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Exploring AI integration in biology self-learning: A TAM-based analysis among high school students in Ho Chi Minh City

Duy Tran Thanh [1], Van Pham Dinh [2*], Hien Nguyen Van [3]

[1] Saigon University, Ho Chi Minh City, VIETNAM
[2] Ho Chi Minh City University of Education, Ho Chi Minh City, VIETNAM
[3] Hanoi National University of Education, Hanoi, VIETNAM

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Abstract

As artificial intelligence (AI) continues to shape education, its role in self-directed learning, particularly in biology, remains underexplored. This study investigates AI adoption among high school students in Ho Chi Minh City using the technology acceptance model (TAM), integrating structural equation modeling, thematic analysis, and latent Dirichlet allocation topic modeling. Findings challenge traditional TAM assumptions, revealing that while perceived usefulness positively influences attitude toward use, it does not significantly predict behavioral intention. Additionally, perceived ease of use is not a strong predictor of AI adoption, highlighting the unique demands of biology education. A key finding is that adoption constraints, including concerns about AI accuracy, privacy, and limited experimental capabilities, significantly hinder AI adoption. Students predominantly use AI for exam preparation and homework support, rather than for exploratory learning or experimental simulations. AI-based quizzes are perceived as the most useful, whereas open-ended AI chatbots are less engaging for biology learning. The study underscores that biology students require AI tools that extend beyond theoretical learning to include laboratory simulations, data analysis, and experimental design support. To enhance AI adoption, this study recommends AI literacy programs for students and educators, the development of AI-driven virtual laboratory tools, and improved accuracy and reliability of AI-generated biological content. Institutional policies should support AI integration by ensuring accessibility, training, and regulatory oversight. By addressing these limitations, AI can transition from a passive knowledge provider to an active facilitator of scientific discovery in biology education.

Keywords: AI in education, self-learning, biology, technology acceptance model, AI literacy

INTRODUCTION

Background

Artificial intelligence (AI) has emerged as a transformative force in education, offering a myriad of applications that enhance teaching and learning processes across various disciplines. AI-driven educational tools have the potential to personalize learning experiences, automate administrative tasks, and provide real-time feedback, thereby fostering greater engagement and comprehension among students (Holmes et al., 2019). The integration of artificial intelligence in education (AIED) encompasses a wide array of applications, including adaptive learning platforms, intelligent tutoring systems, and automated assessment tools, all of which contribute to an enriched learning environment. In the context of high school education, AI is particularly valuable in addressing individual learning needs and promoting self-directed learning (Zawacki-Richter et al., 2019).

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✉ ttduy@sgu.edu.vn ✉ vanpd@hcmue.edu.vn **(*Correspondence)** ✉ hiennv@hnue.edu.vn

Contribution to the literature

- This study contributes to the literature by examining AI adoption in biology self-learning among high school students in Ho Chi Minh City, Vietnam, a context underexplored in prior research, using an extended technology acceptance model (TAM) integrated with structural equation modeling (SEM), thematic analysis, and latent Dirichlet allocation (LDA) topic modeling.
- Unlike previous studies that broadly apply TAM to educational technology, it reveals discipline-specific insights, showing that adoption constraints (ACs) like AI accuracy and limited experimental capabilities uniquely hinder biology education, challenging traditional assumptions about perceived usefulness (PU) and ease of use as primary drivers.
- By highlighting the need for AI tools to support laboratory simulations and experimental design, this work advances scholarship on tailoring AI to meet the practical and theoretical demands of STEM education in developing regions.

Within the domain of biology education, AI applications are increasingly being explored to facilitate the comprehension of complex biological concepts. Traditional pedagogical methods often struggle to accommodate diverse learning styles and paces, leading to knowledge gaps and reduced student motivation. AI-based solutions, such as virtual laboratories, AI-assisted tutoring, and interactive simulations, provide students with personalized, interactive, and immersive learning experiences (Chen et al., 2018). These technologies allow for the visualization of intricate biological processes, fostering a deeper understanding and retention of biological knowledge. However, the widespread adoption of AI in high school biology education is hindered by several challenges, including limited teacher familiarity with AI technologies, concerns regarding the reliability of AI-generated content, and accessibility issues.

The TAM, initially proposed by Davis (1989), serves as a robust theoretical framework for examining technology adoption in educational settings. According to TAM, PU, and perceived ease of use (PEOU) are critical determinants influencing users' attitudes and behavioral intentions (BI) towards technology adoption. In the context of AIED, these factors play a pivotal role in shaping students' willingness to integrate AI tools into their learning processes. Extending the original TAM framework, contemporary studies have incorporated additional constructs, such as subjective norms, facilitating conditions, and self-efficacy, to better capture the complexities of AI acceptance in educational environments (Teo, 2011).

Recent scholarly works like Holmes et al. (2019) and Zawacki-Richter et al. (2019) underscore the potential of AI to revolutionize education while simultaneously highlighting key challenges that must be addressed to ensure successful implementation. These challenges encompass a lack of adequate teacher training, ethical concerns related to data privacy, and varying levels of digital literacy among students. Despite these barriers, AI-driven educational platforms have demonstrated their effectiveness in enhancing personalized learning experiences, increasing student engagement, and improving conceptual understanding of biological topics.

Despite the growing body of research on AI applications in education, several critical gaps remain, particularly concerning high school biology education. Most existing studies focus on teachers' perspectives and institutional readiness, with insufficient exploration of high school students' attitudes and experiences with AI in biology education. Studies such as Zhang and Aslan (2021) highlight the necessity of understanding student-centered perspectives to design effective AI tools that align with their learning preferences and cognitive abilities' Role in self-directed learning. While considerable attention has been given to AI's role in formal classroom settings, little research exists on its potential to support self-directed learning, which is essential for students requiring additional practice outside the classroom. Research by Yaseen et al. (2025) suggests that AI-based tools can facilitate autonomous learning by offering personalized feedback, but there is limited empirical evidence on their effectiveness in fostering independent study habits. A study examining the integration of AIED within Hong Kong's K-12 schools identified three primary approaches: learning from AI, learning about AI, and learning with AI; and found that various interconnected first-order and second-order barriers impede progress, suggesting that schools should employ tailored strategies to address these challenges effectively (Wang & Cheng, 2021).

Although TAM has been widely utilized to study technology adoption, its specific applicability to AI-based learning environments in high school biology necessitates further validation and the inclusion of additional constructs, such as ACs. Zhang et al. (2023) confirms that traditional models may not fully account for the unique factors associated with AI adoption in education, indicating a need for expanded frameworks.

