

Integrating AI in language education: Artificial intelligence in Language Education: A Smart Partner or a Formidable Competitor?

Jihan Bayram 

Independent Researcher, Maaref University of Applied Sciences, Syria

Corresponding Author: e-mail: Jihan.Bayram@mas.edu.syAvailable online at: <https://doi.org/10.66422/RJMU.ID.66>

Received: 10 May 2026

Revised: 22 June 2026

Accepted: 28 July 2026

Abstract— Artificial intelligence (AI) is rapidly reshaping language education by introducing adaptive, personalized, and continuously available learning environments. This conceptual paper examines whether AI should be understood as a smart pedagogical partner or a formidable competitor to human educators. Drawing on Second Language Acquisition theories, particularly Krashen's Input and Affective Filter hypotheses, alongside constructivist perspectives, the paper explores how Intelligent Tutoring Systems, Large Language Models, and conversational AI can provide individualized comprehensible input, reduce foreign language anxiety, and support scaffolded learning. It also considers the pedagogical value of automated feedback, gamification, and adaptive interaction. At the same time, the discussion addresses emerging concerns related to cognitive offloading, algorithmic bias, data privacy, linguistic hegemony, and excessive dependence on automated systems. The paper argues for a human-centered hybrid model in which AI supports routine instructional functions while teachers retain responsibility for cultural interpretation, emotional engagement, critical thinking, and meaningful interpersonal communication.

Keywords— Conversational AI, Input Hypothesis, Scaffolding and Fading, Gamification, Human-centered Pedagogy, AI Literacy, Linguistic Hegemony.

I. INTRODUCTION

In the modern multilingual landscape, the dream of providing every student with a private, 24/7 language tutor has shifted from a futuristic fantasy to a digital reality. However, as Artificial Intelligence becomes an integral part of the classroom, educators face a critical question: is this technology a smart partner that enhances the human experience, or a formidable competitor that threatens to sanitize the soul of language learning? It is a profound shift in how we define the relationship between teacher, student, and machine.

This paper explores the transition from traditional, rigid computer programs to the current era of Intelligent Tutoring Systems (ITS) and Large Language Models (LLMs). As a conceptual review, this study reflects existing literature and pedagogical theories to evaluate the implications of AI integration rather than presenting new data. While AI offers unprecedented opportunities to lower student anxiety

and provide personalized feedback at scale, it also introduces significant risks regarding data privacy, algorithmic bias, and the potential for cognitive offloading. By examining the intersection of machine precision and human-centered pedagogy, this study argues that the most effective future for language education lies in a hybrid model—one where AI handles the mechanical drudgery of instruction, freeing the human mentor to focus on the subtle cultural and emotional connections that no algorithm can replicate.

II. Theoretical Framework & Literature Review

To explore the pedagogical shift, the following sections provide a theoretical analysis of the way AI fits into the broader landscape of Second Language Acquisition (SLA). To really see AI as a "smart partner" rather than just a

tool, we need to examine the way it fits into the bigger picture of Second Language Acquisition (SLA), the

philosophy of "Constructivism", and the way educational technology has evolved over the years (Vygotsky, 1978).

The actual "efficacy of AI tools in the classroom is deeply rooted in Stephen Krashen's Monitor Model" (1982). Specifically, these tools help bring two of his most famous concepts to life namely the Input Hypothesis and the Affective Filter Hypothesis. The Input Hypothesis and "i + 1" (Krashen, 1982) suggests that language acquisition occurs when learners are exposed to "comprehensible input that is slightly beyond their current level of proficiency, a concept known as i + 1" (Krashen, 1982). In a traditional classroom, a single teacher often struggles to provide i + 1 input to thirty different students simultaneously. AI-driven Intelligent Tutoring Systems (ITS) solve this scalability problem by using adaptive algorithms to analyze a student's current proficiency (i) and dynamically generating content that provides the necessary challenge (+ 1) (Gass, 2017). Through natural language processing (NLP), these systems ensure the input is neither too simplistic (leading to boredom) nor too complex (leading to frustration).

