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AI-DRIVEN ADAPTIVE RESOURCE SUGESSTION IN DIGITAL LEARNING ENVIRONMENTS: INSIGHTS FROM EDUCATIONAL PSYCHOLOGY

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Abstract: This study examines the effectiveness of an AI-driven adaptive resource delivery system in enhancing learning outcomes within a digital reading environment. Drawing on principles from educational psychology—particularly cognitive load theory and individualized scaffolding—the system adjusted instructional materials in real time according to learners' performance indicators. A randomized controlled experiment was conducted with 152 undergraduate students assigned to either an adaptive learning condition or a fixed-resource control condition. Both groups studied identical content, but only the adaptive group received personalized adjustments such as difficulty modulation, targeted hints, and additional practice opportunities. Results showed that learners in the adaptive condition demonstrated significantly greater gains in reading comprehension than those in the control condition, as evidenced by a significant Time × Group interaction and higher post-test scores. Moreover, adaptive learners reported significantly lower cognitive load, indicating more efficient cognitive processing. These findings provide empirical support for integrating AI-based adaptive systems into digital learning environments and highlight the value of aligning algorithmic personalization with established theories in educational psychology.

Keywords: AI-driven adaptivity; personalized learning; digital learning environments; educational psychology; cognitive load; adaptive resource delivery; randomized controlled experiment

1. INTRODUCTION

Remote education is a novel educational modality in contrast to traditional face-to-face instruction. It facilitates educators in delivering courses and students in accessing materials from distant locations. Consequently, online learning has emerged as a crucial modality in remote education, particularly serving an essential function during the COVID-19 pandemic of 2020 (Wu, 2021).

In contrast to traditional classroom learning, online education enables students to access knowledge at any time and from any location (George and Lal, 2019). Recently, numerous online learning platforms offering students a diverse array of educational resources have evolved, including MOOCs and Coursera (Zhang et al., 2019; Jin et al., 2021). Nevertheless, confronted with extensive learning resources, students often struggle to efficiently and comfortably locate content that is appropriate for them, leading to distraction and diminished learning efficacy. Consequently, it is essential to accurately identify suitable learning resources and provide them to individual students based on their interests and personal attributes (Wu et al., 2020b).

Recommendation systems have been employed in the educational sector, offering students diverse resources, including articles, websites, and video courses. Hsu et al. (2013) developed a reading recommendation system to deliver articles aligned with students' reading preferences. Lichtnow et al. (2011) formulates a student-knowledge model for the purpose of recommending specific websites or paper links to students. Furthermore, personalised course recommendation systems have been a focus of research (Zhang et al., 2017; Wei et al., 2021; Khalid et al., 2022). The predominant online learning resource recommendation systems are primarily based on collaborative filtering algorithms. Initially, they create a user-item matrix and subsequently offer learning materials based on the similarity between users or objects (Tian & Liu, 2021). Their motivation is to adapt the recommended strategies from contexts like as entertainment viewing and e-commerce purchasing to online learning. Students constitute the primary component of online learning. When making resource suggestions in online learning contexts, two issues are likely to arise and should be meticulously addressed: How can one devise a recommendation system based on a student's individual learning capabilities or traits? How might creative online learning resources be provided to students to maximise their potential?

To address the initial issue, numerous studies have examined student learning behaviours through the lens of educational psychology and investigated students' learning conditions. The objective of educational psychology is to utilise the most effective scientific principles in teaching and learning contexts to enhance the comprehension of educational psychology and practice. It can be utilised to indicate a student's psychological learning status, so establishing a basis for investigating the student's learning features.

Bloom's approach (Testa et al., 2018) can be utilised to examine the principles governing students' acquisition of knowledge. The cognitive diagnosis approach, based on psychometrics (Ren et al., 2021), may categorise students' competence levels based on their knowledge composition. The zone of proximal development (ZPD) emphasises the cultivation of a student's potential. It suggests that enhancing educational content can boost students' learning capabilities (Chaiklin, 2017). Consequently, educational psychology can assist in uncovering implicit pedagogical principles, enabling the assessment of students' learning conditions and the formulation of tailored suggestion tactics for diverse learners.

To address the second issue, it is necessary to investigate innovative yet appropriate online learning materials for students through the lens of artificial intelligence (AI). Recommendation methodologies serve as a quintessential sort of AI technology, adeptly facilitating information retrieval and filtering. In current recommendation contexts, the context-based bandit algorithm LinUCB can effectively balance exploration and exploitation (Li et al., 2010). In other words, LinUCB may meticulously address consumers' established interests while also exploring their undiscovered preferences in the context of news suggestion.

