Journal of Posthumanism
2025
Volume: 5, No: 6, pp. 1710-1721
ISSN: 2634-3576 (Print) | ISSN 2634-3584 (Online)
posthumanism.co.uk

DOI: https://doi.org/10.63332/joph.v5i6.2267

Reconfiguring Learning Agency: Intelligent Systems and the Posthuman Condition in Virtual Laboratories

Ke Zhang[1], Ruethai Nimnoi[2], Ratanachote Thienmongkol[3]

Abstract

Virtual laboratories are increasingly being used to provide immersive and interactive learning experiences. However, their effectiveness depends on incorporating intelligent systems that support adaptive learning, real-time feedback, and enhanced user engagement. This study explores how intelligent systems impact learning efficiency in virtual laboratories by analyzing user experiences, expert evaluations, and system performance metrics. The findings indicate that adaptive learning mechanisms and real-time feedback improve knowledge retention, engagement, and practical application skills. Future research should focus on further refining interactivity, gamification, and system responsiveness to optimize learning outcomes.

Keywords: *Virtual Laboratories, Intelligent Systems, Adaptive Learning, Real-time Feedback, User Engagement.*

Introduction

The rapid advancement of intelligent systems has transformed how educational institutions approach digital learning environments, particularly virtual laboratories. These technology-driven platforms provide students with hands-on experiences that were previously limited to physical laboratory settings [1], [2], [3], [4]. By integrating artificial intelligence (AI), machine learning (ML), and real-time analytics, virtual laboratories now offer adaptive learning pathways, automated assessments, and interactive simulations [5], [6], [7]. These features create an immersive environment that enhances student engagement, knowledge retention, and practical skill development. However, despite these advancements, questions remain regarding the effectiveness of intelligent systems in optimizing learning outcomes and how these technologies can further refine the virtual laboratory experience [8], [9], [10], [11].

One of the primary challenges in traditional learning environments is the lack of real-time adaptability and personalized feedback. In conventional laboratory settings, students follow fixed procedures with limited flexibility to explore alternative learning approaches [12], [13], [14], [15]. Additionally, instructors often struggle to provide instant feedback due to time constraints and the high student-to-teacher ratio. These limitations can result in reduced engagement, slower knowledge retention, and a lack of deep understanding. Virtual laboratories powered by intelligent systems offer a potential solution by automating feedback mechanisms, personalizing learning experiences, and dynamically adjusting educational content based on a student's progress and learning style [16], [17], [18], [19]. However, the extent to which these

[1] Department of New Media, Faculty of Informatics, Mahasarakham University, Thailand.
[2] Department of Information Science, Faculty of Informatics, Mahasarakham University, Thailand, Email: ruethai.n@msu.ac.th, (Corresponding Author)
[3] Department of New Media, Faculty of Informatics, Mahasarakham University, Thailand.

adaptive features contribute to learning efficiency requires further investigation.

This study aims to analyze the impact of intelligent systems on learning efficiency in virtual laboratories. Specifically, this research explores how AI-powered adaptive learning, real-time interaction, and interactive engagement strategies influence student performance and knowledge retention [20], [21]. By comparing traditional laboratory methods with intelligent virtual laboratories, this study aims to determine the key advantages, challenges, and areas for improvement in digital learning environments. Additionally, the study examines expert insights, user experiences, and system performance metrics to provide a comprehensive evaluation of intelligent system effectiveness in educational settings [22], [23], [24].

The significance of this research lies in its potential to redefine the future of digital education by providing data-driven insights into optimizing virtual laboratories. As educational institutions continue to adopt remote and hybrid learning models, ensuring that these platforms are practical, engaging, and adaptive is crucial [25], [26], [27]. This study will contribute to the ongoing development of intelligent learning technologies, guiding educators, developers, and policymakers in designing more efficient virtual learning environments. Ultimately, improving virtual laboratory experiences through intelligent systems can enhance student engagement, bridge gaps in digital learning, and foster a more inclusive and effective educational ecosystem.