The Affective Filter Hypothesis: One of the most significant barriers to language acquisition is "foreign language anxiety" (Horwitz, 1986), which raises what Krashen (1982) calls the Affective Filter. When a student is stressed, self-conscious, or unmotivated, the filter is high, blocking the input from reaching the language acquisition device in the brain.

AI serves as a powerful tool for lowering this filter. Research indicates that "students often feel less judged when interacting with a non-human agent" (Khadiji & Behrouzi, 2021). An AI does not sigh, show impatience, or trigger social shame when a student mispronounces a word for the tenth time. By providing a "safe failure space, conversational AI allows for the repetitive practice necessary for fluency without the psychological toll of social evaluation" (Loewen & Isbell, 2022).

The shift from rote memorization to interactive engagement is grounded in Constructivist learning theory, which argues that "knowledge is constructed through experience and social negotiation rather than passively absorbed" (Vygotsky, 1978).

Active Interaction and Scaffolding: In the digital age, AI facilitates a learning by doing environment. Unlike traditional textbooks, which offer static consumption, AI-enabled platforms require active production. When a student engages with a chatbot, they are forced to negotiate meaning—rephrasing questions and correcting their own syntax to be understood. This mirrors Vygotsky's Zone of Proximal Development

(ZPD), where the AI acts as the "More Knowledgeable Other" (MKO), providing just enough scaffolding to help the student complete a communicative task they could not do alone (Luckin, 2017).

Social Constructivism via AI: While AI is not social in the human sense, modern LLMs (Large Language Models) simulate social interaction with remarkable fidelity. "They allow students to participate in situated learning—simulating a trip to a pharmacy or a business negotiation—thereby constructing linguistic knowledge within a functional context" (Richards & Rodgers, 2014). This contextualized practice ensures that vocabulary and grammar are not learned in isolation but are tied to real-world application. For instance, an instructor might implement these applications by tasking students with conducting a 10-minute simulated job interview with GPT-based persona. The student must use specific professional vocabulary, while the AI provides a transcript at the end that highlights where the student's tone was too informal or where word choice could be more precise.

III. The Evolution: From CALL to ICALL

I can enhance it in a more natural, varied, academically sophisticated voice while preserving every existing citation. I'll focus on depth, rhythm, lexical variety, and a less formulaic scholarly style rather than writing specifically to defeat detection systems.

The journey toward what might now be described as the smart partner in language learning did not emerge suddenly with contemporary artificial intelligence. It has been unfolding, sometimes rather awkwardly, for more than half a century. Each technological generation has carried with it a different assumption about what a computer should actually do in the learning process: deliver exercises, store information, connect learners, diagnose errors, adapt instruction, or, more recently, participate in something approaching dialogue. Seen from this longer historical perspective, today's AI-assisted language environments are less a technological rupture than the latest stage in a gradual reimagining of the relationship between learner and machine.

Computer-Assisted Language Learning (CALL)

The earliest period of Computer-Assisted Language Learning (CALL), particularly between the 1960s and the 1980s, was shaped strongly by behaviorist theories of learning. Language was often treated as a system of patterns that could be reinforced through repetition, correction, and continued exposure. Consequently, many early CALL programs relied on what later became somewhat dismissively known as "drill and kill" activities: fill-in-the-blank exercises, vocabulary matching, grammatical transformations, and repeated

multiple-choice questions in which the computer judged a learner's answer as either correct or incorrect (Levy, 1997).

There was a certain logic to this approach. Computers were exceptionally good at repetition. They did not become impatient, tired, or irritated when a learner answered the same grammar item incorrectly for the seventh time. For vocabulary memorization, spelling practice, verb conjugation, or highly controlled grammatical exercises, this consistency could be genuinely useful. Yet the limitations were equally obvious.

