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Technology readiness predictors of AI integration: SEM-PLS evidence from pre-service biology teachers in Indonesia

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ABSTRACT

The rapid advancement of Artificial Intelligence (AI) requires educators to possess adequate technological readiness. However, current literature predominantly focuses on in-service teachers using general acceptance models, often overlooking whether traditional psychological inhibitors remain relevant for 'digital native' students in developing contexts. This study aims to analyze the technology readiness profile of pre-service biology teachers and investigate the predictive effect of Technology Readiness Index (TRI) dimensions Optimism, Innovativeness, Discomfort, and Insecurity on their readiness to integrate AI in biology teaching. Employing a cross-sectional survey design, data were collected from 200 active undergraduate students at Universitas Negeri Surabaya and analyzed using Structural Equation Modeling-Partial Least Squares (SEM-PLS). The model explains a substantial variance in AI readiness (R^2 = 0.538). The results revealed that Optimism acts as the most dominant significant driver, followed by Innovativeness. Crucially, this study offers new evidence that psychological inhibitors (Discomfort and Insecurity) no longer significantly affect AI integration readiness among mature users, challenging common assumptions in early adoption literature. The findings suggest a paradigm shift where pre-service teachers are pragmatic users driven by perceived utility rather than fear. Therefore, curriculum developers and policymakers must shift strategies from anxiety mitigation to the creation of biology-specific "embedded AI" tools that demonstrate tangible pedagogical benefits.

Keywords: Digital maturity, generative AI, readiness factor, science teacher education, technology integration

INTRODUCTION

Artificial Intelligence (AI) is rapidly evolving and becoming a prominent feature of the modern educational landscape, shifting traditional teaching methodologies toward more student-centered, technology-driven pedagogies. AI is increasingly integrated into daily activities and recognized as a potent tool with the potential to reshape various societal sectors, including education (Ayanwale et al., 2024b; Salas-Pilco et al., 2022). The development of AI has advanced at an unprecedented rate, permeating every aspect of life, from healthcare and security to smart homes and online shopping (Nja et al., 2023). In the educational context, AI integration has garnered significant attention due to its potential to revolutionize pedagogical methods, enhance learner engagement, and refine assessment practices (Mnguni, 2024).

In the discipline of biology, specifically, AI integration promises a revolutionary transformation. It offers unprecedented tools for visualizing complex concepts such as genetics and evolution, personalizing instruction through adaptive learning systems, and providing access to safe, cost-effective virtual laboratories. This progress has led to the emergence of the globally recognized field of AI in Education (AIED), which utilizes AI-enabled technologies to implement personalized learning (Ayanwale et al., 2024b). Applications of AI in education include intelligent tutoring systems, adaptive learning systems, and teaching robots (Nja et al., 2023). These tools provide personalized guidance, automate administrative tasks such as grading, and offer instant feedback (Adelana et al., 2024).

Furthermore, AI can streamline pedagogical workflows, equipping teachers with analytical tools to understand student learning patterns and reduce administrative burdens, thereby freeing up time for more meaningful interactions.

Despite its growing influence and potential, the integration of AI into education is not without challenges. These include resource and infrastructure limitations, data privacy concerns, and the risk of perpetuating existing inequalities through the digital divide (Adelana et al., 2024; Mnguni, 2024). However, the full realization of this transformative potential hinges heavily on the readiness of the next generation of educators: pre-service teachers. There is a recognized need to prepare future teachers for an increasingly digital educational environment, which entails developing their AI literacy and competence (Salas-Pilco et al., 2022). Studies indicate that while pre-service and in-service teachers are introduced to AI technologies, significant gaps remain in their understanding and readiness for full-scale implementation (Mnguni et al., 2024; Salas-Pilco et al., 2022). Research on pre-service life science teachers, for instance, reveals complex and often moderate-to-low levels of readiness and behavioral intention to integrate AI. This readiness is influenced by a combination of personal beliefs and perceived competencies, where teachers recognize both the potential benefits and the significant implementation challenges (Mnguni, 2024).