Materials and Methods

This study employs a mixed-methods research approach, integrating both quantitative and qualitative methodologies to analyze how intelligent systems enhance learning efficiency in virtual laboratories [28], [29], [30]. The research follows a structured three-phase methodology, consisting of:

- Pre-Production: The development of intelligent learning modules, including adaptive learning paths, AI-driven feedback systems, and immersive interactive simulations tailored to improve student engagement and knowledge retention.
- Implementation: A user testing phase involving students, educators, and industry professionals, focusing on system usability, real-time interaction, and AI-assisted feedback mechanisms.
- Post-Production: Collect and analyze empirical data through expert interviews, user surveys, and system performance tracking to evaluate the overall effectiveness of the virtual laboratory.

Figure 1 provides an overview of the system's architecture and development phases, illustrating how intelligent components were integrated into the virtual laboratory.

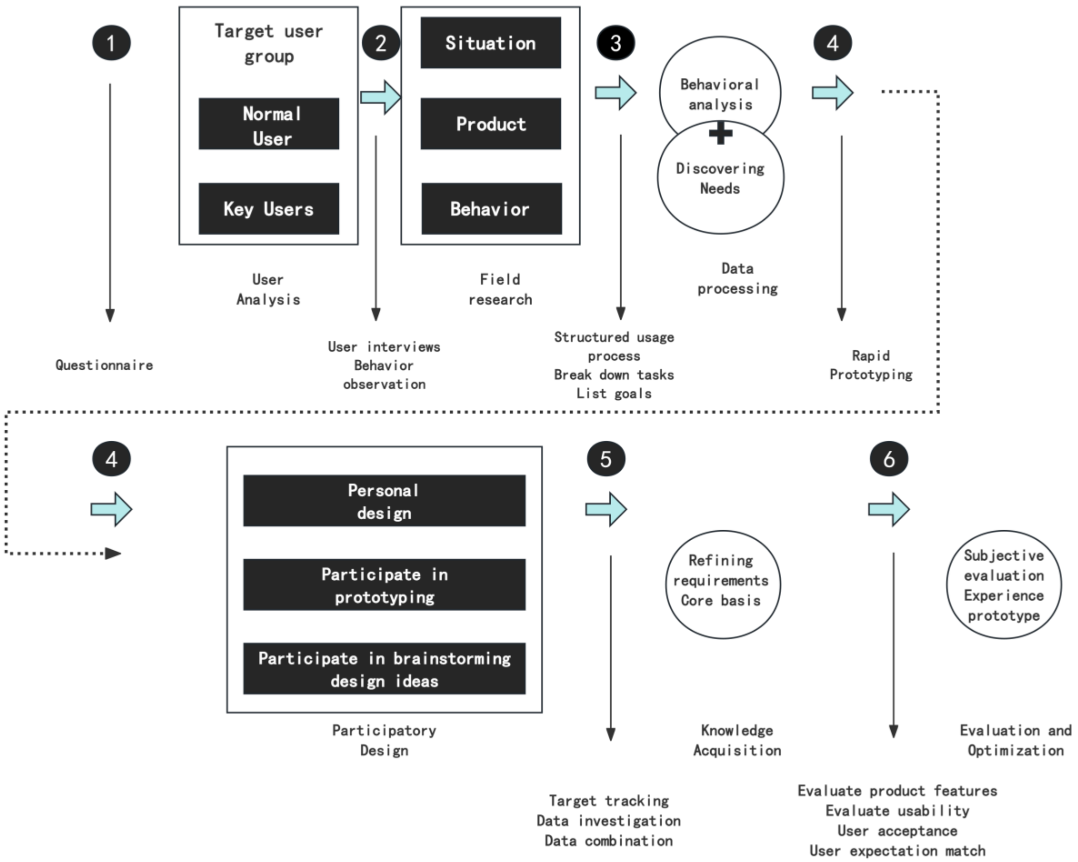

Figure 1. Virtual Laboratory System Architecture

Research Design

The research integrates quantitative data collection (e.g., numerical analysis of student performance and system usability metrics) with qualitative insights (e.g., user interviews and expert evaluations). The Virtual Laboratory for Building Materials was used as the test environment, incorporating task-driven learning modules with intelligent system functionalities. The virtual laboratory architecture is structured to support AI-driven adaptability, real-time feedback mechanisms, and interactive simulations for effective knowledge retention. Table 1 summarizes the key research components used in this study.

