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Factors Shaping Pre-service Biology Teachers' Acceptance of Generative Artificial Intelligence

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ABSTRACT

The rapid diffusion of generative artificial intelligence (GAI) has introduced new opportunities and challenges for teacher education, particularly within STEM disciplines, specifically biology education. This study investigates the determinants of generative AI acceptance among Generation Z pre-service biology teachers by integrating constructs from the Technology Acceptance Model and Diffusion of Innovation theory with pedagogically grounded variables. Using a quantitative cross-sectional survey design, data were collected from 318 pre-service biology teachers enrolled at two Indonesian universities. Partial least squares structural equation modeling (PLS-SEM) was employed to examine the relationships among trialability, relative advantage, perceived compatibility, trust, feedback quality, perceived assessment quality, subjective norms, perceived ease of use, perceived usefulness, attitude, behavioral intention, and acceptance of generative AI. The results indicate that trialability, relative advantage, and compatibility significantly predict perceived ease of use, while relative advantage and trust significantly influence perceived usefulness. Feedback quality and subjective norms positively shape attitudes toward generative AI, whereas perceived assessment quality shows no significant effect. Perceived ease of use and attitude emerge as key predictors of behavioral intention, which strongly determines acceptance. The findings highlight the central roles of affective, social, and trust-related factors in shaping generative AI adoption among future biology teachers. This study contributes to the emerging literature on AI in STEM teacher education and offers practical implications for designing pedagogically meaningful and responsible AI integration in teacher preparation programs.

Key word: Educational technology, Generative Artificial Intelligence, PLS-SEM, Pre-service biology teacher, Technology acceptance model

I. INTRODUCTION

The emergence of generative artificial intelligence (generative AI) marks a new phase in the digital transformation of education, with models such as ChatGPT, Gemini, and Copilot enabling text generation, content creation, and adaptive feedback in real time. Unlike earlier educational technologies focused on information retrieval, generative AI can synthesize information, generate instructional content, and provide formative assessment at scale (Dewi et al., 2024; Lee et al., 2024). These capabilities support student-centered learning environments emphasizing personalization and engagement. As adoption expands across educational levels, generative AI is increasingly viewed as a transformative force shaping pedagogical practices, while also raising concerns about ethics, cognition, and academic integrity (Akpan et al., 2025; Baig & Yadegaridehkordi, 2024).

Beyond instructional enhancement, generative AI supports metacognition, conceptual understanding, and disciplinary literacy (Hsiao & Tang, 2025). In STEM education, AI-mediated feedback and explanations can scaffold reasoning and inquiry processes. However, its rapid adoption introduces challenges such as misinformation, over-reliance, and reduced critical thinking (Chaushi et al., 2024). While prior studies have explored AI acceptance among students and educators, research remains uneven across disciplines. Understanding how learners perceive and intend to use generative AI is therefore crucial for informing effective and responsible implementation, particularly among pre-service teachers who will shape future classroom practices (Y. Wang et al., 2025).

Generative AI holds particular relevance for pre-service biology teachers, as biology learning often requires explanation, visualization, and conceptual clarification. AI-generated explanations, diagrams, and feedback can support understanding of complex topics such as genetics, physiology, and ecological systems. Additionally, generative AI can assist with lesson planning, inquiry design, and assessment development, which are central to teacher education (Agathokleous et al., 2023). As pre-service teachers transition from content knowledge to pedagogical knowledge, generative AI may serve as a mediational tool supporting this process.

Pre-service teachers, largely belonging to Generation Z, are characterized by high digital exposure and familiarity with technology-mediated learning. While this may encourage openness toward AI tools, digital familiarity does not necessarily equate to critical AI literacy, particularly in ethical and pedagogical dimensions (Acosta-Enriquez et al., 2024). Therefore, examining AI acceptance among this group requires consideration of both their technological readiness and their limitations in applying AI meaningfully in educational contexts. Analyzing generative AI acceptance among pre-service biology teachers is important as they will act as future implementers of educational innovation. Their perceptions influence whether AI is integrated effectively into teaching practice. Biology's inquiry-based and conceptually complex nature aligns with the affordances of generative AI for explanation, simulation, and feedback. At the same time, understanding acceptance during teacher preparation provides insight into future professional behaviour and supports the development of relevant training, curricula, and institutional strategies.

