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INTEGRATION OF ARTIFICIAL INTELLIGENCE TOOLS IN TYPES OF INDEPENDENT LEARNING

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Abstract

The rapid advancement of artificial intelligence technologies has opened new horizons for organizing independent learning, enabling the adaptation of the educational process to individual learner needs across various forms of autonomous educational activity. This article examines the principal directions for integrating artificial intelligence tools into types of independent learning, including distance learning, blended learning, mobile learning, adaptive learning, and personalized learning. The analysis addresses technological capabilities, pedagogical effects, and limitations of deploying generative models, intelligent tutoring systems, analytics dashboards, and chatbots within each of the identified types of independent learning. Drawing on meta-analytic evidence and empirical research findings, the article demonstrates that interactive and dialogic artificial intelligence systems provide the broadest positive effects for the development of self-regulation and metacognitive skills, whereas analytical and supportive tools strengthen specific regulatory subprocesses. The article concludes with recommendations for pedagogical design of intelligent learning environments oriented toward the development of learner autonomy.

Keywords: artificial intelligence, independent learning, distance learning, blended learning, mobile learning, adaptive learning, personalized learning, intelligent tutoring systems, generative artificial intelligence, metacognitive regulation

Introduction

The contemporary educational system is undergoing a period of profound transformation driven by the mass integration of artificial intelligence technologies into the learning process. Independent learning, understood as a form of educational activity in which the learner independently determines objectives, selects content, resources, and methods, and evaluates achieved results, is becoming increasingly demanded in the context of societal digitalization and the necessity of continuous professional development. Artificial intelligence opens fundamentally new possibilities for organizing, supporting, and assessing independent learning, enabling the personalization of educational content, adaptation of the pace and trajectory of material acquisition, and provision of continuous feedback without direct instructor involvement.

The theoretical foundation of independent learning derives from the concept of M. Knowles, who viewed self-directed learning as a process in which the individual actively participates in diagnosing their own needs, formulating goals, identifying resources, selecting strategies, and evaluating outcomes. This concept emphasizes autonomy, self-regulation, and active learner participation, qualities that are particularly vital in open and distance educational contexts where students independently shape their educational trajectories. Artificial intelligence technologies can amplify this autonomy by providing personalized resources and approaches, thereby enhancing learners' capacity for successful activity in autonomous educational environments.

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Types of independent learning differ in the degree of learner autonomy, the nature of resources employed, the organization of learning time and space, as well as the forms of interaction with educational content and subjects of the educational process. The principal types of independent learning include distance learning, blended learning, mobile learning, adaptive learning, and personalized learning. Each of these types presents specific requirements for artificial intelligence tools, determining the particularities of their integration and pedagogical application. The purpose of this article is to systematize the directions for integrating artificial intelligence tools into the identified types of independent learning and to identify patterns of their effective deployment.

Literature review

Independent learning is conceptualized across three interlocking levels: cognitive-metacognitive regulation, motivational-affective regulation, and behavioral regulation. Cognitive-metacognitive regulation encompasses planning, monitoring, evaluation, elaboration, and critical thinking. Motivational-affective regulation involves goal orientation, task value, self-efficacy, and anxiety control. Behavioral regulation comprises time management, effort regulation, environment structuring, and help-seeking. These dimensions are not static; they evolve across the temporal phases of learning, including the forethought phase (goal setting and strategic planning), the performance phase (attention focusing and progress monitoring), and the self-reflection phase (performance evaluation and attribution formation).

Artificial intelligence-based interventions can be grouped according to their primary regulatory affordances. Feedback and coaching agents provide explanations or reflective prompts, primarily engaging learners' metacognitive monitoring and evaluation processes. Adaptive practice and mastery systems enhance self-efficacy, persistence, and effort regulation by aligning task difficulty with learner progress. Analytics dashboards that embed metacognitive nudges promote planning, progress monitoring, and effective time management. Planning and co-authoring tools support goal setting and task strategy development, while conversational intelligent tutoring systems foster elaboration and critical thinking. The mode of assistance delivery also matters significantly: user-initiated support tends to preserve autonomy and promote deeper engagement, whereas proactive prompts may introduce automation bias and reduce active reflection.

