Adaptive learning model in the field of gamification

Zhansaya Bekaulova[1,*,†], Nurzhan Duzbayev[1,†], Gulnar Mamatova[1,†], Mukhamedi Bersugir[2,†] and Nurbek Bekaulov[1,†]

[1] International Information Technology University, 34/1 Manas St., Almaty, 050000, Kazakhstan
[2] Abai Kazakh National Pedagogical University, 13 Dostyk St., Almaty, 050010, Kazakhstan

Abstract

Adaptive learning refers to a process that utilizes specialized algorithms to create personalized learning paths tailored to the unique needs of each student. In the context of gamification, this approach integrates game-based elements, such as scoring systems, challenges, and rewards, to engage and motivate learners. Technologies like e-learning, m-learning, and blended learning are increasingly being combined with gamification to enhance the educational experience. These systems not only shift from a teacher-centered model to a student-centered one but also transform the learning process into an interactive and engaging experience. While the teacher's role evolves into that of a mentor, guiding students to achieve their maximum potential through intelligent and adaptive technologies, gamification introduces elements of competition and collaboration, further boosting motivation. This article examines adaptive learning systems, such as Knewton and Smart Sparrow, and their integration with gamification techniques to assess knowledge retention, identify gaps, and offer personalized course components, thereby creating a tailored and engaging learning strategy for students.

Keywords

learning, adaptive learning, scoring systems, smart technologies, m-learning, blended-learning, graph theory

1. Introduction

The rapid advancement of digital technologies has led to significant changes in various fields, including education. One of the most promising innovations is adaptive learning, which uses algorithms to customize learning paths according to the unique needs of each student. This approach not only improves the effectiveness of knowledge acquisition but also helps address individual learning gaps. In parallel, gamification, which introduces game elements such as rewards, challenges, and leaderboards into the learning process, has gained popularity as a tool for increasing student motivation and engagement (Adams Becker et al., 2017) [1].

Gamification fosters competition, goal setting, and real-time feedback, which enhances learner engagement and transforms the learning process into a more interactive experience. When combined with adaptive learning models, gamification can further personalize and enrich the educational experience, providing tailored and motivating learning environments (Adu & Poo, 2014) [2].

Adaptive learning systems like Knewton and Smart Sparrow assess students' knowledge levels, identify gaps, and offer customized content to fill those gaps. By incorporating gamification, these systems become even more engaging, offering a rewarding and enjoyable learning process (Henderson, 2014) [3]. This combination of adaptive learning and gamification not only enhances knowledge retention but also promotes continuous learning by using real-time rewards and personalized challenges (Tseng et al., 2017) [4].

DTESI 2024: 9th International Conference on Digital Technologies in Education, Science and Industry, October 16–17, 2024, Almaty, Kazakhstan

* Corresponding author.
† These authors contributed equally.
zh.bekaulova@iitu.edu.kz (Zh. Bekaulova); n.duzbayev@iitu.edu.kz (N. Duzbayev); mamatovag@gmail.com (G. Mamatova); bersugir68@mail.ru (M. Bersugir); n.bekaulov@iitu.edu.kz (N.Bekaulov)
0009-0000-9339-9222 (Zh. Bekaulova); 0000-0002-7989-9463 (N. Duzbayev); 0009-0007-6338-6093 (G. Mamatova); 0000-0003-0889-2069 (M. Bersugir); 0009-0002-8862-3191 (N. Bekaulov)

This paper explores the integration of adaptive learning and gamification, presenting a comprehensive review of how these two approaches can create highly personalized and engaging learning experiences, tailored to meet the needs of modern learners.

Thanks to such educational technologies, it is possible to structure the learning process at all stages of student involvement at an advanced level, systematically assessing their subject achievements, and cultivating knowledge, skills, competencies, and capabilities. Furthermore, adaptive learning computer systems act as a type of "mentor" and "counselor" in fostering several critical traits and qualities in students, as well as in developing their essential skills, competencies, and professional abilities.