AI holds transformative potential for biology education by enabling personalized, adaptive, and interactive learning experiences that bridge conceptual gaps and foster deeper understanding of complex scientific phenomena. This is particularly critical in biology, a subject that combines abstract reasoning with practical experimentation. However, the integration of AI into secondary biology education is challenged by limited infrastructure, insufficient teacher training, and students' varying levels of digital literacy and trust in AI systems.

To address these challenges, this study extends the TAM by introducing the construct of AC, which captures barriers specific to the nature of biology learning–such as the need for experimental accuracy and simulation. The research investigates how core TAM constructs–PU, PEOU, ATU, and AC–collectively influence students' BI to adopt AI tools in self-learning biology.

Additionally, the study examines AI usage patterns reported by students to understand the real-world educational purposes for which AI tools are applied, including concept comprehension, memorization, and experimentation. By integrating SEM and LDA topic modeling, this mixed-methods approach triangulates quantitative acceptance factors with qualitative usage behaviors. The findings aim to inform the design of AI-enhanced biology curricula and instructional strategies that are pedagogically effective, experimentally supportive, and contextually relevant for students in developing countries.

Hypotheses

To address the identified gaps and extend the TAM framework, this study proposes the following hypotheses to enhance our understanding of AI adoption in high school biology education:

H1. PU of AI tools positively influences students' attitudes towards using AI for self-learning in biology.

H2. PEOU of AI tools positively influences students' attitudes towards using AI for self-learning in biology.

H3. ATU positively influences students' BI to use AI tools for self-learning in biology.

H4. AC negatively influence students' attitudes towards using AI for self-learning in biology.

H5. PEOU positively influences PU of AI tools for self-learning in biology.

H6. AC negatively influence PEOU and PU of AI tools.

By empirically testing the proposed hypotheses, this study seeks to generate a deeper understanding of the determinants influencing the adoption of AI tools in high school biology education. It further aims to propose evidence-based strategies for addressing the contextual, pedagogical, and technological barriers that may hinder effective AI integration into self-directed biology learning.

MATERIALS AND METHODS

Research Design

This study employs a mixed-methods research design, integrating both quantitative and qualitative approaches to comprehensively investigate the adoption of AI tools in high school biology education. The quantitative component aims to test the proposed hypotheses based on the TAM, while the qualitative component seeks to provide deeper insights into students' experiences and perceptions regarding AI adoption. A cross-sectional survey design is used to collect data at a single point in time, allowing for the analysis of current AI adoption trends and barriers.

Participants

The study sample comprises high school students from various educational institutions in Ho Chi Minh city, Vietnam. A stratified random sampling method was used to ensure a representative sample based on factors such as grade level, geographic location, and access to technological resources. The inclusion criteria for participation were:

(1) currently enrolled in a biology course,

(2) access to AI tools for learning purposes, and

(3) willingness to participate in the study.

A total of 341 students participated in the survey.

Instrumentation

A structured questionnaire was developed to measure the constructs of the extended TAM framework, PU, PEOU, ATU, BI, and AC. The questionnaire was divided into five sections:

Demographic information

Age, gender, grade level, access to technology, and frequency of AI tool usage.

Perceived usefulness

Adapted from Davis (1989), this section included items:

1. Question 1 (PU_understand): *Using AI tools helps me understand complex biological systems (e.g., ecosystems, cellular processes).*
2. Question 2 (PU_experiment): *AI tools help me perform better in biology lab work by assisting with data analysis and experimental design.*
3. Question 3 (PU_memorized): *AI tools make it easier for me to remember large amounts of biology information (e.g., terms, processes).*

Perceived ease of use

Items measuring students' perceptions of the ease with which AI tools can be used:

1. Question 1 (PEOU_stimulate*): The AI tool is easy to use for simulating complex biological processes (e.g., mitosis, photosynthesis).*
2. Question 2 (PEOU_experiment*): I can easily use AI tools to help with lab-related tasks like analyzing data or setting up experiments.*
3. Question 3 (PEOU_overall): *Overall, I find AI tools easy to use for my biology self-study*.

Attitude toward use (ATU) and behavioral intention

Based on validated scales from prior TAM studies, questions included:

1. Question 1 (ATU_difficulty): *I enjoy using AI tools because they help me understand challenging biology topics, like genetics or evolution.*
2. Question 2 (ATU_experiment): *Using AI tools makes biology lab work (e.g., experiments, data analysis) more interesting and easier to manage.*
3. Question 3 (ATU_practical): *I find AI tools helpful for solving real-world biology problems (e.g., environmental issues, health-related problems).*
4. Question 4 (ATU_overall): *Overall, I have a positive attitude toward using AI tools in biology self-study.*
5. Question 5 (BI_complicating): *I intend to continue using AI tools to help with complex biology topics (e.g., ecology, cellular biology).*
6. Question 6 (BI_experiment): *I will use AI tools to help me prepare for lab work and experiments in biology*.
7. Question 7 (BI_overall): *I would recommend AI tools to my peers for understanding difficult biology topics.*

Adoption constraints

Items addressing barriers such as accessibility, technical support, and perceived trustworthiness of AI-generated content.

1. Question 1 (AC_use): *Lack of understanding of how to use AI for biology*.
2. Question 2 (AC_accuracy): *Concerns about AI accuracy or reliability*.
3. Question 3 (AC_cost): *Difficulty in accessing AI tools for many reasons (flatform charges, time for computer using…).*
4. Question 4 (AC_trained): *I need more training on how to effectively use AI tools for biology study.*

The questionnaire employed a five-point Likert scale (1 = strongly disagree, 5 = strongly agree) to capture responses.

Barriers, benefits, challenges, and improvement

To further enrich the study's qualitative component, four open-ended questions were devised and presented to respondents. These questions aimed to elicit detailed narratives on specific aspects of AI tool adoption in high school biology education. The themes addressed by the questions included barriers to adoption, perceived benefits, encountered challenges, and suggested improvements. The responses were subjected to narrative analysis, providing comprehensive insights into students' experiences and perceptions.

Data Collection Procedure

Data collection was conducted over a three-month period through online surveys distributed via school communication platforms and social media groups. Before data collection, informed consent was obtained from both students and their guardians, ensuring ethical compliance.

