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Development of AI-Enhanced Learning Environment to Reduce Cognitive Load and Strengthen Mental Resilience in Biotechnology Learning

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ABSTRACT
Biology learning in higher education, particularly in biotechnology, faces complex challenges due to excessive cognitive load experienced by Generation Z and Alpha students. This study aimed to develop and validate an AI-enhanced learning environment (AI-ELE) prototype specifically designed for biotechnology courses to reduce cognitive load, strengthen mental resilience, and foster 21st-century skills. Using a Research and Development (R&D) design, this study proceeded through two phases: Phase 1 (needs analysis) and Phase 2 (prototype development), which is the focus of this article. Needs analysis was conducted through surveys and focus group discussions with 100 students to identify sources of cognitive load in biotechnology learning. The prototype integrates an AI-assisted personalized learning system, an adaptive scaffolding mechanism, and an intelligent feedback module built upon Cognitive Load Theory and Self-Determination Theory. Expert validation was carried out by five specialists in instructional design, educational technology, and biology. Validation results showed an average expert score of 4.2/5.0, and the System Usability Scale (SUS) score reached 72.4, indicating an acceptable level of usability. The developed instruments—Cognitive Load Scale (CLS), Mental Resilience Inventory (MRI), and 21st Century Skills Assessment (21CSA)—demonstrated high reliability (Cronbach's alpha > 0.80). The findings confirm that the AI-ELE prototype is valid and ready for pilot implementation. This study contributes to the growing body of knowledge on technology-enhanced biology education and provides a practical framework for integrating AI tools into university-level biotechnology courses.

INTRODUCTION

Higher education in the 21st century faces unprecedented complexity in preparing students to thrive in a rapidly evolving digital era. Biology learning, particularly in domains such as biotechnology, cell biology, and microbiology, demands that students simultaneously process highly complex information with a high degree of element interactivity (Chen et al., 2023). This complexity frequently results in excessive cognitive load, which refers to the total mental effort required when processing information in working memory (Sweller, 1988). Such overload is particularly acute among Generation Z and Generation Alpha students (born 1997–2024), who are the first generation to grow up fully immersed in digital technology from birth (Ziatdinov & Cilliers, 2021).

Generation Z and Alpha learners are characterized by shorter attention spans, strong preferences for visual and interactive content, and high dependency on technological platforms (Kumar et al., 2024). The COVID-19 pandemic further accelerated these trends by dramatically shifting learning onto digital platforms, with compounding effects on their social and psychological development. These characteristics pose a significant challenge in biotechnology education, where deep conceptual understanding and higher-order thinking skills are non-negotiable requirements.

Cognitive Load Theory (CLT), originally formulated by Sweller (1988) and subsequently refined, postulates that human working memory has a finite capacity when processing novel information. Three types of cognitive load have been identified: intrinsic load (arising from the inherent complexity of the material), extraneous load (caused by poor instructional design), and germane load (associated with productive schema formation) (Sweller et al., 2019). In biotechnology, students are routinely required to process abstract molecular concepts, complex nomenclature, and microscopic visualizations concurrently, making cognitive overload both common and detrimental to learning outcomes (Graham et al., 2025).

Artificial intelligence (AI) has emerged as a transformative force in educational settings, offering the potential to optimize cognitive load through adaptive and personalized learning experiences (Mohamed et al., 2025). AI-powered tutoring systems and intelligent learning environments have been shown to improve students' intrinsic motivation, learning efficiency, and academic performance by systematically personalizing instructional content (D'Mello & Graesser, 2023). However, the integration of AI specifically within biology education remains underexplored, particularly with respect to its combined impact on cognitive load reduction and the strengthening of students' mental resilience (Khan et al., 2024).

Mental resilience is a crucial construct in contemporary higher education. Students who demonstrate academic resilience are capable of sustaining motivation and maintaining high academic performance despite encountering stress and setbacks (Martin & Marsh, 2006). Research confirms that academic resilience is positively correlated with psychological well-being and the capacity to manage educational demands (Wixcey et al., 2025). Conversely, students with low resilience are disproportionately vulnerable to academic anxiety, burnout, and eventual withdrawal from higher education (Xu et al., 2025). The development of instructional strategies that simultaneously address cognitive demands and build psychological resilience thus represents a critical priority for educators (Clarke et al., 2024).

