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Artificial Intelligence–Driven Adaptive Learning and Microlearning Integration in Enhancing Self-Regulated Learning and Critical Thinking among Adult Digital Learners

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Abstrak

Penelitian ini bertujuan untuk menganalisis secara mendalam pengaruh integrasi Artificial Intelligence (AI) berbasis Adaptive Learning dan Microlearning terhadap pengembangan kemampuan berpikir kritis serta metodologi self-regulated learning pada pembelajar dewasa dalam lingkungan e-learning. Perkembangan teknologi pendidikan yang didukung oleh Big Data Analytics telah mendorong terjadinya personalisasi pembelajaran secara ekstrem, sehingga memungkinkan sistem secara otomatis menyesuaikan materi, kecepatan, dan jalur belajar berdasarkan performa individu. Penelitian ini menggunakan pendekatan kualitatif interpretatif dengan desain Exploratory Sequential Mixed-Methods, yang diawali dengan penyebaran kuesioner sebagai tahap penyaringan dan dilanjutkan dengan wawancara mendalam terhadap 25 pembelajar digital aktif. Hasil penelitian menunjukkan bahwa sistem adaptif berbasis AI secara signifikan meningkatkan efisiensi kognitif dengan mengurangi waktu yang dihabiskan pada materi yang telah dikuasai, sehingga peserta didik dapat mengalokasikan lebih banyak energi mental pada aktivitas analisis, aplikasi konsep, dan pemecahan masalah kompleks. Selain itu, personalisasi yang diberikan sistem turut meningkatkan kesadaran metakognitif, kemampuan mengidentifikasi kelemahan konsep, serta kemandirian dalam mengatur strategi belajar. Meskipun demikian, sebagian kecil responden mengungkapkan kekhawatiran bahwa sistem yang terlalu optimal berpotensi mengurangi pengalaman eksploratif dan proses trial-and-error yang penting bagi kreativitas. Penelitian ini menawarkan kerangka Holistic Cognitive Assessment (HCA) sebagai model evaluasi alternatif yang mengintegrasikan data performa adaptif dengan penilaian kualitatif untuk mengukur kontribusi sistem terhadap keterampilan berpikir tingkat tinggi secara lebih komprehensif.

Kata kunci: *Pembelajaran Adaptif, Kecerdasan Buatan, Pembelajaran Mikro, Pembelajaran Mandiri, Berpikir Kritis, Analisis Big Data*

Abstract

This study aims to provide an in-depth analysis of the influence of Artificial Intelligence (AI)-based Adaptive Learning and Microlearning integration on the development of critical thinking skills and self-regulated learning methodology among adult learners in e-learning environments. The rapid advancement of educational technology supported by Big Data Analytics has enabled extreme personalization, allowing systems to automatically adjust content, pacing, and learning pathways based on individual performance patterns. This research employed an interpretive qualitative approach using an Exploratory Sequential Mixed-Methods design, beginning with a screening questionnaire and followed by in-depth semi-structured interviews with 25 active digital learners. The findings reveal that AI-driven adaptive systems significantly enhance cognitive efficiency by minimizing time spent on previously mastered material, thereby enabling learners to allocate greater cognitive resources toward analytical reasoning, conceptual application, and complex problem-solving tasks. Furthermore, hyper-personalization contributes to improved metacognitive awareness, better identification of conceptual gaps, and stronger self-regulation strategies. However, a minority of participants expressed concerns that highly optimized adaptive systems may reduce exploratory trial-and-error experiences that are essential for creativity development. This study proposes a Holistic Cognitive Assessment (HCA) framework that integrates adaptive performance metrics with qualitative evaluation as a more comprehensive approach to measuring higher-order cognitive skill development within AI-supported learning systems.

Keywords: Adaptive Learning, Artificial Intelligence, Microlearning, Self-Regulated Learning, Critical Thinking, Big Data Analytics

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1. INTRODUCTION

The education sector has undergone a substantial transformation over the past decade due to rapid technological advancement. What was once characterized by conventional classroom instruction and standardized curricula has evolved into a digitally mediated learning ecosystem that emphasizes flexibility, accessibility, and personalization. Recent global education reports indicate that digital platforms are no longer supplementary tools but have become structural components of formal and non-formal learning systems (UNESCO, 2021). The expansion of educational technology (EdTech) has reshaped how knowledge is accessed, constructed, and evaluated, particularly in online and blended learning environments (OECD, 2022). This transformation marks a shift from static content delivery toward data-informed, learner-centered instructional design supported by algorithmic systems (World Bank, 2020).

