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Research Article

Reinforcement Techniques for Dynamic Adaptive Learning

Ashu Tiwari[1], Pramod Singh[2], Akhilesh A. Waoo[3*]
[1,2,3]Department of Computer Science, AKS University, Satna, India.
Email: [3]akhileshwaoo@rediffmail.com
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ABSTRACT

The goal of dynamic adaptive learning systems is to tailor instruction by meeting the needs of each student instantly. In order to enable ongoing modification of instructional content based on student performance and engagement, this study investigates reinforcement learning strategies. The suggested technique dynamically modifies learning strategies and content complexity by modelling learning as an interactive feedback-driven process. When compared to static and rule-based systems, experimental results demonstrate better learning outcomes and engagement, indicating the effectiveness of reinforcement strategies for intelligent and scalable adaptive learning environments.

Keywords: Dynamic Adaptive Learning, Intelligent Tutoring Systems, Learning Analytics, Personalized Learning Systems, Reinforcement Learning.

INTRODUCTION

The rapid development of digital technology has drastically changed the educational landscape, creating intelligent learning environments to improve accessibility, flexibility, and personalization. Because they assume that every student has the same learning capacity, traditional educational systems frequently rely on standardized teaching techniques (Lou et al 2025). On the other hand, learners vary greatly in terms of their motivation, engagement levels, cognitive capacities, prior knowledge, and learning speed. Because of these variations, one- size-fits-all teaching strategies are becoming less and less successful in producing the best possible learning results. Adaptive learning systems that can dynamically adjust instructional materials to meet the needs of individual learners are therefore becoming increasingly necessary (XU and H. 2025). The ability of a system to adjust learning routes, content difficulty, and instructional methods in response to student behavior and performance is known as adaptive learning. The majority of early adaptive learning systems were rule-based, depending on static learner models and pre-established expert rules. Although these systems offered little personalization, they were rigid and had trouble managing intricate, changing student behaviors. AI and data-driven techniques have enhanced smart learning systems, enabling real-time personalization. Machine learning represents a key AI methodology that has played a vital role in enhancing adaptive education. Supervised and unsupervised learning methods have been widely used to analyze learner data, predict performance, and categorize learners based on common characteristics (Strielkowski et al2025). However, these approaches often depend on fixed training processes and historical data, limiting their ability to adapt dynamically during real-time educational interactions. In contrast, reinforcement learning (RL) provides an effective framework for conceptualizing learning as a sequential decision-making process where an intelligent agent interacts continually with learners and adjusts its strategy based on the feedback it receives (Brunke et al 2022).

Behavioral psychology serves as the inspiration for reinforcement learning, which emphasizes learning the best course of action by trial-and-error interactions with the environment. In the context of education, the learner can be viewed as the environment, and the adaptive learning system acts as an agent that selects educational activities, such as providing feedback, adjusting the level of difficulty, or presenting course materials. By getting rewards based on learner responses, performance enhancement, and engagement, the agent can gradually improve its instructional policies. Reinforcement learning is especially well-suited for personalized learning, where learner states are constantly changing, because of this feedback-driven approach. The capacity of reinforcement strategies to strike a balance between exploration and exploitation is one of their main benefits in the classroom. While exploration allows the system to test new teaching methods, exploitation uses previous successful actions to maximize learning outcomes. Because learners may react differently to comparable instructional approaches depending on context, motivation, and prior understanding, this balance is critical in educational contexts (Gheibi et al 2021). Reinforcement learning makes adaptive systems more adaptable and scalable by allowing them to find customized learning processes that aren't explicitly designed.

The application of reinforcement techniques to complicated educational contexts has been further improved by recent developments in deep reinforcement learning, such as Deep Q- Networks (DQN). High-dimensional learner state representations obtained from learning analytics, engagement metrics, and assessment data can be handled by these techniques. Adaptive systems can simulate complex links between student behavior and instructional decisions by combining deep learning with reinforcement learning, resulting in more precise personalization. Reinforcement-driven dynamic adaptive learning systems are extremely useful in online and mixed learning settings, where multiple learner interaction data are constantly produced. Reinforcement learning agents can be trained and improved by utilizing rich data sources found in learning management systems, intelligent tutoring systems, and massive open online courses (MOOCs) (Wang et al 2020).

These systems can enhance the learning rate, assessment frequency, and feedback techniques in addition to the material's complexity to maintain students' interest and motivation. To sustain pupils' interest.