The primary contributions of this research can be summarized as follows:

- The research offers a theoretical foundation for the creation of adaptive learning systems.
- The research improves students' self-awareness and encourages self-assessment as a method of adaptive learning within the system framework.
- The research makes a significant contribution to the literature on adaptive e-learning systems by examining learning effectiveness and satisfaction through empirical studies.

The remainder of the paper is structured as follows: Section II addresses the problem. Section III refers the methodology of adaptive learning model. Section IV reviews the characteristics of existing literature. Section IV outlines the system model of adaptive testing. Section V proposes an algorithm for evaluating student competencies based on adaptive learning. Section VI presents the experimental outcomes and their implementation. Section VII analyzes the results. Finally, Section VIII wraps up the paper.

2. Problem identification

The integration of adaptive learning models with gamification introduces a series of complex challenges that impact the overall efficacy and efficiency of educational systems. Adaptive learning is designed to tailor educational experiences to the specific needs of individual learners, whereas gamification incorporates elements of game design to enhance engagement and motivation. The confluence of these approaches necessitates addressing several key issues [5]:

- Complexity of Integration: The amalgamation of adaptive learning systems with gamification entails the integration of advanced algorithms and interactive game mechanics into educational platforms. This complexity can pose significant challenges in terms of system design and implementation, requiring that these diverse technologies function cohesively to deliver a unified educational experience.
- Overload of Content and Detail: Adaptive learning systems necessitate the provision of extensive and detailed content to effectively personalize the educational experience. When gamified, this content must be managed carefully to prevent cognitive overload. It is imperative to achieve an optimal balance between comprehensive content and engaging presentation to ensure effective learning without overwhelming students.
- Frequent Assessment and Feedback: Adaptive learning frameworks rely on continuous assessment to refine and customize the learning experience. The incorporation of gamification elements, such as real-time feedback and rewards, further necessitates frequent evaluations. However, an excessive frequency of assessments or feedback can lead to learner fatigue and potentially diminish the overall effectiveness of the learning process.
- Ensuring Effective Engagement: While gamification aims to enhance learner engagement through elements such as rewards, challenges, and leaderboards, ensuring that these components are truly effective in sustaining student motivation is a complex task. The design

and implementation of gamified elements must be carefully aligned with educational goals to avoid superficial engagement and to ensure meaningful participation.

- Data Privacy and Security: The integration of adaptive learning and gamification often involves the collection and analysis of substantial amounts of personal data concerning student performance and preferences. Safeguarding this data and ensuring compliance with privacy regulations is a critical issue that must be addressed to protect student information and maintain trust in the educational system.
- Measuring Effectiveness: Evaluating the impact of adaptive learning combined with gamification requires the development of robust metrics and evaluation frameworks. Traditional measures of educational effectiveness may be insufficient to capture the nuances of gamified learning experiences, necessitating the creation of new methodologies to accurately assess the outcomes and benefits of these integrated approaches.

Addressing these issues is essential for maximizing the advantages of combining adaptive learning with gamification. Solutions must be developed with careful consideration of both technological and pedagogical factors to enhance the overall efficacy of the educational process [6].

3. Methodology of the adaptive learning algorithm

Below in Fig. 1. the methodology of the adaptive learning algorithm is presented:

1. Sampling scheme. At this stage a set of modules is formed, consisting of modules implementing insufficiently studied competencies. Competence Kj is considered insufficiently studied in two cases. Firstly, if the student has not studied it before, i.e. HRj = ∅. Secondly, if the competence is lost, i.e. the level of its development, according to the forgetting curve, has fallen below the Rnorm level over time [7].
2. Search P. The genetic algorithm described below is used to find a learning path.
3. Presentation P. The student is provided with the first module from P. The training modules are implemented in the distance learning environment.
4. Knowledge assessment. Within the framework of the distance learning system a test is formed to check the level of knowledge on the output competencies of the module.
5. Updating S. After the test, the student's current level of knowledge on the history of HRj is updated.
6. Check the end of the course. The course ends in two cases. First, when the course time expires, i.e. if Ttek ≥ Tkon. Second, if all competencies are studied at a satisfactory level, i.e. KS = K, KF = ∅.We specifically ask workshop organizers to point authors to this requirement in their instructions on the workshop home page.