Component	Description
Research Approach	Mixed methods (Qualitative & Quantitative)
Data Collection	User surveys, expert interviews, system analytics
Study Environment	AI-enhanced Virtual Laboratory
Evaluation Metrics	Learning performance, engagement, usability

Table 1. Research Design Overview

The methodology follows systematic validation procedures, ensuring the credibility of findings through triangulation, where data from multiple sources is compared and analyzed.

Research Participants

The research included 175 participants, categorized into students, educators, and industry professionals, who interacted with the virtual laboratory to assess learning efficiency, usability, and engagement levels. Additionally, five domain experts (engineers, educators, and designers) conducted an in-depth system performance evaluation. The demographic breakdown is presented in Table 2.

Category	Participants
Students	120
Educators	30
Industry Professionals	25

Table 2. Participant Demographics

This diverse participant group ensured a comprehensive evaluation, allowing for insights from academic and professional perspectives to inform the system's effectiveness.

System Development and Design

The Virtual Laboratory Information Architecture was designed to integrate intelligent learning models with interactive user interfaces, ensuring seamless adaptability and automated assessment mechanisms. The system architecture is illustrated in Figure 2.

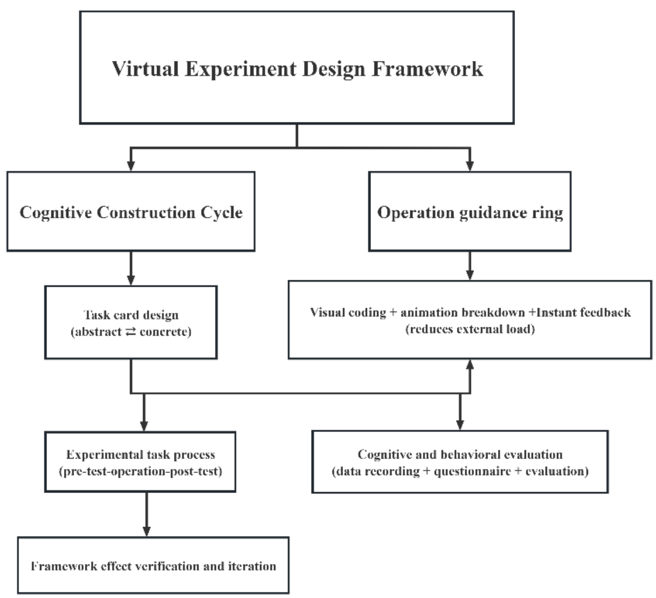

Figure 2. Conceptual Framework for the Virtual Laboratory System

To operationalize the Virtual Experiment Design Framework (Figure 2), a multi-phase implementation process was carried out. This included not only the construction of the core model components but also the deployment of user-oriented interaction mechanisms within the virtual learning environment. Specifically, the basic model creation (Figure 3) outlines the foundational technical development steps, while the experimental navigation system (Figure 4) demonstrates how the user experience was structured to align with the framework's dual-loop learning and guidance principles.