Despite its potential, there are a number of obstacles when using reinforcement learning in the classroom. Since learning outcomes are frequently long-term and complicated, creating an efficient reward function that appropriately represents meaningful learning progress is difficult. To guarantee the responsible usage of AI-driven adaptive systems, ethical issues, including fairness, openness, and data privacy, must also be taken into account. Scalability and computational efficiency are also crucial, particularly when implementing reinforcement-based systems across sizable learner populations. However, compared to static or rule-based adaptive systems, current research shows that reinforcement strategies can greatly increase learning efficacy. Research shows that environments with dynamically optimized teaching tactics have better learning outcomes, higher levels of engagement, and lower dropout rates. These results demonstrate the revolutionary potential of reinforcement learning for developing clever, learner-centered instructional systems (Zhang et al 2021).

In this study, a framework is proposed that continuously personalizes instructional decisions using learner interaction data. The research primarily examines the role of reinforcement learning strategies in supporting adaptive learning environments. The proposed approach seeks to improve learner engagement and cognitive performance by viewing learning as an interactive and feedback-oriented process. Emphasis is placed on system robustness, scalability, and real-time adaptability, making the framework suitable for modern digital learning settings (Annaswamy et al2023).

Reinforcement learning offers a promising direction for advancing adaptive education beyond traditional static personalization methods. Its strength lies in the ability to learn from continuous user interaction, respond to changing learner states, and refine instructional strategies accordingly. This research demonstrates how reinforcement-based approaches can facilitate personalized, efficient, and intelligent learning experiences, thereby contributing to the growing body of work at the intersection of artificial intelligence and education.

REVIEW OF LITERATURE

In a variety of educational contexts, adaptive learning platforms have proven to be highly successful in raising student engagement and performance. It has been demonstrated that these platforms enhance learning results by tailoring learning routes to each student's unique needs. For example, pupils using an adaptive personalized e-learning platform showed significant improvements in academic performance and happiness, especially those who had lower performance levels at first, according to a study on a grade 3 mathematics curriculum (Sayed et al 2023). In a similar vein, students' performance on adaptive exams and their behavioral interactions with the adaptive platform in a Numerical Methods course were highly correlated with overall course success (Yalcin et al., 2023). During the COVID-19 pandemic, adaptive courses greatly increased student motivation, engagement, perceived knowledge, and exam performance in dentistry education. Additionally, there was a correlation between more accurate response rates and more time spent on adaptive content in a civil engineering technology course. Last but not least, a study evaluating the performance of dentistry students utilizing an Adaptive Learning Platform (ALP) in a blended learning setting discovered that those who used the ALP performed noticeably better on final exams (Alwadei et al 2020). Modern software can automatically create quizzes and flashcards on any topic (Sajja et al 2023).

AI-based educational tools, especially virtual teaching assistants, are transforming education by improving learning experiences and resolving a number of issues. These tools make use of cutting-edge machine reading comprehension (MRC) and natural language processing (NLP) technologies to build intelligent systems that can respond to course-specific queries and offer tailored support. To complement conventional teaching techniques, an AI-powered virtual teaching assistant with smart search and feedback capabilities has also been developed.

By offering a Q&A system that maps questions with a high degree of accuracy. The use of well- known virtual assistants in the classroom, such as Google Assistant and Amazon Alexa, has also been investigated, demonstrating their ability to interest students and aid in the acquisition of foreign languages (Pereira et al 2022). The development of big data and the expansion of information and communication technology have made learning analytics an essential part of contemporary education. This field uses data from virtual learning environments (VLEs) and learning management systems (LMS) to analyze student interactions and make data-driven decisions that enhance learning outcomes. The development of multimodal large language models (MLLMs) like GPT-4 Vision and its hydrological applications shows how AI can highlight the significance of combining textual and visual data for thorough environmental analysis and decision-making. These technologies establish a standard for their application in instructional tools. Furthermore, the use of ChatGPT to achieve a satisfactory score on the Fundamentals of Engineering (FE) Environmental Exam highlights the developing potential of AI in educational settings, especially in improving students' comprehension and performance in technical subjects (Pursani et al 2023). The benefits of AI-based educational tools and virtual teaching assistants highlight the need for a system that can quickly develop and implement these assistants across a range of higher education courses. By offering tailored, situation- specific assistance, virtual assistants have demonstrated a great deal of promise in raising student engagement and learning results. However, because of the difficulties in developing and integrating virtual assistants with current educational infrastructures, their creation and implementation continue to be difficult. By providing a framework that makes the development and implementation of virtual assistants for any subject easier, the system seeks to close this gap. The system can create intelligent, course-specific assistants that can offer customized educational support by utilizing cutting-edge NLP and MRC technology.