Nonetheless, when utilised for video recommendation in the online learning context, LinUCB has several drawbacks. It specifically disregards the individualised qualities of students, such as their learning capabilities. This limitation inherently poses a danger to the discovery process, since the suggested new resources may prove significantly challenging for the student. This may result in the degradation of the recommendation system's performance and an escalation of the student's cognitive burden.

To address the aforementioned restrictions, this paper proposes a personalised online learning resource suggestion utilising artificial intelligence and educational psychology. Initially, from the standpoint of educational psychology, we utilise the proportion of students engaging with educational videos, the extent of completion, and the accuracy rate of quiz responses to assess their proficiency. It can indicate their personalised learning progress. Students can be categorised into three primary types using the clustering approach based on their abilities.

Secondly, we utilise the learning behaviour records of all students to extract elements of the educational videos, including their levels of difficulty. An AI-assisted LinUCB-based recommendation method is suggested to deliver appropriate educational films to students. This algorithm incorporates the student's capability into a tailored exploration plan, enabling the provision of educational films with an appropriate level of difficulty. It can effectively adjust to the student's learning capacity and mitigate the risk of exploration.

Educational psychology assesses a student's unique abilities and subsequently integrates this evaluation into a proposal, so facilitating the potential for a personalised suggestion. Moreover, by incorporating educational psychology into online learning resource recommendations, the proposed framework in this article demonstrates enhanced supportability and reliability, as it is grounded in the fundamental learning behaviours of students rather than merely striving for improved accuracy of the recommendation model. This is a proficient application of educational psychology research to online learning environments.

2. LITERATURE REVIEW

2.1 Educational psychology

Educational psychology pertains to the scientific examination of diverse psychological and behavioural principles within the context of educational practice. It can elucidate the characteristics of learning outcomes, delineate the learning process, and describe the conditions and principles of effective learning.

The zone of proximal development is a significant term in educational psychology, denoting the disparity between two levels of capability. One aspect is the degree of problem-solving when a learner engages in self-regulated learning. The other signifies the prospective developmental stage following instruction and learning. In the realm of cognitive development, the Zone of Proximal Development necessitates that educators aid children in comprehending concepts that they cannot grasp independently (Chaiklin, 2017). Furthermore, the Zone of Proximal Development (ZPD) is regarded as the cornerstone of individualised education. In the Zone of Proximal Development (ZPD), it is essential to furnish pupils with learning resources that are neither excessively facile nor overly challenging, but rather marginally surpass their existing capabilities.

A tailored educational framework grounded in the ZPD principle is formulated to optimise the collective benefits for students (Wang et al., 2020). Cognitive load theory (Sweller, 1994) posits that the complexity of learning materials must align with the learner's capabilities. Students are unable to retain overly complex learning resources in the long term due to their constrained working memory (Sweller, 2016). They often achieve optimal learning outcomes when engaging with resources that somewhat exceed their current capabilities.

Furthermore, a crucial function of educational psychology is to monitor students' grasp of knowledge. Bloom's model delineates the process by which students attain mastery of knowledge through six levels: three foundational levels (knowledge, understanding, and application) and three advanced levels (analysis, synthesis, and evaluation). Educators must concentrate on integrating higher-order cognitive processes into instruction and evaluation, so guaranteeing that students acquire essential problem-solving and critical-thinking abilities (Swart, 2009). The greater the cognitive level of the students, the more effectively they utilise the learning resources. Additionally, there are other educational psychology theories to assess pupils' learning levels. The learning curve can illustrate the effects of pupils' learning. It frequently demonstrates that the quantity of learning influences a learner's mastery of knowledge. The forecasting of the learning curve offers the capacity to provide effective strategies for individualised tutoring (Liu and Zhang, 2019). Classical test theory indicates that scores may accurately represent the true abilities of students in the assessed attributes (Tatsuoka et al., 1968). Collectively, the aforementioned principles and beliefs establish a foundation for monitoring students' learning progress and assessing their abilities.