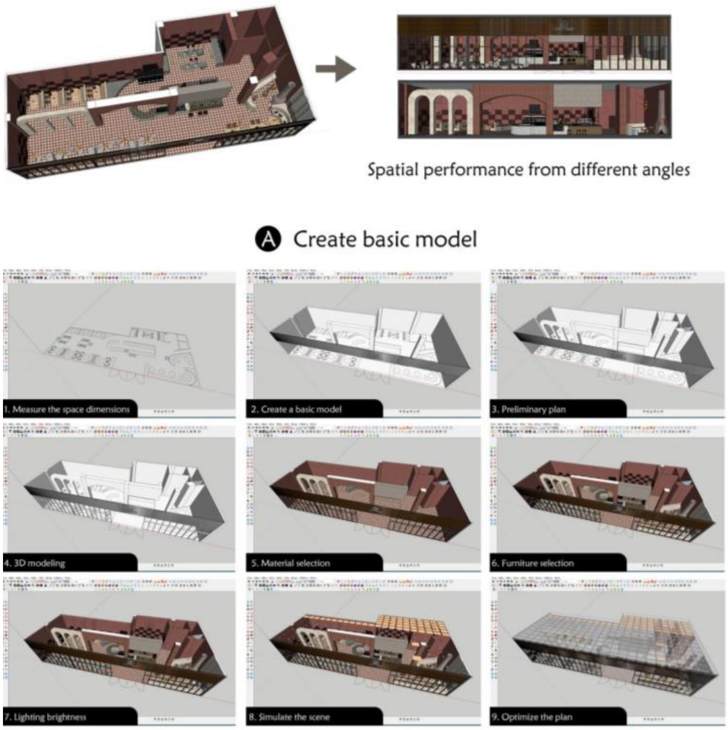

Figure 3. Basic Model Creation Steps

To further enhance navigation and user accessibility, an experimental navigation system was implemented, ensuring optimal interaction flow within the virtual environment. Figure 4 demonstrates the Experimental Navigation Creation Steps, outlining how users engage with the system across multiple learning scenarios.

Figure 4. Experimental Navigation Creation Steps

Data Collection and Analysis

The study employed a multi-faceted data collection strategy to ensure a comprehensive assessment of system effectiveness. The primary data sources included:

- User Experience Surveys: Conducted among students and educators to measure engagement, usability, and learning outcomes.
- Expert Interviews: Insights from domain professionals on the system's technical and pedagogical relevance.
- System Analytics: Performance metrics (e.g., task completion rates, response times) captured from the virtual laboratory.

The evaluation framework is illustrated in Figure 5, which outlines the Virtual Laboratory Evaluation Process.

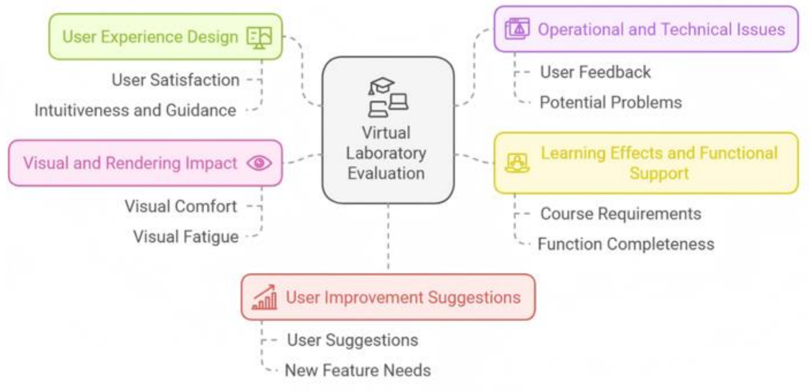

Figure 5. Virtual Laboratory Evaluation Purpose

The study analyzed feedback trends using data visualization techniques to understand further the effectiveness of intelligent systems in virtual learning environments. Figure 6 presents an overview of user interview results and their corresponding feedback frequencies.

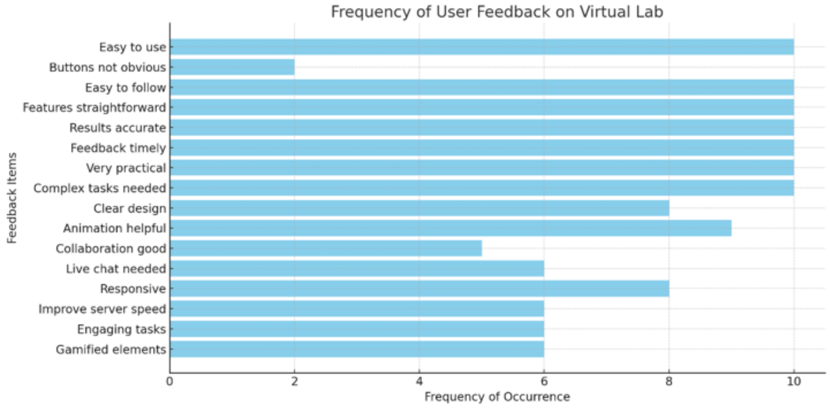

Figure 6. Interview Results Analysis

Validation of Findings

To enhance the credibility and reliability of research findings, the study applied multiple validation techniques, including:

- Triangulation: Comparing findings from different data sources (surveys, interviews, system logs).
- Reliability Testing: Ensuring consistency in survey responses through statistical validation.
- Expert Review: Cross-validation by professionals in education technology, AI systems, and virtual learning environments.