Human language rarely behaves in neat binary categories. A sentence may be grammatically acceptable but pragmatically inappropriate; another may contain a technical error while still communicating its intended meaning perfectly well. Early CALL could detect deviation from a predetermined answer, but it could not meaningfully interpret intention, ambiguity, politeness, irony, register, or the countless shades of meaning that make real communication so complicated.

In this sense, the machine functioned primarily as an electronic workbook. It could present material faster and more consistently than paper, but its intellectual role remained narrow.

The emergence of Communicative CALL during the 1980s and, more visibly, throughout the 1990s began to loosen this rigid instructional model. As communicative approaches to language teaching gained influence, educators became increasingly interested not merely in whether learners could reproduce correct structures but whether they could actually use language for meaningful interaction. Computers gradually became gateways through which learners could communicate with other people. Email exchanges, online discussion boards, early chat rooms, multimedia activities, and later web-based language tasks created possibilities that had been difficult to imagine during the behaviorist era.

This development was important, although there was an interesting paradox at its center. The computer was becoming increasingly important to communication while remaining largely uninvolved in the communication itself. It carried messages, displayed information, connected participants, and provided access to authentic materials, but it did not genuinely interpret what the learner was saying. The machine was a medium—a sophisticated one, certainly—but still mostly a passive intermediary.

Intelligent CALL (ICALL) and the Integration of Artificial Intelligence

The movement from conventional CALL toward Intelligent Computer-Assisted Language Learning (ICALL) introduced a much more ambitious question: what if the computer could do more than present content or facilitate communication? What if it could begin to interpret learner language?

That shift marks one of the most consequential developments in the history of educational technology. Rather than functioning solely as a delivery platform, ICALL sought to give computing systems some capacity to analyze linguistic performance, identify patterns in learner errors, infer possible causes, and respond differently depending on the needs of the individual learner. Artificial Intelligence, Natural Language Processing (NLP), Computational Linguistics, and learner modeling became increasingly intertwined with language pedagogy.

This theoretical movement from passive technological tools toward more active instructional participants finds perhaps its clearest practical expression in Intelligent Tutoring Systems (ITS). Such systems attempt, admittedly with varying degrees of success, to reproduce selected elements of what a skilled human tutor does naturally: observe performance, recognize recurring difficulties, modify the level of challenge, choose appropriate feedback, and decide when direct correction may be less useful than explanation or guided discovery.

The distinction sounds subtle, but pedagogically it is substantial. Traditional CALL asks, in effect, “Was this answer correct?” Intelligent CALL attempts to ask a more complicated set of questions: “What kind of error is this? Why might the learner have made it? Has this pattern appeared before? What explanation is likely to help? And what should happen next?”

During the 1990s and early 2000s, much of ICALL research concentrated on error analysis. Systems were designed to identify not merely that an error had occurred but, where possible, the linguistic mechanism behind it. Researchers became particularly interested in mistakes that appeared systematically among speakers of particular first languages, since some learner errors can be connected to cross-linguistic transfer or interference. In this period, ICALL systems increasingly attempted to distinguish among grammatical, lexical, morphological, and syntactic difficulties rather than treating every deviation as the same type of failure (Heift & Schulze, 2007).

This represented an important departure from the blunt corrective logic of earlier systems. A learner who

writes “He go to university every day,” for example, does not necessarily need to be told simply that the sentence is wrong. A more intelligent system can identify the specific subject–verb agreement problem, recognize whether similar errors have occurred previously, and offer an explanation that addresses the underlying grammatical pattern rather than merely replacing the incorrect form.

Still, these systems were constrained by the technological environment of their time. Rule-based architectures could be remarkably sophisticated within narrow domains, yet they often struggled with unexpected formulations, creative language use, context-dependent meaning, and learner responses that fell outside anticipated patterns. Human communication, as always, proved stubbornly resistant to complete formalization.

The Modern Era: Adaptive and Context-Sensitive Language Support

Contemporary ICALL systems have moved considerably beyond these earlier limitations, particularly with the expansion of machine learning, deep learning, large-scale language models, speech recognition, and increasingly sophisticated NLP architectures. The emphasis is shifting from error detection toward adaptive feedback—feedback that responds not only to the form of an error but also to its context, probable intention, learner proficiency, and sometimes even the broader history of interaction.

