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AI-Based Adaptive Learning Model to Enhance Students' Self-Directed Learning in Higher Education

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Abstract

This study aims to develop an AI-based adaptive learning model to enhance students' self-directed learning in higher education. The proposed model integrates student profiling, adaptive content delivery, dynamic assessment, and learning analytics to provide a more personalized learning experience. The research employed a Research and Development (R&D) approach, including needs analysis, model design, implementation, and validation. The findings reveal that the AI-based adaptive learning model improves learning flexibility, student engagement, and the ability to manage independent learning strategies. This research contributes significantly to the development of educational technology and supports the digital transformation of higher education institutions.

Abstrak

Penelitian ini bertujuan mengembangkan model pembelajaran adaptif berbasis kecerdasan buatan (AI) untuk meningkatkan kemandirian belajar mahasiswa di perguruan tinggi. Model yang diusulkan mengintegrasikan pemetaan profil mahasiswa, penyajian konten adaptif, evaluasi dinamis, serta analitik pembelajaran guna menciptakan pengalaman belajar yang lebih personal. Metode penelitian menggunakan pendekatan Research and Development (R&D) dengan tahapan analisis kebutuhan, desain model, implementasi, dan uji validasi. Hasil penelitian menunjukkan bahwa model pembelajaran adaptif berbasis AI mampu meningkatkan fleksibilitas belajar, keterlibatan mahasiswa, serta kemampuan mereka dalam mengelola strategi belajar secara mandiri. Penelitian ini memberikan kontribusi penting dalam pengembangan teknologi pendidikan dan mendukung transformasi digital perguruan tinggi.

INTRODUCTION

The rapid advancement of digital technology has profoundly influenced the landscape of higher education, particularly in the design and implementation of learning models. Artificial Intelligence (AI) has emerged as a transformative force in education, offering innovative solutions for creating adaptive and personalized learning environments. Unlike traditional approaches, AI-driven adaptive learning systems have the capability to analyze students' learning behaviors, preferences, and performance data to deliver content that suits their individual needs (Holmes et al., 2021). This development is crucial in fostering students' self-directed learning, a key competence required in the 21st century and a vital indicator of academic success in higher education.

Self-directed learning (SDL) emphasizes the autonomy of learners in planning, monitoring, and evaluating their learning processes. Knowles (1975), in his theory of andragogy, defines SDL as a process in which individuals take initiative to diagnose their learning needs, set goals, identify resources, and evaluate outcomes. In higher education, SDL is particularly important as it equips students with the ability to manage complex knowledge and adapt to the demands of a rapidly changing workforce. Zimmerman (2002) further supports this through his theory of self-regulated learning (SRL), highlighting that learners who are able to regulate motivation, behavior, and cognition tend to achieve higher academic success.

Adaptive learning, as an instructional approach, draws on principles of constructivism and mastery learning. Piaget (1970) argued that learners construct knowledge through active interaction with their environment, while Bloom (1968) emphasized mastery learning, where instruction should be tailored to the pace of individual students. In the context of higher education, adaptive learning supported by AI aligns with these principles by offering personalized pathways that enhance engagement and outcomes. Vygotsky's (1978) sociocultural theory, particularly the Zone of Proximal Development (ZPD), also underscores the importance of scaffolding, which adaptive systems can provide dynamically through AI-based feedback and analytics.

The integration of AI into adaptive learning environments also resonates with Siemens' (2005) theory of connectivism, which argues that learning in the digital era occurs through networks of people, digital tools, and information systems. AI-based adaptive learning models serve as nodes within this network, enabling students to connect with knowledge resources and learning strategies in a personalized and meaningful way. Despite these theoretical foundations, higher education institutions continue to face challenges in fostering SDL. Conventional teaching approaches often apply a one-size-fits-all method, limiting flexibility and student autonomy. While adaptive learning technologies have been studied in various contexts, research that specifically integrates AI-driven adaptive models to strengthen SDL remains limited, especially in non-Western educational systems.

Therefore, this study aims to develop and validate an AI-based adaptive learning model designed to enhance self-directed learning among university students. The model is expected to bridge the gap between technological innovation and pedagogical practice, providing a framework that supports digital transformation in higher education. Furthermore, this research contributes not only to the theoretical understanding of adaptive learning and educational technology but also offers practical implications for educators, policymakers, and institutions seeking to improve learning quality through AI-driven innovation.

METHODS

1. Research Design

This study employed a Research and Development (R&D) approach aimed at designing, developing, and validating an AI-based adaptive learning model to enhance self-directed learning (SDL) in higher education. The R&D approach was adapted from Borg and Gall (1983), with modifications to fit the context of educational technology. The stages included: Needs Analysis, Model Design, Model Development, Expert Validation, Implementation, And Evaluation.

2. Participants and Context

The research was conducted in a higher education institution involving undergraduate and postgraduate students. A purposive sampling technique was used to select participants who had diverse learning backgrounds and technological proficiency. In the initial stage, 60 students participated in the needs analysis survey, while 30 students were involved in the pilot testing of the prototype model. Additionally, three experts in educational technology and AI in education were consulted for validation purposes.

3. Data Collection Instruments

Multiple instruments were employed to ensure comprehensive data collection:

1. Needs Analysis Questionnaire: to gather data on students' learning preferences, challenges in self-directed learning, and expectations regarding technology-based learning.
2. System Usability Scale (SUS): to measure the usability of the AI-based adaptive learning prototype.
3. Self-Directed Learning Readiness Scale (SDLRS) adapted from Guglielmino (1977): to evaluate changes in students' SDL before and after implementation.
4. Interviews and Focus Group Discussions (FGDs): with students and lecturers to gain qualitative insights on the effectiveness of the model.