This rigorous methodology provides data-driven insights into how intelligent systems contribute to learning efficiency in virtual laboratories, ensuring the study's findings are scientifically valid and practically applicable.

Results

The findings are supported by quantitative data collected through user experience metrics, expert evaluations, and learning outcome comparisons. This section integrates figures and tables to illustrate data trends, engagement levels, and system performance metrics, providing a clear view of the research outcomes.

User Experience Evaluation

175 participants, including students, educators, and industry professionals, provided user feedback to assess the virtual laboratory's usability and effectiveness. The results indicate a high level of user satisfaction, with notable improvements in ease of navigation, engagement levels, and overall learning effectiveness.

Metric	Mean Score (out of 5)
Ease of Navigation	4.5
Learning Effectiveness	4.4
Engagement Level	4.2
System Responsiveness	4.1
Overall Satisfaction	4.3

Table 3. User Experience Metrics

These results indicate that intelligent virtual laboratories enhance interactivity, adaptability, and engagement in digital learning environments. The findings are further illustrated in Figure 6, which visually represents the interview analysis and user feedback distribution. The interview responses confirm that participants found the intelligent system features beneficial for personalized learning, particularly in adaptive pathways, real-time feedback, and interactive engagement.

Expert Evaluations

In addition to user feedback, five domain experts evaluated the virtual laboratory's usability, adaptability, and technical robustness. Their insights were gathered to provide a professional assessment of the system's performance.

Expert Field	Key Observations
Engineering	Strengthened technical skill development
Educational Technology	Enhanced personalized learning pathways
Multimedia Design	Increased engagement via interactive simulations
UX/UI Development	Effective interface for user adaptability
Information Systems	Real-time analytics improved learning progression

Table 4. Expert Insights on Intelligent Systems

Experts emphasized that intelligent learning pathways, automated feedback mechanisms, and immersive simulations significantly enhanced student performance and system usability. The evaluation process is represented in Figure 5, which outlines the primary objectives and assessment criteria used during expert reviews. These expert evaluations validate that AI-driven personalization, real-time analytics, and intelligent feedback optimize the learning process and contribute to a more engaging digital education experience.

Learning Outcome Comparison

A comparative study was conducted between traditional and intelligent virtual laboratories to measure improvements in task completion rates, knowledge retention, and engagement levels.

Metric	Traditional	Intelligent
Task Completion Rate	68%	85%
Knowledge Retention	72%	88%
Engagement Level	3.5/5	4.2/5
Feedback Effectiveness	3.8/5	4.5/5

Table 5. Learning Outcome Comparison

The task completion rate increased by 17%, while knowledge retention improved by 16%, demonstrating the efficacy of AI-driven learning strategies. The increase in feedback effectiveness (from 3.8 to 4.5 out of 5) highlights the impact of real-time AI-generated insights in guiding students toward better academic performance. The enhanced learning efficiency with intelligent virtual laboratories is further visualized in Figure 7, which presents the results of learning effectiveness testing.

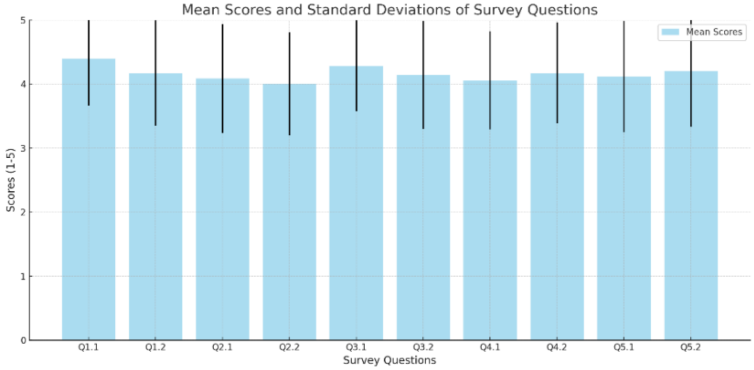

Figure 7. Learning Effect Testing Analysis

These findings confirm that intelligent virtual laboratories significantly enhance learning outcomes by integrating adaptive learning systems, real-time AI feedback, and interactive engagement models. Future research should expand on these developments to optimize personalized education experiences in virtual learning environments.