Consider verb tense, an apparently simple example that reveals how substantial this shift actually is. Earlier systems might identify that a learner used the past simple where the present perfect was expected and provide the correct form. A more advanced system can potentially explain how each tense changes the speaker’s perspective on time, why one construction sounds more natural in a particular discourse context, and how alternative choices subtly alter meaning. Correction becomes explanation; explanation can become dialogue.

The same pattern appears elsewhere. Modern systems may distinguish between grammatical accuracy and stylistic appropriateness, identify awkward collocations, suggest alternative registers, analyze pronunciation, generate individualized practice materials, or adapt the difficulty of subsequent activities according to previous performance. Increasingly, they can also respond to open-ended language rather than requiring learners to choose from tightly controlled options.

This matters because language acquisition itself is not linear. Learners hesitate. They experiment. They

overgeneralize a grammatical rule that worked yesterday and suddenly fails today. Sometimes they knowingly produce an imperfect sentence because it communicates the idea quickly enough. At other times, what appears to be a linguistic error is actually evidence of a deeper conceptual misunderstanding. A genuinely useful intelligent learning environment must somehow accommodate this messiness rather than pretend it does not exist.

The historical evolution from CALL to ICALL is not merely a story about more powerful computers. It reflects a changing conception of the machine’s pedagogical identity. Early CALL positioned the computer largely as a rigid tutor—reliable, repetitive, and authoritative, but limited in interpretation. Communicative CALL repositioned it as a conduit through which human interaction could occur. ICALL, particularly in its contemporary forms, is pushing the technology toward something qualitatively different: a responsive collaborator capable of adjusting, questioning, explaining, and interacting.

The phrase computer-as-partner should, of course, be used cautiously. A computational system does not become a human teacher simply because it can generate convincing feedback, nor does technological responsiveness automatically amount to pedagogical wisdom. Yet the direction of change is difficult to ignore. The computer is no longer restricted to telling learners whether an answer matches an answer key. Increasingly, it participates in the learning process itself, reacting to individual performance and helping learners navigate the ambiguity, irregularity, and contextual complexity that define real language use.

The movement from computer-as-tutor to computer-as-partner, then, captures more than technological progress. It represents a broader conceptual shift—from technology designed primarily to control and evaluate learner responses toward technology intended to accompany learning, adapt to it, and perhaps even participate in the learner’s evolving understanding of language. That distinction is crucial, because the future of intelligent language learning may depend less on how much information a system can process than on how intelligently, sensitively, and contextually it can respond to the human being on the other side of the screen.

Conversational AI: Enhancing Multilingual Instruction

Conversational AI represents the frontier of the smart partner paradigm in language education. Unlike static software, these systems utilize Natural Language Processing (NLP) and Neural Machine Translation (NMT) to engage learners in dynamic, unpredictable,

and context-aware dialogue. This section explores how the technical affordances of Conversational AI—specifically Large Language Models (LLMs)—transform the acquisition of lexical precision, phonetic clarity, and situational competence.

In traditional classrooms, a teacher's feedback is often "delayed or generalized due to the sheer volume of students. Conversational AI disrupts this by providing immediate critiques, which are essential for preventing the fossilization of linguistic errors" (Brandl, 2023).

AI agents analyze student input for semantic accuracy and word choice. When a student uses an imprecise term—for instance, using "big" instead of "spacious" to describe a room—the AI can offer immediate synonyms tailored to the context. This "recasting" technique, where the AI repeats the student's idea using more sophisticated or correct language, allows for implicit learning. According to research by Schmidt and Strasser (2022) note, "immediate lexical feedback from AI increases 'noticing,' a cognitive process where learners consciously register the gap between their current interlanguage and the target language".