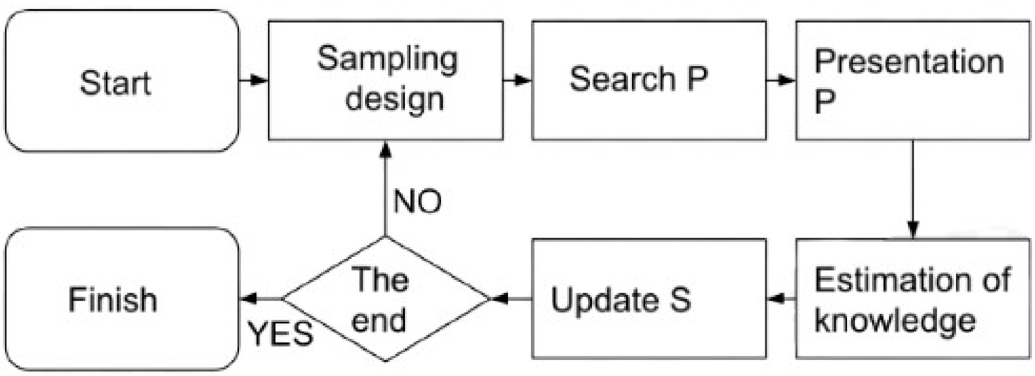

Figure 1: General structural diagram of the adaptive learning algorithm.

4. Related work

In this section, the key characteristics of existing methods are outlined.

4.1. Knewton adaptive learning system

The Knewton adaptive learning system, established by Jose Ferreira, is discussed in [8]. Knewton offers courses that continuously adjust to the individual characteristics of each learner. Unlike traditional approaches, where knowledge gaps accumulate and one must grasp a topic before moving on to the next, Knewton aims to address this issue by adapting the learning process. However, the implementation of this concept has faced challenges and the idea was not fully realized.

4.2. SmartSparrow adaptive learning system

Henderson [9] presents another adaptive learning tool, SmartSparrow, which empowers educators to create interactive courses and leverage the system's intelligent features to customize the curriculum for each student. Over a dozen courses have been developed using this platform, primarily at the university level. SmartSparrow thus stands out as a robust online tool for developing a new generation of interactive and adaptive courses. Despite its extensive resources, this platform does not offer constant and real-time adaptability, making it a valuable but somewhat limited resource, as discussed in [10].

4.3. Math Garden adaptive learning system

Englisch et al. [11] describe the Math Garden system, an adaptive learning tool designed to enhance mathematical skills through an online environment tailored to students' levels. This service is accessible to families, schools, and other educational institutions. However, it has a notable limitation: it focuses exclusively on improving math skills.

5. The algorithm of adaptive learning model

The fundamental idea of adaptive learning is to build an optimal trajectory for creating effective course modules for a student. A module is a logically minimal unit of academic information that can be presented in various formats such as text, graphics, video, audio, or any other interactive form and is connected to other units [12]. Designing a trajectory for a module is a multi-criteria optimization problem. Given the specifics of university curricula, specifically the fixed time allotted for mastering the course material, the criterion for optimality can be considered as achieving the highest level of skills by the end of the course in the minimum necessary time. For a course, understanding a module can be expressed as:

$$F(PTcon) = TM / R(Tcon) \rightarrow min. \quad (1)$$

where P — is the learning path (the sequence of completing and learning modules),

TM— is the maximum time for mastering the modules,

R— is the degree of residual knowledge.