Meta-analytic evidence synthesizing findings from 32 empirical studies comprising 92 effect sizes and 3,029 participants has demonstrated that artificial intelligence-based interventions meaningfully strengthen self-regulated and self-directed learning, though in differentiated rather than uniform ways. The most reliable effects are observed in the forethought phase, indicating that artificial intelligence is most effective when supporting planning and goal setting. The performance phase shows more variable outcomes, reflecting the design sensitivity of real-time systems. The self-reflection phase benefits modestly from artificial intelligence analytics tools, though the depth of reflective engagement depends on how these tools are integrated into the learning environment.

Integration of Artificial Intelligence in Distance Learning

Distance learning represents a form of educational activity in which the learner and instructor are separated spatially and temporally, and interaction occurs primarily through information and communication technologies. In the context of distance learning, learner autonomy reaches its maximum degree, as there is no direct pedagogical presence and control. It is precisely in this context that artificial intelligence tools acquire particular significance as means of supporting autonomous educational activity.

The integration of artificial intelligence into distance learning occurs along several directions. First, intelligent tutoring systems function as virtual mentors, assessing learner readiness for acquiring new material, diagnosing gaps in prerequisite knowledge, and adapting educational content to

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individual needs. A four-step assessment approach integrated into self-directed learning with artificial intelligence has been proposed, encompassing assessment of readiness to learn, assessment of learning goals, assessment of student motivation, and assessment of learning outcomes. Each of these stages requires specific instrumental solutions based on artificial intelligence.

Assessment of readiness to learn involves gathering information on learners' efficacy in relevant foundational concepts before introducing advanced topics. Artificial intelligence can evaluate this readiness through diagnostic tests, conversational probing, or analysis of prior performance data. Assessment of learning goals allows the system to identify the extent of interaction required, whether the topic needs to be broken into more manageable learning units, and whether the learner is aiming for theoretical mastery or practical application. Assessment of motivation enables the system to adapt its interaction style to match the learner's approach, whether deep, surface, or strategic. Finally, assessment of learning outcomes can take the form of conceptual quizzes, application-based problem-solving questions, or qualitative gap analysis.

Second, generative artificial intelligence models, such as large language models, provide the generation of personalized educational content, including explanations, examples, exercises, and instructional scenarios. These models can adapt the lexical level, structure of exposition, and complexity of material in accordance with the individual characteristics of the learner. Research has shown that fine-tuned language models demonstrate scoring accuracy comparable to or exceeding traditional machine learning approaches when evaluating open-ended responses in educational tasks.

Third, learning analytics dashboards aggregate behavioral trace data into visual representations that enable learners to monitor their own progress, identify patterns in their study habits, and make informed decisions about time allocation and strategy adjustment. The FLoRA platform exemplifies this approach, providing formative process assessment feedback on self-regulated learning through embedded metacognitive nudges. Such systems transform raw interaction data into actionable insights, allowing learners to see, for example, how their help-seeking behavior correlates with performance improvements, or how their time distribution across topics relates to mastery levels.

However, the integration of artificial intelligence into distance learning is associated with certain limitations. Continuous monitoring of learner behavior creates detailed profiles that may be used for purposes beyond formative educational support, including institutional accountability reporting, predictive risk modeling, and commercial profiling. Learners may not be fully aware of the extent of data collection or the inferences drawn from their behavioral traces. Transparent data governance policies, learner control over data sharing, and the minimization of data collection to genuinely educational purposes are essential safeguards.

Integration of Artificial Intelligence in Blended Learning

Blended learning, or blended learning, represents a hybrid form of educational activity that combines traditional face-to-face instruction with elements of distance learning. In this context, independent learning is not fully autonomous but functions in dialectical unity with instructor-guided learning. The integration of artificial intelligence into blended learning requires particular attention to coordination between automated support and pedagogical presence.

