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Personalized Learning Through AI: From Rule-Based Systems to AI Mentors*

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Abstract
Artificial intelligence (AI) has the potential to greatly facilitate student learning by providing personalized instruction tailored to each student's individual needs and knowledge level. Although personalized learning is widely considered as one of the most effective teaching methods, it has been difficult to implement in traditional classrooms. In this context, AI offers a viable alternative. Various AI tools now perform key pedagogical functions, such as diagnosing learners' knowledge levels, recommending content and learning paths, and providing feedback and personalized learning based on learners' profiles. Since these tools differ in their capabilities and personalize learning in different ways, they should be applied differently according to pedagogical purposes and learner variables when implemented in educational settings. This study introduces five stages of AI-powered personalization grounded in learning theories. These stages take into account various factors, including technological capabilities, learner characteristics, and curricular structures at the elementary, secondary, and college levels. We further illustrate how these five stages can be applied to language education at different school levels. Finally, we present the pedagogical implications of using AI in education and address the challenges that must be considered for its effective and equitable implementation.

Key words: Artificial intelligence, personalized learning, affective computing, AI mentor, language learning
Applicable level: primary, secondary education

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I. INTRODUCTION

In recent years, advancements in artificial intelligence (AI) have begun to reshape various aspects of education. Although AI is still evolving, it presents emerging opportunities that can support learners in multiple ways. These include diagnosing students' current knowledge levels, providing tailored support and feedback, generating customized content and activities, and analyzing learning progress. Personalization is the most powerful of these capabilities, with the potential to deliver significant pedagogical benefits to learners of diverse backgrounds.

Personalized learning has long been recognized as one of the most effective instructional approaches. However, despite its effectiveness, incorporating personalized learning into schools has mostly been impractical due to class size, resource limitations, and cost. While AI cannot replace teachers, it offers a promising means of mitigating these challenges. AI-powered adaptive learning systems and intelligent tutoring systems are reshaping pedagogical practice by tailoring instruction to the needs of individual learners (Jose et al., 2025). Leveraging vast educational datasets and machine learning methods, these systems analyze learner characteristics, prior experiences, learning progress, and outcomes. Based on this information, AI systems provide dynamic content recommendations, targeted interventions, and curriculum adjustments (Jian, 2023; Maghsudi et al., 2021; Sasikala & Ravichandran, 2024). While their efficiency and effectiveness in promoting learning still depend on their design and implementation, recent AI-driven personalization systems build on earlier adaptive and intelligent tutoring approaches by enabling more scalable delivery and flexible feedback (Bang & Lee, 2024; Jose et al., 2025; Joshi, 2024).

AI can also bring numerous pedagogical benefits to language learning. It can generate an endless amount of reading material, questions, and exercises tailored to learners' language proficiency levels and interests. AI can assist with writing, correct lexicogrammatical errors, serve as a conversational partner for speaking practice, and respond to learners' specific questions about the language (Lee & Jeon, 2022. With AI tutors, students can learn English anytime, anywhere. Furthermore, practicing English speaking with AI partners greatly reduces language anxiety (Jeon et al., 2023). Finally, AI-powered language learning platforms can foster intercultural competence by exposing learners to diverse linguistic and cultural contexts through simulated dialogues and authentic materials (Godwin-Jones, 2023).

However, the presence of AI in classrooms does not automatically ensure meaningful learning. Its effectiveness depends on thoughtful instructional design that aligns technology with pedagogical goals and learner needs. Given the wide range of AI applications, educators must consider each technology's unique affordances relative to specific learning objectives and student populations. Critical factors that shape the success of AI-powered personalization include learner characteristics such as prior knowledge, developmental stage, cognitive styles, and motivational states (Jian, 2023). Similarly, curricular complexity varies across educational stages, requiring different levels of AI sophistication. Therefore, AI must be deliberately adapted to educational contexts, curricular frameworks, and learner diversity. While AI offers opportunities, it also introduces challenges and risks. These include concerns over data privacy, algorithmic bias, and the potential to widen the digital divide (Bang & Lee, 2024, 2025; Sha et al., 2021). This study explores two research questions: 1) How can AI-powered personalized learning be mapped according to multiple factors, such as learner variables and curriculum differences? and 2) What are the pedagogical implications and challenges of using AI in education?

II. LITERATURE REVIEW

1. Learning Theories and Educational Technologies

Instructional methods and educational technologies, including AI, can be aligned with and categorized by learning theories. Behaviorism views learning as a process of stimulus and response, in which desired behaviors are encouraged through consistent reinforcement (Skinner, 1968). The earliest phase of educational technology was firmly rooted in behaviorist principles, emphasizing observable behaviors, repetition, and reinforcement. Computer-assisted instruction in the 1970s followed a similar pattern, using drill-and-practice software to reinforce correct responses and correct errors. In this approach, technology merely served as a stimulus-response delivery mechanism, and learning was measured by the accuracy and speed of responses (Burton et al., 2004).

