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Research Article

Digital Skills, School Field Introduction, and Teaching Readiness among Preservice Economic Teachers: The Mediating Role of AI Utilization

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Abstract
This study aims to examine the role of artificial intelligence (AI) utilization as a mediating variable in the relationship between digital skills and school field introduction on the teaching readiness of preservice economics. This research employed a quantitative approach using structural equation modeling–partial least squares (SEM-PLS) with SmartPLS 4. The sample consisted of 113 economics education students from several universities in Malang, East Java of Indonesia, which selected through purposive sampling. The results indicate that digital skills and school field introduction have a positive and significant effect on teaching readiness, both directly and indirectly through AI utilization. In addition, AI utilization acts as a significant mediator, although with a relatively small effect in strengthening the contribution of internal and external factors to the professional readiness of prospective teachers. These findings highlight the importance of integrating AI technology in teacher education to enhance pedagogical competence and prepare future teachers for digital-era learning environments.

Keywords: artificial intelligence, digital skills, preservice economics teachers, teaching readiness

INTRODUCTION

Education plays a fundamental role in shaping the quality of human resources and determining the progress of a nation (Sheyin, 2024). A quality education process is influenced by the interaction between teachers and students in the learning environment (Wang et al., 2022). Therefore, teachers are required to possess adequate professional competence and readiness in carrying out their roles in the classroom (Romanyuk et al., 2022). Professional teachers are not only expected to master learning materials and teaching methods, but also to be able to plan, implement, and evaluate the learning process effectively (Afriadi et al., 2023). In this context, teaching readiness becomes an essential aspect that must be possessed by prospective teachers before entering the professional teaching environment.

Teaching readiness refers to the physical condition, knowledge, work attitude, and pedagogical skills that enable prospective teachers to perform their teaching duties effectively in real classroom situations (Almusawi & Durugbo, 2024). Adequate teaching

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readiness allows prospective teachers to adapt to the learning environment and manage classroom activities appropriately (Mane, 2025). Previous studies have shown that teaching readiness influences the quality of learning and students' academic outcomes (Kurniawan et al., 2023; Almulla, 2022). Various factors can influence teaching readiness, including internal factors such as motivation, teaching interest, and digital competence, as well as external factors, such as teaching practice experiences and institutional support (Dewi et al., 2025).

In the era of 21st-century learning, digital skills have become one of the key competencies that prospective teachers must possess (Rahimi & Mosalli, 2025). Digital skills enable teachers to access diverse learning resources, utilize digital learning media, and integrate technology into the teaching and learning process (Adeshina, 2024). The integration of digital technology in education has significantly transformed teaching strategies and learning environments. However, a prior study indicates that the digital skills of prospective teachers remain varied, with some still categorized at a moderate to low level (Ismiyati et al., 2022). This condition presents a challenge for teacher education institutions in preparing future teachers who are capable of utilizing digital technology effectively in the classroom.

Besides internal competencies such as digital skills, experiential learning through teaching practice also plays an important role in developing teaching readiness (Nirmala et al., 2025). One of the important programs in teacher education is the school field introduction, which provides students with opportunities to experience real teaching situations in schools. Through school field introduction activities, prospective teachers can apply theoretical pedagogical knowledge, understand student characteristics, observe classroom management practices, and develop their teaching abilities in authentic educational settings (Tuti et al., 2022). A prior work has also demonstrated that school field introduction experiences contribute to the professional readiness of prospective teachers and their readiness to pursue teaching careers (Rahmadiyani et al., 2020).

However, the development of modern education is increasingly influenced by rapid technological advancements, particularly the emergence of artificial intelligence (AI). AI has become a strategic technology capable of transforming various sectors, including education (George & Wooden, 2023). AI refers to computer systems designed to simulate human intelligence in performing tasks such as problem-solving, data analysis, and decision-making (Sarker, 2022). In the educational context, AI technologies can assist teachers and students by providing personalized learning recommendations, automated assessment systems, and intelligent tutoring support (Zhang et al., 2023). The application of AI in education has also been reported to enhance the quality of teaching and learning processes as well as improve students' competencies (Osetskyi et al., 2020).