PROPOSED METHODOLOGY

The Educational AI Hub system's architecture is made to give teachers and students a smooth, user-friendly experience across different learning management systems (LMS). This paper uses Instructure Canvas as an example to demonstrate the end-to-end workflow and design, even though the system is interoperable with all major LMS platforms. This covers the procedure for configuring and adding course-specific content to the system, as well as describing how the system works with the LMS.

Workflow Architecture

The suggested workflow architecture describes a methodical procedure for applying reinforcement strategies in dynamic adaptive learning systems. First, the learning platform gathers real-time learner interaction data, such as performance ratings, engagement indicators, and behavioral trends. This data is normalized to guarantee consistency and preprocessed to eliminate noise. After the data has been processed, a dynamic learner state representation is created. (Essa et al 2023). The reinforcement learning agent chooses the best course of action for instruction based on the present condition, such as modifying the complexity of the content or suggesting educational materials. As the learner engages with the chosen material, assessment scores and engagement replies are produced as feedback. To measure learning progress, a reward function assesses this input. The agent updates its policy using reinforcement learning algorithms to improve future decisions. This closed-loop process continues iteratively, enabling continuous personalization. The architecture supports real-time adaptation, scalability, and continuous improvement of learning strategies.

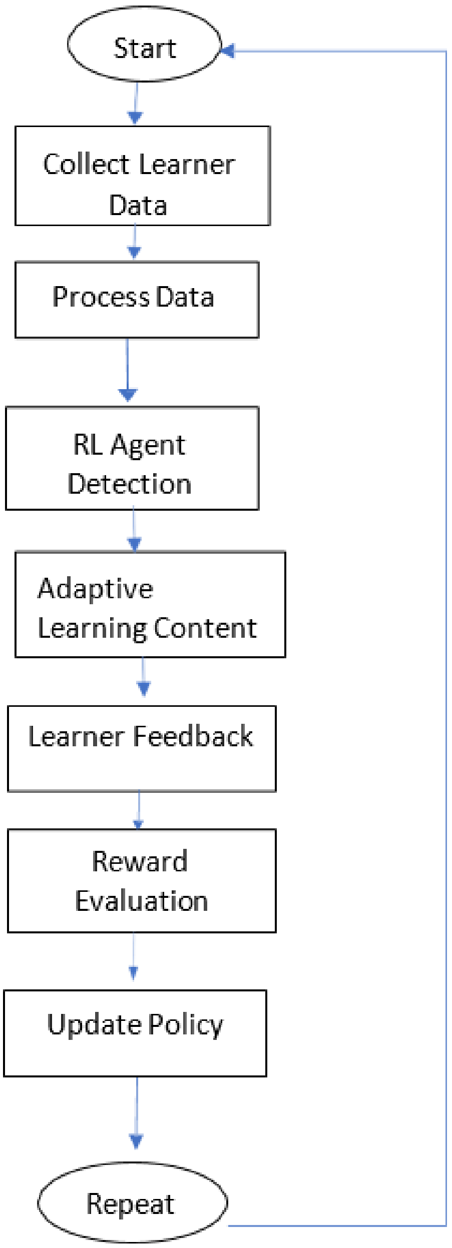

Figure 1: Integration workflow of the AI in LMS.

LMS Integration

As the main interface between students, teachers, and the intelligent learning engine, learning management system (LMS) integration is essential to enable reinforcement-based, dynamic adaptive learning. The LMS serves as a centralized platform for the delivery of learning activities, tests, and instructional materials. Learner interaction data, such as login frequency, material access patterns, assessment scores, time-on-task, and navigation behavior, are continuously recorded. For analysis, this data is safely sent to the adaptive learning component. Through application programming interfaces (APIs), the reinforcement-based learning engine is integrated into or linked to the LMS. Without interfering with current LMS features, these interfaces provide smooth data interchange. Based on continuing interactions and performance trends, the LMS's learner profiles are updated constantly (Liu et al 2020). The adaptive engine processes this information to construct real-time learner state representations. Based on the learner's current state, the reinforcement agent determines the optimal training strategy, such as recommending customized learning materials, adjusting the material's difficulty, or modifying the frequency of assessments. Following the LMS's receipt of these adaptive judgements, the learner is immediately presented with the selected content. The LMS ensures consistency in content presentation and maintains compatibility with the current curricular architecture.