The imperative to cultivate 21st-century skills—encapsulated by the 4C framework of critical thinking, creativity, communication, and collaboration—is well established in global educational policy and practice (Partnership for 21st Century Learning, 2019; OECD, 2019). The World Economic Forum (2024) has consistently emphasized that employers prioritize these competencies alongside domain-specific knowledge. Biotechnology education, with its inherently multidisciplinary and inquiry-based nature, offers an ideal context for integrating 21st-century skills development within a content-rich curriculum (Care et al., 2018).

Despite growing evidence supporting the potential of AI in education, significant gaps remain. No study has comprehensively integrated cognitive load reduction, mental resilience strengthening, and 21st-century skills development within a single AI-powered learning model specifically designed for university-level biotechnology courses. Additionally, existing research has largely focused on earlier student cohorts, leaving the unique characteristics of Generation Alpha insufficiently addressed.

This study therefore seeks to address these gaps by developing and validating an AI-Enhanced Learning Environment (AI-ELE) prototype tailored for biotechnology learning. The present article specifically reports on Phase 1 (needs analysis) and Phase 2 (prototype development) of a two-year R&D project. The objectives of this study are: (1) to identify sources of cognitive load experienced by students in biotechnology courses; (2) to design an AI-ELE prototype grounded in CLT and Self-Determination Theory; (3) to validate the prototype through expert review; and (4) to assess initial usability through a pilot evaluation.

METHOD

Research Design

This study adopted a Research and Development (R&D) design following the ADDIE framework (Analyze, Design, Develop, Implement, Evaluate), integrated with expert validation procedures. The present report covers the Analysis and Development phases, corresponding to Phase 1 (Needs Analysis) and Phase 2 (Prototype Development) of the larger research project. A mixed-methods approach was employed: quantitative data were collected through validated instruments and usability scales, while qualitative data were gathered through focus group discussions (FGDs) and semi-structured interviews.

Participants

Phase 1 involved 100 undergraduate Biology Education students enrolled in the Biotechnology course at a state university in West Java, Indonesia. Purposive sampling was used to ensure representation across different academic achievement levels. For expert validation, five validators were recruited: two specialists in instructional design, two in educational technology, and one in biology content. For usability testing, 15 students participated in a preliminary user-testing session.

Instruments

Three core instruments were developed and validated in this study. The first instrument, the Cognitive Load Scale (CLS), is a 20-item instrument adapted from the NASA-TLX and validated CLT instruments, measuring intrinsic, extraneous, and germane cognitive load on a 7-point Likert scale (1 = very low, 7 = very high). The second instrument, the Mental Resilience Inventory (MRI), is a 25-item instrument adapted from the Academic Resilience Scale (Cassidy, 2016) and the Connor-Davidson Resilience Scale, measuring emotional regulation, adaptability, and perseverance. The third instrument, the 21st Century Skills Assessment (21CSA), is a rubric-based instrument assessing 4C competencies (critical thinking, creativity, communication, collaboration), aligned with the P21 Framework (Partnership for 21st Century Learning, 2019).

Content validity was established through expert review (Content Validity Index, CVI > 0.80). Reliability was assessed using Cronbach's alpha computed from a sample of 30 students prior to the main implementation phase.

AI-ELE Prototype Development

The AI-ELE prototype was developed as a web-based platform integrating a Learning Management System (LMS) with AI tools. The platform was built upon three core instructional components: (1) AI-Assisted Personalized Learning, which dynamically adjusts content complexity based on each student's interaction data; (2) an Adaptive Scaffolding System, which automatically activates scaffolds—such as concept maps, annotated diagrams, and worked examples—upon detecting cognitive overload indicators; and (3) an Intelligent Feedback Mechanism, which provides real-time formative feedback and metacognitive prompts to encourage self-regulated learning.