Effective AI integration demands more than mere technical mastery; it requires psychological readiness to adapt, data literacy, ethical reasoning, and pedagogical beliefs aligned with innovation. This readiness is often shaped by an individual's set of beliefs and emotions toward new technology. 'Readiness to integrate AI' is defined as a multidimensional construct encompassing not only the technical competence to operate AI tools but also the psychological propensity (optimism and innovativeness) to adopt these technologies in pedagogical contexts. It reflects a state of mental preparedness where pre-service teachers perceive AI not as a threat, but as an enabling partner in biology instruction. Several key factors determine this readiness. Teachers' attitudes toward AI, anxiety levels, self-confidence, and self-transcendent goals (the desire to benefit society) significantly influence their engagement and readiness to learn about AI (Ayanwale et al., 2024b). Belief in their ability to learn and teach AI or technological self-efficacy is a highly influential predictor of engagement (Ayanwale et al., 2024a). However, many pre-service teachers report low confidence, often stemming from a lack of training and hands-on experience with AI technologies (Mnguni, 2024). This lack of confidence and training constitutes a major barrier (Mnguni et al., 2024). On the other hand, emotional barriers such as anxiety or the fear that AI will dehumanize teaching can be rooted in threats to teachers' professional identity. Additionally, teacher readiness is shaped by their perception of its relevance to their teaching practice and whether they believe it can be used for social good (Jatileni et al., 2023).

Various frameworks have been used to measure technology adoption readiness, such as Technology–Organization–Environment (TOE), Technology Acceptance Model (TAM), and Unified Theory of Acceptance and Use of Technology (UTAUT) (Hradecky et al., 2022; Jöhnk et al., 2021). However, these models essentially focus on the organizational context or explain the acceptance and use of technology, rather than the psychological readiness of users (Hradecky et al., 2022). In addition, some approaches adapt scales from other technological contexts, such as e-learning, or combine variables from existing models to assess AI readiness, which potentially overlooks the complexity and unique characteristics of AI (Li & Liang, 2025). In contrast to these approaches, the Technology Readiness Index (TRI) is specifically designed to measure the psychological tendency of individuals or groups to embrace new technology through a balance between driving factors (optimism and innovation) and inhibiting factors (discomfort and insecurity) (Parasuraman & Colby, 2015). This comprehensive psychological perspective makes the TRI superior and relevant as a basis for measuring technological readiness, especially for complex technologies such as AI, because psychological readiness is a key prerequisite before technology adoption and use can take place effectively.

However, the weakness of previous studies is their tendency to generalize technological anxiety as a universal obstacle. This perspective often fails to take into account the level of digital maturity of modern prospective teachers, who may no longer view artificial intelligence (AI) as a threat like previous generations because they are more frequently exposed to the use of artificial intelligence (Rahman et al., 2025). Therefore, in addition to simply comparing models, there is an urgent need to empirically test whether traditional psychological barriers (discomfort and uncertainty) remain influential predictors of readiness for AI integration in learning for pre-service teachers who are frequently exposed to this technology, or whether a paradigm shift has occurred.

To systematically measure this readiness, the Technology Readiness Index (TRI) framework provides a robust analytical lens. The TRI measures an individual's propensity to embrace new technologies through four key psychological dimensions: Optimism (positive belief in technology's benefits) and Innovativeness (tendency to be a pioneer), which act as "drivers." Conversely, Discomfort (perceived lack of control) and Insecurity (distrust and skepticism) act as significant "inhibitors" (Parasuraman & Colby, 2015). Although the potential of AI in biology education is immense, a gap remains in understanding how the general technology readiness of pre-service biology teachers correlates with their specific readiness to adopt AI tools. Consequently, this study focuses on analyzing the technology readiness of pre-service biology teachers using the TRI approach, as well as investigating the interrelationship between readiness profiles (drivers and inhibitors) and their preparedness to integrate Artificial Intelligence into future biology teaching practices.