In blended learning environments, artificial intelligence tools serve as a bridge between face-to-face and distance components of the educational process. During face-to-face sessions, artificial intelligence can analyze discussions in real time, generate prompts for the instructor regarding the group's level of understanding, identify learners requiring additional support, and form personalized assignments for independent work between sessions. In the distance component of blended learning,

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artificial intelligence provides continuous support that maintains learning motivation and prevents learner attrition during periods between face-to-face meetings.

Chatbots and virtual assistants play a central role in the integration of artificial intelligence into blended learning. These systems are capable of engaging in dialogic interaction in natural language, answering learner questions, providing explanations on demand, and stimulating reflective thinking through structured conversational prompts. Research has shown that conversational intelligent tutoring systems demonstrate consistently strong effects across nearly all self-regulated learning outcomes, highlighting the central role of dialogic interaction and feedback exchange in autonomous learning. These systems are particularly effective in language learning and medical education domains, where iterative dialogue and reflective practice are essential components of competency development.

Adaptive practice systems in blended learning adjust task difficulty in accordance with learner progress, enhancing self-efficacy and persistence. When the system detects that a learner has successfully mastered a certain level of difficulty, it automatically offers more complex tasks; when difficulties arise, the system provides additional explanations and simplified exercises. This adaptability is particularly valuable in blended learning, where the instructor cannot daily monitor the individual progress of each learner.

An important aspect of artificial intelligence integration in blended learning is maintaining the balance between automation and human presence. Excessive automation may lead learners to rely on algorithmic support at the expense of developing their own regulatory skills. Effective design presupposes the gradual fading of artificial intelligence support as learner competence grows, transferring increasing responsibility for self-regulation from the system to the learner. This approach, known as the fading scaffold, requires careful calibration of the level of automated support in accordance with individual developmental trajectories.

Integration of Artificial Intelligence in Mobile Learning

Mobile learning, or mobile learning, represents a form of educational activity conducted through mobile devices and applications in conditions of learner mobility. This type of independent learning is characterized by the fragmentation of learning time, contextual dependence of learning, and the necessity of adapting content to limited screen spaces and variable connectivity conditions. The integration of artificial intelligence into mobile learning requires accounting for these specific constraints and affordances.

In mobile learning, artificial intelligence tools are optimized for microlearning: brief, targeted learning interactions that the learner can conduct during breaks between other activities. Generative artificial intelligence models can create personalized microcontent, including brief explanations, quick comprehension checks, and contextual prompts delivered at optimal moments based on analysis of the learner's daily schedule and cognitive state.

Voice interfaces and natural language processing play a particularly important role in mobile learning, as they enable learners to interact with educational content without the necessity of text input on small screens. Voice assistants can read learning materials aloud, conduct oral tests, explain complex concepts, and engage in dialogic practice, for example, in foreign language learning. Research has shown that voice interaction with intelligent systems increases engagement and usability in mobile educational contexts.

Contextual adaptability is a key advantage of artificial intelligence in mobile learning. Systems can adapt educational content to the learner's current location, time of day, weather conditions, and other contextual factors. For example, a language learning application may offer vocabulary related to

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restaurants when the learner is in an area with high cafe concentration, or suggest relaxation materials when the system detects elevated stress levels based on wearable device data.

However, mobile learning with artificial intelligence faces technical constraints, including limited computational power of mobile devices, the necessity of offline operation under unstable internet connectivity, and energy efficiency requirements. Contemporary solutions include hybrid architectures where part of processing is performed on the device and part in the cloud, as well as progressive web applications that provide native application functionality without requiring installation.

Integration of Artificial Intelligence in Adaptive Learning

Adaptive learning represents a form of educational activity in which content, pace, methods, and learning trajectory are dynamically adjusted in accordance with the individual characteristics of the learner, including current knowledge level, learning style, pace of material acquisition, and motivational profile. Artificial intelligence is the technological core of adaptive learning, as it is machine learning algorithms that enable the recognition of patterns in learner data and the generation of personalized recommendations.