As cognitivism gained influence in the 1980s and 1990s, educational technology shifted toward modeling learners' internal mental processes rather than their external behaviors. Cognitivism focuses on learners' cognitive processes, such as memory and recall; learning styles; and previous knowledge and background information, all of which can influence learning. Accordingly, cognitivism-based technologies emphasized how learners acquire, process, and store information. These technologies focused on metacognition, schema development, and problem-solving skills rather than rote memorization. One of the most widely used approaches is the intelligent tutoring systems (ITS), which employs learner models to diagnose misconceptions, provide learning support, and adapt feedback to individual needs (Anderson et al., 1995). Multimedia learning environments that integrate text, images, and audio also play a significant role in this approach by managing cognitive load and supporting learners with different learning styles (Mayer, 2001). These principles have been further validated by recent large-scale studies. For instance, Steenbergen-Hu and Cooper (2014) reported that intelligent tutoring systems significantly improve conceptual learning and problem-solving.

Since the late 1990s, constructivist perspectives have shaped collaborative and authentic learning environments (Jonassen, 1999; Vygotsky, 1978). Since core tenets of constructivism include interaction, collaboration, self-directed learning, active learning, and knowledge construction, educational technologies have evolved to facilitate self-directed, inquiry-based learning, project-based activities, and authentic assessment (Kim & Hannafin, 2011; Tam, 2000). These technologies include interactive Web 2.0 tools, learning management systems, and immersive virtual environments that support situated learning, social interaction, and knowledge co-construction. Recently, AI-powered platforms, virtual labs, and metaverse-based classrooms have extended constructivist principles by enabling learners to engage in real-world problem solving within interactive contexts, often with real-time adaptive scaffolding and peer collaboration tools. Empirical findings also highlight the effectiveness of such environments. For example, Lee (2025) and Lee and Ahn (2025) reported that metaverse-based language learning environments enhance social interaction, learner agency, and situated communication. Jeon et al. (2023) and Lee and Jeon (2022) demonstrated that AI promotes learners' communicative skills by facilitating interactive and authentic dialogue, as well as providing more opportunities for meaning negotiation.

2. AI in Education

AI in education can support the learning theories discussed in the previous section. From a behaviorist perspective, AI can replicate and improve upon this approach by providing immediate feedback, automated reinforcement, and personalized practice loops (Holmes et al., 2022; Luckin et al., 2016). For example, AI-driven quiz systems analyze student errors and automatically generate additional practice problems that target weaknesses. These systems ensure repeated exposure until the correct behavior is formed. In this context, AI is most effective for skill acquisition and acts as a reinforcer by automating drills, feedback, and practice. In the context of language learning, AI systems can generate extensive materials for reading, vocabulary, and grammar practice, offering learners continuous access to drills and exercises. AI systems can also provide speaking practice through automated prompts, enabling learners to rehearse and reinforce oral skills.

Cognitivism focuses on mental processes, such as attention, memory, and schema development (Anderson et al., 1995; Mayer, 2001). AI supports learning within this framework by modeling cognitive states and scaffolding knowledge acquisition. AI-driven adaptive e-learning platforms adjust the pace and sequence of lessons within this framework to reduce cognitive overload and manage the balance between challenge and learner capacity. AI enhances cognitivist instruction by adapting content dynamically to learners' mental processes, ensuring knowledge is processed and stored efficiently. In language learning, cognitivist approaches consider learners' characteristics, learning preferences, and prior knowledge, providing learning materials and activities accordingly. For instance, adaptive reading platforms gradually introduce new vocabulary in familiar contexts to promote schema development and long-term retention. In cognitivist theory, AI acts as a tutor by diagnosing misconceptions, adapting the sequence of information, and scaffolding the processing of information. This ultimately helps learners understand concepts (Anderson et al., 1995; Ma et al., 2014).

Since constructivism considers the construction of knowledge to be a key element of learning (Jonassen, 1999; Vygotsky, 1978), AI supports learning by facilitating authentic, collaborative, and active learning experiences. To this end, various technologies are employed. In language education in particular, AI-powered writing assistants provide iterative feedback, encouraging learners to reflect on and refine their ideas. This promotes metacognition and self-regulation. AI agents can also function as collaborators or role-playing partners in language learning. Opportunities to practice English speaking are limited in English as a Foreign Language (EFL) situations; however, AI agents and chatbots greatly expand these opportunities for EFL students (Lee & Jeon, 2022). AI-driven virtual reality allows students to engage in simulated real-world environments where they can practice English with an AI agent (Lee et al., in press). Within the constructivist framework, AI acts less as a controller and more as a partner or facilitator. This helps learners build meaning through interaction with the system and their peers. In other words, AI functions as a knowledgeable peer within a zone of proximal development, co-constructing knowledge with learners and enabling them to surpass their current level (Sinha et al., 2024; Tran et al., 2025).