METHOD

This study employed a quantitative approach utilizing a cross-sectional survey design to analyze the relationship between technological readiness and the integration of Artificial Intelligence (AI) in learning among pre-service biology teachers. The research instrument was a questionnaire designed to collect numerical data for statistical analysis. The target population encompassed all pre-service biology teachers, while the study sample consisted of 200 active undergraduate students from the Biology Education Study Program at Universitas Negeri Surabaya (UNESA), representing pre-service educators at a Teacher Education Institution (LPTK). Participants were selected using a purposive sampling technique, based on the criterion that they were active students with prior experience in using digital technology during their coursework. Although first-year students are still in the early stages of their pedagogical training, they were included in the sample because the curriculum at UNESA integrates courses related to educational technology from the first semester onwards. Therefore, they have sufficient exposure to the digital learning environment to form a valid perception of the integration of artificial intelligence in biology learning.

The research instrument was developed by adapting the Technology Readiness Index (TRI) framework, which comprises four dimensions: Optimism, Innovativeness, Discomfort, and Insecurity (Parasuraman & Colby, 2015). The instrument consisted of 20 indicators measured on a 5-point Likert scale. In the research model, TRI dimensions were positioned as exogenous variables, while the readiness to integrate AI in learning was established as the endogenous variable. All indicators were structured to capture respondents' perceptions regarding their preparedness to utilize AI-based technologies in biology learning activities.

To ensure the rigor of the instrument, the measurement model was evaluated based on established thresholds. Convergent validity was confirmed using Average Variance Extracted (AVE) values > 0.50 and Outer Loadings > 0.70. Discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT) with a threshold of < 0.90. Finally, internal consistency reliability was verified using Composite Reliability (rho_c) with acceptable values set above 0.70 (Hair et al., 2021).

Data collection was conducted online via Google Forms, with informed consent obtained at the beginning of the survey to ensure voluntary participation and maintain respondent confidentiality. Data analysis proceeded in two stages. First, descriptive analysis was performed to outline respondent characteristics and data distribution trends for each indicator. Second, the structural model and inter-variable relationships were tested using Structural Equation Modeling-Partial Least Squares (SEM-PLS) via SmartPLS 4.0 software. The survey data were analyzed using SEM-PLS to validate the measurement model and examine relationships between various factors, such as the impact of optimism or discomfort on the perceived utility of AI technology (Lemke et al., 2023). This testing included an evaluation of the measurement model to assess convergent validity, discriminant validity, and construct reliability, followed by an evaluation of the structural model to examine path coefficients, t-statistics, p-values, and the coefficient of determination (R^2). SEM-PLS was selected for its robustness in testing complex models with relatively limited sample sizes and its focus on predicting relationships between latent variables (Chatterjee & Bhattacharjee, 2020).

RESULTS AND DISCUSSION

The respondent profile indicates a high degree of homogeneity, with the sample comprised entirely of undergraduate students from the Biology Education study program. Demographically, the distribution across cohorts is balanced, primarily concentrated between first-year students and final-year students, with the remainder distributed across the third and fifth semesters (Table 1).

Table 1. Respondent distribution

Year	Total	Percentage
1	78	39%
2	18	9%
3	26	13%
4	78	39%

The data reveals a mature level of AI adoption, suggesting that AI technologies are well-integrated into the respondents' academic routines. This is evidenced by usage frequency, where the majority of respondents are categorized as 'Advanced' or 'Heavy Users' users (>10 times), followed by ' Moderate Users' (3–10 times). Only a small fraction remains in the initial adoption stage ‘Novice Users’ (Table 2). Notably, despite the high frequency of interaction, weekly usage duration appears efficient. The predominant group reported a short duration of use ('<2 Hours'), followed by moderate duration ('2–5 Hours') and high duration ('6–10 Hours'). Intensive users exceeding 10 hours per week constitute a minority (Table 3).