The platform was designed in accordance with three CLT principles: reduction of extraneous load through coherent multimedia design, optimization of germane load through problem-based tasks, and management of intrinsic load through progressive content sequencing. Self-Determination Theory (Deci & Ryan, 2000) informed the motivational architecture by addressing autonomy (learner-controlled pathways), competence (progressive badging), and relatedness (collaborative reflection forums). Mental resilience support was embedded through motivational messaging and psychoeducational micro-modules on academic stress management.

Expert Validation Procedure

Expert validation was conducted using a structured evaluation rubric assessing five dimensions: content accuracy, instructional design quality, AI integration appropriateness, usability, and resilience-support features. Each dimension was scored on a 5-point Likert scale (1 = very poor, 5 = very good). An average score of ≥ 4.0/5.0 was set as the threshold for proceeding to pilot testing. Qualitative feedback from validators was subsequently used to refine the prototype.

Usability Testing

Usability was assessed using the System Usability Scale (SUS), a validated 10-item instrument widely used in educational technology research. A SUS score of ≥ 68 was adopted as the benchmark for acceptable usability (Brooke, 1996). Fifteen students accessed the prototype for 60 minutes and subsequently completed the SUS questionnaire, followed by a brief reflective interview.

Data Analysis

Quantitative data from validation surveys and SUS scores were analyzed using descriptive statistics (means, standard deviations, percentages) using SPSS version 26.0. Reliability of the developed instruments was computed using Cronbach's alpha. Qualitative data from FGDs and validator feedback were analyzed thematically following Braun and Clarke's six-phase framework. Ethical clearance was obtained from the institutional research ethics board prior to data collection, and all participants provided written informed consent.

RESULTS AND DISCUSSION

Results

Phase 1 – needs analysis results

Findings from the needs analysis survey and FGDs with 100 students revealed significant challenges in biotechnology learning. The majority of students (78%) reported experiencing high cognitive load when studying abstract molecular processes such as recombinant DNA technology, PCR mechanisms, and gene expression regulation. Specifically, 65% indicated difficulty in simultaneously processing complex diagrams, technical terminology, and procedural sequences. These findings corroborate Chen et al. (2023), who demonstrated that high element interactivity in scientific content is a primary driver of intrinsic cognitive load.

Furthermore, 71% of students described experiencing academic anxiety and motivational decline when confronted with complex biotechnology assessments, indicating limited mental resilience in the academic context (Xu et al., 2025). FGD discussions further revealed that students felt the pace of conventional lectures did not accommodate their individual learning needs, and that feedback was typically too delayed to be corrective in real time. These findings strongly supported the rationale for developing an adaptive AI-powered learning environment. A summary of the key challenges identified is presented in Table 1.

Table 1. Summary of Needs Analysis: Major Challenges in Biotechnology Learning

Challenge Area	Percentage (%)	Predominant Concern
Cognitive overload from complex content	78	Simultaneous processing of diagrams and terminology
Lack of real-time feedback	74	Delayed corrective information during learning
Academic anxiety and burnout	71	Reduced motivation during complex tasks
Insufficient adaptive learning support	68	One-size-fits-all instructional pace

Challenge Area	Percentage (%)	Predominant Concern
Poor collaborative learning opportunities	59	Limited peer interaction and co-construction

Source: Authors' Survey Data (2025)

Phase 2 – AI-ELE prototype development

Based on the needs analysis, the AI-ELE prototype was developed with a focus on four biotechnology topics: (1) recombinant DNA technology, (2) polymerase chain reaction (PCR), (3) microbial fermentation, and (4) genetic engineering applications. Each module was structured as a learning unit incorporating pre-assessment, adaptive content delivery, scaffolded practice activities, collaborative discussion tasks, and AI-generated formative feedback.

The AI component was built upon large language model APIs integrated within a custom LMS interface. The system was programmed to detect cognitive overload indicators—including extended response latency (>30 seconds on concept questions), repeated incorrect responses (≥2 on the same item), and early module-exit behavior—and to trigger appropriate scaffolding interventions accordingly. This approach aligns with recommendations from D'Mello and Graesser (2023), who emphasized the importance of detecting and responding to cognitive and emotional states in intelligent tutoring systems.