III. FIVE STAGES OF AI-POWERED PERSONALIZED LEARNING SYSTEMS

Based on learning theories and prior studies (e.g., Holmes et al., 2022; Luckin et al., 2016), we categorized AI-powered personalization in education into five stages, which are arranged by the breadth and integration of the personalization functions provided to learners. Each stage is unique in terms of learning data, content, pace, path, and instructional methods.

1. Stage 1: Rule-based Personalization

At its most basic level, personalization relies on predefined rules and static learner attributes, such as age, grade, subject, and preferences. This stage is largely based on behaviorism. Systems at this stage offer content recommendations, reminders, and basic goal-setting prompts. However, they do not adapt in real time. This stage is more akin to rule-based automation, which remains common in learning management systems. For instance, a primary school student who selects “English” receives a set of age-appropriate reading materials that does not adapt based on prior performance. Key functionalities at this stage include recommending learning content based on keywords selected by the learner, offering learning content and activities according to predefined learning objectives, and providing automated study reminders. Common examples of this stage in language learning include drills and practice for speaking, vocabulary learning sets, and grammar learning materials at different difficulty levels predefined for each grade level. It should also be noted that rule-based personalization can sometimes malfunction due to overfitting or conflicting rules. This issue can be mitigated by implementing rule-specific testing and a teacher feedback loop.

The following are examples of AI educational tools in Stage 1:

- Starfall (Phonics): Launches the same activity whenever a letter or word is clicked.
- BBC Bitesize (Language Section): Delivers content based on the learner’s grade level and subject selection.
- Oxford Owl (Early Readers): Assigns fixed-level phonics and reading texts solely based on grade band, not real-time mastery.

2. Stage 2: Data-driven Personalization

The second stage involves personalization driven by descriptive analytics or basic machine learning applied to learner performance records, activity patterns, and preferences. At this stage, systems can adjust difficulty levels, recommend content sequences, and adapt scheduling formats based on historical learner data. For example, if a student repeatedly struggles with specific equations, the systems will automatically assign targeted practice sets. Key functionalities at this stage include analyzing student performance and learning pace to provide personalized recommendations. For example, the systems can present question types that were previously answered incorrectly until mastery is achieved. These systems can automatically adjust difficulty levels based on students’ quiz results or learning outcomes. Additionally, they analyze study time and activity logs to modify learning schedules and optimize how and for how long students engage with materials. The systems also provide customized content recommendations by analyzing user preferences and learning patterns. For instance, they can determine whether learners respond better to video- or text-based instructional materials and adjust content delivery accordingly.

The following are examples of AI educational tools in Stage 2:

- Blue Canoe: Analyzes learner pronunciation to identify weaknesses and provide targeted practice exercises.
- Newsela: Delivers the same article at different reading levels based on the learner's assessed Lexile score.
- Busuu: Recommends practice and activities based on learners' past performance data.
- Memrise: Adjusts review frequency and item difficulty based on learner accuracy history and spaced-repetition metrics.

3. Stage 3: Adaptive AI-powered Personalization

This stage introduces sophisticated systems with several advanced capabilities. AI algorithms analyze learning patterns in real time, automatically recommending content to address knowledge gaps or reinforce weak concepts. Natural language processing (NLP) allows AI tutors to respond immediately and contextually to student inquiries, creating a more interactive and responsive learning environment. These systems can detect challenging concepts automatically and provide supplementary lectures, practice problems, or alternative explanations tailored to each student's needs. They also offer interactive learning assistance via AI-powered conversational feedback systems that engage students in meaningful dialogue about their progress and provide personalized guidance. Regarding language learning, real-time speech recognition capabilities allow for immediate pronunciation correction and targeted language learning support. These capabilities provide instant feedback on verbal and written communication skills, thereby enhancing the development of linguistic competency. However, in this stage, if AI-powered conversational feedback does not sufficiently analyze learner competencies and preferences, adaptive content delivery may fail. This makes it difficult to detect diagnostic errors. Implementing system features that establish criteria and conditions for student competency development can enable online calibration when necessary.

The following are examples of AI educational tools in Stage 3:

- ELSA Speak: Uses AI speech recognition technology to provide instant pronunciation feedback.
- Lingvist: Tracks vocabulary usage and recommends new words or grammar patterns tailored to the learner.
- Duolingo: Analyzes students' learning outcomes in real time and provides language learning content, practice, and feedback using the adaptive learning system.
- Grammarly: Delivers real-time, context-sensitive feedback on grammar, vocabulary, and style using NLP.