Data Analysis

The collected data were analyzed using R statistical software. The analysis involved several steps:

1. *Descriptive statistics:* Mean (M), standard deviation (SD), and frequency distributions were calculated using the 'dplyr' package to summarize the data (Yarberry, 2021).
2. *Reliability and validity analysis:* Cronbach's alpha and composite reliability were computed using the 'psych' package to assess the internal consistency of the survey constructs. Confirmatory factor analysis (CFA) was conducted using the 'lavaan' package to evaluate construct validity (Revelle, 2023).
3. *SEM:* The hypothesized relationships among TAM variables were tested using the 'lavaan' and package in R, assessing model fit indices such as comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR) (Rosseel et al., 2014).
4. *Qualitative thematic analysis*: Open-ended responses from the survey were analyzed using thematic coding to identify recurring themes related to students' experiences and perceived barriers to AI adoption. The analysis was conducted using the 'tidytext' and 'tm' packages for text preprocessing, tokenization, and sentiment analysis. To further explore the thematic structure of the qualitative data, LDA was utilized with 'topicmodels' package (Grün et al., 2017; Silge & Robinson, 2016; Rizopoulos, 2006).
5. *Visualization*: Data insights and thematic patterns were visualized using the 'ggplot2' (Wickham,

Table 1. Demographics summary of participants

Variable	Category	Percentage
Sex	Male	51.61%
	Female	48.39%
Age	16 - < 18	61.58%
	14 - < 16	36.07%
	≥ 18	1.17%
	< 14	1.17%
Area	Urban	93.55%
	Suburban	3.23%
	Rural	2.35%
	N/A	0.88%
Grade	11th grade	48.97%
	10th grade	31.38%
	12th grade	19.65%
Often	Occasionally	37.24%
	Weekly	28.45%
	Daily	15.54%
	Rarely	11.14%
	Monthly	4.99%
	Never	2.64%

2016) and 'semPlot' (Epskamp, 2015) package to facilitate a clear interpretation of findings.

Ethical Considerations

Ethical approval for the study was obtained from the institutional review board. Participants were assured of confidentiality and anonymity, with data used solely for research purposes. Students were informed of their right to withdraw from the study at any point without repercussions.

The materials and methods outlined in this study provide a robust framework for investigating the adoption of AI tools in high school biology education. The combination of quantitative and qualitative methods ensures a comprehensive understanding of factors influencing AI adoption, offering valuable insights for educators and policymakers.

RESULTS

Demographics and Descriptive Statistics

Participant demographics

Table 1 presents the demographic characteristics of the student sample, including sex, age group, residential area, grade level, and frequency of AI tool usage for learning purposes. These variables help contextualize students' backgrounds and their exposure to AIED settings. The sample consisted of 51.61% male and 48.39% female students. Most participants were aged 16 - < 18 (61.58%), followed by those aged 14 - < 16 (36.07%). A small minority were < 14 or ≥ 18 (each 1.17%). Regarding residence, 93.55% of students lived in urban areas, with few from suburban (3.23%) and rural regions (2.35%). The remaining 0.88% did not report this information. In terms of grade level, 11th graders made up the largest group (48.97%), followed by 10th (31.38%) and 12th grade (19.65%) students.

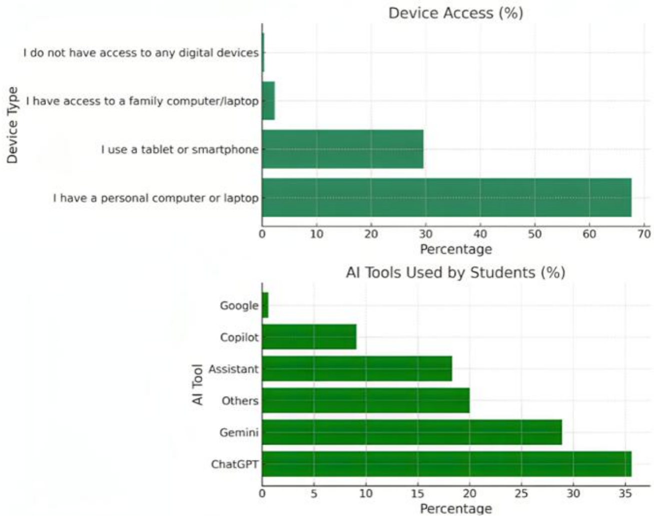

Figure 1. Students' access to digital devices and usage of AI tools for biology self-study (Source: Authors' own elaboration, using R)

As for AI learning frequency, 37.24% used AI occasionally, 28.45% weekly, and 15.54% daily. Less frequent use was reported by 11.14% (rarely), 4.99% (monthly), and 2.64% (never).

These demographics highlight a predominantly urban, mid-to-upper secondary student population with varied exposure to AI tools.

Access to digital resources and use of AI tools for biology learning

Figure 1 present an overview of students' access to digital devices and their usage of AI tools. As shown in part a in **Figure 1**, a substantial majority of students (65.1%) reported owning a personal computer or laptop, while 29.3% used tablets or smartphones for their studies. Access to a family-shared device was noted by 5.0% of respondents, and only a marginal 0.6% indicated having no access to digital devices at all. In terms of AI tool usage (**Figure 1**), ChatGPT was the most frequently used tool (35.2%), followed by Gemini (28.1%). Other tools–including Assistant (14.2%), Copilot (9.3%), and Google (0.8%)–were used to a lesser extent, with a combined category of less common tools (labelled "others") accounting for 15.0% of responses. These findings highlight both strong digital access and the growing adoption of AI-based educational tools among students.

Descriptive statistics of TAM constructs

Figure 2 presents the mean scores of individual items across five TAM constructs: PU, PEOU, ATU, BI, and ACs. The highest scoring item was AC_accuracy (M = 3.98), indicating strong concerns about the accuracy of AI-generated content. Similarly, BI_overall (M = 3.95)

