Research on Challenges and Strategies of Students' Adaptive Learning within AI

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Abstract. It's acknowledged that an adaptive e-learning system can be efficient for users to conduct personalized learning in which learners could choose appropriate content and preferred models based on artificial intelligence (AI) recommendations. Nowadays, the rapid development of adaptive platforms, fueled by the evolution of machine learning and AI, incontestably brings innovative potential to the educational field. However, there are many unavoidable challenges followed by the swift process of integrating AI and other technologies into adaptive learning practices. Through the extensive review of previous research on adaptive e-learning and comprehensive analysis of their prominent outcomes, the paper focuses on exploring the challenges of adaptive learning within AI that students are facing and proposing possible solutions. It's found that adaptive learning is mainly experiencing the challenges involving how to avoid data bias and protect personal privacy, making continuous evaluations of users, lack of emotion monitoring and technological support for both students and teachers and the technology integration and inequity. To deal with the increasing problems, some practical strategies are presented, such as properly governing data for learning management, conducting continuous evaluation and prediction for users, and visualizing cognition, which can be supportive of students' professional development in adaptive learning.

Keywords: Adaptive learning, challenges and strategies, Artificial Intelligence (AI), personalization.

1. Introduction

Nowadays, adaptive e-learning has developed into an effective educational method that is attaining increasing popularity because of its enormous scalability and enormous potential to offer flexibility and personalized learning experiences for users.

Shute and Towle once initially defined adaptive e-learning as a straightforward learning action conceptually, namely self-regulated learning carried out in front of an internet-connected computer [1]. They proposed a well-recognized adaptive learning framework that consists of three models, including learner model, content model, and tutor model as well as one engine named adaptive engine. With the recent rapid development of adaptive systems and e-learning platforms, especially promoted by the revolution of artificial intelligence (AI) and other advanced technologies utilized in the educational field, adaptive learning can be regarded as an educational methodology that employs technology and data analytics to make each student's learning experience customized.

Considering the diverse conditions of learners, ZHU explained the concept of Adaptive Learning more precisely. He held the view that adaptive learning helps to evaluate students' present cognitive level and learning state and projects their learning trajectory for the future by leveraging artificial intelligence technology [2].

While Minn proposed two fundamental adaptive abilities that a successful adaptive learning platform must possess [3]. One is to give highly precise, timely, and useful feedback while addressing problems. The other is to construct the available content flexibly based on individuals' skill proficiency [3]. This viewpoint puts clearer requirements on the development of adaptive learning and the adaptive users themselves and proves that the main subject of adaptive learning is always a human being. There is a need to integrate the various available technologies to become a customized learning platform for users.

Therefore, a well-designed adaptive learning mechanism makes it possible to intelligently offer the optimal learning paths and resources to fit each student's unique learning requirements.

However, this integration of personalized learning and AI-led technologies is not a simple task, which requires complex considerations such as large data collection and processing, changes in the users' emotional perceptions and preferences, and how to continually evaluate these factors to make adaptive learning more accurate.

While there have been literature reviews on the subject of adaptive learning management systems, the focus of these studies was on current issues and advancements as well as trends, approaches, designs, and relationships. A paucity of research has reviewed the present challenges in adaptive e-learning while suggesting workable solutions based on outstanding outcomes.

Based on this, the work presents a comprehensive review of the main current challenges and problems that users may encounter during the implementation of adaptive systems. Then it discusses feasible strategies that are crucial for its practical application. This research attempts to overcome the difficulties in providing high-quality online education by utilizing the enormous potential that a personalized e-learning system possesses, which could provide beneficial paradigms for promising adaptive learning in the future.

2. Challenges of Adaptive Learning

It is a commonly accepted fact adaptive learning systems come in a variety of forms, from straightforward mechanisms with built-in rules to intricate mechanisms with genetic algorithms, which can maximize self-directed online behaviors. Furthermore, the majority of educators have acknowledged the advantages of adaptive learning, and some earlier research suggested its positive effects on student's learning outcomes [4].