Table 2. Respondent usage frequency

Category	Total	Percentage
Heavy Users	108	54%
Moderate Users	86	43%
Novice Users	6	3%

Table 3. Respondent weekly usage duration

Duration	Total	Percentage
< 2 Hours	82	41%
2 - 5 Hours	56	28%
6 - 10 Hours	48	24%
> 10 Hours	14	7%

Analysis of platform preferences highlights a trend of multimodal usage, where students tend to leverage a combination of AI tools simultaneously. ChatGPT emerged as the foundational and most dominant platform, utilized by nearly all respondents. This is followed by Google Gemini/Bard in second place and Perplexity AI in third. specialized platforms such as Claude.ai, Elicit.org, and Blackbox AI function as supplementary tools with lower usage percentages (Table 4).

Table 4. Respondent platform preferences

Platform	Total	Percentage (from total respondent)
ChatGPT	198	99%
Google Gemini / Bard	145	72.5%
Perplexity AI	98	49%
Blackbox AI	8	4%
Claude.ai	12	6%
Elicit.org	8	4%
Microsoft Copilot	4	2%
Lainnya (Research Rabbit, Qwen, Deepseek)	9	4.5%

Regarding the purpose of utilization, AI has established itself as an essential academic aid, dominated by two primary functions. The highest priorities for respondents are 'Searching for research references' and 'Discussing/ Clarifying biological concepts. 'Other significant objectives include 'Summarizing learning materials' and 'Completing assignments/reports.' Conversely, the utilization of AI for 'Creating learning media' was reported by a smaller segment of respondents (Table 5).

Table 5. Respondent purpose of utilization

Purpose	Total	Percentage (from total respondent)
Searching for research references	170	85%
Discussing/Clarifying biological concepts	165	82.5%
Summarizing learning materials	120	60%
Completing assignments/reports	115	57.5%
Creating learning media	60	30%
Validating Opinions	4	2%

The evaluation of the measurement model focused on assessing convergent validity, discriminant validity, and construct reliability. Convergent validity was examined using outer loadings and Average Variance Extracted (AVE) values (Figure 1). In the initial assessment, the outer loading for indicator INV 4 fell below the recommended threshold of 0.70 (Table 6). Consequently, this indicator was eliminated, and the model was re-estimated (Figure 2).

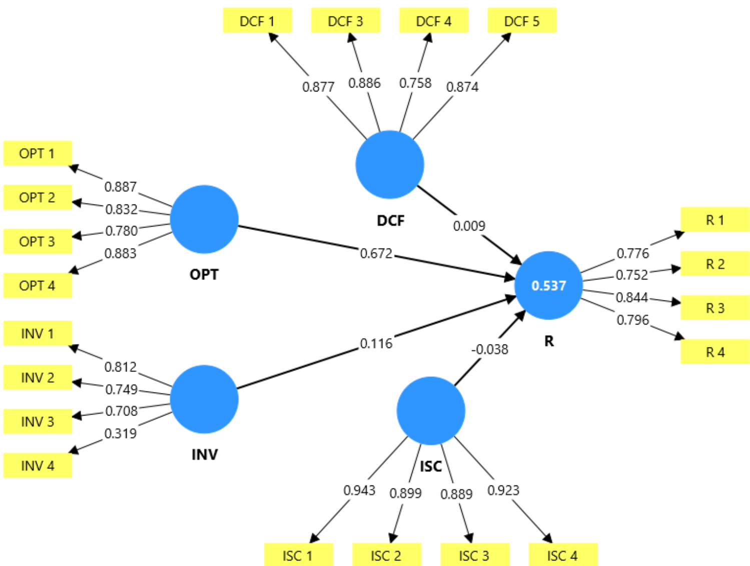

Figure 1. SEM-PLS construct model initial testing

Table 6. Outer loadings initial testing

	DCF	INV	ISC	OPT	R
DCF 1	0.877				
DCF 3	0.886				
DCF 4	0.758				
DCF 5	0.874				
INV 1		0.812			
INV 2		0.749			
INV 3		0.708			
INV 4		0.319			
ISC 1			0.943		
ISC 2			0.899		
ISC 3			0.889		
ISC 4			0.923		
OPT 1				0.887	
OPT 2				0.832	
OPT 3				0.780	
OPT 4				0.883	
R 1					0.776
R 2					0.752
R 3					0.844
R 4					0.796