One of the most significant developments within this transformation is the emergence of Artificial Intelligence (AI)-driven Adaptive Learning systems. Unlike traditional e-learning models that provide identical content to all users, adaptive systems analyze behavioral and performance data to dynamically adjust learning pathways, pacing, and assessment formats (Holmes et al., 2019). Learning analytics powered by Big Data enable predictive modeling of learner progress, facilitating early intervention and personalized feedback mechanisms (Ifenthaler & Yau, 2020). Empirical studies have demonstrated that adaptive systems improve engagement and academic persistence by identifying knowledge gaps in real time (Zawacki-Richter et al., 2019). Consequently, AI integration is increasingly viewed as a mechanism for optimizing cognitive efficiency and improving instructional precision in digital environments (Chassignol et al., 2022).

Parallel to the rise of adaptive systems, microlearning has gained prominence as an instructional design strategy that delivers content in concise, focused segments. Microlearning structures information into short modules, often combined with multimedia and interactive elements, to enhance retention and engagement (Shail, 2019). Research indicates that segmented learning formats reduce cognitive overload and improve immediate knowledge transfer (Major & Calandrino, 2021). When combined with AI algorithms, microlearning sequences can be scheduled according to individualized spaced repetition models, maximizing memory consolidation (Kulik & Fletcher, 2020). This convergence between adaptive AI and microlearning represents a significant shift from standardized instruction toward highly responsive digital pedagogy.

Despite these advancements, a critical gap remains in understanding the broader cognitive implications of hyper-personalized learning systems. While existing studies predominantly measure outcomes such as completion rates, grades, or efficiency indicators (Bond et al., 2020), limited attention has been given to complex higher-order cognitive skills, including critical thinking and self-regulated learning. Theoretical perspectives on digital pedagogy suggest that excessive optimization may inadvertently reduce opportunities for productive struggle and exploratory reasoning (Selwyn, 2021). At the same time, proponents argue that by automating lower-level tasks, AI may free cognitive resources for analytical and reflective processes (Luckin et al., 2022). Therefore, investigating how adaptive AI and microlearning integration influences critical thinking development and self-regulated learning methodology among adult learners becomes both timely and necessary within contemporary educational discourse.

2. METHOD

This study employed an interpretive qualitative approach to explore adult learners' perceptions and lived experiences regarding the integration of Artificial Intelligence (AI)-based Adaptive Learning and Microlearning systems. Interpretive qualitative inquiry is particularly appropriate when the objective is to understand subjective meaning construction within digital environments (Creswell & Poth, 2019). Rather than testing predetermined hypotheses, this approach prioritizes depth of understanding and contextual interpretation of participants' narratives (Merriam & Tisdell, 2021). The research design adopted an Exploratory Sequential Mixed-Methods framework, in which preliminary quantitative data collection informs subsequent qualitative exploration (Ivankova & Wingo, 2020). This design allows researchers to identify patterns through initial screening before conducting in-depth investigation to explain emerging phenomena (Plano Clark & Ivankova, 2019)

The study was conducted in a fully virtual environment, reflecting the digital nature of the learning phenomenon under investigation. Contemporary research emphasizes that online spaces constitute legitimate research sites when the phenomenon itself is digitally mediated (Salmons, 2022). Data were collected over a three-month period from adult learners actively engaged in AI-supported e-learning platforms. The target population consisted of individuals aged 25–45 who had prior experience using adaptive learning systems with automated content recommendations. Purposeful sampling was applied to ensure that participants met specific inclusion criteria relevant to the research objectives (Campbell et al., 2020). A total of 25 participants were selected as key informants, consistent with qualitative research standards that prioritize data saturation over numerical representativeness (Hennink et al., 2019).