4. Stage 4: Emotion-aware and Autonomous Learning Adjustment

This stage incorporates cognitivism and constructivism to some extent. In Stage 4, AI employs affective computing and multimodal sensing to monitor learner engagement and emotional state. This technology integrates facial expressions, voice tone, and physiological data to autonomously adjust the learning plan. For example, AI can use webcam and heart rate data to detect decreased attention and then transition to an interactive quiz format while providing a motivational message. These systems go beyond basic attention detection by incorporating comprehensive biometric monitoring through eye movement tracking. This allows for a more precise evaluation of cognitive load and focus patterns. AI can recognize elevated stress indicators and autonomously recommend breaks to prevent burnout and maintain optimal learning conditions. At this stage, AI also features adaptive pacing mechanisms that automatically reduce content volume and pivot to review-focused activities when fatigue patterns emerge. This ensures sustained engagement without cognitive overload.

Regarding language learning, since language anxiety is a significant barrier to speaking a foreign language, emotion-aware AI technologies can lower students' negative emotions, such as anxiety, frustration, and stress, while cultivating positive emotions, increasing motivation, and fostering a willingness to speak while learning a language (Chen et al., 2025). However, this stage still remains largely experimental due to challenges in emotion recognition accuracy, privacy issues, and cultural bias. In addition, since content for language education can be distributed globally via the Internet and emotion-aware AI technologies often display biases across different demographic groups, potentially limiting their equitable application, this stage should also be evaluated in terms of its cross-cultural validity.

The following are examples of AI educational tools in Stage 4:

- Affective AutoTutor: Detects confusion, frustration, or boredom through analysis of facial expressions and behavior, and adjusts explanations, hints, or pace accordingly.
- EMOTE Project: Uses vision, audio, and posture recognition to detect emotions and offer praise or change activities to re-engage the learner.
- MindSpark (advanced pilot): Combines performance data with webcam gaze tracking to detect disengagement and insert gamified breaks before resuming lessons.

Starting at Stage 4, systematic monitoring is necessary. AI must be able to detect bias in emotion recognition because inaccurate results can have an inappropriate impact on student competency analysis and content recommendations.

5. Stage 5: Fully Integrated AI mentor

The fifth and final stage is an aspirational, highly integrated AI system that serves as a long-term learning partner. Combining academic personalization (Stages 1–4) with goal-setting, metacognitive coaching, and career guidance, it supports learners in achieving their long-term goals. The system promotes reflective practices to improve self-regulation, suggests projects that align with learners' interests, and adjusts learning paths according to long-term goals. For example, a student aspiring to a career in language education could receive guidance from an AI mentor for several years. The mentor would recommend coursework, project-based activities, and research opportunities.

While there are existing prototypes, such as GPT-4–based tutoring systems, no current solution fully realizes Stage 5's vision. Comprehensive systems in Stage 5 would design and continuously refine multi-year learning plans tailored to specific long-term objectives, such as college admission requirements or professional certification pathways. The AI mentor would make ongoing adjustments based on the student's evolving performance and changing aspirations to ensure the learning plan remains aligned with the student's personal and professional development goals. Additionally, the system could recommend project-based learning activities that involve real-world problem-solving scenarios, requiring language learners to integrate communication, critical thinking, and collaboration skills. These tasks would encourage learners to move beyond formulaic expressions in English and use language more spontaneously, creatively, and contextually. The AI would also function as a metacognitive coach, by providing tools and frameworks that help students analyze and optimize their learning processes. Ultimately, this would foster greater self-awareness and autonomous learning capabilities that extend far beyond traditional academic boundaries. This function can cultivate students' self-regulated learning, enabling them to monitor and correct their own language errors (Lee, 2023).

The following are examples of AI educational tools in Stage 5:

- Khanmigo (Khan Academy): Provides personalized academic support to students and lesson-planning assistance to teachers.
- MentorAI: Allows learners to configure and train their own AI mentor, which is tailored to their personal goals and learning style and provides ongoing feedback and guidance.
- Century Tech: Builds long-term learning profiles to deliver personalized roadmaps and feedback across multiple subjects.

In order to reach Stage 5, more research is needed on topics such as the collection and analysis of short-term and long-term data, the corresponding privacy protection system, the accountability of AI mentors in decision-making, and the distribution of authority between educators and learners. The five stages of AI-powered personalization are characterized by distinctive features across learning data, learning content, learning pace, learning path, and instructional methods, as summarized in <Table 1>.

