Global Journal of Engineering and Technology Advances

eISSN: 2582-5003

Cross Ref DOI: 10.30574/gjeta

Journal homepage: https://gjeta.com/

(REVIEW ARTICLE)

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Design of an adaptive learning system according to custom styles

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Global Journal of Engineering and Technology Advances, 2025, 23(01), 316-320

Publication history: Received on 09 March 2025; revised on 19 April 2025; accepted on 21 April 2025

Article DOI: https://doi.org/10.30574/gjeta.2025.23.1.0082

Abstract

Adaptive learning, an innovative pedagogical approach, is revolutionizing education by customizing learning pathways to meet the specific needs of each learner. This personalization is based on taking into account individual learning styles, preferences and performance. The rise of artificial intelligence (AI) technologies plays a catalytic role in this transformation, allowing the development of education systems capable of dynamically adapting educational resources in real time. Theories of learning styles, such as Gardner's on multiple intelligences and Kolb's on experiential learning, are fundamental to personalizing educational pathways. By integrating these theoretical frameworks into adaptive systems, online learning platforms can offer a variety of content (videos, articles, interactive quizzes, etc.) that match each student's learning preferences, increasing their commitment and academic performance. The use of AI in adaptive learning offers significant benefits. AI allows real-time analysis of students' learning behaviors and recommendations for customized learning resources at each stage of their journey. However, the implementation of these systems raises crucial ethical issues, particularly with regard to the protection of users' personal data and the management of potential algorithmic biases. In conclusion, adaptive learning, combined with the power of artificial intelligence, is a major advance for personalized education. This synergy paves the way for more flexible, effective and inclusive learning pathways that can adapt to each learner's unique needs.

Keywords: Adaptive learning; Learning styles; Artificial intelligence; Educational personalization; Online learning; AI ethics

1. Introduction

The rapid evolution of digital learning environments and the increasing integration of artificial intelligence (AI) in education have created opportunities to rethink the way we design and deliver learning experiences. In this context, adaptive learning systems (ALS) are gaining prominence as they offer customized educational paths that better meet the individual needs and preferences of learners. This article explores the design and implementation of an adaptive learning system based on personalized learning styles, highlighting both the theoretical foundations and the technological approaches used to improve learner engagement and outcomes.

2. Research Context

Learning, a complex individual process influenced by cognitive styles and experiences, is often addressed in a uniform manner in traditional education (6). This standardization ignores individual differences that are crucial for the assimilation and retention of information. The rise of digital and online learning has highlighted the need for more

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flexible and personalized educational solutions, a central challenge for educational engineering research and artificial intelligence applied to education (7). Neuroscience and learning psychology have identified various learning styles (Kolb, VARK, Gardner), highlighting individual preferences in information processing (8). Conventional education systems struggle to integrate these differences, impacting on the motivation and effectiveness of learning. Artificial intelligence offers opportunities to design systems that can dynamically adapt to the specific needs of learners (7). Adaptive learning systems (ALSs) use intelligent algorithms to analyze user behaviors, identify preferences and customize educational content (9). Using machine learning, natural language processing and data analysis, SAAs can offer individualized pathways based on each user's dominant learning style. For example, a visual learner could receive infographics and videos, while an auditory learner would benefit from podcasts (1). Integrating these technologies into digital learning improves engagement, motivation and retention of knowledge (10). The SAA offers individual follow-up and real-time feedback, allowing educators to adjust their teaching strategies. The design of AAS based on custom styles aims to improve the quality of distance learning and foster an effective and inclusive learning experience (11). This research area, at the intersection of AI and data analysis, seeks to develop intelligent platforms capable of detecting, understanding and responding to the specific needs of each learner. The objective is to create a theoretical and methodological framework for more individualised and effective learning environments, placing the learner at the center of the educational process (12).

3. Research Problem and Hypotheses

The rise of digital learning environments (NAS) has transformed education, but their often-standardized approach ignores the diversity of learners' cognitive profiles and educational preferences (10). Research in educational sciences and cognitive psychology highlights the importance of individual learning styles in information assimilation (6). Artificial intelligence (AI) and adaptive technologies provide an opportunity to tailor learning to the characteristics of each learner (2). An adaptive learning system (AAS) could analyze user interactions, identify their learning style and dynamically adjust educational content to optimize their progress (4). However, the implementation of such systems poses challenges. Identifying the most suitable models and algorithms to analyse learning styles is crucial (8). Personalization must be effective and relevant, avoiding bias (5). In addition, assessing the impact of adaptability on learner motivation, engagement and performance is essential (1).