In higher education, AI-based tools have become increasingly popular in supporting students' learning processes (Luo et al., 2025). Technologies such as intelligent learning platforms and AI-based applications facilitate students in accessing learning materials, developing instructional content, and increasing learning motivation (Dogan et al., 2023). For instance, generative AI tools such as ChatGPT provide opportunities for students to engage in independent and collaborative learning by offering explanations, feedback, and academic assistance. AI technologies can also support teachers in improving teaching effectiveness through automated evaluation systems, adaptive learning strategies, and data-driven instructional decision making (Zhang et al., 2023).

Despite the growing number of studies discussing digital skills, teaching practice experiences, and the integration of AI in education, a research gap still exists. Previous research has primarily examined the direct influence of digital skills or teaching practice experiences on teaching readiness (e.g., Omah & Mohmad, 2023; Mane, 2025). However, limited studies have explored the mediating role of AI utilization in the relationship between digital skills, school field introduction experience, and teaching readiness, particularly among prospective economics teachers. Moreover, empirical research focusing on the integration of AI in teacher education within the context of Indonesian higher education remains limited. Prior studies have highlighted that the integration of AI technologies in higher education can improve technological literacy and learning effectiveness among prospective teachers (Sari et al., 2025; Andrian et al., 2025). Nevertheless, the potential role of AI utilization as an intermediary factor in strengthening teaching readiness has not been widely investigated.

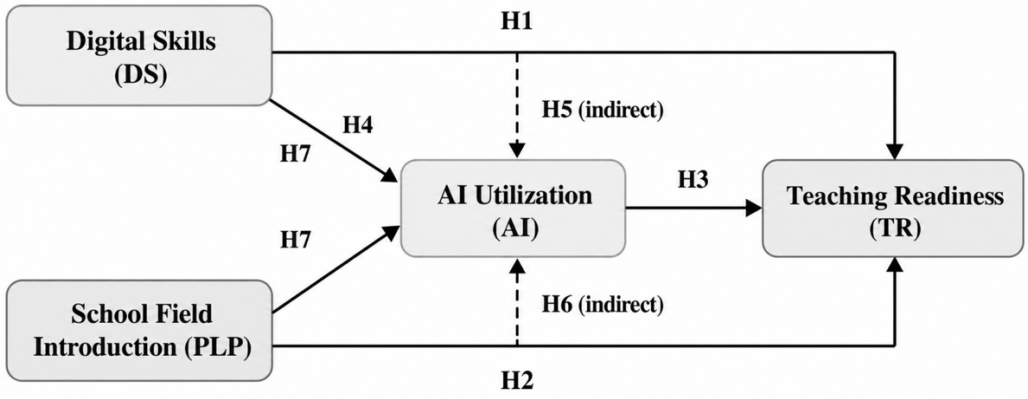
Based on these considerations, this study aims to fill the gaps by examining the influence of digital skills and school field introduction on the teaching readiness of prospective economics teachers. The findings are expected to contribute to the literature on teacher readiness in the digital era by extending the understanding of how technological competence, field-based teaching experience, and AI adoption collectively shape prospective teachers' preparedness. In addition, this study provides useful insights for teacher education institutions in designing more responsive and future-oriented preparation programs. The results can help institutions strengthen digital skills training, improve the quality of school field introduction programs, and integrate AI-based learning tools into pedagogical courses.

This article is organized as follows. The first section presents the introduction, followed by the research method section describing the research design and data analysis procedures. The next section presents the research results and discussion, and the final section concludes the study and provides recommendations for future research.

METHOD

The quantitative approach in this study was applied to examine the role of AI utilization as a mediating variable in the relationship between digital skills and school field introduction on the teaching readiness of preservice economics (see Figure 1).