Table 1

Five Stages of AI-powered Personalization in Education

Category	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
Learning Theories	Behaviorism (involves fixed stimulus–response, repetition, identical rule-based responses)	Still mostly behaviorism (analyzes learner performance data, adjusts difficulty)	Cognitivism (involves real-time diagnosis of cognitive states, schema formation, knowledge structuring)	Cognitivism + Constructivism in part (considers cognitive, emotional, and motivational states)	Constructivism (offers AI as a partner/mentor, supports self-directed learning, long-term goals, reflection)
Learning Data	Basic learner information	Learner's past performance	Real-time analysis of	Contextual and environmental	Comprehensive learner profile

	(grade level, gender, performance, etc.)	data, predefined preferences, and activity logs (descriptive analytics, basic ML); historical learner data (e.g., quiz scores, Lexile levels, pronunciation error logs)	learning patterns using advanced AI (deep learning, NLP, real-time tracking); Continuously updating learner model with real-time inputs (e.g., participation, speech recognition, dialogue interactions)	awareness (e.g., learning environment: device, location, emotional state detected through environmental cues) and multimodal data (e.g., various biodata, affective/behavioral signals)	(e.g., goals, preferences, learning style, metacognitive data)
Learning Content	Use of standardized, non-adaptive drills and materials	Difficulty adjustments based on past learning performance	Generation of tailored practice materials based on real-time responses	Emotion- & context-sensitive content; context-appropriate learning content	Targets long-term, holistic goals, personalized problems and content aligned with learner goals
Learning Pace	Pre-set pace determined by the instructor	Pace adjusted through analysis of past performance and patterns	Automatic, real-time pace modification	Context- and bio-informed pace adjustment	Autonomous pace control aligned with the learner profile and long-term goals
Learning Path	Selection within a predefined curriculum	Branching based on learner performance	Real-time reconfiguration of the learning path	Path adjustment reflecting contextual and affective data	Personalized learning pathways aligned with short- and long-term learner goals
Instructional Method (AI Collaboration)	Uniform instruction with teacher-controlled difficulty	Assignment recommendations based on learning outcomes	Real-time feedback and scaffolding	Context- and affect-sensitive personalized instruction	Individualized learning plans with AI collaboration and automation

IV. DIFFERENTIATED AI FUNCTIONALITIES ACROSS EDUCATIONAL STAGES

1. Cognitive and Emotional Development

Implementing AI-powered personalization in education requires careful calibration to align with students' developmental stages. Different stages of education have distinct cognitive and emotional characteristics that necessitate different technological approaches. For example, the degree of student autonomy and learning motivation changes significantly across stages, which strongly influences learning at each stage. Therefore, AI systems must adapt their supportive roles accordingly (Dignath & Büttner, 2008; Ward et al., 2025).

During their elementary years, children are in a critical phase of cognitive development characterized by concrete operational thought (Bjorklund & Causey, 2017). During this period, their thinking becomes more logical yet remains tied to concrete, observable situations. Emotional stability plays a decisive role at this stage because children have a strong need for encouragement and positive reinforcement, which directly influences their persistence in learning (Wang & Oyam, 2024). Learning at this age is best supported by play-based activities and storytelling that capture their natural curiosity. Regarding language learning specifically, children most effectively acquire vocabulary and basic sentence structures through songs, games, and stories that integrate meaning with repetition (Pinter, 2017). Additionally, elementary students are typically under close supervision from parents and teachers, and extrinsic rewards and praise are effective motivators (Mueller & Dweck, 1998).

Secondary school marks the beginning of adolescence, a time of significant cognitive and emotional changes. During this period, students begin to demonstrate advanced abilities such as abstract thinking, complex problem-solving, and critical reasoning. These abilities allow students to engage with complex learning material and experiment with various study methods. Additionally, secondary education is a transitional period during which students gradually develop self-directed learning capabilities. Adolescents increasingly demand independence, and at the same time, social interaction and collaborative learning become important (OECD, 2025; Xie et al., 2022). Therefore, peer norms and teacher support continue to play significant roles (Steinberg & Monahan, 2007). During this period, learning requires greater analytical depth and adaptive feedback mechanisms that can respond flexibly to students' rapidly changing needs. In the context of language learning, adolescents can engage in complex communication tasks such as debates, project-based learning, and various types of essay writing. These tasks require higher-order thinking skills in addition to basic language skill acquisition.

Students in higher education typically exhibit cognitive maturity, advanced self-directed learning, and autonomous goal setting (Mallillin, 2024). At this stage, students are expected to engage in discipline-specific academic writing, complex research projects, and professional communication tasks that demand intellectual rigor and specialized skills. In addition to performance outcomes, higher education requires cultivating metacognitive skills such as monitoring and regulating learning strategies, managing stress, and maintaining resilience in the face of rigorous academic demands (Holmes et al., 2022).

2. Learning Objectives and Curricular Complexity

Because students' cognitive and emotional statuses differ across educational stages, the complexity of educational goals and curriculum structures varies as well, requiring different levels of AI sophistication. At the elementary level, educational goals focus on acquiring foundational knowledge and developing basic learning habits (Ningsi & Hartono, 2025). In other words, primary schooling is geared toward basic academic goals that enable lifelong learning, such as understanding foundational concepts and developing social skills in cooperation and play. The curriculum is relatively simple and structured, emphasizing literacy, numeracy, and integrative skill-building, and elementary education generally features the lowest level of curriculum complexity (Bajarias et al., 2024). In terms of language learning, it is essential to develop foundational literacy skills including reading comprehension, writing, and oral communication in this educational stage.

