causal relationships, as it captures a snapshot of AI adoption at a single point in time without considering the dynamic nature of technology adoption and its influencing factors. Furthermore, extraneous factors such as economic or policy changes during the study period may have influenced the results.

Addressing these limitations in future research can further advance our understanding of AI adoption in different educational contexts. Longitudinal studies could provide deeper insights into the causal relationships between AI adoption and educational outcomes, capturing changes over time and the impact of evolving factors. Expanding the scope to include different regions or educational levels and exploring additional factors, such as cultural influences and organizational support, can offer a more comprehensive understanding of the phenomenon.

This research makes significant theoretical, practical, and methodological contributions. Theoretically, it expands the understanding of AI technology adoption among elementary school teachers, contributing to developing theories on technology adoption in education. Practically, the study offers a new model for AI-based teaching and learning, guiding the design of training programs and enhancing educational quality. Methodologically, the research employs a systematic and scientific approach, ensuring the validity and reliability of its findings through comprehensive data collection and appropriate statistical analysis.

The implications of this study are multifaceted, addressing educational policy, teacher training, infrastructure development, and future research directions. Policymakers can use the findings to develop policies that support AI integration in education and allocate resources effectively. Comprehensive training programs for teachers can be designed to enhance technological skills and information literacy regarding AI. Additionally, the research underscores the need for adequate facilities and infrastructure to support AI technology, prompting schools to invest in technological upgrades and establish robust support systems. Targeted interventions can address psychological barriers, such as teachers' attitudes and beliefs about AI, fostering a more positive attitude towards AI adoption.

In conclusion, this research provides valuable insights into AI adoption in primary education. Its findings offer theoretical and practical contributions and can potentially guide future research, policy development, and educational practice. The study underscores the importance of tailored approaches to technology adoption, considering educators' specific needs and contexts, with the ultimate goal of enhancing the effectiveness and sustainability of AI integration in education.

ACKNOWLEDGEMENTS

This research was supported by Asia e University, Kuala Lumpur, Malaysia. We extend our heartfelt gratitude to our colleagues from Asia e University and Universitas Kuningan for their invaluable insights and expertise, which greatly assisted in the progression of this research. Their contributions were instrumental in shaping the direction and depth of this study, even though they may only partially concur with some of the interpretations and conclusions presented in this paper. We also acknowledge the continuous support and encouragement from our families and friends, whose understanding and patience allowed us to dedicate time and effort to this work. Finally, we appreciate the constructive feedback from our peer reviewers, which helped us enhance the quality and clarity of this research.

REFERENCES

[1] R. Niikura *et al.*, "Artificial intelligence versus expert endoscopists for diagnosis of gastric cancer in patients who have undergone upper gastrointestinal endoscopy," *Endoscopy*, vol. 54, no. 08, pp. 780–784, 2022.

[2] S. R. R. P. Supriadi, S. U. Haedi, and M. M. Chusni, "Inovasi pembelajaran berbasis teknologi Artificial Intelligence dalam Pendidikan di era industry 4.0 dan society 5.0," *Jurnal Penelitian Sains dan Pendidikan (JPSP)*, vol. 2, no. 2, pp. 192–198, 2022.

[3] S. Nemorin, A. Vlachidis, H. M. Ayerakwa, and P. Andriotis, "AI hyped? A horizon scan of discourse on artificial intelligence in education (AIED) and development," *Learn Media Technol*, vol. 48, no. 1, pp. 38–51, 2023.

[4] T. Nazaretsky, M. Cukurova, and G. Alexandron, "An instrument for measuring teachers' trust in AI-based educational technology," in *LAK22: 12th international learning analytics and knowledge conference*, 2022, pp. 56–66.

[5] W. Holmes and I. Tuomi, "State of the art and practice in AI in education," *Eur J Educ*, vol. 57, no. 4, pp. 542–570, 2022.

[6] M. M. E. I. Bali, M. P. Kumalasani, and D. Yunilasari, "Artificial Intelligence in Higher Education: Perspicacity Relation between Educators and Students," *Journal of Innovation in Educational and Cultural Research*, vol. 3, no. 2, pp. 146–152, 2022.

[7] K. Alhumaid, S. Naqbi, D. Elsori, and M. Mansoori, "The adoption of artificial intelligence applications in education," *International Journal of Data and Network Science*, vol. 7, no. 1, pp. 457–466, 2023.

[8] A. C. Starks and S. M. Reich, “What about special ed?“: Barriers and enablers for teaching with technology in special education,” *Comput Educ*, vol. 193, p. 104665, 2023.

[9] N. K. S. Astini, “Tantangan implementasi merdeka belajar pada era new normal covid-19 dan era society 5.0,” *Lampuhyang*, vol. 13, no. 1, pp. 164–180, 2022.