Since the course completion time TconTconTcon is constant, it can be omitted when writing the objective function (2.1). The objective function involves integer programming, as the array of learning modules consists of their identifiers represented by integer values. Additionally, the placement of the problem is quite discretionary: as will be shown later, not all sequences of problem blocks are suitable. Consequently, taboo problems can only be described in discrete mathematical terms as relations to sets. Classical optimization algorithms are not suitable for solving such problems, so genetic algorithms are chosen for this purpose. To extrapolate the remaining level of knowledge at the end of the course based on the results of intermediate tests, a model based on the rate of forgetting information is used. No other sufficiently motivated model exists that would correspond to the numerical prediction of the knowledge level of students who will study in the future, based on their learning history. The use of Bayesian networks does not provide greater prediction accuracy (except for adaptive testing functions), but requires significant computational resources [13]. The good decision speed allows the use of machine learning technologies (e.g., in Snapet 3), but achieving sufficient prediction accuracy in courses containing at least 150-200 modules requires a database of tens of thousands of completed learning paths. Thus, in the initial stage of training implementation, it is necessary to use statistical models (such as Bayesian belief networks) or models based on the rate of forgetting information [14].

In static student modeling is presented in Fig.2, users are allowed to explicitly provide information to the model. In this approach, the student model is built and updated using information obtained directly from the user [15].

In automatic student modeling, information about the user is collected by tracking the user's behavior patterns while using the system. The student model can be updated based on preferred learning content, time spent on content, and answers received from questions or tests [16].

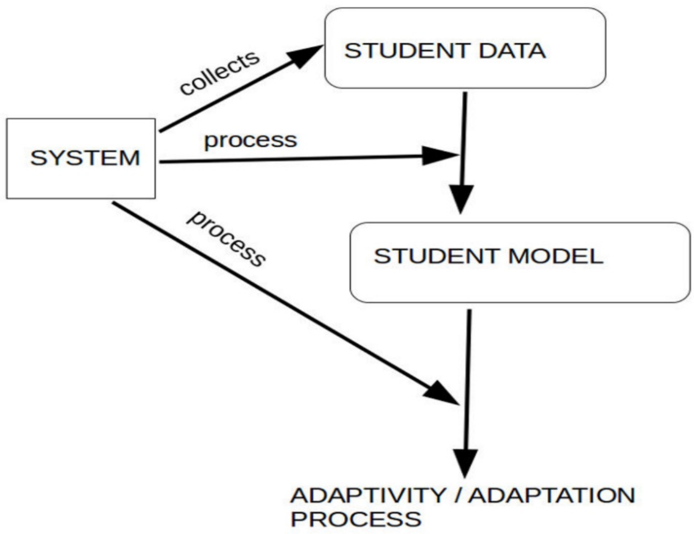

Figure 2: Modeling students in adaptive educational systems.

In the development of an adaptive distance learning system, it is essential to ensure that the management of the program is as user-friendly as possible to facilitate ease of use for learners [17].

Below, Figure 3 illustrates the functionalities available to users of the adaptive distance learning system (ADLS) software.

Use case diagrams are an integral tool in the design and analysis of systems, particularly within the context of adaptive learning systems. These diagrams provide a graphical representation of the interactions between users (actors) and the system, specifying the various functionalities or use cases that the system supports. By delineating these interactions, use case diagrams facilitate a clearer understanding of system requirements, user needs, and the overall functionality of the system.