The SDT-informed motivational architecture addressed three basic psychological needs: autonomy through learner-controlled navigation pathways, competence through progressive competency badging, and relatedness through collaborative inquiry features. This design approach is supported by Mohamed et al. (2025), who found that SDT-based instructional design effectively fosters intrinsic motivation in AI-enhanced learning environments.

Expert validation

Expert validation yielded an overall mean score of 4.2/5.0 (SD = 0.31), which exceeded the predefined threshold of ≥ 4.0/5.0, confirming the prototype's readiness for pilot testing. Detailed scores for each validation dimension are presented in Table 2.

Table 2. Expert Validation Results for AI-ELE Prototype

Validation Dimension	Mean Score	SD	Category
Content Accuracy and Relevance	4.4	0.24	Very Good
Instructional Design Quality	4.3	0.33	Very Good
AI Integration Appropriateness	4.1	0.38	Good
User Interface and Usability	4.0	0.29	Good
Resilience-Support Features	4.2	0.35	Very Good
Overall Mean	4.2	0.31	Very Good

Note: Scale 1–5; threshold for prototype readiness ≥ 4.0.

Content accuracy received the highest score (4.4), reflecting the rigorous peer review of biotechnology curriculum materials. The AI integration dimension received the lowest score (4.1), underscoring the ongoing challenge of ensuring that AI-generated feedback is pedagogically sound and transparent—a challenge consistent with broader discourse in the AI in Education literature (World Economic Forum, 2024). Validators recommended strengthening the explainability of AI-generated feedback, and this revision was incorporated before usability testing.

Instrument reliability

All three instruments demonstrated high reliability. The CLS achieved a Cronbach's alpha of 0.87, the MRI yielded $\alpha = 0.84$, and the 21CSA produced an inter-rater reliability of ICC = 0.82. These values exceed the widely accepted threshold of $\alpha > 0.70$ (Cassidy, 2016), confirming their suitability for implementation in the subsequent experimental phase. Details are presented in Table 3.

Table 3. Reliability Summary of Developed Instruments

Instrument	Items (n)	Reliability Coefficient	Type	Interpretation
Cognitive Load Scale (CLS)	20	α = 0.87	Cronbach's Alpha	High
Mental Resilience Inventory (MRI)	25	α = 0.84	Cronbach's Alpha	High
21st Century Skills Assessment (21CSA)	16 criteria	ICC = 0.82	Inter-rater Reliability	High

Note: Threshold for acceptable reliability: α or ICC > 0.70.

Usability testing

The SUS assessment produced a mean score of 72.4, exceeding the accepted benchmark of 68 and falling within the 'Good' usability category. Students found the interface intuitive and the AI-generated feedback helpful for self-monitoring. Reflective interviews indicated that adaptive scaffolding was particularly appreciated: students reported feeling less overwhelmed when the system automatically presented supplementary visual explanations upon detecting difficulties. These findings are consistent with Toh and Tasir (2024), who demonstrated that adaptive mobile learning applications can significantly reduce perceived cognitive load in biology contexts.

Minor usability issues identified included occasional delays in AI response generation and an initially unfamiliar navigation menu. These issues were addressed in a subsequent interface revision. The mean time-on-task for completing one biotechnology module was 47 minutes, indicating reasonable engagement without excessive cognitive burden.

Discussion

The validated AI-ELE prototype represents a meaningful advancement in the integration of AI technology within biology education. By simultaneously addressing cognitive load through CLT-based design, motivation and resilience through SDT-aligned features, and 21st-century skills through collaborative inquiry tasks, this prototype offers a holistic instructional model that addresses documented gaps in the literature.

The strong expert validation scores across all five dimensions confirm both theoretical fidelity and practical appropriateness. The finding that AI integration received the lowest validation score is noteworthy and consistent with broader debates in the field: ensuring that AI-generated feedback is accurate, transparent, and pedagogically aligned remains a complex engineering and instructional challenge (World Economic Forum, 2024; Khan et al., 2024). Future iterations should incorporate explainable AI (XAI) principles to address validator concerns.