However, evidence-based research on adaptive learning remains limited as adaptive platforms or systems are still in their infancy [5]. To put it in another way, adaptive learning is still developing and evolving. Despite its acknowledged advantages and growing popularity, the widespread application of adaptive learning is still quite restricted. Combined with the review of previous research, it is obvious that adaptive learning is facing various barriers and challenges when being implemented.

2.1. Data Bias, Security, and Privacy

The process of adaptive modeling involves dealing with an enormous amount of data about student interactions. These are used to analyze collected parameters, evaluate engaged models, to assess learners' performance to strengthen learning behaviors. However, human learning is subject to complexity. Therefore, measuring students' mastery of certain knowledge or skills and providing them with on-the-spot problem-solving assistance with the help of collected data are intrinsically challenging tasks [3, 5].

Even though researchers frequently implicitly assume that the data they chose are of high quality to avoid noise as much as possible and that students also used the platform as intended, the situation in adaptive learning gets more complex and unpredictable because some students may cheat or arbitrarily guess answers to the questions [6].

In addition, the system itself might introduce bias into the data it collects using attrition bias resulting from individual variances in mastery learning or statistical bias related to technical problems or mechanical disorders during the data collection process.

What's more, concomitantly, another primary challenge is ensuring the privacy and security of student data within AI-powered adaptive learning systems. The right to use, learner privacy, and learning data security will all be considered during the analysis process [7]. Given that there are numerous hazards, such as cyberattacks, system vulnerabilities, physical security breaches, and insider threats, associated with the safeguarding of personal information, collecting and analyzing sensitive learner information requires robust data protection measures, compliance with privacy regulations (e.g., GDPR, CCPA), and ethical considerations regarding data usage, storage, and sharing.

2.2. Continuous Evaluation

The adaptive system demands that the learner's master level of knowledge and skills be tracked to identify the information that the learner does not understand yet [8]. Thus, problems inherently exist in constantly identifying and evaluating the condition of the learner, which is achieved by assessments.

Nevertheless, devising proper methods of assessing and aligning them to the content for developing learners is a laborious task [9]. This means that an ill-suited evaluation response could indicate a lack of understanding of multiple distinct concepts for modeling. In a similar vein, it is not always the case that understanding every knowledge concept is demonstrated by a valid response to an assessment question.

It is undeniable that personalized systems rely on multimodal data sets, user logs, accessible resources, and evaluation outcomes to meet adaptive e-learning requirements [10]. However, the fact that these elements are continuously fluctuating makes it tough to determine and utilize reasonable intervals and updates to compute the result. Additionally, this could also vary according to the evolutionary students.

Therefore, correct assessment and constantly updated data make great demands on timely feedback and actionable adaptation based on continuous evaluation results. Feedback mechanisms are preferable to deliver personalized insights, recommendations, and interventions that support learning goals, address misconceptions, encourage meta-cognitive strategies, and promote self-regulated learning.

2.3. Lack of Emotion Monitoring in the Learner Model

The learner model, also called as student model or user model, reflects the learner characteristics and the traits of knowledge students possess, providing a relatively abstract representation of a learner that plays an essential part in the adaptive learning process [1, 6]. Different from the computer, human beings lack storage and processing capacity, but they do possess seven emotions, six senses, and sophisticated physical and psychological abilities [11]. In that, they will have a complex influence on the learning process subtly. However, the emotional demands of students are not easily met by the mechanical nature of typical human-computer interaction. There is always a complicated research gap in adaptive learning environments regarding emotions and personality, which are important in adaptive operations like feedback [12].

Sungkur and his partners proposed an eye-tracking system to identify learners' interests and behavior [13]. Junokas et al. suggested an effective system for improving learning practices based on multi-modal learning environments that integrate gesture recognition models [14]. While deep learning patterns of this kind have been applied to the classification of emotions, the field of adaptive learning has not shown much progress in monitoring natural language and emotional states. It can be said that there is no distinguished breakthrough in that field. In other words, the earlier systems cannot comprehend learners' feelings and cannot truly emotionally realize adaptive learning.

Consequently, a feasible adaptive learning algorithm and model that are completely capable of comprehending the mental processes and emotions of the brain are required to carry out human tasks. However, this AI-based method of emotion modeling can be rather troublesome and flawed.