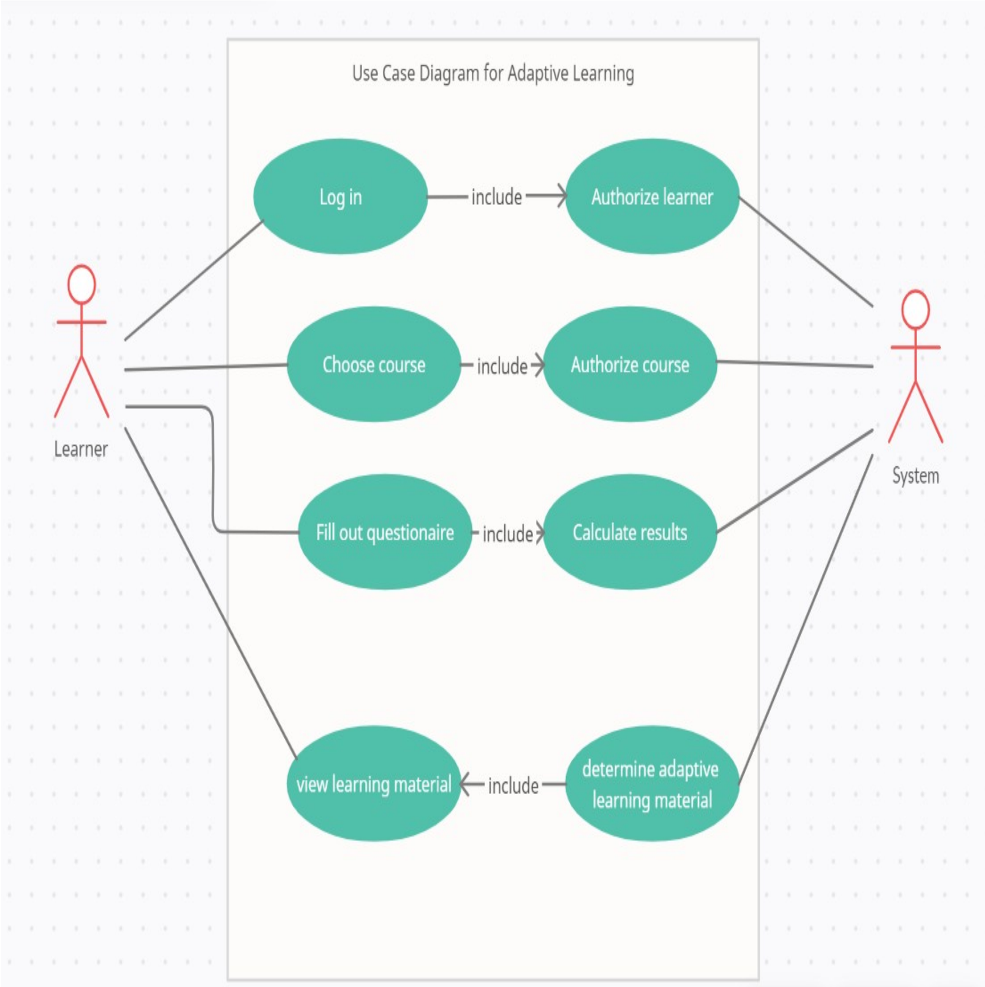

Figure 3: Use Case Diagram.

A use case diagram visually represents the functional requirements of a system by illustrating the interactions between actors and use cases. Actors represent external entities that interact with the system, such as students, teachers, or administrators. Use cases are specific functionalities or services provided by the system that fulfill the needs of the actors. The primary purpose of use case diagrams is to capture and document these interactions in a manner that is both comprehensible and actionable.

Use case diagrams are a fundamental tool in the development and analysis of adaptive learning systems. They provide a structured approach to understanding and documenting system requirements, facilitating effective design, communication, and validation processes. By accurately representing the interactions between users and the system, use case diagrams play a crucial role in ensuring that adaptive learning systems meet the needs of their users and achieve their intended educational outcomes [18].

Initially, learners must register in the system. After registration, they can access the question database on their dashboard and begin a test. Learners also have the option to skip a question and return to it later. The system provides a histogram that highlights the learner's strengths and weaknesses. At the end of the test, the system assesses the learner's level and may suggest directions for further skill development based on their initial competencies [19].

Flowcharts are used to visually represent the sequence of steps and decisions required to complete a process. Each step in the sequence is depicted in the form of a diagram. The steps are connected by lines and directional arrows, allowing viewers to logically follow the process from start to finish. A flowchart is a powerful business tool. When designed and constructed correctly, it effectively and efficiently conveys information about the stages of a process. Figure 4 illustrates the algorithm for the program developed for the adaptive distance learning system [20].