[10] C. F. B. Hartanto, S. Octavianus, and A. M. Paduppai, “Kesiapan Sumber Daya Manusia Pendidikan dalam Difusi Inovasi Teknologi Informasi di Lembaga Pendidikan,” in *Prosiding Industrial Research Workshop and National Seminar*, 2022, pp. 1412–1418.

[11] C. Antonietti, M.-L. Schmitz, T. Consoli, A. Cattaneo, P. Gonon, and D. Petko, “Development and validation of the ICAP Technology Scale to measure how teachers integrate technology into learning activities,” *Comput Educ*, vol. 192, p. 104648, 2023.

[12] M. Dharani, D. S. Chakravarthi, V. Varghese, B. M. Ali, and K. V Nagendra, “Influence of Artificial Intelligence Technology on Teaching Slow Learners,” *International Journal of Early Childhood*, vol. 14, no. 04, p. 2022, 2022.

[13] R. Aggarwal, N. Girdhar, and others, “The role of artificial intelligence in the education sector: possibilities and challenges,” *Machine Learning, Blockchain, and Cyber Security in Smart Environments*, pp. 17–39, 2022.

[14] Y. Dai *et al.*, “Collaborative construction of artificial intelligence curriculum in primary schools,” *Journal of Engineering Education*, vol. 112, no. 1, pp. 23–42, 2023.

[15] M. H. BATUBARA, “Penerapan Teknologi Artificial Intelligence dalam Proses Belajar Mengajar di Era Industri 4.0 dan Sociaty 5.0,” *Kampus Merdeka Seri 1: Menilik Kesiapan Teknologi Dalam Sistem Kampus*, p. 53, 2020.

[16] J. S. Devi, M. B. Sreedhar, P. Arulprakash, K. Kazi, and R. Radhakrishnan, “A path towards child-centric Artificial Intelligence based Education,” *International Journal of Early Childhood*, vol. 14, no. 03, p. 2022, 2022.

[17] E. A. Kolog, S. N. O. Devine, S. B. Egala, R. Amponsah, J. Budu, and T. Farinloye, “Rethinking the implementation of artificial intelligence for a sustainable education in Africa: Challenges and solutions,” in *Management and Information Technology in the Digital Era*, vol. 29, Emerald Publishing Limited, 2022, pp. 27–46.

[18] K. R. Ririh, N. Laili, A. Wicaksono, and S. Tsurayya, “Studi Komparasi Dan Analisis Swot Pada Implementasi Kecerdasan Buatan (Artificial Intelligence) Di Indonesia,” *Jurnal Teknik Industri*, vol. 15, no. 2, pp. 122–133, 2020.

[19] K. Kim and K. Kwon, “Exploring the AI competencies of elementary school teachers in South Korea,” *Computers and Education: Artificial Intelligence*, vol. 4, p. 100137, 2023.

[20] L. Rahadiantino, A. Fahmi, H. W. Aparamarta, S. K. Moerad, and A. M. Shiddiqi, “Implementasi Pembelajaran Artificial Intelligence Bagi Siswa Sekolah Dasar di Kota Batu, Malang, Jawa Timur,” *Jurnal Inovasi Pendidikan dan Pembelajaran Sekolah Dasar*, vol. 6, no. 1, pp. 92–101, 2022.

[21] E. Subowo, N. Dhiyaulhaq, and I. W. Khasanah, “Pelatihan Artificial Intelligence untuk Tenaga Pendidik dan Guru Sekolah Dasar Muhammadiyah (Online Thematic Academy Kominfo RI),” *Abditeknika Jurnal Pengabdian Masyarakat*, vol. 2, no. 2, pp. 83–90, 2022.

[22] W. S. Davis, “HIPO (hierarchy plus input-process-output),” in *The information system consultant’s handbook*, CRC Press, 2019, pp. 503–510.

[23] A. Parasuraman, “Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies,” *J Serv Res*, vol. 2, no. 4, pp. 307–320, 2000.

[24] V. Venkatesh and F. D. Davis, “A theoretical extension of the technology acceptance model: Four longitudinal field studies,” *Manage Sci*, vol. 46, no. 2, pp. 186–204, 2000.

[25] N. Hakiem, J. M. Muslimin, I. Subchi, and A. R. Ahlan, “The impacts of perceived trust and perceived validity on the religious electronic resource acceptance,” *ICIC Express Letters*, vol. 16, no. 9, pp. 1019–1026, 2022.

[26] R. Rosalina, M. C. Utami, N. Kumaladewi, S. J. Putra, and others, “The psychometric and interpretative analyses for assessing the end-user computing satisfaction questionnaire,” in *2017 5th International Conference on Cyber and IT Service Management (CITSM)*, 2017, pp. 1–6.