Secondary education introduces greater complexity and cognitive demands. During this stage, students are encouraged to achieve proficiency in subject-specific knowledge across core disciplines, as well as develop analytical and critical thinking skills for solving complex problems (Cipra & Dermer, 2022). They transition from acquiring surface-level knowledge to developing a deep conceptual understanding, as well as problem-solving skills (Reeve & Cheon, 2024). Differentiated and specialized tracks (e.g., STEM or humanities) become more common, as does preparation for assessments and future career paths. As students encounter more abstract concepts and theoretical frameworks, secondary education introduces intermediate complexity. The curriculum structure allows for greater student choice and independence while still providing significant guidance (Leeuwen & Janssen, 2019; Reeve & Cheon, 2024).

At the higher education level, students are expected to engage in advanced, discipline-specific learning. This type of learning requires independent inquiry, critical synthesis, and the creation of new knowledge. The highly flexible curriculum allows for student-directed pathways that align with personal and professional aspirations. Complex thinking development is central to higher education and is best fostered through learning scenarios that address real-world challenges and promote systemic and innovative problem solving (Ramírez Montoya et al., 2025). The curriculum structure is highly flexible and student-directed, demanding significant autonomy and self-regulation.

In general, learning goals and objectives should be responsive to students' cognitive and socio-affective development, as well as their various needs. Curriculum structures differ across school levels, becoming progressively more complex at higher stages. This developmental trajectory highlights the importance of aligning instructional design and support systems with learners' evolving cognitive, emotional, and social capacities.

3. Recommendations for School Levels

Since learning goals, objectives, curricula, and learner characteristics vary by educational stage, AI-based personalization should be tailored accordingly. For elementary students, maintaining engagement with interactive elements and providing consistent positive feedback are essential for fostering confidence and healthy learning habits. Due to the underdevelopment of self-regulated learning at this level, AI technology functions most effectively as a supplementary tool that sparks interest and helps establish foundational learning behaviors rather than offering independent guidance or complex decision-making support. In the realm of language learning, AI can enhance this process further by offering interactive dialogues, pronunciation practice, and personalized feedback, making early language learning engaging and confidence-building (Pinter, 2017).

For secondary school students, AI systems should strike a balance between supporting autonomy and providing appropriate guidance. Specifically, they should provide more sophisticated learning analysis and adaptive feedback to encourage independent thinking, while offering safety nets to prevent students from becoming overwhelmed by their expanding responsibilities (Shao et al., 2023). In addition, AI systems should facilitate group activities and provide emotional support that acknowledges and addresses the complex social dynamics of this age group (OECD, 2025; Xie et al., 2022). Regarding language learning, AI can bolster learning activities by simulating authentic conversational scenarios, facilitating collaborative tasks, and offering adaptive feedback that reinforces linguistic proficiency and intercultural awareness (Reinhardt, 2019).

For higher education students, AI can support their needs by offering personalized academic and career guidance aligned with their goals. This guidance directly influences students' motivation and future planning by helping them connect their current learning with their long-term aspirations. In language learning, AI can serve as an intelligent assistant, offering real-time feedback on speaking and writing, as well as adaptive language training tailored to academic and professional contexts (Lee & Jeon, 2022; Sajja et al., 2023).

Specifically, we can apply the school levels to the five stages of AI-powered personalization. In Stage 1, elementary school students first acquire foundational concepts through rule-based learning. As students advance to middle and high school, they require broader subject choices and more diverse individual learning goals, necessitating a more fine-grained approach to content delivery. For elementary students in Stage 2, maintaining motivation and interest is paramount, so AI should adjust task difficulty and formats based on basic performance data. In secondary school, this stage is critical for establishing individualized learning patterns by analyzing achievement data and recommending optimal content. For higher education learners, Stage 2 personalization emphasizes performance analysis to support adaptive practice and goal-oriented learning strategies in various academic areas.

In Stage 3, at the elementary level, AI should focus on fostering comprehension and engagement through interactive feedback. At the secondary school level, AI should provide deeper, real-time analyses tailored to specific learning objectives. These analyses could diagnose misconceptions and supply targeted remediation. Stage 4 should be applied across all levels of schooling since emotional support and stress and anxiety management are critical for learners of every age. For instance, AI can detect fatigue or frustration, adjust pacing, suggest breaks, and provide motivational feedback. In Stage 5, at the elementary level, AI should nurture creativity and curiosity through exploratory and project-based activities. For secondary school learners, AI should optimize individualized learning strategies while gradually strengthening self-regulation. In higher education, AI should offer a full range of learning support services, such as career exploration, long-term planning, and mentoring for post-college pathways. <Table 2> summarizes the applications of AI-powered personalization stages for different levels of schooling.