Modern AI integrations often include Automatic Speech Recognition (ASR) capable of phoneme-level analysis. These systems can visualize the difference between a student's pronunciation and the target standard. For example, "a student struggling with the th sound in English or the letter u in French receives visual or descriptive cues on tongue placement and airflow" (McCrocklin, 2019). This granular feedback loop as McCrocklin adds, enables a "drill-down" approach where students can repeat a specific sound until the AI validates the clarity, fostering phonetic precision that is often overlooked in communicative-heavy human classrooms.

Beyond individual words, the mastery of a language requires an understanding of prosody—the rhythm, stress, and intonation that give speech its natural flow. Historically, computers struggled with this, sounding robotic and stilted. However, the advent of Large Language Models (LLMs) and high-fidelity text-to-speech (TTS) has bridged this gap.

LLMs like GPT-4 or Claude 3.5 are "trained on vast corpora of human dialogue, allowing them to mimic the pragmatic nuances of native speakers, such as the use of fillers ("um," "well"), contractions, and idiomatic expressions" (Chiu et al., 2023). By interacting with an LLM, students are exposed to a living version of the language rather than the sanitized, formal versions often found in textbooks.

Recent studies suggest that learners subconsciously engage in "prosodic entrainment"—the tendency to mimic the rhythm and tempo of their conversational partner (Levis & McCrocklin, 2021). When an AI provides a high-fidelity, prosodically accurate response, the student is more likely to adopt natural intonation patterns. This is particularly vital for tonal languages like Mandarin or pitch-accent languages like Japanese, where the melody of a sentence is as important as its vocabulary.

One of the most powerful applications of Conversational AI is its ability to facilitate situational learning through role-play. This allows students to apply theoretical knowledge to high-stakes scenarios in a low-stakes digital environment.

Case Study: The "Ordering Food" Scenario

In a pilot study conducted at a multilingual university, students used an AI agent to simulate a restaurant interaction.

The AI was programmed to introduce "friction"—such as telling the student an item was out of stock or misunderstanding their order. This forced students to use "repair strategies," a key component of communicative competence. The result was a measurable increase in student confidence when they eventually performed the task in a real-world setting (Rezaei & Ludwig, 2023).

Case Study: Professional Narratives and Job Interviews

For advanced learners, AI can simulate professional environments, such as a job interview or a project pitch. The AI can be prompted to adopt different personas: a "tough interviewer," a "curious client," or a "supportive colleague." By navigating these varied social registers, learners build "genuine" verbal competence—the ability to shift tone and vocabulary based on the social context (Godwin-Jones, 2021).

To prevent students from becoming overwhelmed or, conversely, under-challenged, educators must implement specific pedagogical frameworks for AI integration. A common pitfall is the "Open Prompt" problem, where a student does not know what to say to the AI.

The Scaffolding Framework

Teachers should structure AI interactions using a step-by-step approach:

- **Controlled Phase:** The AI provides multiple-choice prompts or sentence starters to help the student begin the conversation.
- **Guided Phase:** The AI asks open-ended

questions but provides "hints" or "translation bubbles" if the student pauses for too long.

- Free Phase: The student engages in unscripted dialogue, with the AI only intervening if there is a total communication breakdown (Stockwell, 2022).

Educators must act as "architects of interaction." By pre-programming the AI's "system prompt," teachers can ensure the tool stays within the student's Zone of Proximal Development (ZPD). For example, a prompt might read: "Act as a friendly shopkeeper. Use B1-level English. If the student makes a grammatical error, do not stop them; instead, repeat their sentence back correctly in your response" (Warschauer & Matuchniak, 2020). This ensures the AI remains a smart partner that facilitates flow rather than a formidable competitor that discourages the learner.

Conversational AI does not replace the need for human interaction; rather, it prepares the student for it. By providing a sandbox for lexical and phonetic experimentation, it ensures that when students enter a real-world multilingual environment, they do so with a foundation of hard linguistic skills and soft communicative confidence. The key to this enhancement lies in the balance between the AI's technical precision and the educator's pedagogical structure.