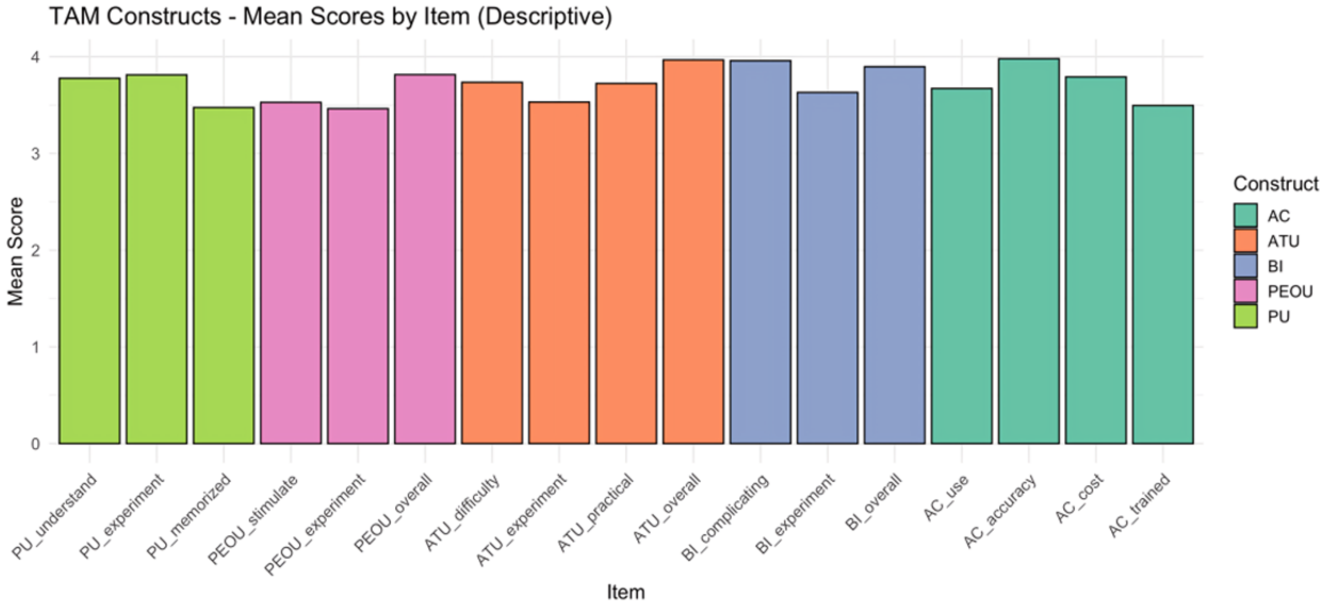

Figure 2. M scores of TAM constructs across survey items in AI-supported biology learning (Source: Authors' own elaboration, using R)

and ATU_overall (M = 3.94) reflect a positive attitude and intention toward AI use. Among the PU items, PU_experiment showed the highest M (M = 3.81), while PU_memorized scored the lowest (M = 3.55). For PEOU, the ease of using AI for experimentation (PEOU_experiment) scored moderately (M = 3.65), suggesting some usability challenges. The AC_trained had the lowest overall score (M = 3.56), indicating students' perceived need for more AI-related training. Collectively, these results highlight that while students generally show favorable perceptions and intentions toward AI use in biology education, concerns about accessibility and effective use remain.

Reliability Analysis: Internal Consistency of TAM Constructs in Biology Education

The Cronbach's alpha reliability scores indicated strong internal consistency across all measured constructs (**Table 2**). The PU scale (α = 0.74) showed acceptable reliability, with item-wise correlations demonstrating that AI tools were particularly useful in helping students understand complex biological systems (0.83), assisting with biology laboratory work (0.81), and supporting memorization of biology-related knowledge (e.g., terminology, processes) (0.80). The removal of any single PU item did not significantly increase reliability, suggesting that the construct was well-formed.

For PEOU (α = 0.77), students consistently rated AI tools as easy to use for simulating biological processes (e.g., mitosis, photosynthesis) (0.84) and setting up experiments in biology labs (0.86). The relatively high item-to-total correlations indicated that AI's usability features were a key factor influencing students' willingness to engage in self-directed learning of complex biological topics.

Table 2. Reliability analysis using Cronbach's alpha

Construct	I	RA	SA	AR	M	SD
PU	3	0.74	0.75	0.49	3.7	0.87
PU_understand	341	0.83				
PU_experiment	341	0.81				
PU_memorized	341	0.80				
PEOU	3	0.77	0.78	0.54	3.6	0.86
PEOU_stimulate	341	0.84				
PEOU_experiment	341	0.86				
PEOU_overall	341	0.79				
ATU	4	0.82	0.82	0.53	3.7	0.84
ATU_difficulty	341	0.78				
ATU_experiment	341	0.81				
ATU_practical	341	0.82				
ATU_overall	341	0.81				
BI	3	0.77	0.77	0.53	3.8	0.87
BI_complicating	341	0.85				
BI_experiment	341	0.83				
BI_overall	341	0.80				
ACs	4	0.88	0.88	0.64	3.7	0.99
AC_use	341	0.87				
AC_accuracy	341	0.88				
AC_cost	341	0.88				
AC_trained	341	0.79				

Note. *Cronbach's alpha values above 0.7 indicate acceptable reliability (Nunnally, 1978); I: Item; RA: Raw_alpha; SA: Standard_alpha; & AR: Average_r

The ATU construct had a reliability score of 0.82, reflecting a strong consensus that AI tools make biology learning more engaging, laboratory work easier to manage (0.81), and real-world biological problem-solving more accessible (0.82). This suggests that students found AI tools valuable for interpreting experimental results, structuring hypotheses, and conceptualizing abstract biological topics.

The BI scale (α = 0.77) demonstrated that students intended to continue using AI for learning difficult

Table 3. CFA results

Construct	Items	Standard_lambda_minimum	Standard_lambda_maximum	AVE	CR
PU	3	0.62	0.77	0.53	0.74
PEOU	3	0.68	0.82	0.55	0.78
ATU	4	0.69	0.78	0.54	0.80
BI	3	0.62	0.80	0.57	0.79
ACs	4	0.64	0.88	0.64	0.86

Note. AVE: Average variance extracted; CR: Composite reliability; AVE values above 0.50 indicate good convergent validity; & CR values above 0.70 indicate adequate internal consistency

Table 4. SEM results

Path	Estimate	Standard_error	Z_value	p_value	Standard _estimate
PU → ATU	0.569	0.199	2.859	0.004	0.612
PEOU → ATU	0.351	0.206	1.703	0.089	0.361
ATU → BI	4.483	7.075	0.634	0.526	4.033
PU → BI	-2.503	4.423	-0.566	0.571	-2.420
AC → ATU	0.072	0.033	2.165	0.030	0.096
PEOU → PU	0.985	0.093	10.537	0.000	0.943
AC → PEOU	0.303	0.051	5.924	0.000	0.392
AC → PU	-0.054	0.045	-1.203	0.229	-0.066

biology concepts (0.85), preparing for lab work (0.83), and recommending AI tools to peers for biology self-study (0.80). The high item-wise correlations indicated that the role of AI in improving knowledge retention, comprehension, and problem-solving abilities was well recognized.

Lastly, the ACs construct had the highest reliability ($\alpha = 0.88$), highlighting key barriers including concerns about AI accuracy (0.88), difficulties accessing AI tools (0.88), and the need for more AI training in biology contexts (0.79). The strong correlation among constraint-related items indicated that infrastructure, digital literacy, and trust in AI-driven content remain primary concerns among students.

Confirmatory Factor Analysis: Model Fit in Biology Education

The CFA results demonstrated that the AI-adoption model fit the data well (**Table 3**), with key fit indices indicating a strong model: CFI = 0.931, TLI = 0.914, RMSEA = 0.078, and SRMR = 0.044. All factor loadings exceeded the recommended threshold of 0.60, confirming the construct validity of the model. These results suggest that students' acceptance of AI tools in biology self-study was meaningfully captured by the core constructs of the TAM. In particular, AI tools were found to enhance learning by supporting experimental tasks and helping students grasp abstract biological concepts through memorization aids and simulations. This reinforces the relevance of TAM for understanding technology use in STEM education and supports the integration of AI into high school biology learning environments.