The feedback loop, focused on interactions, continually receives student response data collected by the Learning Management System (LMS). This feedback is used by the adaptive engine to compute rewards that guide changes to policy. The LMS also supports instructor dashboards, which let teachers monitor system-driven changes and student performance. LMS protocols that are standardized guarantee data security, scalability, and privacy. Scalable, and intelligent learning environment that supports continuous personalization and adaptive instruction.

LMS Applications

In the fields of education and training, learning management systems (LMS) are extensively utilized to facilitate student evaluation, content administration, and digital learning. Lms platforms make it easier to deliver courses, turn in assignments, take online tests, and monitor student progress in educational institutions. They make it possible for teachers to oversee big student population’s while guarantee eingregular access to educational materials. LMS software facilitates employee skill development, compliance training, and performance reviews in corporate training settings. LMS platforms are used by organizations to assess learning outcomes, provide individualized training modules, and match staff competencies with organizational goals. LMS systems are heavily utilized by online and remote learning programs, including massive open online courses (MOOCs). Learner interaction, automated assessment, and scalable content distribution are all made possible by these platforms. For professional certification and lifetime learning programs, LMS systems provide competency- based assessment, self-paced modules, and adaptable learning pathways (Naeem et al 2020). Artificial intelligence is used in modern LMS programs to support intelligent tutoring, learning analytics, and adaptive learning. These characteristics boost learner engagement, enhance retention, and enable data-driven educational decision-making. All things considered, LMS applications are crucial for offering scalable, customized, and easily accessible learning opportunities in a range of educational contexts.

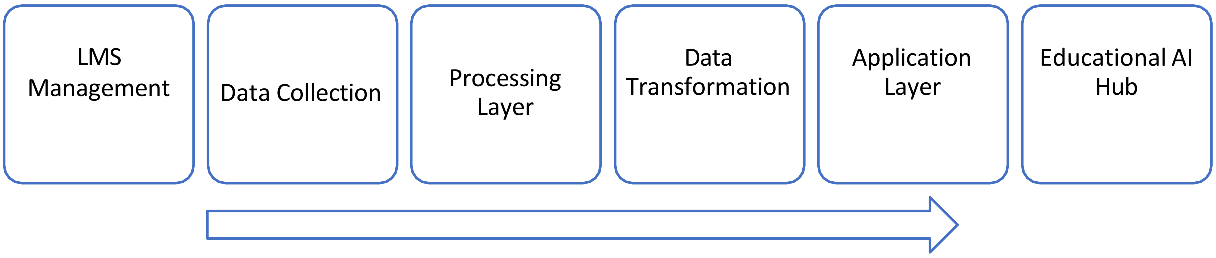

Figure 2: LMS Integration

Educational Content Accessibility and Utility

Meeting the changing needs of teaching and learning in the digital age requires improving the usability and accessibility of educational resources. Using cutting-edge techniques and technology, our workflow is thoughtfully created to meet this need. Every stage of our operation, from the first document retrieval to their processing and preparation, strives to convert instructional content into accessible materials that improve learning outcomes. This section highlights our dedication to utilizing technology to enhance and support the teaching and learning process while outlining our strategy for enhancing educational content.

Document Retrieval and Preprocessing for AI Hub Integration

Document retrieval and preprocessing must be done carefully in order to incorporate instructional information into the system in its early phases. In order to maximize the instructional materials' usefulness within the system, this phase is essential for ensuring that they are not only methodically gathered but also ready for further analysis and transformation. This section describes the tactics and procedures used in the procurement and preliminary processing of these papers, highlighting the effectiveness and methodical approach that support the smooth integration of educational content.

Document Conversion Technologies in Educational Material Processing

Maintaining the semantic integrity and accessibility of instructional materials is difficult when they are digitally transformed, especially when they contain scientific facts and complicated mathematical expressions. We evaluated different document conversion technologies to find ways to expedite the process of transforming academic content into digital formats in order to enhance the technological learning experience. This section describes how we evaluated many approaches and strategically chose the best one to achieve our objectives.