2.4. Insufficient Train and Support for Students and Teachers

Mirata et al. once highlighted the importance of organizational challenges for they became even more salient than technological issues and teaching and learning issues [15]. The organizational issues just include essential resources, tactical instruction, institutional support, personnel policies, and quality assurance within adaptive experiences. In addition, Bailey et al. also acknowledged that effective adaptive e-learning requires professional assistance and training [4].

No doubt emerging demands are placed on educators and students by adaptive learning. On one hand, considering the immaturity of the role of the student, insufficient digital literacy and technical skills can be the major part they need to improve. Even if students might be accustomed to using cutting-edge technology, their abilities might need to be adjusted for the classroom and concentrated on achieving discipline-related goals. On the other hand, teachers, usually appearing in instructional roles, even have the possibility of possessing inadequate digital competence. Moreover, the majority of staff members are under a lot of strain from their enormous workloads, therefore they might not have enough time to investigate AI-assisted alternative teaching methods.

Therefore, both staff and students need to develop the necessary competencies and expertise as well as receive top-notch training and ample support services to ensure that they can acquire valuable information and skills to succeed in adaptive e-learning platforms.

2.5. Technology Integration and Inequity

Technology integration is increasingly becoming the foundation of the majority of adaptive learning models in use today. Tlili et al. used hybrid techniques based on a smart educational game to model learners' features during adaptive learning [16]. Zou & Xie also suggested a customized approach that offers learning paths that may be modified to accommodate varying degrees of course difficulty [17]. Each of them emphasized the significance of quality elements that can be well used in adaptive environments, like robust adaptive systems and outstanding usability.

However, the inconsistency of algorithms and the poor interoperability among diverse adaptive systems and platforms would increase the learning burden of students and affect learning efficiency. Without the incorporation of innovative technology, such as basic algorithms and operating modes, it is difficult to obtain a more universal and operable learning mode. Meanwhile, the sharing of quality data can mitigate the Matthew effect, which makes it easy to reduce imbalances in the development of adaptive learning.

As mentioned in the misconception of the "technological omnipotence theory", the capabilities of AI are not that sufficient to fully support all requirements of adaptive e-learning, especially in the aspect of technology inequity and resource availability [18]. It is common knowledge that adaptive education cannot be implemented sustainably without the appropriate technology infrastructure in place. All students do not, however, have fine access to certain infrastructure (software or hardware) in relatively isolated and less developed areas, like some places in South Africa [14]. It appears that many first-order infrastructure impediments have not been overcome.

That's how it goes. It became a challenge to offer cost-effective adaptive learning experiences to every student and an uphill work to ensure educational equity for all students worldwide.

3. Strategies for Adaptive Learning

Nevertheless, the challenges outlined in the prior sections are not entirely insurmountable. On the contrary, it is frequently possible to find some workable attempts to address these issues by looking for pertinent research or perceptive advice on adaptive learning.

3.1. Governing Data for Learning Management

Present adaptive learning systems, mostly use the centralized server management method, which has some flaws listed in the previous chapter, such as data bias, data disclosure, Matthew effect, and low efficiency for learning.

To deal with these issues and better manage the learning data during adaptive interaction, Li proposed the combination of intelligent graphic code and blockchain technology initially to manage and process data in a distributed and decentralized way [11]. Information is stored, transmitted, and interpreted with the use of smart code chains, geometric algorithms, and structured encryption. The outstanding merits of code chain technology, which combines the best features of blockchain with smart code, are as follows: high efficiency with quicker transmission and larger storage, personalized and traceable data collection in the whole process, shareable network nodes worldwide, distributed storage and decentralized data management for efficient personal learning without a central server, connectivity of learning content and resources across different systems, and decreased risk of disclosure of personal information with anonymous participates.

In this way, this innovative code chain technology can meet the functional requirements of an effective and secure adaptive learning system and offer critical support for the management of adaptive learning data.