Structural Equation Modeling: Hypothesis Testing and AI Adoption Pathways

The SEM analysis provided empirical support for several core relationships within the extended TAM framework (**Table 4** and **Figure 3**). A notably strong and statistically significant path was found from PEOU to PU ($\beta = 0.943$, $p < 0.001$), indicating that students who found AI tools easier to operate were more likely to perceive them as beneficial for their learning–particularly in tasks such as understanding biological systems or completing laboratory simulations.

PU was also a significant predictor of ATU, with a standardized estimate of $\beta = 0.612$ ($p = 0.004$), highlighting that students' perceptions of usefulness were key drivers of their positive attitudes toward AI adoption. In contrast, the direct effect of PEOU on ATU ($\beta = 0.361$, $p = 0.089$) was not statistically significant, suggesting that ease of use, while important for PU, may not alone shape students' attitudes.

Regarding the external factor AC, its influence on PU was weak and non-significant ($\beta = -0.066$, $p= 0.229$), implying that concerns such as access limitations or doubts about AI accuracy do not significantly alter students' perception of usefulness. However, AC did have a small but statistically significant effect on ATU ($\beta = 0.096$, $p = 0.030$), suggesting that reducing these external barriers could slightly enhance students' attitudes toward AI.

When evaluating BI, the model revealed that ATU had the highest standardized path coefficient ($\beta = 4.033$), but the effect was not statistically significant due to a high standard error ($p = 0.526$), indicating limited explanatory power. The direct paths from PU to BI ($\beta = -2.420$, $p = 0.571$) and from AC to BI were also non-significant, suggesting that these variables influence intention only indirectly.

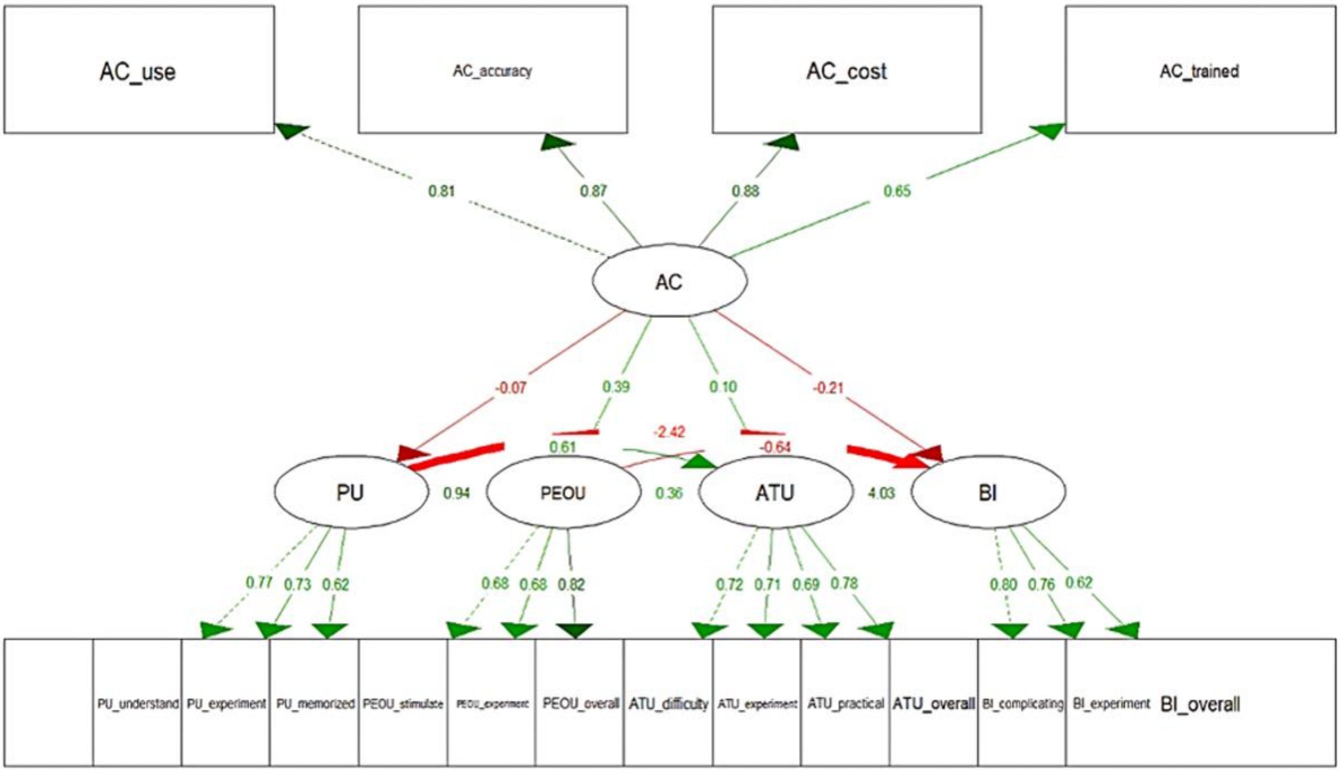

Figure 3. SEM Plot of TAM (Source: Authors' own elaboration, using R)

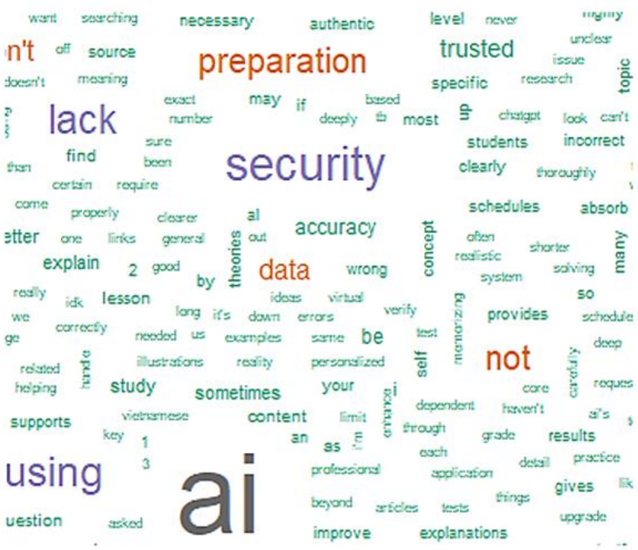

Figure 4. Word cloud of survey responses (Source: Authors' own elaboration, using R)

Mediation analysis confirmed that ATU fully mediated the effect of PU on BI. Although PU did not have a direct effect on BI, its influence was transmitted through students' attitudes, consistent with TAM assumptions (**Figure 3**). These findings partially diverge from earlier research (Teo, 2011) , where PU typically had a direct impact on BI. In this study, the findings underscore the importance of fostering positive attitudes to strengthen students' commitment to using AI tools in biology education.