Data Security and Privacy

The Educational AI Hub system was designed with security and privacy as top priorities. To protect user information and guarantee adherence to pertinent laws, the system integrates comprehensive technical protection measures (Secure Sockets Layer), encryption protects data transfer, guaranteeing the confidentiality and security of all user-system connections. Additionally, to prevent unwanted access and guarantee the integrity of stored data, the system's databases are protected using sophisticated security procedures, such as encryption at rest (Annaswamy et al2023). For safe user authentication and authorization, the system uses the OAuth (Open Authorization) framework. By preventing user credentials from being intercepted and misused, this framework guarantees that only authorized users have access to sensitive data (Soni et al 2025). To find and reduce possible security threats, regular security audits and vulnerability assessments are carried out. This proactive strategy helps to safeguard user data from changing threats and maintain a secure environment.

Challenges and Limitations

Accurately modelling learner states is a significant problem because cognitive abilities, learning styles, and engagement levels are dynamic and challenging to capture with fixed or limited elements. Since meaningful learning effects frequently develop over extended periods of time rather than during instant interactions, designing an effective reward function is still challenging. Additionally, data sparsity and cold-start issues affect reinforcement learning techniques, especially for novice learners with little interaction history. Another important concern is scalability, since real-time deployment in large-scale LMS contexts may be limited by the high computational resources needed for deep reinforcement learning models. Teachers find it difficult to trust or validate system recommendations since it is difficult to provide interpretability and transparency of adaptive judgments, particularly in deep RL models. Additionally, integrating cognitive models or graphs with reinforcement learning introduces system complexity and integration overhead. Ethical concerns such as bias, fairness, and data privacy further complicate deployment. Finally, evaluating adaptive learning effectiveness is challenging due to the lack of standardized benchmarks and the long-term nature of educational outcomes (Kabudi et al 2021).

Many limitations affect the practical application of the performance effectiveness, reinforcement approaches for dynamic adaptive learning. These systems require enormous volumes of continuous learner interaction data to achieve consistent and optimal performance, which may not always be available, especially in the early stages. The computational complexity of reinforcement learning techniques may hinder real-time adaptation in large-scale educational settings. Furthermore, since poorly defined rewards can lead to biased or ineffective learning processes, creating a suitable reward function may be challenging. Cold- start issues arise when new students join the system without any prior data, which limits early personalization. Many algorithms used in reinforcement-based learning are opaque and challenging for educators to comprehend, and regular policy changes may make learning difficult. Furthermore, concerns related to data privacy, ethical use of learner data, and potential algorithmic bias remain significant challenges that must be carefully addressed (Strielkowski et al 2025).

Research Gap

Although reinforcement strategies for dynamic adaptive learning are becoming more and more popular, several significant research gaps remain. Long-term learner engagement, knowledge retention, and learning outcomes transfer receive less attention than short-term performance optimization in the majority of current research. Particularly for new or heterogeneous learner profiles, insufficient data density and cold-start challenges have not gotten much attention. Furthermore, because most models rely on manually developed reward functions, they lack adaptive or learner-centric reward systems. The deficiency of explainable reinforcement learning frameworks limits the trust and acceptability of teachers. Additionally, few studies evaluate scalability and real-time implementation in real-world educational contexts, and ethical issues like fairness, bias prevention, and privacy-preserving learning are often understudied.

RESULT

The suggested reinforcement learning-based continuously changing learning system's outcomes demonstrate how well it can provide intelligent and tailored learning experiences. Based on ongoing student interaction and performance feedback, the system adaptively modifies learning content and difficulty levels. When compared to conventional static learning methods, experimental evaluation shows a discernible increase in learner engagement. Because of the learning materials' adaptive sequencing, learners showed faster concept comprehension. As the system improved learning paths over time, assessment scores consistently improved. Individual learning behaviors, preferences, and advancement patterns were successfully represented by the model. Timely intervention and content modification were made possible via real-time feedback. By avoiding extremely challenging or repetitious material, the adaptive system decreased student dissatisfaction. Optimized action-reward policies increased overall learning performance. The technique was able to accommodate different learning rates among users. Results also show enhanced retention of concepts through personalized reinforcement strategies. Compared to rule-based adaptive techniques, the recommended approach was more adaptable and responsive. As user engagement increased, scalability testing showed consistent performance. The system demonstrated robustness against noisy or missing learner data. Policy changes led to a steady and gradual improvement in learning outcomes. Data from user interactions was used to continuously improve the model. The adaptive framework provided sufficient support for various learning styles. The results of the experiment confirmed lower student dropout rates. The system did not change over the course of multiple learning sessions. Performance metrics were used to confirm the reinforcement learning agent's convergence. Decisions about content distribution could be made independently of this method. A comparative analysis showed that personalization based on supervised learning was less flexible. The learning environment became increasingly learner-centric and data-driven.