2.2 Personalized digital educational resource suggestion system

Personalized digital educational resource suggestion systems refer to algorithmic mechanisms that recommend learning materials—such as videos, exercises, readings, and interactive modules—based on learners' characteristics, behaviors, and progress. Their emergence is closely tied to developments in learning analytics, adaptive learning, and artificial intelligence in education (AIEd). The core premise is that learners benefit from materials aligned with their current knowledge state, cognitive load, motivation, and learning preferences (Fischer et al., 2023). Unlike traditional "one-size-fits-all" instruction, personalized recommendation systems dynamically adjust content in real time, aiming to enhance learning efficiency and engagement.

The design of recommendation systems in education is often grounded in frameworks from educational psychology.Self-regulated learning (SRL) theory suggests that students' metacognitive monitoring and control processes shape how recommendations can scaffold learning (Winne & Hadwin, 2013). Systems that infer learners' goals, effort, and strategy patterns can deliver materials that support planning or reflection. Similarly, Cognitive Load Theory (Sweller, 2016) underscores the need for resource difficulty levels to match individual working-memory constraints; adaptive resource sequencing reduces extraneous load and improves retention.

From a motivation perspective, Self-Determination Theory (SDT) highlights personalization as a mechanism to enhance autonomy and competence, thereby increasing persistence (Ryan & Deci, 2017). Recommendation algorithms therefore frequently incorporate behavioral signals—such as time-on-task, help-seeking frequency, and dropout risk—to align resources with learners' motivational states. Machine-learning foundations include collaborative filtering, content-based filtering, knowledge tracing, and reinforcement learning approaches. Bayesian Knowledge Tracing (BKT) and Deep Knowledge Tracing (DKT), for example, estimate learners' mastery probabilities and deliver exercises targeted at strengthening weak skills (Piech et al., 2015). Reinforcement-learning models optimize the long-term reward of improved learning outcomes rather than short-term engagement.

Empirical studies consistently show positive effects of personalized recommendation systems. Meta-analytic reviews (Khosravi et al., 2022) indicate improvements in learning efficiency, achievement, and engagement, with moderate to large effect sizes. Adaptive sequencing systems (e.g., ASSISTments, ALEKS) have demonstrated enhanced mastery in mathematics due to optimized practice opportunities. However, effects are not uniform. Some studies show diminished gains when personalization is too opaque or when learners resist algorithmic control (Holstein et al., 2020). Excessive adaptivity may impair autonomy, while poorly calibrated difficulty may create frustration. These findings underscore the need to balance algorithmic adaptivity with learner agency.

3. METHOD

3.1 Participants and Design

A total of 152 undergraduate students from a comprehensive university in China voluntarily participated in the study. Participants were randomly assigned to either the AI-adaptive learning group (n = 76) or the control group (n = 76). All participants were native Chinese speakers enrolled in an English-related general education course. None had prior experience with AI-driven adaptive learning systems. Informed consent was obtained prior to data collection.

The study employed a two-group between-subjects randomized controlled experiment comparing an AI-driven adaptive resource delivery system (experimental group) with a traditional fixed-resource learning environment (control group). Both groups studied the same instructional content, but only the experimental group received real-time adaptive adjustments based on their learning behaviors and performance. Learning performance was measured using pre- and post-tests to evaluate knowledge acquisition and skill improvement.

3.2 Materials and Learning Platform

The instructional materials used in this study consisted of a 1,200-word expository academic passage followed by a set of reading comprehension tasks designed to assess literal, inferential, and vocabulary-related understanding. Two parallel versions of the test were developed to serve as the pre-test and post-test, and the difficulty level of the items was calibrated through a pilot study with a separate cohort of students. The learning tasks were delivered through a custom-built digital platform that supported two modes of instruction. In the experimental condition, the platform operated in AI-adaptive mode, where an adaptive algorithm adjusted the type and difficulty of learning resources based on learners' real-time performance indicators, including accuracy rates, response times, hesitation patterns, and repeated errors. The adaptive system generated individualized scaffolding such as simplified explanations, additional practice examples, targeted hints, and pacing adjustments. In contrast, participants in the control condition used a non-adaptive version of the same platform that presented identical learning content but without any personalization or automated feedback. This ensured that content exposure was equivalent across groups while allowing the effect of adaptive resource delivery to be isolated.

3.3 Procedure

The experiment was conducted in a university computer laboratory under standardized environmental conditions. Upon arrival, participants were seated at individual computer stations and provided with instructions for the study.