Table 2

Five Stages of AI-powered Personalization for School Levels

Stage	Elementary education	Secondary education	Higher education
(Key Learner Characteristics)	• Foundational knowledge & habit formation • Play, storytelling, interactivity • Need for external motivation	• Conceptual understanding & problem-solving • Growing autonomy, peer influence, exam/career	• Diverse learner profiles with specialized goals • Advanced mastery & independent research

	& emotional support	pressures • Transition to self-regulation	• High autonomy & career planning
1	• Content based on age and grade (e.g., multiplication basics for Grade 3) • Recommendations by subject/topic • Fixed vocabulary lists by grade level for foreign language learning • Rule-based phonics or basic pronunciation drills	• Content recommendations based on learning history • Progress tracking along the fixed curriculum, suggesting advanced modules • Automated reminders and notifications based on fixed schedules • Predefined grammar practice by level • Rule-based reading passages for L2 learners	• Recommendations by subject and career track • Standardized academic skill modules (e.g., academic writing basics)
2	• Analyze learning speed and error patterns to recommend exercises • Recommend content by learning style (visual, auditory, experiential) • Gamified reward system to boost motivation • Adaptive word review based on errors in spelling/meaning • Data-driven recommendations for listening comprehension clips	• Performance analysis by subject to suggest review materials • Automatic provision of extra resources for weak concepts • Adaptive grammar drills for frequently missed items • Personalized reading comprehension passages at different Lexile levels	• Adaptive practice for various subjects, including language learning • Personalized vocabulary sets for academic writing • Data-driven recommendations for L2 proficiency exams
3	• Real-time feedback based on comprehension analysis • Voice recognition tutor for pronunciation correction • Reading ability analysis with book recommendations • AI storytelling companion for language dialogue practice	• Answer analysis with explanations tailored to mistakes • NLP-based AI answers student questions • AI-driven adaptive test preparation • Adaptive essay scoring with feedback on structure/grammar	• Automated concept explanations through Q&A systems • Strategic study recommendations for university goals • Real-time dialogue simulation in the target language • Adaptive writing suggestions for academic writing
4	• Emotion/voice analysis to adjust content style • Game elements added if fatigue detected • Detect frustration during	• Mode change upon detecting low concentration • Encouragement messages via emotional analysis • Peer-collaboration support	• Stress/anxiety analysis to adjust learning strategies • Emotion-aware AI mentor to monitor workload • Switching to peer dialogue

	speaking practice and switch to easier prompts • Encouragement messages to reduce foreign language anxiety	with emotion monitoring • Emotion-aware adjustment when learners hesitate in L2 speech • Supportive feedback to sustain motivation in grammar/writing tasks	simulations when learner shows disengagement • Support for public speaking & presentations in L2
5	• Learn the student's long-term style and set goals • Recommend creative activities based on interests • Mentor-guided reflective journals in a second language	• Long-term learning plan design with goal adjustments • Content for career exploration • Recommend debate or role-play projects in L2 • Guide multi-year language portfolio development	• Discipline- and career-specific L2 mentoring (e.g., business English, academic publishing) • Personalized essay and writing support • Long-term mentoring for academic/professional L2 writing and speaking

Overall, higher levels of schooling tend to use later stages more frequently due to greater curriculum complexity, but each stage can be applied across all levels, as shown in <Table 2>. Curriculum complexity is a strong predictor of the minimum AI stage required, and as students advance to higher levels of schooling, AI integration shifts toward fostering more complex abilities. This progression highlights the importance of aligning AI functionalities with learners' cognitive development to promote meaningful growth at every stage (Anderson & Krathwohl, 2001; Holmes et al., 2022; Luckin et al., 2016).

However, it should be noted that there is often a discrepancy between the goals of AI-supported education and how it is implemented across school levels. Ideally, the cultivation of higher-order thinking skills, such as critical thinking, problem-solving, and creativity, should begin early. In practice, however, AI-powered personalization at the elementary level primarily supports lower-order thinking skills, such as remembering and understanding. Furthermore, emotional and motivational needs justify the use of higher stages, even for younger learners (Vistorte et al., 2024; Yaseen et al., 2025). Thus, school levels do not need to be confined to a single stage of personalization. For instance, an elementary student with anxiety could benefit from Stage 4 emotional recognition, while a gifted middle school STEM student could thrive with Stage 5 mentorship for project-based learning. Similarly, in language learning, Stages 1–3 are generally most appropriate for skill acquisition, while Stage 4 should be integrated to foster emotional resilience and engagement and reduce language anxiety and stress for all age groups. Therefore, stage selection should be goal-driven rather than strictly age-driven.