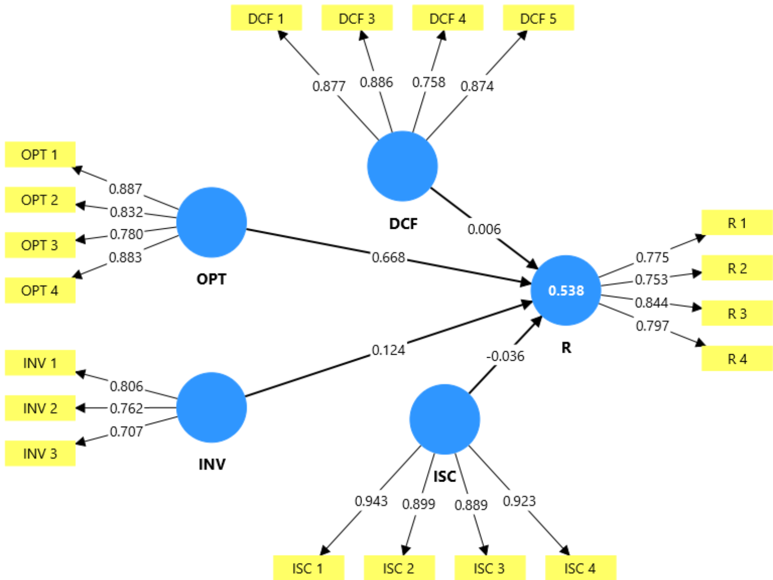

Figure 2. SEM-PLS construct model final testing.

Table 7. Outer loadings final testing.

	DCF	INV	ISC	OPT	R
DCF 1	0.877				
DCF 3	0.886				
DCF 4	0.758				
DCF 5	0.874				
INV 1		0.806			
INV 2		0.762			
INV 3		0.707			
ISC 1			0.943		
ISC 2			0.899		
ISC 3			0.889		
ISC 4			0.923		

	DCF	INV	ISC	OPT	R
OPT 1				0.887	
OPT 2				0.832	
OPT 3				0.780	
OPT 4				0.883	
R 1					0.775
R 2					0.753
R 3					0.844
R 4					0.797

Subsequent analysis revealed that all remaining outer loadings in the revised model exceeded the 0.70 criterion (Table 7). Furthermore, the AVE values for all constructs satisfied the recommended benchmark of >0.50, specifically: DCF (0.723), INV (0.577), ISC (0.835), OPT (0.717), and R (0.628) (Table 8). Collectively, these findings confirm that the measurement model demonstrates satisfactory convergent validity.

Table 8. Average Variance Extracted (AVE)

Indicator	AVE
DCF	0.723
INV	0.577
ISC	0.835
OPT	0.717
R	0.628

Discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT) criterion. The analysis revealed that all inter-construct HTMT values remained below the recommended threshold of 0.90. Specifically, the highest HTMT value was identified between the R and OPT constructs (0.814), which falls well within the acceptable range (Table 9). These results demonstrate that each construct in the study is empirically distinct and does not exhibit significant overlap with other constructs, thereby confirming that the requirements for discriminant validity have been met.

Table 9. Heterotrait-Monotrait Ratio (HTMT)

	DCF	INV	ISC	OPT	R
DCF					
INV	0.548				
ISC	0.268	0.219			
OPT	0.538	0.674	0.344		
R	0.413	0.634	0.284	0.814	

Construct reliability was assessed using Composite Reliability *(rho_c)*. The analysis indicates that all constructs exhibited high levels of internal consistency, surpassing the recommended threshold of 0.70. Specifically, the computed reliability values were: DCF (0.912), INV (0.803), ISC (0.953), OPT (0.910), and R (0.871) (Table 10). These findings demonstrate that the measurement instruments employed in the study possess strong internal consistency and reliability.