This study adopts an integrated framework incorporating innovation diffusion and technology acceptance constructs, including trialability, compatibility, relative advantage, trust, feedback quality, assessment quality, and subjective norms. These variables capture both cognitive and social dimensions of technology evaluation. Perceived ease of use and usefulness influence attitudes and behavioural intention, which in turn predict acceptance. This framework enables a more comprehensive understanding of how pre-service biology teachers evaluate generative AI in educational contexts (Chen et al., 2025; Li, 2025).

Despite increasing attention to generative AI, research in teacher education—particularly in STEM contexts—remains limited. Existing studies often overlook pedagogical constructs such as feedback and assessment quality. Additionally, limited research examines how trust, compatibility, and social influence interact in shaping acceptance among Generation Z teacher candidates. By addressing these gaps, this study contributes to a more nuanced, discipline-specific understanding of generative AI acceptance and offers a pedagogically grounded perspective for its integration into future biology teaching practice.

Hypothesis for this study are:

H1: Trialability (TR) has a positive effect on Perceived Ease of Use (PEU).

H2: Trialability (TR) has a positive effect on Perceived Usefulness (PU).

H3: Relative Compatibility (RC) has a positive effect on Perceived Ease of Use (PEU).

H4: Relative Compatibility (RC) has a positive effect on Perceived Usefulness (PU).

H5: Relative Advantage (RA) has a positive effect on Perceived Ease of Use (PEU).

H6: Relative Advantage (RA) has a positive effect on Perceived Usefulness (PU).

H7: Trust in Generative AI (TGAI) has a positive effect on Perceived Usefulness (PU).

H8: Feedback Quality (FQ) has a positive effect on Attitude toward Generative AI (AGAI).

H9: Perceived Assessment Quality (PAQ) has a positive effect on Attitude toward Generative AI (AGAI).

H10: Subjective Norms (SN) have a positive effect on Attitude toward Generative AI (AGAI).

H11: Perceived Ease of Use (PEU) has a positive effect on Perceived Usefulness (PU).

H12: Perceived Ease of Use (PEU) has a positive effect on Behavioral Intention (BI).

H13: Perceived Usefulness (PU) has a positive effect on Attitude toward Generative AI (AGAI).

H14: Perceived Usefulness (PU) has a positive effect on Behavioral Intention (BI).

H15: Attitude toward Generative AI (AGAI) has a positive effect on Behavioral Intention (BI).

H16: Behavioral Intention (BI) has a positive effect on Acceptance of Generative AI (ACGAI).

II. RESEARCH METHOD

This research adopted a quantitative survey design to gather and analyze numerical data obtained through structured questionnaires. Through this survey method, the study investigated predictors of generative Artificial Intelligence (AI) acceptance among pre-service biology at a single point in time, without manipulating the sample or introducing experimental treatments. A cross-sectional strategy was implemented to provide a snapshot of participants' generative AI acceptance, while avoiding challenges commonly associated with longitudinal research, including time-related confounding factors and participant dropout (X. Wang & Cheng, 2020). The quantitative approach facilitated objective and reliable data analysis and enabled statistical testing to reveal patterns, associations, and trends between the predictor variables and generative AI acceptance (Bloomfield & Fisher, 2019).

This study involved 318 Generation Z pre-service biology teachers. Participants were recruited through convenience sampling, a method that allowed data to be collected quickly and with ease, though it may limit the broader applicability of the findings (Stratton, 2021). Despite this limitation, the sample was considered appropriate due to the participants' strong familiarity with technology in both personal and academic contexts. Table 1 provides an overview of the respondents' demographic profiles. The participants represented two universities in Indonesia. In terms of gender, 32.07% of the respondents were male and 67.92% were female, indicating a predominantly female sample. With respect to year of study, 30.50% were first-year students, 31.76% second-year, 25.79% third-year, and 11.95% fourth-year, suggesting a relatively proportional distribution across academic levels.