The reliability of all three instruments constitutes a methodological contribution in its own right. Integrated measurement frameworks capable of simultaneously assessing cognitive load, mental resilience, and 21st-century skills within a single study remain scarce (Wixcey et al., 2025; Brockbank & Feldon, 2024). The availability of these validated instruments will support the planned quasi-experimental phase and enable rigorous comparative analysis between experimental and control groups.

The SUS score of 72.4 confirms that the platform is technically accessible without introducing additional extraneous cognitive load—a critical consideration in technology-enhanced learning (Mugisha & Arguel, 2025). Qualitative feedback confirming appreciation for adaptive scaffolding aligns with meta-analytic evidence from Steenbergen-Hu and Cooper (2014), who found that intelligent tutoring systems consistently produce superior learning outcomes in complex science subjects. These convergent findings collectively position the AI-ELE as theoretically grounded, expertly validated, reliably instrumented, and practically usable for full-scale implementation.

CONCLUSION AND SUGGESTION

This study successfully developed and validated an AI-Enhanced Learning Environment (AI-ELE) prototype for biotechnology learning in higher education. Grounded in Cognitive Load Theory and Self-Determination Theory, the prototype integrates AI-assisted personalized learning, adaptive scaffolding, and intelligent feedback mechanisms to holistically address cognitive, motivational, and skill-development needs of Generation Z and Alpha students. Phase 1 needs analysis confirmed that 78% of students experienced high cognitive load and 71% reported academic anxiety in biotechnology learning, underscoring the urgency of adaptive instructional solutions. Phase 2 prototype development produced a robust tool validated by five experts (mean score 4.2/5.0) and assessed as usable by students (SUS = 72.4). All three developed instruments demonstrated high reliability ($\alpha > 0.80$; ICC = 0.82), establishing a rigorous measurement framework for the subsequent experimental phase.

Future studies should proceed to implement and evaluate the AI-ELE across broader student populations and additional biology subjects, including cell biology and microbiology, as planned in the full-scale quasi-experimental phase. Researchers are also encouraged to explore the integration of learning analytics dashboards to enable real-time monitoring of students' cognitive and emotional states by instructors. At the policy level, higher education institutions in Indonesia are encouraged to consider AI-enhanced adaptive learning platforms as a strategic response to the documented learning challenges among Generation Z and Alpha students, particularly in STEM disciplines.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this article.

AUTHOR CONTRIBUTIONS STATEMENT

Conceptualization, M.H. and C.; methodology, M.H. and C.; data curation, M.H.; formal analysis, M.H.; investigation, M.H. and C.; validation, C. and C.T.; writing—original draft preparation, M.H.; writing—review and editing, M.H., C., and C.T.; supervision, C. and C.T.; project administration, M.H. All authors have read and agreed to the published version of the manuscript.

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DECLARATION OF GENERATIVE AI SOURCES

During the preparation of this manuscript, the author(s) used Claude (Anthropic) for language refinement and structural editing. All generated content was carefully reviewed, revised, and verified by the author(s), who take full responsibility for the final content of the manuscript.

REFERENCES

Brockbank, R. B., & Feldon, D. F. (2024). Cognitive reappraisal: The bridge between cognitive load and emotion. *Education Sciences, 14*(8), 840. https://doi.org/10.3390/educsci14080840

Brooke, J. (1996). SUS: A "quick and dirty" usability scale. In P. W. Jordan, B. Thomas, B. A. Weerdmeester, & A. L. McClelland (Eds.), *Usability evaluation in industry* (pp. 189–194). Taylor & Francis.