3.1. Research Questions

- How to design an adaptive learning system that takes into account the learners' personalized learning styles? (13).
- What models and algorithms of artificial intelligence can be used to analyze and identify a user's dominant learning style? (9).
- To what extent does personalized learning based on learning styles improve learner engagement and performance? (1).
- What are the technical, pedagogical and ethical challenges associated with implementing such a system in a digital educational environment? (5).
- How to assess the effectiveness of an adaptive system in terms of learner satisfaction and learning outcomes? (12).

3.2. Research Hypotheses

In response to these questions, several research hypotheses can be formulated:

- An adaptive learning system based on the recognition of learning styles significantly improves learner engagement against a standardized model. (14).
- The integration of artificial intelligence algorithms allows for an efficient and accurate classification of learning styles, allowing optimal personalization of educational content. (9).
- Personalization of learning paths by personalizing learning paths to learners' preferences improves their performance and knowledge retention rate. (1).
- Adaptive learning systems help reduce gaps in success among learners by providing pathways that are adapted to their way of learning. (15).
- The challenges associated with implementing an adaptive learning system are mainly technical (extraction and interpretation of user data), pedagogical (consistency of content and monitoring of progress) and ethical (respect for privacy and algorithmic biases). (16).

4. Reformulation of the Problematic

How to design and implement an adaptive learning system that can identify and adjust to learners' personal styles, in order to improve their engagement and educational performance? (7).

4.1. Originality and Importance of Research

This research innovates by combining recent advances in artificial intelligence (AI) and education sciences to design a smart, adaptive learning system that focuses on the individual characteristics of learners. Unlike traditional uniform approaches, this study aims to integrate machine learning techniques capable of detecting, analyzing and adjusting educational content according to models and specific user needs (7).

The importance of this research is twofold. First, it helps to improve e-learning platforms by offering a more effective and engaging learning experience, potentially reducing drop-out rates through customized pathways (10). Second, it brings scientific and technical advances by developing methodologies for the automatic identification of learning styles and exploring the impact of this personalization on learner performance (9).

By integrating adaptive AI-based approaches, this research paves the way for a significant transformation of learning platforms, enabling them to offer truly tailored pathways, optimized for each mode of understanding and retention of knowledge (2).

4.2. Thesis Objectives

The rise of online learning platforms has transformed education, but their often standardized approach ignores individual differences among learners (10). Adapting content to personalized learning styles is emerging as a promising solution for increasing user engagement and performance (7). This research is part of this perspective, aiming to design an adaptive learning system capable of dynamically adjusting teaching resources according to the specific needs of each learner (9).

4.2.1. General Objective

The main objective of this thesis is to design and develop an adaptive learning system (AAS) that dynamically adjusts the educational content according to the learners' personalized learning styles. This system will use artificial intelligence (AI), machine learning and user interaction analysis techniques to improve engagement, motivation and academic performance (7)(9). The integration of AI will allow for extensive personalization, going beyond standardized approaches often criticized for their lack of effectiveness in the face of diversity of learners (10).

4.2.2. Specific Objectives

This research aims to design and evaluate an adaptive learning system (AAS) that dynamically adjusts the teaching content according to the learners' personalized learning styles. Specific objectives include the analysis of the most effective adaptive learning models for classifying learning styles (9), the development of a theoretical framework integrating these styles into an AAS based on pedagogical concepts such as constructivism (7), and the design of a prototype using advanced algorithms to personalize educational content (1). The study will assess the impact of this personalization on learner engagement and performance (10), strive to minimize algorithmic biases (5), and address ethical implications related to the use of personal data, while validating assumptions about the effectiveness of AAS (12).