Table 1. Research Subject

Sample	N	Percentage
Gender		
Male	102	32.07%
Female	216	67.92%
Year of Study		
First year	97	30.50%
Second Year	101	31.76%
Third year	82	25.79%
Fourth year	38	11.95%
Total	318	100%

The main instrument used for data collection in this study was adapted from (Almogren et al., 2024) to assess generative AI acceptance. A back-translation procedure was employed to maintain linguistic precision and conceptual alignment between the original scale and its translated counterpart. This procedure involved translating the instrument into the target language and then translating it back into the original language independently to detect and address discrepancies in wording or meaning (Ozolins et al., 2020). All variables in this study were consistently measured using three items for each construct. The variables included Trialability (TR), Relative Compatibility (RC), Relative Advantage (RA), Trust in Generative AI (TGAI), Feedback Quality (FQ), Perceived Assessment Quality (PAQ), Subjective Norms (SN), Perceived Ease of Use (PEU), Perceived Usefulness (PU), Attitude toward Generative AI (AGAI), Behavioral Intention (BI), and Acceptance of Generative AI (ACGAI). Each item is measured using a five-point rating scale, as it allows for capturing nuanced differences in respondents' perceptions while maintaining clarity and consistency in measurement and analysis. To evaluate the instrument's appropriateness for the study context and participant group, a pilot test was carried out. Reliability analyses showed Cronbach's alpha values between 0.80 and 0.91, demonstrating very strong internal consistency across constructs and confirming that the items were measuring stable and coherent dimensions.

Data were obtained through Google Forms, an online survey tool that supports efficient, paperless data collection and reduces errors that may occur through manual data processing. This digital format also allowed researchers to monitor participant responses in real time. To promote accurate comprehension of the questionnaire items, the researcher remained present throughout the survey process and provided clarification when needed, fostering a supportive environment that encouraged thoughtful and honest participation. In addition, respondents participated voluntarily and were informed that their answers would be treated confidentially and would not influence their academic standing.

Observing these ethical considerations was crucial for safeguarding the validity and integrity of the research data. Data analysis was performed using Smart PLS to apply partial least squares structural equation modelling (PLS-SEM) version 24, which included evaluations of both the measurement and structural models (Agusalim, 2025; Ghanbar, 2024). PLS-SEM was selected due to its suitability for examining complex predictive relationships among constructs, particularly since the primary aim of the study was to predict and explain Behavioural Intention (BI) among pre-service teachers. This analytical approach is also advantageous for research involving large samples and for models with multiple latent variables and indicators, as it provides efficient estimation and robust outcomes (Memon et al., 2021). Prior to model assessment, the dataset underwent screening procedures to ensure quality, including checks for missing responses, coding accuracy, and the detection of outliers.

The measurement model was assessed by examining indicator loadings, internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity via Average Variance Extracted (AVE), and discriminant validity based on established criteria. Once the measurement model demonstrated satisfactory validity and reliability, the structural model was evaluated. Smart PLS generated path coefficients, t-statistics, and p-values to determine the significance of hypothesized paths. Furthermore, effect sizes (f^2) were calculated to assess the magnitude of each predictor's influence on endogenous constructs, in accordance with recommendations from Hair et al., (2022) and Vaithilingam et al., (2024).

III. RESULT AND DISCUSSION

A. Descriptive Statistics and Normality

The descriptive statistics indicate that the mean values for all items cluster around three on a five-point scale, suggesting moderate to moderately high agreement levels among pre-service biology teachers regarding factors related to generative AI acceptance. Standard deviations below one demonstrate relatively low variability in responses. Examination of skewness shows predominantly small negative values, indicating slight left-tail tendencies and a pattern in which respondents tended to choose higher response options. Excess kurtosis values vary around zero, ranging from slightly negative to moderately positive, reflecting distributions that are generally mesokurtic to mildly leptokurtic. These patterns collectively suggest that the data do not exhibit severe departures from symmetry or peaked-ness. Therefore, with skewness and kurtosis remaining within commonly accepted thresholds for psychometric research, the item distributions can be considered approximately normal. Such properties support their suitability for use in parametric analyses, including structural equation modeling and related inferential techniques.