Thematic Analysis: Student Perceptions of AI in Biology Learning

Word cloud

Using qualitative text mining, responses were analyzed for key themes related to AI in biology self-learning.

This word cloud provides a visual representation of the most frequently mentioned words in students' responses regarding AI tools in biology self-learning (**Figure 4**). The larger the word, the more frequently it appears in the dataset, suggesting key concerns, benefits, and challenges students associate with AI tools.

Dominance of "AI" and "information": The largest word, "AI", reflects the central focus of discussions, reaffirming that AI tools are a key aspect of self-learning in biology. The prominence of "information" suggests that students perceive AI as a major source of knowledge retrieval, reinforcing AI's role in improving access to biology-related materials.

Security and trust issues: Words like "security," "trusted," and "accuracy" indicate concerns about the reliability of AI-generated content. This aligns with previous studies highlighting that AI adoption is often hindered by trust issues, particularly in educational contexts where accuracy is critical (Luckin et al., 2016; Zawacki-Richter et al., 2019).

Preparation and understanding: Words like "preparation," "understanding," and "explanations" suggest that AI tools are seen as useful in structuring and

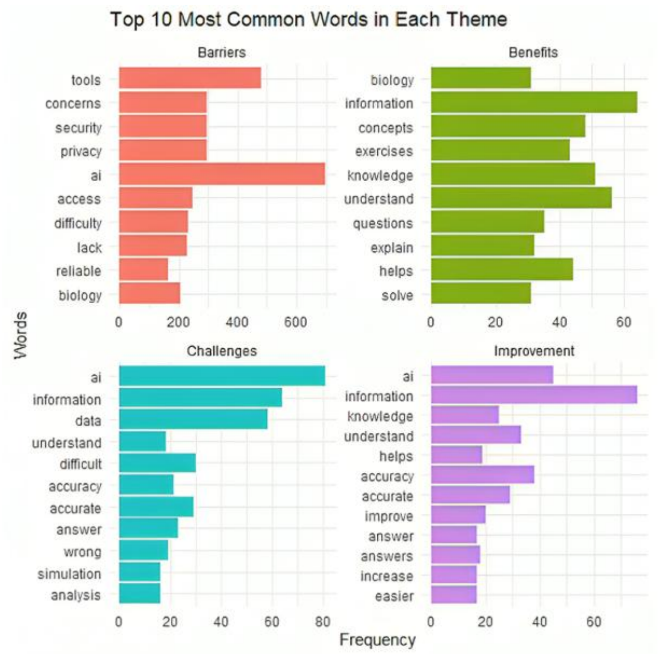

Figure 5. Top common words investigated in responses: Barriers, benefits, challenges, and improvement (Source: Authors' own elaboration, using R)

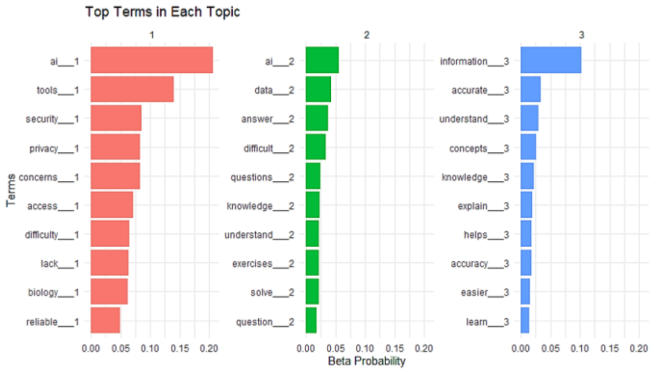

Figure 6. LDA plot extracts topics for AI usage in biology self-learning (Source: Authors' own elaboration, using R)

comprehending biology concepts. This supports previous findings that AI tools can aid in active learning and concept reinforcement (Huang et al., 2020; Owolarafe et al., 2024; Zhai et al., 2021).

Barriers to AI use: Terms like "lack," "wrong," and "not" highlight common frustrations or limitations students experience when using AI for biology studies. This might be linked to concerns about misinformation, technical difficulties, or lack of training in using AI effectively.

Data and accuracy concerns: The presence of "data," "accuracy," and "clarifying" suggests that students may struggle with evaluating AI-generated content for scientific correctness. These concerns align with the findings from Cronbach's alpha and TAM-SEM analysis, which suggest that students' PU and PEOU are significantly impacted by AI's ability to provide reliable and accurate information.

Thematic analysis: Key trends in AI adoption

We conducted thematic analysis on students' qualitative responses and identified four central themes (**Figure 5**):

Barriers to AI adoption: Concerns about AI's accuracy in biology (e.g., AI's inability to interpret complex biological data correctly); Access constraints (e.g., limited institutional support, difficulty in finding AI tools tailored for biology education). This supports our TAM findings that AC negatively impacts PU (Hakimi & Shahidzay, 2024).

Perceived benefits of AI in biology learning: AI helps understand biology topics (e.g., genetics, cell biology, ecology); AI improves self-study efficiency (e.g., summarizing textbooks, assisting with simulations). This confirms why PU positively influences ATU.

Challenges of integrating AI into biology studies: Students reported difficulty applying AI to experimental biology; AI tools are seen as more suitable for theoretical learning than hands-on biology research. This helps explain why PU does not predict BI, as practical applications of AI in biology remain limited (Chai et al., 2013).

AI improvement suggestions: Students suggest better AI training, improved accuracy, and integration with biology curricula. These findings align with previous research suggesting AI tools must be adapted to specific domains (Tanveer et al., 2023).

Topic modeling results in relation to AI adoption in biology self-learning

Topic modeling results from an LDA analysis, which helps identify underlying themes in the text data. The three bar plots correspond to the top terms in three different topics extracted from the text (**Figure 6**).

The topic modeling results provide crucial insights into the perspectives of students in Ho Chi Minh City regarding the role of AI in their biology self-learning. The extracted topics reflect a mix of barriers, challenges, and benefits associated with AI tools in education. When interpreted alongside the TAM and SEM results, these findings highlight key trends and areas for improvement in AI-driven self-learning experiences.

Topic 1. Barriers and concerns in AI adoption (red):

1. This topic strongly aligns with AC in the SEM results.
2. Words like "security," "privacy," "concerns," "access," "reliable" suggest that students have significant worries about data protection, tool reliability, and accessibility issues.
3. The presence of "difficulty" and "biology" indicates that students struggle with AI tools in understanding biological concepts, which lowers PEOU.

4. Implication: These barriers act as a major limitation in AI adoption, negatively affecting students' ATU and, consequently, their BI to use AI tools.