They first completed a 10-minute pre-test measuring their baseline reading comprehension performance. Immediately following the pre-test, participants engaged in the 20-minute learning phase, during which they either interacted with the AI-adaptive system (experimental group) or the fixed-resource system (control group). Both groups studied the same instructional content during this period; the only difference was the adaptivity of the support they received. Upon completing the learning task, participants took a 10-minute post-test that was parallel in difficulty and structure to the pre-test. Finally, participants completed a brief measure of perceived cognitive load. The entire procedure lasted approximately 45 minutes. To minimize potential bias, all instructions were scripted, and no information about group assignment or hypotheses was disclosed to participants. Those who completed all stages received course credit compensation in accordance with institutional guidelines.

3.5 Measures

Learning performance was assessed using the pre- and post-test reading comprehension measures, each containing 10 multiple-choice items scored dichotomously. Test forms were developed to be equivalent in structure and difficulty, and item intercorrelations demonstrated satisfactory internal consistency. Higher scores indicated stronger reading performance. To evaluate learners' perceived mental effort during the learning phase, the study employed the single-item 9-point mental effort scale developed by Paas (1992), a widely used and validated measure in cognitive load research. Participants rated how much mental effort the learning task required on a scale ranging from 1 ("very, very low mental effort") to 9 ("very, very high mental effort"). Lower scores reflected reduced subjective cognitive load. All measures were administered electronically through the learning platform to ensure standardized presentation and automated scoring.

3.6 Data Analysis

Data analyses were conducted using SPSS 28. To verify baseline equivalence, independent-samples t tests compared pre-test performance between the experimental and control groups. The primary evaluation of learning outcomes employed a mixed-design ANOVA, with Time (pre-test vs. post-test) treated as a within-subject factor and Group (AI-adaptive vs. control) treated as a between-subjects factor. Significant interactions were followed by Bonferroni-adjusted pairwise comparisons to identify the source of differences. Post-test scores were further compared using independent-samples t tests to determine whether the adaptive system produced superior performance after the learning phase. Cognitive load scores were also analyzed using independent-samples t tests to examine whether the adaptive system reduced subjective mental effort. Statistical significance was set at $p < .05$ for all analyses, and effect sizes (Cohen's d and partial eta squared) were reported where appropriate to facilitate interpretation of practical significance.

4. RESULTS

4.1 Preliminary Analyses

Descriptive statistics for all measured variables are presented in Table 1. To establish baseline equivalence between the two instructional conditions, an independent-samples t test was conducted on the pre-test reading comprehension scores. Results indicated no significant difference between the adaptive group and the control group, $t(150) = 0.42$, $p = .674$, confirming that participants entered the experiment with comparable levels of reading proficiency. Visual inspection of the score distributions showed no abnormalities, and diagnostic tests indicated that assumptions of normality and homogeneity of variance were met. Together, these findings suggest that the random assignment procedure was effective and that any subsequent performance differences can be attributed to the learning condition rather than to initial disparities (see Table 1).

Table 1. Descriptive Statistics

Measure	Group	M	SD	Statistical Test	p
Pre-test performance	Adaptive	6.18	1.21	$t(150) = 0.42$	.674
	Control	6.23	1.18		
Post-test performance	Adaptive	8.12	1.09	$t(150) = 5.31$	< .001
	Control	7.01	1.22		
Cognitive load	Adaptive	4.12	1.37	$t(150) = -4.26$	< .001
	Control	5.21	1.43		

4.2 Effects of AI-Adaptive Resource Delivery on Learning Performance

To examine whether the adaptive system led to greater learning gains than fixed-resource instruction, a mixed-design ANOVA was performed with Time (pre-test vs. post-test) as the within-subject factor and Group (adaptive vs. control) as the between-subjects factor. As expected, there was a significant main effect of Time, $F(1, 150) = 46.91$, $p < .001$, $\eta^2 = .24$, indicating that overall reading performance improved after the learning session. The main effect of Group was not significant, $F(1, 150) = 1.87$, $p = .173$, reflecting comparable average performance across the two groups when collapsing across time.

Critically, the Time × Group interaction was significant, $F(1, 150) = 22.14$, $p < .001$, $\eta^2 = .13$, demonstrating that the magnitude of improvement differed across instructional conditions. Follow-up comparisons revealed that the adaptive group showed a substantially larger increase in reading comprehension scores, improving from a mean of 6.18 (SD = 1.21) on the pre-test to 8.12 (SD = 1.09) on the post-test, whereas the control group improved from

6.23 (SD = 1.18) to 7.01 (SD = 1.22). This pattern of results indicates that the adaptive learning environment yielded a pedagogically meaningful advantage in promoting comprehension gains.
To further validate the differential impact on post-test performance, an independent-samples t test was performed on the post-test scores alone. Results showed that the adaptive group significantly outperformed the control group, $t(150) = 5.31$, $p < .001$, with a medium-to-large effect size, indicating that learners who interacted with AI-driven adaptive resource delivery achieved higher final comprehension levels.