3.2. Continuous Evaluation and Prediction

Constant evaluation can flexibly assist in determining each learner's unique skill set and personal characteristics, which represent their progressive evolution and constant path of development. While the evaluations are important, it is also required to identify the assessment frequency and to predict possible learning behaviors that can be used to improve the overall learning experience.

According to recent studies, Eldenfria and associates 2019 introduced a novel strategy for enhancing e-learning engagement based on the OCAM, an Online Continuous Adaptation Mechanism, with the assistance of EEG signals [19]. They developed an intelligent system that can timely track EEG signals and modify online course content flexibly based on an assessment of how engaged the student is. Lokare and Jadhav's AI-based learning style prediction model makes relatively precise predictions about learning preferences based on variables including emotional changes, attention, mental exertion, cognitive process, and facial expressions [20]. By giving users immediate feedback, all of the proposed models have the potential to significantly increase the efficacy of continuous evaluation and prediction for adaptive learning.

Meanwhile, from the perspective of the students themselves, the meta-cognitive evaluation of individual learning may significantly inspire learners to make progress in future learning [3]. Thus, the meta-cognitive review is indispensable in AI-based adaptive systems through ongoing evaluations of each provided learning model.

3.3. Visualized Cognition and Emotion

It has been discussed that the formation of learners' feelings of learning experience can be hampered and their motivation for self-learning would be undermined by the lack of cognitive and emotional visualization services. The chief cause might be that the adaptive learning system must comprehend how people learn and how their brains work. However, the current knowledge and exploration of the human brain is still relatively restricted at this point, hence, the development of information-gathering technologies that synchronize whole-brain cognition with local reactions is imperative [21].

After reviewing the recent research, the distinguished and effective way is to optimize the approach of visualizing cognition and emotion for adaptive learning. Wang et al. created the Mindolm, an open learner model, which can be used for visualizing adaptive cognition as a mind map [22]. Suhaimi underlined how crucial it is to use EEG to identify elusive emotions and put forward a novel method for presenting stimuli through virtual reality (VR) in 2020 [21]. In 2024, Zhu proposed the kind of model named knowledge-resource-objective for operating knowledge graphs where visualized data was collected through the Neo4j graph database. With the help of KRO, the related information was processed by the BiLSTM-CRF model to achieve cognitive and emotional visualization [2]. It concluded that the KRO model effectively optimizes knowledge structure and visualizes learners' cognitive states.

There is still a long way to go before the visual representation of knowledge systems and learners' cognitive states or processes are realized, even though previous researchers made it easier to visualize them and aided with precise learning paths and resource allocation for intelligent adaptive learning models. Moreover, there is very limited data on human emotions, and even worse unavailable information about spirit, values, and soul, despite huge existing knowledge sample data [22]. Given this, interdisciplinary integration is very necessary, which must be closely linked to psychology, mathematics, data statistics, machine learning, brain science, and other relevant sciences. Research on adaptive learning can be more likely to make significant advances in this direction.

3.4. Related Support and Professional Development

To deal with the possible problems mentioned in previous sections in terms of technological support and resources when implementing the adaptive teaching and learning practice, some helpful recommendations are proposed as follows. First, prior attention needs to be paid to the infrastructure's accessibility, including internet connectivity, necessary hardware and software, and quality equipment, to make things as accessible as possible for users. Adaptive learning is difficult to deploy without a foundational infrastructure in place.

Second, hiring qualified instructors is essential for providing instructors and students with the high-quality training and support they need to advance their knowledge and proficiency when learning in adaptive environments. Moreover, the beliefs of users for adaptive learning may be positively impacted by their access to affordances of adaptive technology [15].

Third, considering that the actual conduct of adaptive learning practice is cost-consuming, there is a need to control resource allocation and technology fitness. For example, it is feasible to distribute different adaptive resources depending on the divers needs of users and to choose adaptive technologies according to their characteristics, like interestingness or practicability. The appropriate allocation of resources and professional support can also prepare for adaptive teaching across studying phases, such as the transition from high school to university.

In addition, leadership commitment, local authority collaboration, and policy support can also be important solutions to improve effective adaptive implementation.

