Journal of Instructional and Development Researches
Homepage: https://www.journal.iel-educationorg/index.php/JIDeR
e-ISSN: 2807-5471; p-ISSN: 2807-548X

JIDeR, Vol. 5, No. 4, August 2025

Page: 400-406

Preliminary Validation of the AI Technology Acceptance Instrument for Primary Educators

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DOI: https://doi.org/10.53621/jider.v5i4.580

Informasi Artikel

Article History:
Received: 6 Juli 2025
Revised: 23 Agustus 2025
Accepted: 24 Agustus 2025
Published: 31 Agustus 2025

Keywords:
AI tools;
Elementary school;
Pilot study;
Technology acceptance;
Validity reliability;

ABSTRAK

Education in Indonesia has undergone substantial transformation with the widespread integration of technology. In this context, technology training for teachers is essential to enhance the quality of teaching and learning in elementary schools. However, only approximately 30% of teachers report feeling adequately prepared to integrate technology into their instructional practices. This reveals a gap between the increasing demand for educational technology and teachers' readiness to adopt it. This pilot study aims to evaluate the reliability and construct validity of an adapted instrument designed to measure elementary school teachers' acceptance of artificial intelligence (AI) technology in East Jakarta, Indonesia. The study incorporates six key constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEU), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention (BI), and Perceived Trust (PT), with a total of 22 proposed indicators. Data were collected from 61 elementary school teachers who completed a structured questionnaire based on the proposed research model. The results indicate that the instrument meets the required thresholds for both construct validity and reliability. However, only 21 indicators met the established criteria, with one indicator excluded due to low factor loading. The findings from this preliminary study provide a valid foundation for applying the instrument in larger-scale research on teachers' acceptance of AI technologies in educational settings.

INTRODUCTION

Recent developments in the field of Artificial Intelligence (AI) have experienced significant acceleration. The rapid advancement of AI has catalyzed its application across various domains of life, particularly in the field of education (R. et al., 2023). The effective integration of technology in educational contexts is not solely determined by the availability of hardware and software, but is also shaped by a set of interrelated supporting factors (Zhao et al., 2023). These include the readiness of digital infrastructure, educators' technological competencies, institutional policy support, and a culture of learning that is adaptive to innovation.

Adequate infrastructure such as stable internet connectivity and access to digital devices forms the foundational basis for implementing educational technologies (Haleem et al., 2022). Equally critical is the pedagogical competence of educators in integrating technology into teaching and learning processes, which greatly influences its overall effectiveness (Ifinedo & Kankaanranta, 2021). In addition, institutional support through professional development programs, incentives, and progressive policies plays a pivotal role in facilitating successful digital transformation (Zhang & Chen, 2024). A school culture that embraces change and fosters collaboration further contributes to the establishment of a responsive learning environment that keeps pace with technological advancements (Rahimi & Oh, 2024). Accordingly, strengthening these supporting dimensions constitutes a key prerequisite for building a sustainable and inclusive digital education ecosystem.

The advancement of Artificial Intelligence (AI) technologies has had a significant impact on the field of education, including at the elementary school level (Barakina et al., 2021). In recent years, the utilization of AI by primary school teachers has shown notable growth, particularly in lesson planning, content personalization, and the assessment of student learning outcomes (Almuhanna, 2025). AI technologies enable teachers to access data-driven recommendation systems, analyze individual student learning needs, and identify learning difficulties at an early stage (Ahmad et al., 2024). Moreover, AI-powered learning platforms can assist teachers in designing activities that align with students' diverse learning styles (Luo, 2023).

Despite its potential, the implementation of AI in primary education still faces several challenges (Kim & Kwon, 2023). These include limited digital literacy among teachers, insufficient school infrastructure, and the absence of clear policies to govern the ethical and responsible use of technology (Villar-Onrubia et al., 2022). Therefore, enhancing teachers' competencies in AI literacy and providing systemic support from educational institutions are critical to fostering the effective and sustainable integration of AI in primary schools (Zhang & Zhang, 2024).

The acceptance of technological innovation in education plays a critical role in advancing instructional innovation, particularly regarding the integration of Artificial Intelligence in Education (Alam & Mohanty, 2023). As a result, there has been growing attention to the factors that influence teachers' acceptance of AI technologies (Wang et al., 2021). In this context, the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) have been widely employed. These models have been adapted to incorporate key constructs such as Perceived Usefulness (PU) and Perceived Ease of Use (PEU). Furthermore, the framework integrates two essential components from the UTAUT model Social Influence (SI) and Facilitating Conditions (FC).