In adaptive learning, artificial intelligence tools function at several levels. At the content level, adaptive systems dynamically select educational materials corresponding to the learner's current level of competence. This includes not only selecting tasks of appropriate difficulty but also adapting the format of information presentation: video for visual learners, audio for auditory learners, interactive simulations for kinesthetic learners. Collaborative filtering algorithms can recommend resources that have proven effective for learners with similar learning profiles.

At the process level, adaptive artificial intelligence systems analyze learner behavioral traces in real time, including time spent on each resource, navigation sequence, frequency of returning to previous materials, help-seeking patterns, and interaction intensity. Based on this analysis, the system can determine whether the learner is experiencing difficulties, becoming distracted, or is in a state of productive flow, and correspondingly adjust the level of support.

At the assessment level, adaptive systems employ computer-adaptive testing algorithms that select each subsequent question based on the response to the previous one, thereby maximizing the informational value of each test item and minimizing testing time. These algorithms are based on item response theory and require rigorous psychometric validation to ensure unbiased assessment and stable ability estimates.

Metacognitive nudges embedded in adaptive systems promote the development of learner self-regulation. When the system detects that a learner is browsing material too quickly, it may suggest deep reading strategies; when a learner is stuck on a single task, the system may suggest alternative approaches to solution. These nudges transform raw interaction data into actionable insights, enabling learners to develop awareness of their own learning processes.

An important limitation of adaptive learning is the risk of creating a "filter bubble," where the system adapts content so precisely to the learner's current level that it limits their exposure to challenging yet productive tasks necessary for deep learning. Effective adaptive system design must balance comfort and challenge, periodically offering tasks that slightly exceed the learner's current zone of proximal development.

Integration of Artificial Intelligence in Personalized Learning

Personalized learning represents the most advanced form of independent learning, in which the entire educational experience of the learner, from goals and content to methods, pace, and assessment, is constructed on the basis of their individual characteristics, interests, needs, and context. Unlike adaptive learning, which primarily responds to the learner's current state, personalized learning

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proactively shapes the educational trajectory based on a comprehensive profile of the learner's personality.

In personalized learning, artificial intelligence tools function as architects of the educational experience. Based on analysis of data regarding learning preferences, cognitive styles, motivational profiles, career goals, and life circumstances, the artificial intelligence system generates individual learning plans, selects resources, forms learning communities, and designs assessment procedures. This level of personalization requires the integration of data from multiple sources, including educational platforms, social networks, professional networks, and, with adherence to ethical norms, wearable devices.

Generative artificial intelligence models play a central role in personalized learning by creating unique content for each learner. This includes personalized learning scenarios adapted to the learner's specific interests; individual cases and tasks reflecting the learner's professional context; and personalized explanations using examples from domains familiar to the learner. Research has shown that personalized content generated by artificial intelligence increases engagement and depth of understanding compared to generic content.

Planning and co-authoring with artificial intelligence support goal setting and task strategy development in personalized learning. Learners can interact with intelligent systems to formulate learning goals, break complex projects into manageable subtasks, select appropriate resources, and plan learning time. These tools function as cognitive partners, extending the learner's capacity for independent planning without substituting their own agency.

Reflective calibration in personalized learning is achieved through comparative analytics dashboards that enable learners to compare their self-assessments with objective performance data, revealing systematic biases in self-evaluation. Artificial intelligence generates reflective prompts that encourage learners to articulate their reasoning, identify sources of error, and generate improvement strategies. Dialogic artificial intelligence systems can engage learners in structured reflective dialogues that probe the depth and accuracy of their metacognitive awareness.

However, personalized learning with artificial intelligence raises serious ethical and pedagogical concerns. Excessive personalization may lead to intellectual isolation, where learners rarely interact with content and perspectives beyond their individual preferences. There is also the risk of algorithmic determinism, where artificial intelligence systems based on historical data limit learners' educational opportunities, reproducing existing inequalities. Protection against these risks requires designing systems that balance personalization with exposure to diversity, and regular auditing of algorithms for fairness.