Care, E., Griffin, P., & Wilson, M. (Eds.). (2018). *Assessment and teaching of 21st century skills: Research and applications*. Springer. https://doi.org/10.1007/978-3-319-65368-6

Cassidy, S. (2016). The Academic Resilience Scale (ARS-30): A new multidimensional construct measure. *Frontiers in Psychology, 7*, 1787. https://doi.org/10.3389/fpsyg.2016.01787

Chen, O., Paas, F., & Sweller, J. (2023). A cognitive load theory approach to defining and measuring task complexity through element interactivity. *Educational Psychology Review, 35*, Article 63. https://doi.org/10.1007/s10648-023-09782-w

Clarke, A., Thackray, L., & Nightingale, S. (2024). The impact of resilience interventions on university students' mental health and well-being: A systematic review. *Education Sciences, 14*(5), 510. https://doi.org/10.3390/educsci14050510

D'Mello, S. K., & Graesser, A. (2023). Intelligent tutoring systems: How computers achieve learning gains that rival human tutors. In L. Corno & E. M. Anderman (Eds.), *Handbook of Educational Psychology* (pp. 603–629). Routledge. https://doi.org/10.4324/9780429433726-31

Deci, E. L., & Ryan, R. M. (2000). *The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. Psychological Inquiry, 11*(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01

Graham, S., Ayala, J., & Thiessen, A. (2025). Cognitive load theory: Emerging trends and innovations. *Education Sciences, 15*, 458. https://doi.org/10.3390/educsci15040458

Khan, A., Egbue, O., Palkie, B., & Madden, J. (2024). Re-evaluating components of classical educational theories in AI-enhanced learning: An empirical study on student engagement. *Education Sciences, 14*(9), 974. https://doi.org/10.3390/educsci14090974

Kumar, R., Singh, S., & Patel, D. (2024). A systematic literature review of education for Generation Alpha. *Discover Education, 1*, Article 218. https://doi.org/10.1007/s44217-024-00218-3

Martin, A. J., & Marsh, H. W. (2006). Academic resilience and its psychological and educational correlates: A construct validity approach. *Psychology in the Schools, 43*(3), 267–281. https://doi.org/10.1002/pits.20149

Mohamed, A. M., Shaaban, T. S., Bakry, S. H., Guillén-Gámez, F. D., & Strzelecki, A. (2025). Empowering the Faculty of Education students: Applying AI's potential for motivating and enhancing learning. *Innovative Higher Education, 50*, 587–609. https://doi.org/10.1007/s10755-024-09747-z

Mugisha, G., & Arguel, A. (2025). Procedural learning in mixed reality: Assessing cognitive load and performance. *Education Sciences, 15*(3), 339. https://doi.org/10.3390/educsci15030339

OECD. (2019). *Skills for 2030: OECD Future of Education and Skills*. OECD.

Partnership for 21st Century Learning. (2019). *Framework for 21st Century Learning*. Battelle for Kids.

Steenbergen-Hu, S., & Cooper, H. (2014). A meta-analysis of the effectiveness of intelligent tutoring systems on college students' academic learning. *Journal of Educational Psychology, 106*(2), 331–347. https://doi.org/10.1037/a0034752

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Sweller, J., van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. *Educational Psychology Review, 31*, 261–292. https://doi.org/10.1007/s10648-019-09465-5

Toh, T. J., & Tasir, Z. (2024). The impact of a mobile learning application on students' cognitive load and learning performance in biology. *Journal of Information Technology Education: Research, 23*, Article 26. https://doi.org/10.28945/5312

World Economic Forum. (2023). *The Future of Jobs Report 2023*. World Economic Forum.

World Economic Forum. (2024). *Shaping the Future of Learning: The Role of AI in Education 4.0*. World Economic Forum.

Wixcey, H., Cropley, B., & Shearer, D. (2025). *Examining the influence of mental well-being and resilience on academic outcomes in further education learners*. *Research in Post-Compulsory Education*. https://doi.org/10.1080/0309877X.2024.2440501

Xu, M., Zhang, Y., & Li, H. (2025). Psychological resilience and future anxiety among university students: The mediating role of subjective well-being. *Healthcare, 13*(3), 241. https://doi.org/10.3390/healthcare13030241

Ziatdinov, R., & Cilliers, J. (2021). *Generation Alpha: Understanding the next cohort of university students*. *European Journal of Contemporary Education, 10*(3), 783–789. https://doi.org/10.13187/ejced.2021.3.783