B. Outer Loading

The factor loadings indicate that all items load strongly onto their respective latent constructs in the study of pre-service biology teachers' acceptance of generative AI. Loadings range from approximately 0.76 to 0.95, exceeding the commonly accepted threshold of 0.70 for reflective measurement models, thereby demonstrating satisfactory indicator reliability. Constructs such as AGAI, BI, FQ, and PU show particularly high loadings, suggesting that their indicators capture the underlying concepts with precision. Slightly lower but still acceptable loadings are observed for selected items under PEU, RC, and TR, yet none fall below the minimum requirement. Overall, these values support the convergent validity of the measurement model and confirm that the latent variables are well represented by their observed indicators, making them suitable for subsequent structural analysis.

C. Construct Validity and Reliability

Table 2. Reliability and Convergent Validity Results

	alpha	rho_a	rho_c	AVE
ACGAI	0.876	0.879	0.924	0.801
AGAI	0.922	0.924	0.951	0.865
BI	0.869	0.875	0.920	0.793
FQ	0.875	0.876	0.923	0.801
PAQ	0.814	0.814	0.890	0.729
PEU	0.746	0.752	0.855	0.664
PU	0.863	0.865	0.916	0.784
RA	0.832	0.834	0.899	0.748
RC	0.804	0.805	0.885	0.720
SN	0.791	0.800	0.878	0.707
TGAI	0.799	0.800	0.882	0.714
TR	0.756	0.756	0.861	0.674

The internal consistency and convergent validity indices demonstrate strong psychometric properties for the constructs measured in the study on factors shaping pre-service biology teachers' acceptance of generative AI. Cronbach's alpha values as shown in Table 2 range from 0.746 to 0.922, while composite reliability (rho_c) ranges from 0.855 to 0.951, both exceeding the recommended threshold of 0.70 and confirming satisfactory reliability across all constructs. The rho A coefficients show consistent patterns, further reinforcing internal consistency. In terms of convergent validity, the average variance extracted (AVE) values fall between 0.664 and 0.865, exceeding the 0.50 criterion and indicating that each construct explains a substantial proportion of variance in its indicators. Notably, constructs such as AGAI, FQ, PU, and ACGAI exhibit particularly strong reliability and convergent validity, suggesting well-defined latent structures. Collectively, these results confirm that the measurement model performs adequately and is appropriate for subsequent structural assessment within the proposed research framework.

D. Discriminant Validity

The results indicate satisfactory discriminant validity among the constructs assessed in the study on pre-service biology teachers' acceptance of generative artificial intelligence. The square roots of the average variance extracted for each construct are greater than their inter-construct correlations, suggesting that each latent variable shares more variance with its own indicators than with other constructs. Additionally, cross-loadings demonstrate that all items load higher on their intended constructs than on alternative constructs, further supporting discriminant validity. Several constructs exhibit moderately high correlations, particularly between perceived benefits-related variables (such as acceptability, general attitude, frequency of use, and perceived usefulness) and social-norm-related constructs, indicating theoretically consistent associations. Nonetheless, the pattern of relationships shows sufficient distinction among constructs, confirming that each reflects a unique dimension within the proposed framework and is appropriate for inclusion in the structural model.

E. Variance Inflation Factor (VIF)

The variance inflation factor (VIF) values indicate that multicollinearity is not a concern within the measurement model for the study on pre-service biology teachers' acceptance of generative AI. All indicators fall well below the recommended threshold of 5, with most values ranging between approximately 1.3 and 3.7, reflecting acceptable levels of shared variance among items. Slightly higher VIF values appear for attitude- and belief-related constructs, suggesting closer conceptual linkage within those domains, yet still within psychometric norms. Lower

VIF values for ease of use, usefulness, and trust indicators show more distinct measurement contributions. Overall, the results confirm that the reflective indicators do not exhibit harmful redundancy, supporting the reliability and interpretability of subsequent structural analyses.

F. Model Fit

The model fit evaluation suggests that the structural model for the study on pre-service biology teachers' acceptance of generative AI demonstrates acceptable performance. The Standardized Root Mean Square Residual (SRMR) of the saturated model falls the commonly recommended 0.08 threshold, indicating a good fit, while the estimated model shows a slightly higher value that remains within a tolerable range. The d_ULS and d_G indices show reasonable proximity between the empirical and theoretical correlation matrices, with the saturated model fitting more closely as expected in PLS-SEM. Chi-square values are relatively high for both models, which is typical in complex models with numerous observed variables and larger sample sizes.