Figure 1
Research framework



The research population includes students of the economics education study program in several universities in Malang of East Java, Indonesia, namely State University of Malang, Kanjuruhan University of Malang, and Insan Budi Utomo University Malang with a total of 181 people. The sample selection in this study used the purposive sampling technique, the determination of samples based on certain criteria set in accordance with specific objectives and considerations. The number of samples was determined using the Slovin formula with an error rate of 5% (Scott, 2023), so that a sample of 113 respondents was obtained. The data source includes primary data collected directly from respondents through the distribution of questionnaires using the Likert scale. The respondents in this study were undergraduate students majoring in Economics Education who had participated in the school field introduction (ISF) program. This criterion was applied to ensure that respondents possessed both theoretical knowledge and practical teaching experience relevant to teaching readiness.

Table 1
Research instrument

Variable	Indicator	Items	Code	Source
Digital Skills (DS)	Mastery of digital technology	3	DS 1-3	Koehler et al. (2009);
	Operate digital devices and apps	2	DS 4-5	Setiawan et al. (2022)
	Technology readiness	2	DS 6-7	
	Digital integration in learning	2	DS 8-9	
	Understanding context in schools	3	ISF 10-12	
Introduction to the School Field (ISF)	Classroom learning experience	2	ISF 13-14	Rosali et al. (2019)
	Utilization of technology at ISF	2	ISF 15-16	
	Readiness to face challenges at ISF	2	ISF 17-18	
	AI knowledge in education	3	AI 19-21	
	Implementation of AI in learning	2	AI 22-23	
AI Utilization	AI readiness	2	AI 24-25	Holmes et al. (2022);
	Evaluation of AI utilization	2	AI 26-27	Zawacki-Ritcher (2019)
	Teaching skills (psychomotor aspect)	3	RT 28-30	
Teaching Readiness	Knowledge (cognitive aspect)	2	RT 31-32	Murtiningsih (2014).
	Work attitude	2	RT33-34	
	Teaching skills (psychomotor aspect)	2	RT 35-36	

Source: Processed by researchers (2026)

The instrument used a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). This scale was selected to capture respondents' perceptions consistently across all variables. Sample questionnaire items include: "I am able to

integrate digital technology into teaching" (Digital Skills), "ISF helps me understand real classroom situations" (ISF), and "I use AI tools to support learning activities" (AI Utilization). The selection of SEM-PLS as the data analysis technique is based on several considerations. First, SEM-PLS is suitable for analyzing complex models involving mediation relationships. Second, this method is appropriate for studies with relatively small sample sizes. Third, SEM-PLS focuses on prediction and variance explanation, making it relevant for exploratory research in the context of technology integration in education. The research instrument was adapted from previous research and has been re-tested for its validity and reliability (see Table 1).

RESULT

Respondent Profile

This study involved 113 students as respondents, whose demographic profiles were classified based on gender and university of origin, as presented in Table 2. Based on the data obtained, female respondents dominated the sample, with 86 students, representing 76.11% of the total respondents. In contrast, male respondents consisted of 27 students, equivalent to 23.89%. This distribution indicates that the participation of female students in this study was considerably higher than that of male students. In terms of institutional origin, most respondents were students from Universitas Negeri Malang, accounting for 101 students or 89.38% of the total sample. Meanwhile, 5 respondents, or 3.53%, were from Kanjuruhan University of Malang, and 7 respondents, or 6.19%, were from Budi Utomo University.

Table 2
Respondents profile

Category	Frequency	Percentage
Gender		
Male	27	23.89%
Female	86	76.11%
University		
State University of Malang	101	89.38%
Kanjuruhan University	5	3.53%
Budi Utomo University	7	6.19%

Source: Processed by researchers (2026)

Outer Model Test

In the measurement model test, convergent validity and discriminant validity were used. Convergent validity is tested with the criteria of a loading value that must be greater than 0.60. Based on Table 4, convergent validity can be evaluated through the loading factor values of each indicator. The required loading factor value should be greater than 0.60. The results show that most indicators have loading factor values above the threshold. However, two indicators (AI3 and AI7) were removed because their loading values were below the required standard. After the elimination process, all remaining indicators met the loading factor criteria (>0.60), indicating that the measurement model satisfies convergent validity requirements (Chin, 1998).