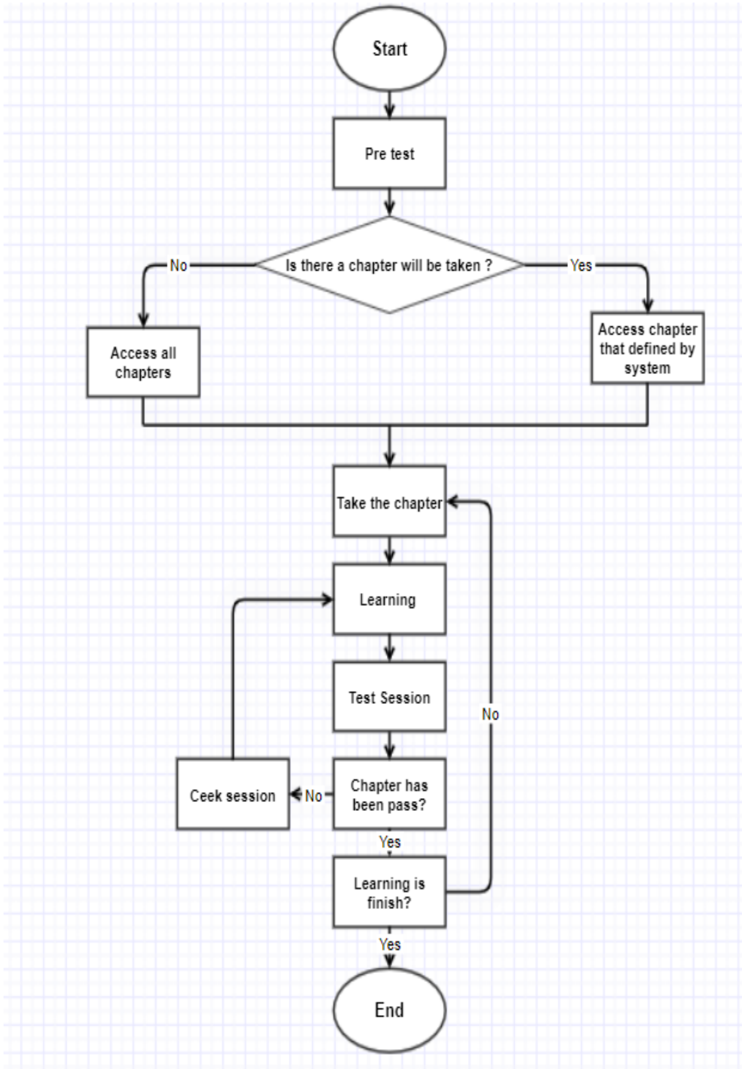

Figure 4: Flow chart Diagram.

6. Experimental results of adaptive testing with elements of gamification with traditional education

An experiment was conducted with adaptive learning involving 10 students studying a single subject using electronic information and an educational environment. Simultaneously, a second group of 12 students studied the same course also using electronic information and an educational environment. However, students in the second group received traditional instruction, with the electronic information and educational environment used solely for the digital presentation of theoretical material in the form of lecture notes and automated knowledge assessment through tests.

While the course content was identical, the methods of content delivery and, consequently, the assessment questions differed. For the second group, the content was uniform for all students, tailored to an average level of educational capability, whereas for the first group, various forms of theoretical material delivery were provided based on the student's assimilation of the material, demonstrating the advantages (or disadvantages) of adaptive learning in terms of students' grasp of the course content. To compare the results, due to the differing group sizes, two students from the second group were randomly excluded. The test results for each group were ordered in ascending order, facilitating visualization and comparison of the outcomes.

The results indicate that students who were taught using the adaptive learning approach achieved higher scores on the final test. Specifically, out of 10 students, four received an "excellent" rating (80-

100 points), while only 2 students from the traditional model achieved an "excellent" rating. The scores demonstrate that, in the vast majority of cases, students trained with adaptive learning performed better on test questions.

As observed, students undergoing adaptive learning exhibited higher scores. This finding provides practical evidence that adaptive learning is more effective than traditional learning.