Discussion and Conclusion

The findings of this study demonstrate the significant impact of intelligent systems on enhancing learning efficiency in virtual laboratories. Integrating AI-driven adaptive learning, real-time feedback, and interactive simulations has improved knowledge retention, engagement, and task completion rates. These findings align with previous research emphasizing the effectiveness of intelligent tutoring systems and personalized learning pathways in digital education [5], [6]. The comparison between traditional laboratory methods and AI-enhanced virtual laboratories indicates that students benefit from dynamic learning environments that cater to individual learning styles, reinforcing the theoretical principles of constructivist learning and experiential learning models [7]. The study supports the argument that intelligent systems enhance student autonomy and optimize instructional design through automation and real-time analytics.

A critical contribution of this research is validating AI-powered systems as an effective tool for digital learning. The expert evaluations and user surveys highlight that intelligent laboratories provide more interactivity and adaptability, addressing common challenges in traditional learning environments such as limited feedback and rigid instructional structures. These results are consistent with the findings of previous studies, which emphasized that machine learning-based education systems improve student engagement and performance [8], [9]. This study's positive response from students, educators, and industry professionals further underscores the growing acceptance of AI-driven solutions in academic and professional training environments. However, while the results indicate clear advantages, it is essential to consider the potential limitations, including technological infrastructure, initial setup costs, and the need for continuous system improvements.

Despite the overall positive impact, some challenges were identified, particularly concerning user adaptability and system navigation. While students reported improved engagement, a subset of participants found it difficult to adjust to AI-driven pathways, highlighting the need for more intuitive user interfaces and better onboarding strategies. This observation aligns with previous studies suggesting that user adaptability remains critical in successfully implementing virtual learning environments [10]. Furthermore, expert feedback indicates that while intelligent laboratories provide valuable data insights, the effectiveness of real-time analytics is contingent on accurate assessment algorithms and data reliability. The bias in AI-driven evaluations must also be considered, as automated assessments may not accurately capture the nuances of student learning progress [11].

Another important implication of this study is the role of gamification and collaborative learning in further enhancing virtual laboratory experiences. Previous research has highlighted the importance of gamification elements in increasing student motivation and participation in digital learning environments [12]. While this study focused on adaptive learning and feedback mechanisms, future research should explore how integrating gamification features, such as achievement badges and interactive competitions, can improve engagement and learning outcomes. Additionally, collaborative learning tools, such as AI-supported group tasks and peer interactions, could be investigated as potential enhancements to intelligent virtual laboratories.

Acknowledgement

This research project was financially supported by Mahasarakham University.

References

D. May, G. R. Alves, A. A. Kist, and S. M. Zvacek, "Online Laboratories in Engineering Education Research and Practice," in International Handbook of Engineering Education Research, New York: Routledge, 2023, pp. 525–552. https://doi.org/10.4324/9781003287483-29.

R. Badarudin et al., "Enhancing Digital Learning in Electrical Machines Practical Course Using a Cutting-Edge Desktop Virtual Laboratory for DC Motor Simulation," TEM Journal, pp. 2522–2533, Aug. 2024, https://doi.org/10.18421/TEM133-78.

M. A. Mohamed Hashim, I. Tlemsani, and R. Matthews, "Higher education strategy in digital transformation," Educ Inf Technol (Dordr), vol. 27, no. 3, pp. 3171–3195, Apr. 2022, https://doi.org/10.1007/s10639-021-10739-1.