Table 4
Results of the convergent validity test

Variable	Indicator	Loading Factor	Decision
Digital Skills (DS)	DS.1	0.767	Valid
	DS.2	0.850	Valid
	DS.3	0.866	Valid
	DS.4	0.788	Valid
	DS.5	0.882	Valid
	DS.6	0.841	Valid
	DS.7	0.812	Valid
	DS.8	0.785	Valid
	DS.9	0.662	Valid
Introduction to the School Field (ISF)	ISF.1	0.754	Valid
	ISF.2	0.689	Valid
	ISF.3	0.682	Valid
	ISF.4	0.696	Valid
	ISF.5	0.623	Valid
	ISF.6	0.746	Valid
	ISF.7	0.679	Valid
	ISF.8	0.697	Valid
	ISF.9	0.773	Valid
AI utilization (AI)	AI.1	0.754	Valid
	AI.2	0.689	Valid
	AI.3	0.682	Valid
	AI.4	0.696	Valid
	AI.5	0.623	Valid
	AI.6	0.746	Valid
	AI.7	0.679	Valid
	AI.8	0.697	Valid
	AI.9	0.773	Valid
Teaching Readiness (RT)	RT.1	0.781	Valid
	RT.2	0.795	Valid
	RT.3	0.719	Valid
	RT.4	0.798	Valid
	RT.5	0.811	Valid
	RT.6	0.809	Valid
	RT.7	0.680	Valid
	RT.8	0.748	Valid
	RT.9	0.755	Valid

Source: Processed by researchers (2026)

Average Variance Extracted

The average variance extracted (AVE) value is used to measure convergent validity at the construct level. The recommended AVE value should be greater than 0.50 (Ghozali & Latan, 2015). This value indicates that the construct is able to explain at least 50% of the variance of its indicators. As shown in Table 5, all variables have AVE values above 0.50. Therefore, it can be concluded that all constructs in this study meet the convergent validity criteria.

Table 5
Results of the AVE

Variable	AVE
Digital Skills	0.535
Introduction to the School Field	0.589
Teaching Readiness	0.653
Utilization of AI	0.500

Source: Processed by researchers (2026)

Table 6
Results of the discriminant validity (cross loading)

Item	Utilization of AI	Readiness	Skills Digital	ISF
AI1	**0.772**	0.608	0.550	0.513
AI2	**0.643**	0.398	0.295	0.371
AI4	**0.638**	0.405	0.391	0.399
AI5	**0.775**	0.606	0.579	0.600
AI6	**0.718**	0.575	0.535	0.510
AI8	**0.708**	0.811	0.627	0.653
AI9	**0.814**	0.611	0.509	0.508
RT1	0.766	**0.597**	0.623	0.554
RT2	0.665	**0.781**	0.617	0.694
RT3	0.629	**0.795**	0.600	0.675
RT4	0.562	**0.719**	0.478	0.584
RT5	0.715	**0.798**	0.649	0.745
RT6	0.708	**0.811**	0.627	0.653
RT7	.652	**0.809**	0.649	0.744
RT8	0.548	**0.680**	0.555	0.531
RT9	0.554	**0.748**	0.581	0.622
DS1	0.561	0.755	**0.626**	0.644
DS2	0.573	0.653	**0.767**	0.670
DS3	0.597	0.634	**0.885**	0.656
DS4	0.596	0.614	**0.866**	0.598
DS5	0.621	0.603	**0.788**	0.538
DS6	0.691	0.692	**0.882**	0.666
DS7	0.608	0.617	**0.841**	0.632
DS8	0.551	0.606	**0.812**	0.652
DS9	0.514	0.568	**0.785**	0.629
ISF1	0.490	0.682	0.662	**0.684**
ISF2	0.600	0.665	0.593	**0.754**
ISF3	0.448	0.585	0.516	**0.689**
ISF4	0.532	0.624	0.535	**0.682**
ISF5	0.421	0.576	0.461	**0.696**
ISF6	0.440	0.522	0.535	**0.623**
ISF7	0.544	0.601	0.535	**0.746**
ISF8	0.408	0.519	0.525	**0.679**
ISF9	0.560	0.626	0.661	**0.697**