Table 3. Model Fit

	Saturated model	Estimated model
SRMR	0.066	0.104
d_ULS	2.878	7.251
d_G	1.369	1.576
Chi-square	4493.803	4642.358
NFI	0.751	0.743

G. Structural Path Results and Hypothesis Testing

The structural model illustrates the relationships among the latent constructs included in the study on pre-service biology teachers' acceptance of generative AI. Each construct is represented by reflective indicators, and the model displays their respective loadings, latent variable scores, and the directionality of hypothesized links. The visualization also incorporates intermediary constructs, highlighting both direct and indirect pathways that shape behavioral intentions and actual acceptance outcomes.

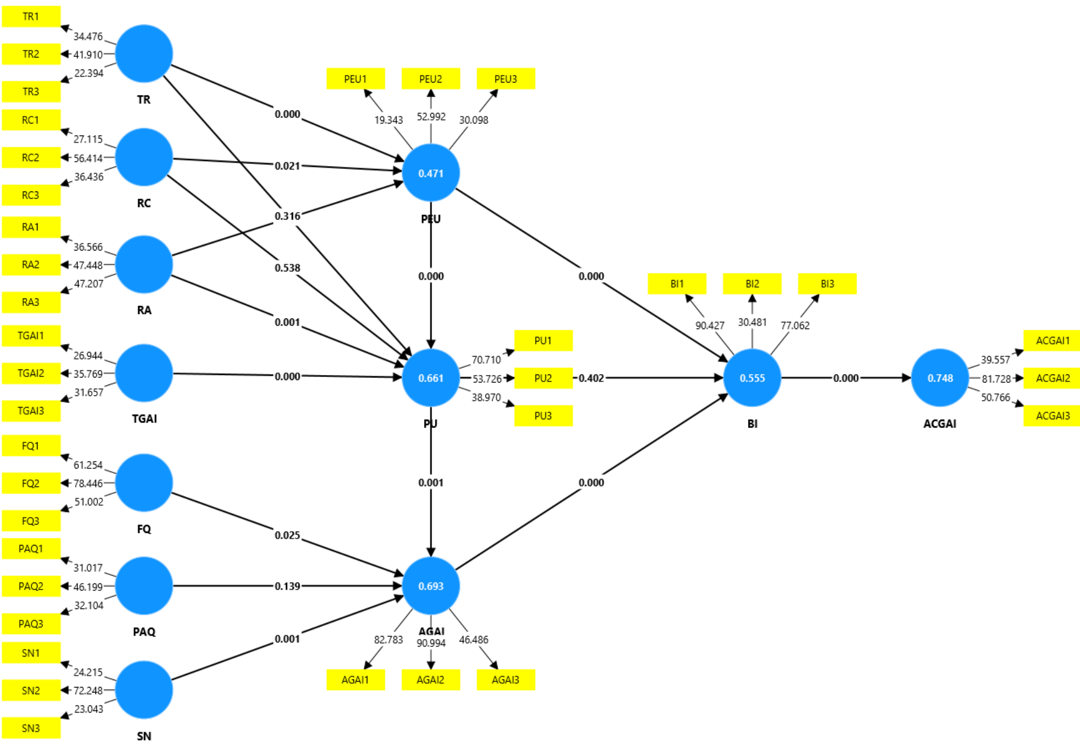

Figure 1. The Structural Model

The results indicate that Trialability (TR), Relative Advantage (RA), and Perceived Compatibility (RC) significantly influenced Perceived Ease of Use (PEU), demonstrating that when pre-service teachers perceive generative AI (GAI) as compatible, easy to try, and offering clear benefits over alternatives, they are more likely to find it easy to operate. However, TR and RC did not significantly affect Perceived Usefulness (PU), suggesting that ease of experimentation and compatibility alone do not guarantee perceptions of pedagogical or practical value. In contrast, RA and Trust in Generative AI (TGAI) both positively predicted PU, confirming that perceived advantage and trust contribute meaningfully to perceived educational utility. Feedback Quality (FQ) and Subjective Norms (SN) significantly shaped Attitudes toward GAI (AGAI), highlighting peer influence and system responsiveness as important motivational factors, while Perceived Assessment Quality (PAQ) did not show a significant effect.