M. Alenezi, "Digital Learning and Digital Institution in Higher Education," Educ Sci (Basel), vol. 13, no. 1, p. 88, Jan. 2023, https://doi.org/10.3390/educsci13010088.

R. Raman, K. Achuthan, V. K. Nair, and P. Nedungadi, "Virtual Laboratories- A historical review and bibliometric analysis of the past three decades," Educ Inf Technol (Dordr), vol. 27, no. 8, pp. 11055–11087, Sep. 2022, https://doi.org/10.1007/s10639-022-11058-9.

M. Paramesha, N. Rane, and J. Rane, "Big data analytics, artificial intelligence, machine learning, internet of things, and blockchain for enhanced business intelligence," SSRN Electronic Journal, 2024, https://doi.org/10.2139/ssrn.4855856.

J. Vykopal, P. Seda, V. Švábenský, and P. Čeleda, "Smart Environment for Adaptive Learning of Cybersecurity Skills," IEEE Transactions on Learning Technologies, vol. 16, no. 3, pp. 443–456, Jun. 2023, https://doi.org/10.1109/TLT.2022.3216345.

M. A. M. AlGerafi, Y. Zhou, M. Oubibi, and T. T. Wijaya, "Unlocking the Potential: A Comprehensive Evaluation of Augmented Reality and Virtual Reality in Education," Electronics (Basel), vol. 12, no. 18, p. 3953, Sep. 2023, https://doi.org/10.3390/electronics12183953.

G. Baxter and T. Hainey, "Using immersive technologies to enhance the student learning experience," Interactive Technology and Smart Education, vol. 21, no. 3, pp. 403–425, Jul. 2024, https://doi.org/10.1108/ITSE-05-2023-0078.

A. N. Ghanbaripour et al., "A Systematic Review of the Impact of Emerging Technologies on Student Learning, Engagement, and Employability in Built Environment Education," Buildings, vol. 14, no. 9, p. 2769, Sep. 2024, https://doi.org/10.3390/buildings14092769.

H. Hysmith et al., "The future of self-driving laboratories: from human in the loop interactive AI to gamification," Digital Discovery, vol. 3, no. 4, pp. 621–636, 2024, https://doi.org/10.1039/D4DD00040D.

M. Colasante, J. Bevacqua, and S. Muir, "Flexible hybrid format in university curricula to offer students in-subject choice of study mode: An ed-ucational design research project," Journal of University Teaching and Learning Practice, vol. 17, no. 3, Sep. 2020, https://doi.org/10.53761/1.17.3.9.

S. G. Essa, T. Celik, and N. E. Human-Hendricks, "Personalized Adaptive Learning Technologies Based on Machine Learning Techniques to Identify Learning Styles: A Systematic Literature Review," IEEE Access, vol. 11, pp. 48392–48409, 2023, https://doi.org/10.1109/ACCESS.2023.3276439.

K. Haim and W. Aschauer, "Fostering Scientific Creativity in the Classroom: The Concept of Flex-Based Learning," International Journal of Learning, Teaching and Educational Research, vol. 21, no. 3, pp. 196–230, Mar. 2022, https://doi.org/10.26803/ijlter.21.3.11.