Table 1
Statistical Data of Test Results for Both Student Groups

	Adaptive prototype	The traditional form of learning
Mean (μ)	77	71.8888
Median	80	73
Lowest value:	55	50
Highest value:	95	94
Range:	40	44
Standard deviation (σ):	15.842979517755	15.602310686736
Mean absolute deviation (MAD):	14	13.56790123457

Table 1 presents the average test scores for the two student groups, along with their means and standard deviations. According to Table 1, the group utilizing the adaptive learning approach has an average score of 0.778912, while the other group has an average score of 0.7188888. The median, mean absolute deviation, and standard deviation values for adaptive e-learning are 80%, 14%, and 15.8%, respectively, whereas for traditional learning, these values are 73.00%, 13.56%, and 15.6%. These data further demonstrate that the adaptive system provides superior learning outcomes compared to traditional methods.

7. Conclusion

This paper explores the concept of adaptive testing within the framework of personalized educational models, aiming to optimize the number of test items presented to students based on their hierarchical skill levels. The adaptive learning model offers a promising solution to address the challenges associated with traditional testing methods, where the “bell curve” effect often leads to a mismatch between the complexity of tasks and individual student abilities. By tailoring test content to each student’s proficiency, adaptive learning models aim to enhance learning outcomes and ensure a more accurate assessment of student capabilities [21].

In contemporary educational settings, adaptive learning systems are increasingly recognized for their ability to dynamically adjust to individual learner differences, thereby facilitating a more personalized learning experience. This study highlights the significance of integrating adaptive learning strategies with e-learning systems, emphasizing the role of theoretical frameworks such as regional forest theory and self-assessment mechanisms. The objective is to improve learning effectiveness by leveraging real-time data to adjust the content and delivery of educational materials in response to student performance [22].

The research presented supports the hypothesis that adaptive learning contributes to better knowledge formation and consolidation by fostering greater student independence, motivation, engagement, and responsibility [23]. The findings are valuable for system developers, educators, and instructional designers, providing insights into the effective implementation of adaptive e-learning environments. Specifically, the results suggest that incorporating adaptive mechanisms and self-assessment tools can significantly enhance the learning experience and outcomes for students [24].

Declaration on Generative AI

The authors have not employed any Generative AI tools.

References

[1] S S. Adams Becker, M. Cummins, A. Davis, A. Freeman, C. Hall Giesinger, V. Ananthanarayanan (2017). NMC Horizon Report: 2017 Higher Education Edition. *The New Media Consortium.*

[2] E.K. Adu, D.C.C. Poo (2014). Smart Learning: A New Paradigm of Learning in the Smart Age. *TLHE Conference*, National University of Singapore.

[3] Henderson J. (2014). "Smart Sparrow targets Next Generation Learning after securing first Round of Funding." *NewSouth Innovations.*

[4] Hsiao-Chien Tseng, Chieh-Feng Chiang, Jun-Ming Su, Jui-Long Hung, Brett E. Shelton (2017). Building Online Adaptive Learning and Recommendation Platform. Emerging Technologies for Education.

[5] Martin Ebner, Sandra Schön, Clarissa Braun, Markus Ebner, Ypatios Grigoriadis, Maria Haas, Philipp Leitner, and Behnam Taraghi. COVID-19 Epidemic as E-Learning Boost? Chronological Development and Effects at an Austrian University against the Background of the Concept of "E-Learning Readiness" // Future Internet. – 2020. – 12. – 94. – 1-20.

[6] Z.T. Zhu, J.Q. Guan, The construction framework of "Network Learning Space for Everyone". China. Educ. Technol. (10), 1–7 (2013).

[7] Abderrahim El Mhouti, Mohamed Erradi, Azeddine Nasseh. Using cloud computing services in the e-learning process: Benefits and challenges // Educ Inf Technol. – 2018. – 23. – 893-909. and organization from a Canadian perspective." Forensic science international 264 (2016): 7-14.

[8] The Knewton platform. (2014). Retrieved from http://www.knewton.com/assets-v2/downloads/knewton-intro-2014.pdf.