Note. DS = Digital Skills; ISF = Introduction to the School Field; RT = Teaching Readiness; AI = AI utilization
Source: Processed by researchers (2026)

As illustrated in Table 6, two indicators (AI3 and AI7) were removed because their loading values were below the required threshold. After removing these indicators, the cross-loading results show that the correlation between each construct and its own indicators is higher than the correlation with indicators of other constructs. This indicates that each latent variable explains its own indicators more than indicators belonging to other constructs. Therefore, the model meets the discriminant validity criteria (Ghozali & Latan, 2015). Composite reliability is used to evaluate the internal consistency reliability of each construct. A construct is considered reliable if the composite reliability value exceeds 0.70. Based on Table 7, all variables have composite reliability values greater than 0.70. Therefore, it can be concluded that all constructs in this study are reliable.

Table 7
Results of the composite reliability

Variable	Composite Reliability	Conclusion
Digital Skills	0.887	Reliable
ISF	0.916	Reliable
Teaching Readiness	0.935	Reliable
Utilization of AI	0.878	Reliable

Source: Processed by researchers (2026)

Inner Model Estimation

R-Square values of 0.75, 0.50 and 0.25 can be concluded that the model is strong, moderate and weak (Ghozali & Latan 2015). The coefficient of determination (R-square) is used to measure the ability of exogenous variables to explain endogenous variables in the structural model. Based on Table 8, the R-square value for the Teaching Readiness variable is 0.584 and the adjusted R-square value is 0.576. This indicates that 58.4% of the variance in teaching readiness can be explained by digital skills and school field introduction, while the remaining 41.6% is explained by other variables outside the model. According to the R-square criteria, this value is categorized as moderate.

Table 8
Results of the coefficient of determination (r-square)

Variable	R-square	R-square adjusted
Teaching Readiness	0.584	0.576
AI Utilization	0.822	0.817

Source: Processed by researchers (2026)

Meanwhile, the R-square value for the AI Utilization variable is 0.822 with an adjusted R-square value of 0.817. This means that 82.2% of the variance in AI utilization is explained by Digital Skills and ISF, while the remaining 17.8% is explained by other variables outside the model. Therefore, the explanatory power of the model for AI utilization is categorized as robust.

The F-square value is used to evaluate the effect size of exogenous variables on endogenous variables. Based on Table 9, Digital Skills have a large effect on Teaching Readiness ($f^2 = 0.316$) and a medium effect on AI Utilization ($f^2 = 0.156$). ISF has a small effect on Teaching Readiness ($f^2 = 0.029$) and a medium effect on AI Utilization ($f^2 = 0.141$). Meanwhile, AI Utilization has a large effect on Teaching Readiness ($f^2 = 0.457$).

Table 9
F-Square Test Results

Variable	f-square	Effect
DS → RT	0.316	Large
AI → ISF	0.156	Medium
ISF → RT	0.029	Small
ISF → AI	0.141	Medium
AI → RT	0.457	Large

Note. DS = Digital Skills; ISF = Introduction to the School Field; RT = Teaching Readiness; AI = AI utilization
Source: Processed by researchers (2026)

Hypothesis Testing

The direct effect results in Table 10 indicate that all examined relationships are positive and statistically significant. AI utilization has a positive effect on teaching readiness, with a path coefficient of 0.367, a t-statistic of 5.540, and a p-value below 0.001. Digital skills also positively influence AI utilization, as shown by a coefficient of 0.414. In addition, digital skills have a smaller but significant direct effect on teaching readiness, with a coefficient of 0.126. ISF shows positive effects on both AI utilization and teaching readiness, with coefficients of 0.394 and 0.494, respectively.