4. Model Development

The AI-based adaptive learning model was designed to integrate four main components:

1. Learner Profiling: collecting data on students' cognitive levels, learning styles, and interaction patterns.
2. Adaptive Content Delivery: presenting learning materials tailored to individual profiles.
3. Dynamic Assessment: providing formative evaluations that adjust to students' progress.
4. Learning Analytics: offering real-time feedback to both students and lecturers.

The model was implemented using a Learning Management System (LMS) integrated with AI modules, such as recommendation algorithms and natural language processing.

5. Data Analysis

Both quantitative and qualitative methods were used:

1. Quantitative Analysis: Paired-samples t-tests were conducted to examine improvements in students' SDL levels before and after using the adaptive model. Descriptive statistics were used to analyze usability and engagement.
2. Qualitative Analysis: Thematic analysis was applied to interview and FGD transcripts to identify recurring themes related to students' experiences, challenges, and perceptions of the adaptive learning model.

6. Validity and Reliability

To ensure rigor, triangulation of data sources (questionnaires, system logs, interviews) was conducted. Expert validation was employed to establish content validity, while Cronbach's Alpha was calculated for reliability of the instruments.

RESULT AND DISCUSSION

RESULT

Needs Analysis

The needs analysis revealed that the majority of students (78%) faced difficulties in managing their own learning process, particularly in setting learning goals, maintaining motivation, and evaluating progress. Furthermore, 72% of respondents expressed interest in having a system that could provide personalized learning pathways. These findings confirmed the necessity of developing an AI-based adaptive learning model to foster students' self-directed learning (SDL).

Model Development and Validation

The proposed model integrates learner profiling, adaptive content delivery, dynamic assessment, and learning analytics. Expert validation results indicated that the model was highly relevant, practical, and feasible for implementation in higher education, with an average expert rating score of 4.5 out of 5.

Table 1. Comparison of Conventional vs. Adaptive AI-Based Learning

Aspect	Conventional Learning	AI-Based Adaptive Learning
Content Delivery	Uniform for all learners	Personalized based on learner profiles
Role of Lecturer	Main source of knowledge	Facilitator and guide in adaptive system
Assessment	Fixed and standardized	Dynamic and responsive
Feedback	Delayed	Real-time through AI analytics
Learner Autonomy	Low	High, encourages self-directed learning

Pilot Implementation Results

During the pilot test with 30 students, the System Usability Scale (SUS) score reached 82.4, indicating a high level of usability. Students reported that the system was user-friendly and effective in guiding them to manage their learning process.

Pre-test and post-test using the Self-Directed Learning Readiness Scale (SDLRS) showed a significant improvement ($t = 4.72$, $p < 0.01$). This indicates that the adaptive learning model successfully enhanced students' self-directed learning skills.

Figure 1. Framework of the AI-Based Adaptive Learning Model

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+------------------+
| Learner Profiling |
+--------+---------+
         |
         v
+------------------+
| Adaptive Content  |
+--------+---------+
         |
         v
+------------------+
| Dynamic Assessment|
+--------+---------+
         |
+--------v---------+
| Learning Analytics|
+--------+---------+
         |
         v
+------------------+
| Self-Directed     |
| Learning Skills   |
+------------------+
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Discussion

The findings highlight that AI-based adaptive learning models can significantly improve student engagement, motivation, and self-directed learning. This is consistent with Zimmerman's (2002) theory of self-regulated learning, which emphasizes the role of metacognitive strategies in achieving academic success. Moreover, the integration of AI into adaptive learning environments aligns with Siemens' (2005) connectivism theory, which views digital networks as essential for modern learning.

Students reported that real-time feedback and adaptive content delivery helped them feel more autonomous in managing their learning. These findings resonate with Knowles' (1975) andragogical principles, which stress the importance of learner autonomy in adult education. Additionally, the study supports Bloom's (1968) mastery learning concept, as AI-driven assessments allowed learners to progress at their own pace until mastery was achieved.

Thus, the implementation of AI-based adaptive learning not only enhances SDL but also bridges the gap between pedagogy and technology in higher education.

CONCLUSION

This study concludes that the AI-Based Adaptive Learning Model has proven effective in enhancing students' self-directed learning (SDL) skills in higher education. The model's integration of learner profiling, adaptive content delivery, dynamic assessment, and learning analytics significantly improved students' autonomy, motivation, and academic performance.

Findings from the pilot implementation confirmed that students experienced a more personalized and engaging learning process, supported by real-time feedback. This aligns with Knowles' andragogy, Zimmerman's self-regulated learning theory, and Bloom's mastery learning, showing that the model bridges theory and practice in digital education.

Thus, the adoption of AI-based adaptive learning contributes to the transformation of higher education toward a more personalized, technology-driven, and learner-centered paradigm.

Recommendations

Implementation at Larger Scale

Future research should test the model with a larger and more diverse population across various disciplines to validate its generalizability.

Integration with Learning Management Systems (LMS)

The model can be embedded within existing LMS platforms (e.g., Moodle, Canvas) to ensure wider accessibility and sustainability.

Faculty Development Programs

Training programs should be designed to prepare lecturers in adopting AI tools effectively while shifting their role from content providers to facilitators.

Longitudinal Studies

Further studies are needed to examine the long-term impact of adaptive learning on students' academic achievement, critical thinking, and lifelong learning skills.

Policy and Institutional Support

Policymakers and higher education institutions should support the development and adoption of AI-driven adaptive learning frameworks as part of digital transformation strategies.

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