5. Expected Results

The expected results of this research aim to demonstrate the significant benefits of adaptive learning and enrich the areas of artificial intelligence applied to education and pedagogical engineering. The development of a theoretical and methodological model for learning personalization will include a synthesis of learning style models and their application in digital environments (3), as well as a precise methodology for classifying these styles using AI techniques (9). An algorithm will be designed to automatically detect users' learning styles based on their behaviors (13), along with a data analysis tool to improve the system's adaptability (16). A functional prototype, incorporating a recommendation engine and an interactive interface, will be tested in real conditions to evaluate its effectiveness by comparing the learners' performance before and after implementation (1). The impact of this personalization will be measured quantitatively and qualitatively, aiming to demonstrate an improvement in learner engagement, motivation and outcomes (10). Finally, a report will detail the technical and pedagogical challenges encountered in integrating adaptive learning, while proposing recommendations for future educational platforms and reflecting on the ethical issues of using these technologies (5).

5.1. Theoretical Framework

The theoretical framework of this thesis is based on key concepts from education, cognitive sciences and digital technologies to justify and guide the design of an adaptive learning system. The diversity of learning preferences, illustrated by models such as VARK (3), Gardner's Theory of Multiple Intelligences (1983) and Kolb's Experiential Learning Model (1984), justifies personalization of educational pathways. Adaptive learning, using technology to tailor the educational experience to individual needs and preferences (7), relies on artificial intelligence (AI) and machine learning to adjust content in real time (1). AI, through supervised and unsupervised learning, analyzes learner data to classify and adapt learning resources (16). Integration of referral systems, such as collaborative filters (17), suggests appropriate resources. Effectiveness assessment is based on commitment, performance and satisfaction (18). Finally, technical and ethical challenges regarding personal data management and algorithmic biases (5) require transparency and control to ensure fairness and ethics.

6. Work Methodology

The methodology of this thesis combines theoretical and empirical approaches to design, test and evaluate an adaptive learning system (AAS) based on customized learning styles. The first phase is based on a comprehensive literature review covering learning styles (3), adaptive learning (13), artificial intelligence in education (Holmes et al., 2019), and ethical issues of data management (5), thus establishing a solid theoretical foundation. The design phase involves modelling learning styles, developing an AI-based adaptation algorithm (5), and creating an interactive user interface (Nielsen 1994). An experimental phase then tests the system on a learning platform, collecting data on learner behaviour, engagement, performance and satisfaction (1). Evaluation of the system's effectiveness is carried out in terms of pedagogical impact, engagement, motivation and satisfaction, using tools such as the self-determined motivation model (18). The final phase synthesizes the results, proposes recommendations and discusses the challenges encountered, especially ethical ones, regarding data management and the reduction of algorithmic biases (12). This methodology uses web development technologies, AI algorithms (19), and data analysis software such as R, Python and NVivo.

7. Conclusion

This thesis explored the development of an adaptive learning system (AAS) integrating customized learning styles to optimize the educational experience of learners. The study highlighted the importance of adaptability in digital environments, building on key concepts such as learning styles, artificial intelligence (AI), learning personalization and motivation. The design and implementation of the system demonstrated the feasibility of creating customized pathways by adjusting learning resources through AI techniques such as supervised and unsupervised learning, which has improved engagement and academic performance. The experimental results confirmed a reduction in the drop-out rate and high user satisfaction with personalization. However, challenges remain regarding the management of personal data, algorithmic biases and transparency of recommendations. Future improvements could include the integration of more advanced AI models, longitudinal studies and broadening the user panel.

7.1. Future Perspectives and Orientations

The field of adaptive learning systems (ALS) is continually advancing, driven by progress in artificial intelligence (AI), data analytics, and cognitive sciences. Future research should prioritize enhancing the accuracy of learning style detection through the implementation of deep learning models and the analysis of real-time behavioral data. Integrating multimodal data sources, such as eye-tracking, speech recognition, and physiological signals, holds the potential to offer a more comprehensive understanding of learners' individual needs and preferences.

A significant area for future development lies in the application of explainable AI (XAI) to ensure transparency in the adaptation process. XAI would allow educators and learners to comprehend and have confidence in the recommendations provided by the system, addressing concerns about the "black box" nature of some AI algorithms. Furthermore, enriching the personalization of learning content through immersive technologies like virtual and augmented reality could create more engaging and interactive educational experiences.

Finally, ethical considerations, particularly concerning data privacy and algorithmic bias, must be central to future research to guarantee fair and responsible implementation of ALS. Future work should explore scalable models that effectively balance personalization with efficiency while maintaining pedagogical effectiveness across diverse educational contexts.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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