Table 10. Composite reliability

Indicator	rho_c
DCF	0.912
INV	0.803
ISC	0.953
OPT	0.910
R	0.871

The evaluation of the structural model commenced with an assessment of the Coefficient of Determination R^2. The analysis revealed an R^2 value of 0.538 for the endogenous variable, Readiness (R) (Table 11). This indicates that 53.8% of the variance in Readiness can be collectively explained by the constructs DCF, INV, ISC, and OPT, suggesting that the model possesses a moderate level of predictive power.

Table 11. Coefficient of determination

Indicator	R^2	R^2-*Adjusted*
R	0.538	0.528

Subsequently, hypothesis testing was conducted by examining the path coefficients. The results demonstrated that Optimism (OPT) exerts a statistically significant positive influence on Readiness (R) coefficients = 0.668; T-Statistics = 10.605; P-Value = 0.000). Similarly, Innovativeness (INV) was found to have a significant effect on R (coefficients = 0.124; T-Statistics = 1.977; P-Value = 0.048). Conversely, the remaining two paths were not statistically significant: Discomfort (DCF) on R (P-Value = 0.924) and Insecurity (ISC) on R (P-Value = 0.577) (Table 12).

Table 12. Path coefficients

Indicator	Path Coefficients	T statistics	P values
DCF -> R	0.006	0.095	0.924
INV -> R	0.124	1.977	0.048
ISC -> R	-0.036	0.558	0.577
OPT -> R	0.668	10.605	0.000
DCF -> R	0.006	0.095	0.924

The structural model evaluation (SEM-PLS) provides critical insights into why this mature user group exhibits a high readiness to integrate AI (Lacuna, 2025). The model demonstrates that the Technology Readiness Index (TRI) framework explains the variance in AI integration readiness (R) with a moderate level of explanatory power. Optimism (OPT) emerged as the most dominant and statistically significant predictor, exhibiting a strong positive path coefficient. This suggests that the primary impetus for pre-service teachers to integrate AI stems from their conviction that the technology is beneficial, efficient, and capable of positively impacting their teaching practices. This belief is likely reinforced by their frequent and recurrent positive experiences in utilizing AI for complex academic tasks (Rahman et al., 2025).

The second "driver" factor, Innovativeness (INV), was also found to have a significant positive influence, albeit with a considerably smaller effect size compared to Optimism. This implies that while the natural propensity to be a pioneer in new technology contributes to readiness, it is secondary to the practical belief in the technology's utility (Kampa, 2023). In essence, these pre-service teachers are driven more by pragmatism (the belief that AI is useful) than by mere novelty seeking (Chen & Zou, 2024).

A particularly compelling and significant finding pertains to the "inhibitor" factors. The path analysis revealed that neither Discomfort (DCF) nor Insecurity (ISC) exerted a significant influence on Readiness (R). This finding deviates from prevalent assumptions regarding technology adoption, yet it is highly plausible within the context of this specific population. As indicated by the descriptive data, respondents are frequent AI users. It is incongruous for individuals who routinely utilize a tool for 2–10 hours per week to harbor significant feelings of discomfort (lack of control) or insecurity (skepticism). It can be inferred that the high frequency of usage and constant practical exposure have effectively neutralized potential psychological barriers that typically exist during the early stages of adoption (Sanusi et al., 2024; Shahid et al., 2024). Concerns identified in other literature, such as "lack of confidence" or "anxiety," appear to have been overcome by this cohort through direct practice and experience (Yue et al., 2024; Zhao et al., 2024).

Overall, this study illuminates a unique relationship between readiness profiles and AI integration among pre-service biology teachers. For a population already deeply integrated with technology, the readiness paradigm shifts. Readiness is no longer predicated on overcoming fear or discomfort, as these inhibitors have rendered themselves irrelevant. Conversely, the readiness for deeper integration is predominantly driven by the validation of perceived benefits (Optimism) (Uren & Edwards, 2023).