Discussion

Analysis of artificial intelligence tool integration across types of independent learning reveals both common patterns and type-specific particularities. A common pattern is the differentiated nature of effects: interactive and dialogic artificial intelligence systems provide the broadest benefits for self-regulated learning, whereas analytical and supportive tools strengthen specific regulatory subprocesses. This indicates that the effectiveness of artificial intelligence integration depends on the correspondence between technological affordances and pedagogical goals and the characteristics of the specific type of independent learning.

In distance learning, where learner autonomy is maximal, artificial intelligence tools must compensate for the absence of pedagogical presence by providing comprehensive support at all stages of self-regulation. In blended learning, artificial intelligence functions as a bridge between face-to-face

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and distance components, requiring careful coordination with the instructor's pedagogical activity. In mobile learning, priority is given to microlearning, contextual adaptability, and voice interfaces, reflecting the specificity of the mobile context. In adaptive learning, artificial intelligence is the technological core, dynamically adjusting content and process based on real-time data analysis. In personalized learning, artificial intelligence serves as the architect of the educational experience, requiring the most complex data integration and the most careful ethical oversight.

Meta-analytic data confirm that the most reliable effects are observed in the forethought phase, indicating the necessity of prioritizing planning and goal-setting tools across all types of independent learning. The performance phase demonstrates more variable results, highlighting the need for adaptive, context-sensitive feedback systems that respond to learner engagement patterns without fostering overreliance. The self-reflection phase receives modest benefit from analytical tools, though the depth of reflective engagement depends on integration design.

Ethical concerns permeate all types of independent learning with artificial intelligence. Continuous behavior monitoring creates detailed profiles vulnerable to commercial or institutional misuse. Adaptive and personalized learning algorithms may reproduce or amplify existing inequalities. Artificial intelligence detection tools for identifying AI-generated student work have proven unreliable due to high false-positive rates, exposing learners to the risk of unfounded accusations of academic misconduct. The more sustainable and pedagogically sound approach is assessment redesign that renders such detection unnecessary, through orientation toward competency-based and performance-based evaluation using experiential and applied tasks requiring judgment, context, and real-world application.

Conclusion

The integration of artificial intelligence tools into types of independent learning represents a multilevel process requiring consideration of the specificity of each form of autonomous educational activity. In distance learning, artificial intelligence compensates for the absence of pedagogical presence through intelligent tutoring systems, generative content, and analytics dashboards. In blended learning, it functions as a bridge between face-to-face and distance components, ensuring continuity of support. In mobile learning, priority is given to microlearning, contextual adaptability, and voice interfaces. In adaptive learning, artificial intelligence is the technological core, dynamically adjusting content and process. In personalized learning, it serves as the architect of the educational experience, requiring the most comprehensive data integration.

Empirical evidence indicates that the most effective systems integrate multiple types of artificial intelligence tools within a coherent pedagogical architecture, progressively transferring regulatory responsibility from the system to the learner. Dialogic and interactive systems provide the broadest benefits for self-regulation development, whereas analytical and supportive tools strengthen specific subprocesses. The most reliable effects are observed in the forethought phase, indicating the necessity of prioritizing planning and goal-setting tools.

For educational institutions, the findings underscore the value of integrating artificial intelligence as a complementary scaffold rather than a substitute for human regulation. Universities and training organizations should adopt artificial intelligence systems that encourage autonomy by gradually fading support and making metacognitive processes explicit. Policies governing artificial intelligence adoption in education should ensure transparency, learner agency, and pedagogical alignment, balancing efficiency with ethical considerations of data privacy, fairness, and responsible use. Strategic adoption of dialogic and interactive artificial intelligence designs may foster deeper learner

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engagement and reflective thinking, ultimately enhancing the capacity for autonomous, lifelong learning.

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