The structural model further showed that PEU positively predicted both PU and Behavioural Intention (BI) to use GAI, underscoring that ease of operation plays a dual role in driving perceived value and future adoption. PU significantly predicted AGAI, indicating that usefulness perceptions influence positive evaluative judgments, although PU did not directly predict BI. This implies that usefulness may operate indirectly through attitudes rather than through behavioral intention. AGAI significantly influenced BI, reinforcing the importance of affective evaluations in technology acceptance among Generation Z pre-service teachers. Finally, BI strongly predicted Acceptance of Generative AI for education (ACGAI), highlighting that intention is a decisive precursor for actual acceptance behavior. Collectively, the findings validate the predictive nature of the proposed model and confirm that affective, social, and cognitive appraisals jointly shape GAI adoption in educational contexts.

Table 4. Hypothesis Testing

Relationship	B	M	SD	T	p	Conclusion
TR -> PEU	0.338	0.340	0.075	4.486	0.000	Accepted
TR -> PU	-0.073	-0.061	0.073	1.004	0.316	Rejected
RC -> PEU	0.192	0.195	0.083	2.302	0.021	Accepted
RC -> PU	0.048	0.043	0.079	0.615	0.538	Rejected
RA -> PEU	0.238	0.237	0.089	2.679	0.007	Accepted
RA -> PU	0.231	0.234	0.069	3.349	0.001	Accepted
TGAI -> PU	0.331	0.325	0.077	4.283	0.000	Accepted
FQ -> AGAI	0.188	0.186	0.084	2.246	0.025	Accepted
PAQ -> AGAI	0.171	0.180	0.116	1.478	0.139	Rejected
SN -> AGAI	0.310	0.305	0.093	3.315	0.001	Accepted
PEU -> PU	0.382	0.378	0.071	5.418	0.000	Accepted
PU -> AGAI	0.240	0.239	0.073	3.291	0.001	Accepted
PEU -> BI	0.395	0.388	0.080	4.914	0.000	Accepted
PU -> BI	0.078	0.081	0.093	0.837	0.402	rejected
AGAI -> BI	0.349	0.353	0.086	4.077	0.000	Accepted
BI -> ACGAI	0.865	0.865	0.017	49.822	0.000	Accepted

The analysis reveals that several innovation-related antecedents have a significant influence on pre-service biology teachers' cognitive evaluations of generative AI (GAI). Trialability, relative advantage, and perceived compatibility all significantly predicted perceived ease of use, indicating that the ability to experiment with GAI tools, perceive relative benefits, and align the technology with existing workflows enhances perceptions of usability. This finding is consistent with diffusion of innovation theory, which emphasizes trialability and compatibility as key drivers of adoption (Rogers, 2003) and aligns with prior studies showing that hands-on experience reduces perceived complexity in educational technologies (Almogren et al., 2024). However, trialability and compatibility did not significantly influence perceived usefulness, suggesting that ease of experimentation does not necessarily translate into perceived pedagogical value. This result supports previous findings that usefulness judgments require deeper evaluations related to instructional effectiveness rather than surface-level interaction (Davis, 1989; Lee et al., 2024).

Relative advantage and trust in generative AI significantly predicted perceived usefulness, indicating that pre-service teachers are more likely to value AI when they perceive clear instructional benefits and trust the system's outputs. This finding is consistent with prior research highlighting trust as a critical determinant in AI adoption, particularly in contexts involving automated feedback and content generation (Gao et al., 2025). Similarly, the importance of relative advantage aligns with existing technology acceptance studies showing that perceived performance gains strongly influence usefulness perceptions (Venkatesh et al., 2003). These results suggest that demonstrating tangible pedagogical benefits and ensuring reliable AI outputs are essential for strengthening teachers' perceptions of AI's educational value.