Data collection was carried out in two sequential stages. The first stage involved the distribution of open- and closed-ended questionnaires to map demographic profiles, frequency of AI platform usage, and initial perceptions of personalization effects. Questionnaire-based screening in mixed-methods research serves to structure participant selection and contextualize qualitative findings (Creswell & Guetterman, 2019). The second stage consisted of semi-structured in-depth interviews designed to explore participants' cognitive experiences, metacognitive awareness, and reflections on trial-and-error processes within adaptive systems. Semi-structured interviewing enables flexibility while maintaining thematic consistency across participants (Kallio et al., 2020). Interviews were conducted synchronously through video conferencing platforms and recorded with participant consent, following digital research ethics guidelines (British Educational Research Association [BERA], 2021).

Data analysis followed a systematic thematic analysis procedure. All interview recordings were transcribed verbatim to ensure analytical accuracy. Thematic analysis was chosen because of its flexibility in identifying patterns of meaning across qualitative datasets (Braun & Clarke, 2021). The analysis process involved multiple stages: familiarization with data, initial coding, theme development, theme review, and interpretative synthesis. Coding was conducted inductively to allow themes to emerge from participant narratives rather than imposing rigid theoretical categories (Nowell et al., 2019). Questionnaire data were analyzed descriptively using percentage distributions to support and contextualize qualitative findings, a strategy commonly recommended in mixed-methods integration (Fetters & Molina-Azorin, 2020).

To ensure credibility and trustworthiness, several validation strategies were implemented. Source triangulation was conducted by comparing questionnaire responses with interview narratives to identify convergence and divergence of findings (Guion et al., 2019). Member checking was applied by inviting selected participants to review summarized interpretations of their statements, thereby enhancing interpretive accuracy (Motulsky, 2021). Additionally, reflexive journaling was maintained throughout the research process to minimize researcher bias and maintain analytical transparency (Berger, 2020). Ethical considerations included informed consent, voluntary participation, data anonymization, and secure digital storage, in alignment with contemporary standards for online qualitative research (Weller et al., 2020). Through these procedures, the methodological framework ensured that the findings authentically represent participants' cognitive and experiential realities within AI-supported learning environments.

3. RESULT AND DISCUSSION

Result

Consistent with the Exploratory Sequential Mixed-Methods design, findings are presented in two phases: (1) descriptive quantitative results from the preliminary questionnaire and (2) in-depth qualitative insights derived from semi-structured interviews.

3.1 Quantitative Screening Results

Descriptive analysis of the 25 participants indicates a high level of engagement with AI-based adaptive learning platforms. Seventy-six percent (76%) of respondents reported using adaptive systems at least three times per week, while 24% engaged with the platforms one to two times weekly.

Regarding perceived effectiveness:

- 80% reported that adaptive sequencing reduced repetitive exposure to already-mastered material.
- 72% stated that automated recommendations improved time management and study efficiency.
- 68% indicated increased awareness of conceptual weaknesses due to real-time feedback features.
- 15% expressed concern that highly structured learning paths limited exploratory learning opportunities.

These quantitative findings suggest a predominantly positive perception of AI-supported personalization in enhancing efficiency and self-regulation. However, the presence of ambivalence regarding hyper-personalization warranted deeper qualitative exploration.

3.2 Qualitative Thematic Findings

Thematic analysis of interview transcripts generated four central themes that elaborated and contextualized the quantitative patterns.

Theme 1: Cognitive Streamlining and Reduced Redundancy

Participants consistently described adaptive systems as mechanisms that filtered out redundant content. They perceived the systems as responsive to their performance patterns, enabling focused engagement with challenging material rather than repetitive memorization.

Theme 2: Strengthening of Self-Regulated Learning (SRL)

Interview data revealed enhanced metacognitive awareness facilitated by instant feedback and performance dashboards. Participants reported becoming more strategic in planning study sessions, monitoring weaknesses, and setting short-term learning goals.

Theme 3: Indirect Facilitation of Critical Thinking

Although AI systems were not perceived as directly teaching critical thinking, participants indicated that increased efficiency in foundational learning freed time for problem-solving, scenario-based tasks, and conceptual application. This shift represented a movement from passive consumption to active cognitive engagement.

Theme 4: Ambivalence Toward Hyper-Personalization

A minority of participants expressed concern that algorithmically optimized pathways occasionally constrained non-linear exploration. They noted that tightly curated recommendations could limit exposure to alternative perspectives or creative problem-solving approaches.