Table 10
Direct effect

	Original sample (O)	T statistics (|O/STDEV|)	P values
AI → RT	0.367	5.540	0.000
DS → AI	0.414	3.789	0.000
DS → RT	0.126	1.972	0.049
ISF → AI	0.394	3.467	0.001
ISF → RT	0.494	6.567	0.000

Note. DS = Digital Skills; ISF = Introduction to the School Field; RT = Teaching Readiness; AI = AI utilization
Source: Processed by researchers (2026)

Table 11
Indirect effect

	Original sample (O)	T statistics (|O/STDEV|)	P values	Sample Mean	Upsilon (υ)	Decision
DS → AI → RT	0.152	3.235	0.001	0.151	0.547	Significant
ISF → AI → RT	0.145	2.705	0.007	0.151	0.227	Significant

Note. DS = Digital Skills; ISF = Introduction to the School Field; RT = Teaching Readiness; AI = AI utilization
Source: Processed by researchers (2026)

The indirect effect results (Table 11) indicate that AI utilization significantly mediates the relationship between digital skills, ISF, and teaching readiness. The indirect effect of digital skills on teaching readiness through AI utilization shows an original sample value of 0.152, a t-statistic of 3.235, and a p-value of 0.001. This means that stronger digital skills enhance prospective economics teachers' readiness not only directly but also indirectly by improving their ability to utilize AI. Similarly, ISF has a

significant indirect effect on teaching readiness through AI utilization, with an original sample value of 0.145, a t-statistic of 2.705, and a p-value of 0.007.

DISCUSSION

The first result indicates that digital skills have a positive and significant effect on the teaching readiness of prospective economics teachers. It shows that the higher the digital competence of prospective teachers, the better their readiness to perform teaching tasks professionally. Digital skills enable prospective teachers to utilize digital technology, manage technology-based learning resources, and adapt learning through digital media. This finding is consistent with the technological pedagogical content knowledge theory, which emphasizes the integration of technology, pedagogy, and content knowledge in effective teaching (Phillips et al., 2025). Teachers with digital skills are able to design innovative and interactive learning environments. Previous studies (e.g., Mane, 2025; Almusawi & Durugbo, 2024) also support these results, showing that technological competence contributes to teacher readiness. This finding extends the existing literature by demonstrating that AI is not merely a supporting tool but plays a transformative role in shaping pedagogical competence in the digital era (Zou et al., 2025).

The results reveal that the school field introduction program has a positive and significant influence on the teaching readiness of prospective economics teachers. Through school field introduction activities, students gain direct experience in real classroom environments to allowing them to apply theoretical knowledge and develop pedagogical, professional, social, and personal competencies. This finding aligns with the Social Cognitive Theory proposed by Bandura (2014), which explains that professional behavior is formed through interactions between personal, environmental, and behavioral factors. School field introduction serves as an experiential learning environment that strengthens students' readiness to become professional teachers. Previous studies by Rahmadiyani et al. (2020) also confirm that school field introduction experiences significantly contribute to career readiness in the teaching profession.

In addition, the results indicate that the utilization of AI has a positive and significant influence on the teaching readiness of prospective economics teachers. AI technologies assist students in accessing learning materials, developing instructional content, and evaluating learning outcomes more effectively. This finding supports the Technology Acceptance Model (TAM) proposed by Davis et al. (1989), which explains that technology adoption is influenced by perceived usefulness and perceived ease of use. AI tools such as intelligent learning platforms and virtual assistants help prospective teachers improve efficiency, creativity, and critical thinking in the teaching process. Previous studies (e.g., Zawacki-Richter et al., 2019; Osetskyi et al., 2020) also confirm that AI contributes to improving learning effectiveness and teacher competence in the digital era.