The structural model also highlights the importance of affective and social factors in shaping attitudes toward generative AI. Feedback quality and subjective norms significantly influenced attitudes, indicating that meaningful system responses and peer influence contribute to positive evaluations. This is consistent with prior studies emphasizing the role of feedback quality in digital learning environments and the influence of social norms in shaping technology-related attitudes (Albadarin et al., 2024). In contrast, perceived assessment quality did not significantly affect attitudes, suggesting that pre-service teachers may not yet critically evaluate AI-generated assessment processes. This finding diverges from some prior research that positions assessment as central to educational technology adoption, indicating a potential gap in teachers' assessment literacy in AI contexts.

Perceived ease of use significantly influenced both perceived usefulness and behavioural intention, reinforcing its central role in technology acceptance models (Davis, 1989). This result is consistent with numerous studies demonstrating that systems perceived as easy to use are more likely to be adopted and valued (Venkatesh et al., 2003). However, perceived usefulness did not directly influence behavioral intention, suggesting that its effect operates indirectly through attitudes. This finding supports extended TAM frameworks where affective responses mediate the relationship between cognitive beliefs and behavioral intention (Almogren et al., 2024). It indicates that even when AI is perceived as useful, positive emotional and evaluative responses remain necessary for adoption decisions.

Attitude toward generative AI emerged as a strong predictor of behavioral intention, confirming the importance of affective evaluations in shaping adoption behaviour among Generation Z pre-service teachers. This aligns with prior research indicating that attitudes play a mediating role between perceptions and intention in emerging technologies (Li, 2025). Furthermore, behavioural intention strongly predicted actual acceptance, consistent with established models such as TAM and UTAUT, where intention is the most immediate determinant of usage behaviour (Venkatesh et al., 2003). This highlights the importance of fostering positive attitudes and intentions during teacher preparation programs to support future AI integration.

The findings carry practical implications for teacher education programs, educational policymakers, and developers of generative AI tools. The strong predictive role of behavioral intention on acceptance highlights the importance of cultivating positive exposure and encouraging voluntary engagement with GAI in training environments. Since perceived ease of use and attitude play central roles in intention formation, teacher preparation curricula may benefit from practical, hands-on workshops that demystify GAI tools and reduce operational barriers. The influence of trust and perceived advantage on usefulness suggests that transparent system behavior, explainable outputs, and demonstrated instructional benefits should be emphasized. Additionally, subjective norms indicate that peer communities, professional learning networks, and collaborative environments may accelerate adoption. Collectively, these implications suggest that acceptance cannot be assumed merely from availability; rather, structured guidance, social endorsement, and pedagogical framing are necessary to support responsible and effective GAI integration in future classrooms.

IV. CONCLUSION

This study expands the existing literature on generative AI acceptance by offering discipline-specific evidence from STEM teacher education, an area that remains underrepresented in empirical research. By focusing on pre-service biology teachers and integrating innovation diffusion, trust-related, affective, and pedagogical constructs, the study provides a more nuanced understanding of how future educators evaluate generative AI beyond purely technical considerations. The findings highlight the importance of examining acceptance within authentic instructional contexts, where social influence, feedback quality, and affective responses shape evaluative judgments alongside cognitive beliefs. In addition, the study offers practical value for curriculum designers, educational institutions, and policymakers by identifying key leverage points that influence acceptance pathways, including ease of use, trust, and attitude formation. The results suggest that teacher preparation programs should move beyond passive exposure to AI tools and instead emphasize guided practice, reflective engagement, and pedagogical alignment. These insights can inform the design of professional learning experiences, institutional policies, and support structures that align generative AI integration with instructional goals, ethical considerations, and the evolving demands of biology education.

Future research should extend this study by exploring generative AI acceptance across diverse cultural contexts to enhance the generalizability of findings beyond pre-service biology teachers in a single setting. Longitudinal studies are also recommended to examine how acceptance, attitudes, and actual usage evolve over time as teachers gain more exposure and experience with AI tools. In addition, future research could incorporate qualitative approaches, such as interviews or classroom observations, to provide deeper insights into how teachers meaningfully integrate generative AI into pedagogical practice and how contextual factors influence decision-making. Investigating the impact of targeted AI training interventions on teachers' competencies, trust, and ethical awareness would further strengthen understanding of effective professional development models. Moreover, examining student learning outcomes and classroom interactions in AI-supported environments can provide evidence of actual educational impact, thereby bridging the gap between acceptance and real instructional effectiveness.

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