As an extension, the proposed model also includes an external variable: Perceived Trust (PT) in technology. Collectively, this conceptual model is designed to examine the determinants that influence teachers' Behavioral Intention (BI) to adopt AI-based technologies in their instructional practice. Previous studies investigating the use of AI technologies such as ChatGPT among university students using the UTAUT model have shown significant impacts on students' Performance Expectancy (PE) and Hedonic Motivation (HM). However, limited attention has been given to other important factors such as Social Influence (SI) and Facilitating Conditions (FC). This study shifts the focus to elementary school teachers, thereby emphasizing the importance of examining FC and SI. Facilitating Conditions are considered a key factor in supporting teachers' capacity to innovate in their teaching practices (Stumbrienė et al., 2024), while Social Influence is shaped by the school environment (Alfadda & Mahdi, 2021), suggesting a strong interrelation between these two constructs.

Meanwhile, in the Technology Acceptance Model (TAM), teachers are generally more inclined to adopt AI technologies based on their perceived usefulness and ease of use rather than other variables. Therefore, this study incorporates Perceived Usefulness (PU) and Perceived Ease of Use (PEU) from the TAM framework, both of which are expected to significantly influence teachers' Behavioral Intention (BI) to use AI tools. In addition, Perceived Trust (PT) is also identified as a crucial factor in enhancing teachers' confidence in using AI technologies. Thus, PT is hypothesized to exert a significant impact on their behavioral intention to adopt such tools in the classroom.

Table 1. Constructs for measuring the acceptance of Educational AI Tools (EAIT).

Perceived Trust (PT)	PT1	I believe that AI technology has the potential to yield positive outcomes in professional work
	PT2	I believe that using AI technology is the best decision
	PT3	I am confident that the outcomes produced by AI technology are reliable
	PT4	I have strong confidence in the reliability and potential of AI technology

Perceived Usefulness (PU)	PU1	The use of AI technology significantly enhances work productivity
	PU2	The use of AI technology can enhance my job performance
	PU3	The use of AI technology is highly efficient in my work
	PU4	I benefit from the use of AI technology
Perceived Ease of Use (PEU)	PEU1	The use of AI technology is easy to learn
	PEU2	The use of AI technology does not require substantial effort
	PEU3	The use of AI technology is very easy
	PEU4	I am able to use AI technology according to my work requirements
Social Influence (SI)	SI1	I have received suggestions from others to use AI technology in my work
	SI2	People around me exert influence on my decision to use AI technology
	SI3	I have received suggestions from others regarding the advantages of using AI tools
Facilitating Condition (FC)	FC1	I have reliable resources to support my use of AI technology
	FC2	I have the knowledge required to use AI technology
	FC3	AI technology is compatible with the IT devices I use
	FC4	I will seek help from others if I encounter difficulties in using AI technology
Behavioural Intention (BI)	BI1	I have decided to continue using AI technology
	BI2	If I start using AI technology, I predict that my colleagues will also adopt it
	BI3	I plan to use AI technology in my work

Table 1 outlines the constructs utilized in this study (Velli & Zafiropoulos, 2024), which include Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) from the Technology Acceptance Model (TAM), as well as Social Influence (SI), Facilitating Conditions (FC), and Behavioral Intention (BI) from the Unified Theory of Acceptance and Use of Technology (UTAUT). Additionally, the model incorporates one external construct, Perceived Trust (PT), which is a novel contribution proposed in this study.

METHOD

This preliminary study was conducted as an initial phase of the proposed research, aimed at examining the validity and reliability of the constructs. The purpose of this assessment is to ensure that the measurement meets established standard criteria. A quantitative survey approach was employed using a structured questionnaire distributed via Google Forms to facilitate rapid data collection (Umam et al., 2024).

A total of 61 elementary school teachers were randomly selected as respondents, and the questionnaire comprised 22 indicators derived from the proposed model. The model includes six constructs: Perceived Trust (PT, 4 items), Perceived Usefulness (PU, 4 items), Perceived Ease of Use (PEU, 4 items), Social Influence (SI, 3 items), Facilitating Conditions (FC, 4 items), and Behavioral Intention (BI, 3 items). Cronbach's Alpha and Average Variance Extracted (AVE) were employed to assess the internal consistency and convergent validity of the constructs.

RESULT AND DISCUSSION

Result

During the preliminary stage, a pilot survey was administered to a sample of 61 public elementary school teachers from various institutions in East Jakarta. All participants completed the questionnaire, and no duplicate entries were identified, maintaining the final respondent count at 61. The estimated completion time for the survey ranged from 5 to 10 minutes. The primary aim of this pilot study was to evaluate the construct validity of each item within the instrument. Descriptive results from the initial analysis are summarized in Table 2.