[9] Henderson, J. "Smart Sparrow targets Next Generation Learning after securing first Round of Funding". NewSouth Innovations – 2014. – 25-27 .

[10] "Smart Sparrow - Adaptive eLearning Platform". Smart Sparrow. Retrieved March 23, 2013.

[11] Norbert Englisch, Jonas Tonndorf-Martini, Ariane Heller, Lucas Gaitzsch, Uranchimeg Tudevdagva, Wolfram Hardt, "Adaptive Learning System in Automotive Software Engineering", Software Telecommunications and Computer Networks (SoftCOM) 2019 International Conference on, pp. 1-5, 2019.

[12] Ying Fang, Zhihong Ren, Xiangen Hu and Arthur C. Graesser. A meta-analysis of the effectiveness of ALEKS on learning // Educational psychology. – 2019. – 39. – 1278-1292.

[13] Vlasenko A.A. Metody i tekhnologii distantsionnogo obecheniya / Vlasenko A.A., Pachevski D.E. // Perspektivniye sredstva multimedia v obrazovatelnom protsesse: meterialy nauch. konf. – Voronezh: VGTU. – 2008.– S. 88–99.

[14] N. P. de Koch, Software engineering for adaptive hypermedia systems. PhD thesis, PhD Thesis, Verlag Uni-Druck, Munich, 2001

[15] Wasim Haidar, Wilfred Blessing, Prashant Johri, Surendra Pal Singh, Sutherlin Sunitha. app: An Effectual Application for Mobile based Student-Centered Learning System // 4th International Conference on Computing Communication and Automation (ICCCA). – Greater Noida, India, 2018.

[16] Z.T. Zhu, H.C. Peng, Y.H. Li, Intelligence education: An approaches to smarter education. Open Educ. Res. 24(4), 13–24 (2018).

[17] Z.T. Zhu, F. Wei, Educational Informatization 2.0: Starting on a journey of intelligence education guided by Smart Education. E-Educ. Res. 9, 5–16 (2018).

[18] Hsiao-Chien Tseng, Chieh-Feng Chiang, Jun-Ming Su, Jui-Long Hung, and Brett E. Shelton. Building Online Adaptive Learning and Recommendation Platform // SETE 2016: Emerging Technologies for Education. – 2017. – 428-432.

[19] Dalal Abdullah Al Johany, Reda Mohamed Salama, Mostafa Saleh. ASSA: Adaptive E-Learning Smart Students Assessment Model // International Journal of Advanced Computer Science and Applications. – 2018. – 9(7). – 128-136.
[20] Z.T. Zhu, D.M. Shen, New paradigm of educational technology research based on Big Data. E-Educ. Res. (10), 5–13 (2013).
[21] Z.T. Zhu, J.Q. Guan, The construction framework of "Network Learning Space for Everyone". China. Educ. Technol. (10), 1–7 (2013).
[22] Pérez-Sánchez, B., Fontenla-Romero, O., & Guijarro-Berdiñas, B. (2018). A review of adaptive online learning for artificial neural networks. Artificial Intelligence Review, 49(2), 281–299. https://doi.org/10.1007/s10462-016-9526-2.
[23] Dounas, L., Salinesi, C., & El Beqqali, O. (2019). Requirements monitoring and diagnosis for improving adaptive e-learning systems design. Journal of Information Technology Education: Research, 18, 161-184. https://doi.org/10.28945/4270.
[24] Dhakshinamoorthy, A., & Dhakshinamoorthy, K. (2019). KLSAS—An adaptive dynamic learning environment based on knowledge level and learning style. Computer Application in Engineering Education, 27(2), 319–331. https://doi.org/10.1002/cae.22076.
[25] Truong, H. M. (2016). Integrating learning styles and adaptive e-learning system: Current developments, prob-lems and opportunities. Computers in Human Behavior, 55(Part B), 1185–1193. https://doi.org/10.1016/j.chb.2015.02.014.