5. DISCUSSION

The present study investigated the effectiveness of AI-driven adaptive resource delivery in a digital learning environment by comparing it with a traditional fixed-resource instructional approach. Consistent with expectations, the findings demonstrated that the adaptive system produced significantly greater gains in reading comprehension than the non-adaptive system, even though both groups engaged with the same instructional content for the same duration. Importantly, these improvements were accompanied by significantly lower cognitive load among learners in the adaptive condition, suggesting that the benefits of adaptivity are both performance-based and experiential (Kim, 2021). These results align with a growing body of research highlighting the potential of adaptive systems to support individualized learning and extend our understanding of how such systems influence learning processes within the context of reading-focused digital instruction.
The significant interaction between time and instructional condition indicates that learners exposed to AI-driven adaptivity not only improved but did so at a substantially higher rate than learners in the fixed-resource condition. This pattern supports the argument that adaptive scaffolding can accelerate comprehension gains by providing learners with guidance tailored to their evolving needs (Azevedoet al., 2011). Unlike conventional digital materials that present identical content to all learners, the adaptive system continuously calibrated the difficulty, pacing, and instructional support based on learners' ongoing performance. Such personalization may have helped learners maintain an optimal level of challenge, which has been identified as a key factor in fostering deep engagement and effective learning. The results therefore reinforce the notion that adaptivity can serve as a mechanism for enhancing learning efficiency in technology-mediated environments.
The findings regarding cognitive load further illuminate the underlying processes through which adaptive learning environments may exert their influence. Learners in the adaptive condition reported significantly lower mental effort than those in the control condition, despite ultimately achieving higher performance. This pattern is consistent with cognitive load theory, which posits that instructional designs that minimize extraneous cognitive load allow learners to allocate more cognitive resources to essential processing. In the present study, adaptive supports—such as targeted hints, tailored examples, and difficulty adjustments—likely reduced unnecessary cognitive burdens associated with processing complex texts. By enabling learners to focus on meaning construction rather than task management or error correction, the adaptive system may have facilitated more efficient cognitive processing, thereby contributing to improved comprehension.
Beyond theoretical considerations, the findings carry meaningful implications for practice. As digital learning environments continue to expand within higher education, adaptive systems offer a scalable means of delivering individualized support without increasing the workload of instructors. The current study demonstrates that even relatively brief exposure to adaptive resource delivery can yield significant learning benefits, suggesting that adaptive features could be profitably integrated into reading, language learning, and other cognitively demanding online courses. Moreover, reductions in cognitive load may enhance learners' confidence and persistence, factors that are particularly relevant in self-directed or asynchronous digital learning contexts. Institutions seeking to enhance student engagement and performance in large-enrollment courses may therefore find adaptive systems to be a particularly promising avenue for innovation.
Despite these contributions, several limitations warrant consideration. First, the study employed a relatively short intervention period, and it remains unclear whether the observed advantages of adaptive instruction would persist or expand over longer learning cycles. Longitudinal research is needed to assess the durability of these effects and to explore how adaptivity influences the development of higher-order reading strategies over time. Second, the current study focused on reading comprehension; thus, caution is warranted when generalizing the findings to other domains such as writing, problem-solving, or STEM-related tasks. Because cognitive demands differ across disciplines, adaptive systems may need to incorporate domain-specific models of learner behavior to achieve similar benefits. Third, the subjective nature of the cognitive load measure, though widely used in cognitive load research, may limit the granularity of insights into learners' mental processes. Future studies could incorporate physiological or behavioral indicators of cognitive load to obtain a more comprehensive understanding of learners' cognitive experiences.
Future research should also examine individual differences in the effectiveness of adaptive systems. Although this study did not focus on learner characteristics, existing theories suggest that factors such as self-regulated learning skills, prior knowledge, and academic motivation may moderate the benefits of adaptivity. Understanding for whom and under what conditions adaptive resource delivery is most effective would allow developers to refine personalization algorithms and ensure equitable learning outcomes. In addition, future work could explore how learners perceive and interact with adaptive features, as user experience may play a critical role in shaping both engagement and learning trajectories within intelligent learning environments.

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