3.5. Integration of Technology and Education

Adaptive learning leverages technologies, such as learning algorithms based on machines, data analytics, artificial intelligence (AI), as well as learning management systems (LMS), to personalize learning experiences. All of them can be defined as adaptive engines to establish the optimal knowledge map for students' adaptive learning. Moreover, modern technology is developing at an ever-increasing rate. AI has trained Google Cloud AI Platform, Microsoft Azure AI, Alpha Go, Deep Blue, Open AI Chat GPT, and other advanced instruments by machine learning that have already outperformed humans.

However, machine learning cannot be used to train and instruct people all the time since education is a lifelong cognitive activity. Any learning system's architecture and underlying logic need to honor the nature of both education and humanity. That is to say, human traits and educational rules and methods should be carefully considered when operating adaptive systems.

In addition to focusing on the educational participants, it is significant to integrate technology with relevant educational theories and pedagogy. The review of adaptive systems reveals that most of them lack a pedagogical foundation and have substantial problems with teaching strategies, rigid learning paths, time and pace management, and maintaining learners' attention [9]. The following major educational theories can be applied to enhance adaptive learning: Constructivism places a strong emphasis on how students actively create their knowledge and understanding via interactions and experiences. Zone of Proximal Development, developed by Vygotsky, highlights the importance of providing learning experiences within the learner's ZPD. It can be understood as the gap between what they can accomplish on their own and with assistance. With Scaffolding, teachers can help students who are working on difficult assignments by offering them organized support and guidance. Behaviorism focuses on observable behaviors, reinforcement, and conditioning. Learning theories not only assist instructional designers in understanding how people retain information and stay focused and motivated in learning but also contribute to more comprehensive instructional models that can better modify adaptive rules or methods, and instructional design principles in adapting instruction.

Only by infiltrating AI technologies into all core aspects of teaching and learning and throughout the entire process with the guidance of beneficial educational theories can adaptive learning tools contribute to a fundamental enhancement of learning theories, methods, and outcomes.

4. Conclusion

To sum up, the application of AI-powered adaptive learning in e-learning has enormous potential to largely affect and even transform the traditional educational landscape. The essay has studied and analyzed previous research related to adaptive learning in terms of basic concepts, operation models, and useful outcomes. Importantly, this literature review especially has shed light on the challenges that adaptive learning is mainly facing and discussed possible solutions to them.

First, considering the potential data bias, disclosure, Matthew effect, low efficiency, and other inherent defects of adaptive e-learning, it is recommended to utilize Li's innovative code chain technology embracing intelligent graphic code and block-chain technology to manage learning data, which can improve the accuracy and security of data processing for students. Second, there is a must to empower adaptive platforms to appropriately conduct the continuous evaluation and prediction for possible learning behaviors due to the continuously fluctuating data and the evolutionary students themselves. To meet this, several outstanding adaptive systems, such as Online Continuous Adaptation Mechanisms (OCAM), can play a great role. Third, there is still a lack of emotion monitoring in the learner model because it is complicated to record human cognition with simple data. Notably, several effective methods, such as electroencephalography (EEG), virtual reality (VR), Mindolm, and knowledge-resource-objective (KRO) models can be used to optimize the approach to visualizing cognitive states. In addition, it is essential to provide professional support and training for the adaptive users, both students and teachers. Resource allocation, technology fitness, and supportive policies can also make sense for successful adaptive learning. Moreover, human traits and pedagogical methods should be considered comprehensively when conducting adaptive learning since education is a lifelong cognitive activity after all. Hence, it is critical to integrate diverse technologies into all aspects of lively educational practice.

Overall, this study highlighted the main challenges students might encounter when they learn in the adaptive platform and discussed potential solutions accordingly. An implication of this essay is the possibility that it could not only provide the adaptive system designers with varieties of feasible instruments or models to tackle underlying problems at their source and optimize them constantly, but can help researchers and users select the most proper methods for adapting learning government at different stages to avoid unnecessary trouble. Meanwhile, this article will also hopefully inspire policymakers and school leaders that high-quality technical support and the appropriate allocation of resources can be of great benefit to the development, implementation, and growth of adaptive learning.

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