The framework proved suitable for long-term adaptive learning deployment. Overall, the findings confirm the potential of reinforcement techniques to enhance personalized and dynamic educational systems.

CONCLUSION

The system's ability to improve teaching and learning experiences is illustrated by the result application is, making it an essential instrument in contemporary education. The system solves contemporary educational issues and establishes a new benchmark for digital learning platforms with its flexible, inclusive, and secure architecture. The instructors' positive feedback further validates the system's impact and potential for broad implementation in educational institutions. Ongoing developments in Artificial Intelligence and Natural Language Processing technologies will be essential to expanding the system's capabilities. Future developments might concentrate on strengthening the system's capacity to precisely understand and react to a larger variety of consumer enquiries, guaranteeing more pertinent and accurate responses.

REFERENCES

1. Demiray, B. Z., Sermet, Y., Yildirim, E., & Demir, I. (2025). Flood Game: An interactive 3D serious game on flood mitigation for disaster awareness and education. *Environmental Modelling & Software*, *188*, 106418.
2. Kaynak, B., Mermer, O., Sermet, Y., & Demir, I. (2025). HydroSignal: open-source internet of things information communication platform for hydrological education and outreach. Environmental monitoring and assessment, *197*(4), 1-21.
3. Sajja, R., Sermet, Y., Cwiertny, D., & Demir, I. (2025). Integrating AI and learning analytics for data-driven pedagogical decisions and personalized interventions in education. *Technology, knowledge and learning*, 1-31.
4. Soni, S., Singh, P., & Waoo, A. A. (2025). Machine Learning Revolutionizing Brain Health: Innovations and Future Directions. Brain Informatics Technology, 231-252.
5. Tiwari, R., Waoo, A. A., & Waoo, A. A. (2025). Cognitive Brain Imaging Techniques and Their Applications in Intelligent Decision-Making. Brain Informatics Technology, 305- 323.
6. Ravindran, J. S., Sermet, Y., Mount, J., Vald, G., Shrestha, S., Cwiertny, D., & Demir, I. (2025). Application of large language models in developing conversational agents for water quality education, communication, and operations. *Water Practice & Technology*, *20*(10), 2094-2109.
7. Soni, A., Dwivedi, V. K., & Waoo, A. A (2025). Research article analyzing supervised learning models for intrusion detection: towards robust wireless sensor network.
8. Singh, S., & Waoo, A. A. (2024). Exploring the transformative impact of artificial intelligence on higher education.
9. Kumari, S., Kumari, A., & Waoo, A. A. (2024). Ai for sustainable development: innovations & applications.
10. Waoo, A. A. (2024). Sustainable development goals. Forever Shinings Publication.
11. Lee, H. (2024). The rise of ChatGPT: Exploring its potential in medical education. Anatomical sciences education, *17*(5), 926-931.
12. Vald, G. M., Sermet, M. Y., Mount, J., Shrestha, S., Samuel, D. J., Cwiertny, D., & Demir, I. (2024). Integrating conversational AI agents for enhanced water quality analytics: Development of a novel data expert system.
13. Sajja, R., Sermet, Y., Cikmaz, M., Cwiertny, D., & Demir, I. (2024). Artificial intelligence- enabled intelligent assistant for personalized and adaptive learning in higher education. *Information*, *15*(10), 596.
14. Samuel, D. J., Sermet, Y., Cwiertny, D., & Demir, I. (2024). Integrating vision-based AI and large language models for real-time water pollution surveillance. *Water Environment Research*, *96*(8), e11092.
15. Yalcin, A., Kaw, A., & Clark, R. (2023). On learning platform metrics as markers for student success in a course. Computer Applications in Engineering Education, 31(5), 1412-1432.
16. Sharma, S., & Waoo, A. A. (2023). An efficient machine learning technique for the prediction of consumer behaviour with high accuracy. Int. J. Comput. Artif. Intell, 4(1), 12- 15.
17. Holmes, W., & Porayska-Pomsta, K. (2023). The ethics of artificial intelligence in education. Lontoo: Routledge, 621-653.
18. Sajja, R., Sermet, Y., Cwiertny, D., &