Implications for Development and Education These findings carry profound implications for instructional media developers and Teacher Education Institutions (LPTK). The data collectively suggest that intervention strategies should no longer center on "encouraging adoption" or "overcoming fear" of AI (Fundi et al., 2024; Ramnarain et al., 2024; Roy et al., 2022). Instead, the study confirms that pre-service biology teachers, as an audience dominated by mature users, have transcended that phase. This is evidenced by the non-significance of traditional psychological inhibitors (Pu et al., 2021). Consequently, developmental efforts focusing on mitigating anxiety or skepticism are likely obsolete for this cohort (Liu, 2025).

Development and implementation strategies must undergo a fundamental shift to leverage the most dominant driver: Optimism. The readiness of these pre-service teachers is pragmatic; they are ready to integrate AI because they fundamentally believe in its utility (Falebita & Kok, 2024; Runge et al., 2025). However, descriptive data reveal a distinct gap: this optimism is currently exercised using general-purpose AI tools (e.g., Google Gemini, ChatGPT) for highly domain-specific tasks, such as "Discussing biological concepts" and "Retrieving research references." This implies an unmet demand and an urgent need for AI learning media specifically designed for biology—tools capable of handling complex concept visualization or virtual laboratory simulations in ways that generic chatbots cannot (Abdulayeva et al., 2025; Özüdogru & Durak, 2025; Zheng et al., 2024).

Therefore, future AI-based biology learning media must be designed and introduced with strategies that exploit this optimism. Developers must explicitly demonstrate utility and efficiency showing how the tool tangibly saves time, automates tasks, or solves specific pedagogical problems in biology (such as lack of access to physical laboratories) (Kurniawan et al., 2024; Nja et al., 2023). Strategies that merely highlight technical sophistication (appealing to Innovativeness) will likely be less effective than those clearly demonstrating the tool's superiority in achieving biological teaching goals (Adelana et al., 2024; Sun et al., 2024).

Finally, data regarding usage purposes, such as "Summarizing materials" and "Concept discussion," indicate that students actively use AI to engage deeply with learning content. This implies a significant opportunity to integrate AI directly into core learning media. There is an urgent need to develop "interactive textbooks" or digital learning modules where AI is no longer an external tool but an embedded feature. For instance, a biology e-book could be equipped with AI features allowing students to highlight complex paragraphs and instantly request a "simplified explanation," "bullet-point summary," or "case example," without leaving the book interface. This "embedded AI" approach would align perfectly with existing workflows and leverage student optimism to create a more efficient and contextualized learning experience (Hu et al., 2025; Ishmuradova et al., 2025).

Although there are significant insights into the shift in psychological barriers, this study acknowledges several limitations. The sample was taken exclusively from one teacher education institution (LPTK), namely Surabaya State University. Although this provides a focused picture of a mature digital environment, the findings may reflect specific institutional infrastructure and may not be fully applicable to prospective teachers in regions with different levels of technology exposure. The inclusion of first-year students in the sample means that some respondents are still in the early stages of developing their pedagogical content knowledge. As a result, their perceptions of artificial intelligence (AI) integration may be more theoretical than practical. Future research should expand the demographic scope to include multiple universities and use a longitudinal design to observe how readiness develops as students gain actual teaching experience.

CONCLUSION

Based on the analysis and discussion, this study concludes that pre-service biology teachers have attained a high level of technological maturity, which has fundamentally altered their readiness profile for AI integration. The high frequency of usage and practical exposure to general-purpose AI tools have effectively neutralized the influence of traditional inhibiting factors. This is statistically substantiated by the non-significant impact of the Discomfort and

Insecurity dimensions on integration readiness. Consequently, current teacher readiness is driven almost exclusively by "driver" factors, particularly Optimism, reflecting a pragmatic conviction that AI delivers tangible utility and efficiency in learning contexts.

The implications of these findings underscore a critical shift in strategy: teacher competence development and instructional media design should no longer focus on mitigating technological anxiety. Conversely, the focus must shift entirely toward capitalizing on user optimism through practical utility. There is an urgent imperative to develop biology-specific learning media such as interactive textbooks with "embedded AI" features that are capable of facilitating complex concept visualization and virtual laboratory simulations, thereby transcending the limitations of the generic chatbots currently in use.

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