Discussion

The findings indicate that AI-driven adaptive learning systems primarily function as cognitive efficiency amplifiers rather than direct instructors of higher-order thinking skills. By automating content differentiation and sequencing, AI reallocates learners' cognitive resources away from repetitive memorization toward analytical engagement. This mechanism aligns with theoretical perspectives suggesting that technological scaffolding can enhance advanced reasoning when foundational cognitive processes are algorithmically managed (Luckin, 2019). Moreover, the reported reduction in redundant exposure reflects principles of cognitive load optimization, whereby minimizing extraneous processing enables deeper conceptual engagement (Sweller et al., 2019).

The observed improvement in self-regulated learning (SRL) further reinforces the pedagogical value of AI personalization. Participants described how real-time analytics and automated feedback supported reflective learning cycles and strategic planning. Such findings correspond with research on adaptive feedback loops demonstrating that performance visualization strengthens self-monitoring and metacognitive awareness (Azevedo & Gašević, 2019; Jivet et al., 2020). In digitally mediated environments, structured prompts and algorithmic recommendations may initially function as external regulatory supports, which over time can be internalized into autonomous regulation skills (Broadbent & Lodge, 2020). Thus, AI systems appear to contribute not only to efficiency but also to the development of independent learning behaviors among adult learners.

Importantly, the development of critical thinking emerged as an indirect outcome rather than a direct instructional effect. Participants indicated that efficiency gains in mastering foundational knowledge created additional time and cognitive capacity for engaging in problem-solving and scenario-based reasoning. This finding resonates with contemporary arguments that reducing extraneous cognitive load facilitates engagement in higher-order cognitive processes (Sweller et al., 2019). Similarly, digital adaptive environments have been shown to create conditions conducive to analytical synthesis when learners are no longer constrained by repetitive tasks (Bai & Guo, 2021). Therefore, AI does not replace critical thinking instruction but may establish enabling conditions for its development.

Nevertheless, the ambivalence toward hyper-personalization reveals a critical pedagogical tension. While algorithmic precision enhances efficiency, education cannot be reduced to optimization alone. Constructivist perspectives emphasize that intellectual growth often emerges from productive struggle, uncertainty, and exposure to diverse viewpoints (Kirschner & Hendrick, 2020). Participants' concerns that tightly structured learning paths limited exploratory trial-and-error experiences echo broader critiques of algorithmic governance in education (Williamson & Eynon, 2020; Knox, 2020). Over-personalized systems risk narrowing epistemic diversity by continuously steering learners toward predicted pathways, potentially constraining creative divergence.

Overall, the integration of AI-based Adaptive Learning and Microlearning demonstrates a moderately strong positive influence on cognitive efficiency and self-regulated learning, with indirect support for critical thinking development. The results suggest that optimal AI implementation in education requires hybrid design principles that balance efficiency-oriented personalization with intentionally designed exploratory spaces. Emerging scholarship advocates for adaptive systems that incorporate structured "exploration modes" to preserve creativity while maintaining algorithmic support (Holmes & Tuomi, 2022). Consequently, AI should be conceptualized not as a replacement for human cognition but as an enabling infrastructure that enhances autonomy, reflection, and higher-order reasoning within digitally mediated learning ecosystems.

3. CONCLUSION

This study concludes that the integration of Artificial Intelligence (AI)-based Adaptive Learning and Microlearning significantly enhances self-regulated learning (SRL) among adult learners by optimizing cognitive efficiency, reducing redundancy in mastered content, and reallocating cognitive resources toward higher-order tasks such as analysis, application, and synthesis. AI-driven personalization indirectly supports critical thinking development through strengthened metacognitive awareness, strategic study planning, and real-time feedback mechanisms that function as cognitive scaffolds, enabling learners to identify conceptual gaps, regulate learning pace, and establish autonomous goals. However, the findings also reveal that excessive algorithmic optimization may restrict exploratory trial-and-error experiences essential for creativity and divergent thinking, underscoring the importance of balanced instructional design. The introduction of the Holistic Cognitive Assessment (HCA) framework offers a comprehensive evaluative model that integrates adaptive performance metrics with qualitative assessments of higher-order reasoning, contributing both theoretically and practically to AI-supported educational design. Practically, the study implies that EdTech developers and instructional designers should embed structured exploration features within adaptive systems to preserve epistemic diversity while maintaining efficiency. For future research, longitudinal and cross-contextual studies are recommended to examine the long-term cognitive implications of hyper-personalization across diverse socio-digital environments and learner populations.

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