V. Nikitenko et al., "Innovative Modes of Distance Education in the Context of 5G Digital Technologies

Implementation," TEM Journal, pp. 1192–1202, May 2024, https://doi.org/10.18421/TEM132-33.
J. Bai, L. Cao, S. Mosbach, J. Akroyd, A. A. Lapkin, and M. Kraft, "From Platform to Knowledge Graph: Evolution of Laboratory Automation," JACS Au, vol. 2, no. 2, pp. 292–309, Feb. 2022, https://doi.org/10.1021/jacsau.1c00438.
S. G. Essa, T. Celik, and N. E. Human-Hendricks, "Personalized Adaptive Learning Technologies Based on Machine Learning Techniques to Identify Learning Styles: A Systematic Literature Review," IEEE Access, vol. 11, pp. 48392–48409, 2023, https://doi.org/10.1109/ACCESS.2023.3276439.
A. Sapriati et al., "The Effect of Virtual Laboratories on Improving Students' SRL: An Umbrella Systematic Review," Educ Sci (Basel), vol. 13, no. 3, p. 222, Feb. 2023, https://doi.org/10.3390/educsci13030222.
I. Zolotová, P. Papcun, E. Kajáti, M. Miškuf, and J. Mocnej, "Smart and cognitive solutions for Operator 4.0: Laboratory H-CPPS case studies," Comput Ind Eng, vol. 139, p. 105471, Jan. 2020, https://doi.org/10.1016/j.cie.2018.10.032.
M. Abrar, W. Aboraya, R. A. Khaliq, K. P. Subramanian, Y. Al Husaini, and M. Al Husaini, "AI-Powered Learning Pathways: Personalized Learning and Dynamic Assessments," International Journal of Advanced Computer Science and Applications, vol. 16, no. 1, 2025, https://doi.org/10.14569/IJACSA.2025.0160145.
H. Yaseen, A. S. Mohammad, N. Ashal, H. Abusaimeh, A. Ali, and A.-A. A. Sharabati, "The Impact of Adaptive Learning Technologies, Personalized Feedback, and Interactive AI Tools on Student Engagement: The Moderating Role of Digital Literacy," Sustainability, vol. 17, no. 3, p. 1133, Jan. 2025, https://doi.org/10.3390/su17031133
M. Injadat, A. Moubayed, A. B. Nassif, and A. Shami, "Machine learning towards intelligent systems: applications, challenges, and opportunities," Artif Intell Rev, vol. 54, no. 5, pp. 3299–3348, Jun. 2021, https://doi.org/10.1007/s10462-020-09948-w.
C.-C. Lin, A. Y. Q. Huang, and O. H. T. Lu, "Artificial intelligence in intelligent tutoring systems toward sustainable education: a systematic review," Smart Learning Environments, vol. 10, no. 1, p. 41, Aug. 2023, https://doi.org/10.1186/s40561-023-00260-y.
H. Wang et al., "Examining the applications of intelligent tutoring systems in real educational contexts: A systematic literature review from the social experiment perspective," Educ Inf Technol (Dordr), vol. 28, no. 7, pp. 9113–9148, Jul. 2023, https://doi.org/10.1007/s10639-022-11555-x.
S. Manca and M. Delfino, "Adapting educational practices in emergency remote education: Continuity and change from a student perspective," British Journal of Educational Technology, vol. 52, no. 4, pp. 1394–1413, Jul. 2021, https://doi.org/10.1111/bjet.13098.
B. L. Moorhouse and K. M. Wong, "Blending asynchronous and synchronous digital technologies and instructional approaches to facilitate remote learning," Journal of Computers in Education, vol. 9, no. 1, pp. 51–70, Mar. 2022, https://doi.org/10.1007/s40692-021-00195-8.
J. Singh et al., "Online, Hybrid, and Face-to-Face Learning Through the Eyes of Faculty, Students, Administrators, and Instructional Designers: Lessons Learned and Directions for the Post-Vaccine and Post-Pandemic/COVID-19 World," Journal of Educational Technology Systems, vol. 50, no. 3, pp. 301–326, Mar. 2022, https://doi.org/10.1177/00472395211063754.
G. Alves et al., "Trends on Computational Thinking, Engineering Education, Technology in Medicine, Qualitative and Mixed Methods, Diversity in STEM, Lab-Based Education, Technology and Education, Gamification and Games for Learning and Smart Learning at TEEM 2022," 2023, pp. 1–21. https://doi.org/10.1007/978-981-99-0942-1_1.
Ö. Anil and V. Batdi, "Use of augmented reality in science education: A mixed-methods research with the multi-complementary approach," Educ Inf Technol (Dordr), vol. 28, no. 5, pp. 5147–5185, May 2023,

https://doi.org/10.1007/s10639-022-11398-6.

A. Granić, J. Nakić, and N. Marangunić, "Scenario-based Group Usability Testing as a Mixed Methods Approach to the Evaluation of Three-Dimensional Virtual Learning Environments," Journal of Educational Computing Research, vol. 58, no. 3, pp. 616–639, Jun. 2020, https://doi.org/10.1177/0735633119859918.