The study also found that digital skills significantly influence the utilization of AI among prospective economics teachers. Students with higher digital competence are more capable of adopting and utilizing AI technologies in learning activities. Digital competence enables students to explore AI applications for learning resource development, teaching material preparation, and learning evaluation. A previous study by Shokeen and Kaur (2022) also confirm that digital competence plays a critical role in technology adoption in education.

The findings show that AI utilization mediates the relationship between digital skills and teaching readiness. Students with robust digital skills are more capable of utilizing AI, which ultimately enhances their teaching readiness. This result is consistent with Social Cognitive Theory (Bandura, 2014), which explains that behavior is influenced by interactions between personal abilities and environmental factors. AI serves as a technological environment that strengthens the influence of digital competence on teaching readiness. A prior work by Zawacki-Richter et al. (2019) also supports the role of AI in improving technological literacy and professional competence among prospective teachers. Indeed, the results also indicate that school field introduction experiences positively influence the utilization of AI. Through field teaching experiences, students become more aware of the importance of technology in supporting effective learning processes. School field introduction encourages students to integrate technological innovations such as AI in teaching practices.

The findings demonstrate that AI utilization mediates the relationship between school field introduction experience and teaching readiness. School field introduction provides practical experience, while AI enhances teaching efficiency and innovation. The integration of both factors contributes to improving the readiness of prospective teachers to face modern educational challenges. Digital competence provides technological capability, while school field introduction offers practical teaching experience. AI then strengthens both factors by supporting learning planning, implementation, and evaluation. These findings highlight that teaching readiness is formed through the interaction of digital competence, field teaching experience, and technological utilization. Together, these elements prepare prospective economics teachers to adapt to the demands of 21st-century education.

This study provides practical implications for curriculum development in teacher education. Universities are encouraged to integrate AI-based learning modules into the curriculum, including training on the use of generative AI tools for lesson planning, assessment, and instructional design. In addition, structured AI training programs should be implemented to enhance prospective teachers' digital competence and readiness for technology-integrated learning environments. Teacher education institutions should also redesign the school field introduction program by incorporating AI-supported teaching practices, ensuring that students gain real experience in applying technology in classroom settings.

CONCLUSION

This study shows that digital skills and school field introduction have a positive and significant influence on the teaching readiness of prospective economics teachers. Digital skills act as internal resources that support technology-based learning management, while school field introduction provides field experience that enriches prospective teachers' pedagogical and professional competencies. The results also indicate that the use of AI has a positive and significant influence on teaching readiness. Furthermore, AI acts as a significant mediating variable in the relationship between digital skills and school field introduction on teaching readiness, with varying degrees of influence. The integration of digital skills, field experience, and the use of AI are important supporting factors in preparing prospective economics teachers to meet the demands of learning in the digital era.

This study has several limitations that should be considered when interpreting the findings. First, the research was conducted only among prospective economics teachers in Malang City; therefore, the findings cannot be generalized to other regions or to prospective teachers from different academic disciplines. Second, the study was conducted within a relatively short period of time, which limits its ability to capture the long-term dynamics of prospective teachers' teaching readiness. Future research is recommended to expand the scope of respondents by involving prospective teachers from various regions and universities in order to obtain more generalizable findings. In addition, future studies can consider using a mixed-methods approach by combining quantitative and qualitative methods to gain a deeper understanding of the factors influencing prospective teachers' teaching readiness. Researchers are also encouraged to include additional variables, such as learning motivation, self-efficacy, or digital literacy, to provide a more comprehensive explanation of the factors that shape teaching readiness in the context of technology-integrated education.

Authors Contribution

A. F. E: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft; S. H: Supervision, Validation, Methodology, Project administration, Writing – review & editing; W. H: Validation, Resources, Writing – review & editing

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Competing interests

The author has declared that there are no conflicts of interest

Data availability

The data were provided upon request to corresponding author (sri.handayani.fe@um.ac.id)

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