Topic 2. AI's role in problem-solving and knowledge acquisition (green):

1. This topic highlights the practical uses of AI in biology learning, particularly in answering questions, solving problems, and analyzing biological data.
2. Strongly linked to PU as students recognize AI's ability to enhance understanding, particularly for difficult topics.
3. Presence of "questions" and "answer" suggests that students use AI for clarification and concept reinforcement in subjects like genetics, evolution, and cellular biology.
4. Implication: While students acknowledge AI's value, the mention of "difficult" and "data" suggests that AI still lacks optimization for seamless application in self-learning contexts.

Topic 3. AI as a learning facilitator (blue):

1. The dominant words "information," "accurate," "understand," "concepts," "knowledge," "explain," "helps" demonstrate a positive perception of AIED.
2. Strong correlation with PU and ATU, indicating that students see AI as a helpful learning assistant that improves their self-study experience.
3. The presence of "learn" and "easier" suggests that students view AI as a tool that reduces cognitive load and makes learning biology more accessible.
4. Implication: This topic aligns with positive adoption factors, suggesting that improving AI explanations and accuracy could further boost student engagement and adoption (BI).

Integration with TAM-SEM Analysis

The structural model revealed a significant mediated pathway from PU to BI through ATU, indicating that students who view AI tools as beneficial for biology learning are more likely to form favorable attitudes, which in turn increase their intention to adopt such tools. This supports the foundational TAM premise and confirms PU as a central determinant of AI adoption behavior.

AC, including concerns about tool reliability, accessibility, and training needs, showed a negative influence on both PU and BI, highlighting the disruptive role of perceived barriers. These findings are consistent with qualitative themes identified through topic modeling (see topic 1), where students expressed skepticism due to limited access and mistrust in AI-generated content. Although the statistical link between AC and BI was not directly significant, its influence on attitudes suggests an indirect suppressive effect on adoption behavior.

While PEOU did not directly predict ATU or BI, it had a strong effect on PU ($\beta = 0.943$, $p < 0.001$), suggesting that usability is a prerequisite for forming positive perceptions of utility. This indirect influence implies that simplifying AI tools may foster adoption by strengthening PU and downstream attitudes.

These structural relationships are reinforced by thematic evidence from students' open-ended responses. Many highlighted AI's value in offering clear, structured explanations–particularly for complex biological processes–and aiding in memorization and experimental preparation. However, others emphasized persistent barriers related to accuracy, security, and equitable access, which align with the quantitative role of AC.

Together, the SEM results and thematic findings converge to underscore that PU is the primary driver of AI adoption in biology self-study, but that its impact is contingent on both usability and the mitigation of external barriers.

DISCUSSION

Participant Demographics and Students' Access to Digital Devices and Their Usage of AI Tools

The demographic characteristics of the surveyed high school students provide foundational insights into their digital readiness and engagement with AI tools in biology education. The majority of respondents were between 16 and < 18 years of age (61.58%) and in 11th and 10th grades (80.35%). This cohort is developmentally situated at a stage where cognitive demands in science education increase significantly, especially in topics requiring abstract reasoning such as genetics or cellular processes. The age group also coincides with the population commonly referred to as "digital natives," who are generally more adaptive to technology use in learning contexts (Prensky, 2001).

Gender distribution was nearly equal, facilitating unbiased gender-based inferences. Notably, 93.55% of the sample came from urban settings, reflecting the concentration of technological infrastructure and access in metropolitan areas. This urban overrepresentation aligns with findings that students in rural Vietnam face persistent digital disparities, despite national efforts to bridge this gap through digital transformation programs (Duong, 2022).

With regard to device access, 67.68% of students reported owning a personal computer or laptop, while 29.63% used mobile devices such as smartphones or tablets. This finding supports prior studies emphasizing the centrality of mobile technology in facilitating digital learning in Vietnamese schools (Hoi & Mu, 2021).

However, a small fraction of students (2.28%) relied on shared family devices, and 0.42% lacked access altogether–underscoring ongoing inequalities that could impact equitable adoption of AI-based learning strategies.

In terms of AI tool usage, students reported high engagement with generative AI platforms. ChatGPT was the most used tool (35.57%), followed by Gemini (28.87%) and Assistant (14.78%), suggesting a strong preference for conversational agents capable of supporting self-directed learning. These trends are in line with global observations where language models like ChatGPT have shown effectiveness in enhancing student inquiry, reflection, and engagement in complex domains like biology (Papaneophytou & Nicolaou, 2025).

However, usage frequency remains moderate: 37.24% reported using AI tools occasionally, 28.45% weekly, and only 15.54% daily. This moderate engagement may stem from barriers such as a lack of formal training, limited curricular integration, and concerns about the trustworthiness or appropriateness of AI-generated content–issues encapsulated in the ACs construct of this study.

Together, these findings highlight a landscape where AI integration in Vietnamese biology education is emerging yet shaped by digital access disparities and pedagogical gaps. Policies that promote teacher training, infrastructural equity, and alignment of AI tools with national curricula will be essential to fully realize the educational potential of AI in biology.

AI Adoption in Biology Self-Learning–A TAM and Thematic Perspective

Integration of quantitative and qualitative findings

The integration of SEM and thematic analysis yields a cohesive understanding of how students perceive and adopt AI tools in biology self-learning. The TAM framework (Davis, 1989; Venkatesh & Davis, 2000) remains applicable in this domain, though certain pathway strengths vary due to contextual factors intrinsic to biology education.

PU emerged as a central predictor of ATU ($\beta = 0.612$, $p < 0.01$), and its influence on BI was significant only when mediated through attitude. This pattern is consistent with prior findings in technology adoption in education (Teo, 2011), suggesting that students recognize AI's functional relevance–particularly in supporting tasks such as problem-solving, understanding biological mechanisms, and accessing structured explanations. The thematic analysis reinforces this: students valued AI for enhancing conceptual clarity, offering adaptive explanations, and supporting independent learning, especially in topics involving abstract or invisible biological processes (e.g., molecular pathways, genetics).

While PEOU significantly influenced PU ($\beta = 0.943$, $p < 0.001$), it did not exert a direct effect on either ATU or BI, indicating that usability is an important enabler but not a standalone motivator for AI adoption in this setting. This aligns with TAM extensions (Venkatesh et al., 2003) that emphasize domain specificity in shaping behavioral responses.

AC–including barriers such as technical inaccuracy, limited access, and lack of training–did not significantly predict PU or BI. However, AC had a modest but significant influence on ATU ($\beta = 0.096$, $p < 0.05$), suggesting that while constraints may not directly deter PU or intention, they subtly shape attitudes and confidence in using AI. This is echoed in the thematic analysis, where students cited concerns over AI reliability, especially in data-sensitive areas such as laboratory work and content memorization.