V. CONCLUSION

The current study explores AI-powered personalized learning in five stages. It is significant because it considers multiple variables, such as learners' cognitive and affective factors, curriculums across school levels, and the different affordances of AI technology. Based on these stages, we suggest how to apply each stage to different school levels to benefit from AI in education. AI has the potential to significantly enhance student learning in various ways. In particular, its ability to address the needs of individual learners and deliver personalized learning experiences can help teachers achieve effective instruction. As AI is flexible and adaptable, it can be aligned with different learning theories, from behaviorism to constructivism, and applied across various stages of personalization depending on instructional goals.

Building on this flexibility, teachers play a central role in guiding how AI is integrated into education. Their responsibilities as curriculum and instructional designers are becoming increasingly critical. Crucially, they should avoid a “one-size-fits-all” approach to AI. Instead, they must thoughtfully integrate AI functions that align with learners’ developmental and cognitive readiness. This ensures that AI supplements, rather than replaces, human scaffolding. For younger learners, teachers can use rule-based and metadata-driven AI tools to promote motivation, curiosity, and foundational skills. In contrast, they can help higher education learners benefit from adaptive, emotionally responsive, mentor-like AI systems that support complex learning objectives and career preparation. Ultimately, the integration of AI in education has redefined the role of teachers. As AI takes over much of the instruction and assessment process, the role of teachers has shifted from being the primary source of knowledge transmission to becoming facilitators and orchestrators of human-AI interaction. This new role emphasizes the importance of pedagogical judgment in determining when to use AI-driven feedback versus human intervention.

Although AI is innovative and revolutionary in education, it can also be disruptive. For example, as AI becomes more prevalent in the classroom, students may become overly dependent on it. To prevent this, AI-powered personalized learning must be designed to sustain student engagement, enhance learning motivation, and foster continuous interaction. Second, using AI may hinder students’ development of higher-order thinking skills. Hence, instead of merely providing immediate answers and solutions, AI-powered learning systems should offer learners opportunities to explore, reason, and solve problems independently. This will further help to cultivate students’ creative and critical thinking skills. Third, while AI can offer adaptive scaffolding, instruction, and feedback, it struggles to replicate the warmth, empathy, and nuanced emotional support that human teachers provide (Bejarano & Coronel, 2025; Liu et al., 2025). Social-emotional learning is especially important for young learners. Therefore, rather than replacing teachers, it is crucial to enable learners to engage in social-emotional learning with the guidance of human educators alongside AI technology. This ensures that young learners do not view AI as a cold substitute for human interaction, but rather as a supportive tool within a caring educational ecosystem.

Most importantly, as AI becomes more deeply embedded in education, cultivating learner agency and self-directed learning becomes indispensable (Godwin-Jones, 2024). Learner agency involves the capacity to make choices, take initiative, and regulate one’s own learning process. Self-directed learning emphasizes metacognitive awareness, goal setting, and persistence (Bandura, 2001; Zimmerman, 2002). Without these qualities, students risk becoming passive recipients of AI-generated recommendations rather than active constructors of knowledge. Therefore, teachers need to intentionally design opportunities for students to reflect on their learning strategies, set personal goals, and use AI feedback as a resource for deeper engagement. When students are supported in cultivating agency and self-regulation, AI becomes a partner in fostering autonomy, critical thinking, and lifelong learning skills, rather than merely a delivery mechanism (Holmes et al., 2022; Luckin et al., 2016).

Although AI is expected to promote educational equity by offering personalized learning to all learners, it may, contrary to expectations, exacerbate existing educational inequities through an AI divide, data and algorithmic biases, inadequate infrastructure for AI-driven digital learning, and a lack of AI literacy. Groups with fewer resources or that are underrepresented may be at a disadvantage when it comes to using AI, which will further increase existing disparities in education (Bang & Lee, 2024, 2025). These issues may be more prevalent in language learning, given the diversity of learners in terms of ethnic backgrounds, geographical differences, first and second languages, and socioeconomic statuses (Baker & Hawn, 2022; Sha et al., 2021). These differences have the potential to create more biases among language learners. It is thus imperative to consider these issues when developing AI learning systems and infrastructure in order to proactively prevent potential harm.

As AI becomes more integrated into education, we may face unforeseen challenges. To maximize student learning and minimize potential harm, we must adopt a balanced and cautious approach that acknowledges the opportunities and risks of AI. This applies to English education as well. Numerous AI tools, including machine translation and generative AI, are prevalent in English classrooms (Lee, 2023; Lee & Jeon, 2022). Furthermore, recent studies have demonstrated that AI models, including Large Language Models (LLMs), have applications beyond basic text generation for conversations (Li et al., 2025). These models can provide learner-tailored contextual understanding and dynamic execution based on retrieval-augmented generation (RAG) and agent architectures specifically for language learning. It seems infeasible to ban AI completely. Therefore, teachers should consider multiple factors, including learners, the learning context, the curriculum, learning goals, and the affordances of AI. They must carefully navigate uncharted territory to facilitate student learning.

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