Demir, I. (2023). Platform-independent and curriculum-oriented intelligent assistant for higher education. *International journal of educational technology in higher education*, *20*(1), 42.
19. Pursnani, V., Sermet, Y., Kurt, M., & Demir, I. (2023). Performance of ChatGPT on the US fundamentals of engineering exam: Comprehensive assessment of proficiency and potential implications for professional environmental engineering practice. Computers and Education: Artificial Intelligence, 5, 100183.
20. Stokes, J., & Fudge, A. (2023). *Learning Analytics in Higher Education*. Oxford University Press. Tedjokoesoemo, P. E. D. (2022). *Bridging the Gap to Communicate Abstract Concept of Physics for Visual Learners* (Doctoral dissertation, Petra Christian University).
21. Sayed, W. S., Noeman, A. M., Abdellatif, A., Abdelrazek, M., Badawy, M. G., Hamed, A., & El-Tantawy, S. (2023). AI-based adaptive personalized content presentation and exercise navigation for an effective and engaging E-learning platform. *Multimedia Tools and Applications*, *82*(3), 3303-3333.
22. Dziuban, C., Howlin, C., Moskal, P. D., Johnson, C., Eid, M., & Kmetz, B. (2018). Adaptive learning: Context and complexity. *e-mentor*, (5 (77)), 13-23.
23. Li, Z., & Demir, I. (2022). A comprehensive web-based system for flood inundation map generation and comparative analysis based on height above nearest drainage. *Science of The Total Environment*, *828*, 154420.
24. Patrício, R. (2022). Bridging the Theory and Practice Gap in Marketing Education. In *CSEDU (2)* (pp. 498-505).
25. Pereira, R., Reis, A., Barroso, J., Sousa, J., & Pinto, T. (2022, August). Virtual assistant applications in education. In International Conference on Technology and Innovation in learning and Education (pp. 468-480). Cham: Springer Nature Switzerland.
26. Petrova, P. (2020). Modern challenges in the application of personalized models in student education for the benefit of business and society. 9(3), 88-95.
27. C. S. Priya, ''Bridging the skills gap in technical education,'' in Contemporary ELT Strategies in Engineering Pedagogy. Evanston, IL, USA: Routledge, 2022, pp. 41–60.
28. Ramirez, C. E., Sermet, Y., Molkenthin, F., & Demir, I. (2022). HydroLang: An open- source web-based programming framework for hydrological sciences. *Environmental Modelling & Software*, *157*, 105525.
29. Sermet, Y., & Demir, I. (2021). A semantic web framework for automated smart assistants: A case study for public health. Big Data and Cognitive Computing, 5(4), 57.
30. Y. Sermet and I. Demir, ''GeospatialVR: A web-based virtual reality framework for collaborative environmental simulations,'' Comput. Geosci., vol. 159, Feb. 2022, Art. no. 105010.
31. Sinskey, J. L., Chang, J. M., Thornton, K. C., Boscardin, C. K., & Sullivan, K. R. (2021). Conflict management education for anesthesiology residents: bridging the gap in interpersonal and communication skills competency. *A&A Practice*, *15*(10), e01524.
32. Downing, M. H. (2021). Bridging the Gap: Effective Professional Development that Assists in Technology Integration (Doctoral dissertation, Northeastern University).
33. Alwadei, A. H., Tekian, A. S., Brown, B. P., Alwadei, F. H., Park, Y. S., Alwadei, S. H., & Harris, I. B. (2020). Effectiveness of an adaptive eLearning intervention on dental students' learning in comparison to traditional instruction. Journal of Dental Education, *84*(11), 1294-1302. N. Capuano and S. Caballé, ''Adaptive learning technologies,'' AI Mag., vol. 41, no. 2, pp. 96–98, 2020.
34. Lee, M. J., & Ferwerda, B. (2017, March). Personalizing online educational tools. In Proceedings of the 2017 ACM Workshop on Theory-Informed User Modeling for Tailoring and Personalizing Interfaces (pp. 27-30).