Contextualizing TAM in biology education

Biology as a subject is concept-heavy, requiring learners to visualize dynamic and abstract processes such as cell division, genetic expression, and ecological interactions (Tibell & Rundgren, 2010). This nature makes it an ideal context for exploring the role of AI in supporting visualization and simulation, two features frequently cited in both student responses and AI education literature. Prior studies have shown that AI technologies, particularly those offering real-time feedback, simulations, and intelligent tutoring, can enhance engagement and understanding in science learning (Xu & Ouyang, 2022).

In this study, students reported that AI tools were helpful in experimental design, simulation of lab work, and analyzing biological data–key facets of biology education where AI can bridge the theory-practice divide. However, limitations were also noted: students were concerned with the factual accuracy of AI-generated content and its applicability to structured laboratory tasks, confirming findings by Wu et al. (2024) on the potential for AI to mislead learners when used without sufficient scientific rigor.

Implications for AI-enhanced laboratory learning

Despite PU's positive influence on students' attitudes and indirect effect on BI, both SEM and qualitative results reveal a gap in the actual adoption of AI for practical laboratory learning. While students recognize AI's potential in simulating biology labs (e.g., virtual dissection, cell cycle modeling), challenges such as data reliability and interpretation remain. These findings support calls for enhanced development of AI-based virtual lab environments that are pedagogically grounded and content-validated (Zhai et al., 2021). Furthermore, improvements suggested by students–

such as enhancing tool accuracy, reducing access barriers, and providing clearer instructional design–are directly aligned with factors influencing ATU and indirectly, BI. These insights suggest that targeted interventions (e.g., training, curriculum integration, and tool refinement) could significantly enhance AI adoption in biology learning.

Thematic Insights: Barriers and Opportunities in AI Adoption

Barriers to AI adoption in biology learning

Our LDA and thematic analysis identified key concerns related to AI reliability, privacy, accessibility, and accuracy:

1. Security & privacy (topic 1 in LDA Analysis): Students expressed skepticism about sharing their biological experiment results with AI systems, fearing privacy breaches and AI misuse.
2. Reliability & accuracy: A significant portion of responses suggested that AI-generated biology content sometimes lacks contextual accuracy, making students hesitant to trust AI over traditional learning resources.
3. Technical barriers (topic 1 & topic 2): Issues with AI accessibility due to cost, digital literacy, and language barriers remain significant concerns. AI tools, particularly in Vietnam, are often English-based, which may limit usability among non-English-speaking students.

The integration of these barriers into the SEM model shows a significant negative impact of ACs on PU and BI, reinforcing the idea that improving AI trustworthiness is essential for widespread acceptance in biology education.

Benefits of AI adoption in biology

The positive themes emerging from the analysis reveal how AI enhances biology education:

1. AI as a conceptual guide (topic 2 & topic 3 in LDA): AI helps simplify complex biological processes, particularly in genetics, evolution, and biochemical pathways, where visualization and simulation aid learning (Kim & Kim, 2022).
2. Automated feedback & knowledge retrieval: AI-powered tools help students recall biological terms and structures, reinforcing knowledge retention through personalized study plans (Schmid et al., 2021).
3. AI and experimental design: Students found AI useful in hypothesis generation, data analysis, and experimental setup, making laboratory work more efficient.

These findings validate prior research that highlights AI's potential in STEM learning environments but uniquely contextualizes it within biology education.

CONCLUSION

This study, conducted in Ho Chi Minh City, utilized SEM with the 'lavaan' package (Rosseel et al., 2014), thematic analysis, and LDA to investigate AI adoption in biology self-learning. The findings suggest that the TAM does not fully account for adoption dynamics in this context, as PU influences ATU but not BI, and PEOU is a weak predictor, diverging from trends in general education (Granić & Marangunić, 2019). Biology students likely prioritize discipline-specific factors, such as AI accuracy and experimental integration, over ease of use.

Thematic analysis identified four key themes: barriers (e.g., concerns about AI accuracy and limited platform access), benefits (e.g., simplified concepts and personalized learning), challenges (e.g., limited experimental simulation capabilities), and suggested improvements (e.g., enhanced data analysis and educator training). LDA revealed three themes: AI limitations, AI as a learning assistant, and its role in laboratory applications. Students primarily use AI for exam preparation and homework, favoring structured tools like quizzes over open-ended chatbots, indicating a focus on short-term memorization rather than deep inquiry (Zawacki-Richter et al., 2019).

Key barriers, including skepticism about AI accuracy, restricted access, and insufficient experimental simulations, hinder adoption. These align with broader challenges in AI education, such as ethical concerns and high development costs (Xu & Ouyang, 2022). To address these, the study recommends developing AI platforms with virtual laboratory simulations to support practical learning, ensuring scientifically validated content to build trust, and providing specialized educator training to enhance integration. Institutional policies should invest in biology-specific AI tools and establish regulatory frameworks to ensure quality and ethical use.

To address these, the study recommends the following:

1. Virtual lab simulations: Develop AI platforms with features for virtual experiments and data analysis to support biology's experimental nature.
2. Scientific accuracy: Ensure AI-generated content is transparent and scientifically validated to address accuracy concerns and build trust.
3. Educator training: Provide specialized training on AI integration in STEM education to enhance effective teaching practices.
4. Institutional support: Invest in biology-specific AI platforms and establish regulatory frameworks to

align tools with pedagogical and scientific standards.

These findings suggest that AI in biology education must evolve beyond generic educational technology models to address the discipline's unique blend of theoretical and experimental learning. Unlike general education, where PU is a strong predictor of technology adoption, biology requires AI tools that facilitate virtual experiments and data analysis. Collaboration among AI developers, educators, and institutions is likely essential to create tailored solutions that enhance both learning and scientific inquiry. This research provides a foundation for future AI-driven innovations in STEM education, urging stakeholders to prioritize discipline-specific needs to realize AI's transformative potential in biology self-learning.

Author contributions: DTT: conceptualized the study, formulated the research objectives, developed the overall research design, created the survey questionnaire, established the research protocol, and conducted the theoretical analysis; **VPD:** designed the mixed-methods framework, ensured the integration of quantitative and qualitative approaches, collected both qualitative and quantitative data, conducted the thematic analysis of qualitative responses, and performed statistical analysis using R; & **HNV:** played a pivotal role in the design of the questionnaire, ensured that the survey accurately captured the perceptions and challenges of AI adoption among educators, involved in the distribution of the survey, facilitated broad participation across different educational contexts in Vietnam, contributed to data analysis, and assisted in the interpretation of quantitative and qualitative results. All authors agreed with the results and conclusions.

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AI statement: The authors stated that no generative AI tools were used for data analysis, content generation, or interpretation of results. All outputs generated by AI tools were critically reviewed, edited, and approved by the authors to ensure accuracy, originality, and compliance with academic standards.

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