Table 2. Instrument validity and reliability test

Construct	Item	Outer Loading	Cronbach Alfa (CA)	Composite Reliability (CR)	Average Confirmatory Extracted (AVE)
PT	PT1	0.907	0.885	0.921	0.741
	PT2	0.891			
	PT3	0.778			
	PT4	0.865			
PU	PU1	0.863	0.816	0.873	0.661
	PU2	0.712			
	PU3	0.779			
	PU4	0.712			
PEU	PEU1	0.598	0.813	0.769	0.667
	PEU2	0.863			
	PEU3	0.780			
	PEU4	0.830			
SI	SI1	0.822	0.793	0.777	0.617
	SI2	0.801			
	SI3	0.935			
FC	FC1	0.872	0.874	0.922	0.789
	FC2	0.898			
	FC3	0.911			
	FC4	0.930			
BI	BI1	0.930	0.788	0.884	0.719
	BI2	0.720			
	BI3	0.879			

Discussion

The results of this study reveal that the reliability values exceed the threshold of 0.70, thereby meeting the established criteria (Hair et al., 2019). This finding is consistent with previous studies, which suggest that values above 0.70 are considered satisfactory (Salloum et al., 2019). As presented in Table 2, indicators with outer loading values below 0.60 were deemed unreliable and subsequently removed to maintain the consistency of the construct measurement. This step was followed by a recalculation of Cronbach's Alpha (CA) to ensure construct reliability. The CA test is commonly employed to evaluate convergent validity, with values above 0.70 indicating that the construct meets the required criteria (Astuti et al., 2022).

Furthermore, to assess the reliability of reflective constructs, Composite Reliability (CR) was utilized. Previous research indicates that CR values tend to be higher than CA values. CR values range from 0 to 1, with a minimum threshold of 0.60 for exploratory studies (Purwanto, 2021; Utari et al., 2021), and 0.70 for confirmatory studies. Higher CR values approaching 1 imply lower measurement error. Additionally, Average Variance Extracted (AVE) was used to examine both convergent validity and the shared variance among items (Chavoshi & Hamidi, 2019). The AVE test measures the amount of variance captured by a latent factor in a reflective model. A minimum AVE value of 0.50 is required (Salehudin et al., 2021). Ideally, AVE should exceed the cross-loading values, as higher AVE scores indicate a lower level of error and stronger convergent validity.

Table 2 presents the results derived from 22 measurement items. One item, PEU1, was removed from the analysis due to its loading value falling below the acceptable threshold

(Desmaryani et al., 2022). Consequently, only 21 indicators were retained for subsequent analysis. As shown in the table, PU4 had the lowest acceptable outer loading value of 0.712, while the highest was observed for SI3, at 0.935. Indicators with outer loading values above the minimum threshold were deemed acceptable, whereas those falling below 0.60 were eliminated from the model (Hair Jr et al., 2021).

In terms of internal consistency reliability, the Cronbach's Alpha (CA) values for all constructs exceeded 0.70, indicating satisfactory reliability. The lowest CA value was 0.788 for the Behavioral Intention (BI) construct, while the highest was 0.885 for Perceived Trust (PT). Composite Reliability (CR) values also met the required criterion (>0.60), with the lowest CR recorded for Social Influence (SI) at 0.777 and the highest for Facilitating Conditions (FC) at 0.922.

Regarding convergent validity, all constructs achieved Average Variance Extracted (AVE) values above the threshold of 0.50, confirming adequate construct validity. The lowest AVE was observed in SI (0.617), whereas the highest was found in FC (0.789). Based on the outcomes of the pilot study reflected in CA, CR, and AVE values it can be concluded that the measurement constructs demonstrate sufficient reliability and validity, and are suitable for broader implementation in future research.

CONCLUSION

Following the evaluation of 22 indicator items across the proposed constructs, the results demonstrated that Cronbach's Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE) all satisfied established threshold criteria. Consequently, the instrument is deemed reliable and valid for application in broader empirical investigations. Furthermore, these findings align with the overarching aim of the study, which is to validate the measurement instrument assessing the determinants of AI technology acceptance among elementary school teachers.

ACKNOWLEDGMENT

The authors gratefully acknowledge the financial assistance provided by the Institute for Research and Community Service, Universitas Muhammadiyah Prof. Dr. Hamka, Indonesia, through Grant No. 308/F.03.07/2024, which substantially contributed to the successful completion of this research.

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