Intelligent Tutoring Systems (ITS) as Digital Assistants

The integration of Intelligent Tutoring Systems (ITS) into language education represents a move toward high-precision pedagogy. Unlike general-purpose AI, an ITS is specifically engineered to model the learner's psychological and linguistic state, providing a customized roadmap for mastering the structural components of language such as writing and grammar. These systems provide the structured feedback necessary for mastering syntax and vocabulary. For instance, in a Spanish Level 1 classroom, an ITS can analyze a student's consistent errors with 'ser' versus 'estar' and automatically generate a personalized set of drill-and-practice exercises that focus specially on those distinctions until the student achieves a 90% accuracy rate before moving to the next module.

A cornerstone of effective instruction is scaffolding—a process where an educator provides temporary frameworks to support a student's learning, which are then gradually removed as the student gains autonomy. In the digital context, ITS provides this through "tiered support," ensuring that the cognitive load remains manageable (Sweller, 2011).

When a student begins a writing task, the ITS may offer "heavy" scaffolding, such as sentence frames,

vocabulary suggestions, and real-time grammar alerts. For a novice learner, the system might highlight a subject-verb agreement error and provide a direct correction. However, as the system detects increased accuracy over time, it shifts to "metalinguistic feedback." Instead of providing the answer, it might simply underline the error and ask, "Does this verb match the plural subject?" (Heift, 2010).

The ultimate goal of an ITS is its own independence in the learner's process. This is known as fading. According to Shute and Rahimi (2017), effective ITS platforms use "stealth assessment" to monitor how long a student pauses before a grammatical choice. If the student demonstrates consistency, the system "fades" the prompts, forcing the learner to rely on their internal linguistic "monitor." This transition from external digital support to internal fluency is critical for authentic writing proficiency.

The intelligence in an ITS lies in its ability to use data analytics to map a student's unique linguistic educational roadmap. This moves away from the one-size-fits-all curriculum toward Adaptive Learning Paths.

An ITS constantly updates a "Learner Model"—a digital representation of what the student knows, what they have forgotten, and where they struggle (Abdi et al., 2020). For instance, if data shows a student consistently misses "past-perfect" tense questions but excels at "future" tenses, the algorithm dynamically re-routes the curriculum. It will bypass the mastered future tense modules and present more complex, varied examples of the past-perfect tense across different contexts such as reading, writing, and listening (Abdi et al., 2020).

To keep students in the "Flow State"—a psychological zone where the challenge perfectly matches their skill—ITS employs Dynamic Difficulty Adjustment. If a "student answers three consecutive questions correctly in under ten seconds, the system recognizes that the current difficulty is too low and immediately introduces more complex syntax or nuanced vocabulary" (Aleven et al., 2016). This prevents the boredom that often leads to student disengagement in standardized language programs.

One of the most significant benefits of ITS is its capacity to automate the administrative side of teaching, particularly regarding repetitive, drill-based exercises and initial grading.

Language teachers often spend a disproportionate amount of time grading repetitive grammar worksheets or correcting basic spelling errors in essays. ITS can handle these tasks with near-perfect accuracy and

instantaneous speed. By automating these "low-level" corrections, the system provides students with the immediate feedback they crave while freeing the teacher from the "red-pen syndrome" (Knutsson et al., 2012).

With the mechanical aspects of language instruction handled by the ITS, the teacher's role undergoes a vital transformation. Instead of spending hours on syntax correction, the educator can utilize the data dashboards provided by the ITS to identify specific classroom trends. For example, "if the dashboard shows that 70% of the class is struggling with conditional sentences, the teacher can dedicate the next live session to a creative, human-led discussion or a cultural role-play involving those structures" (Luckin et al., 2016).

This shift allows teachers to focus on high-level mentorship: fostering cultural empathy, guiding complex debates, and providing the nuanced emotional support that an AI cannot. As noted by Selwyn (2019), "the goal is not to replace the teacher but to "augment" them, removing the drudgery so that the human-to-human connection can remain the heart of the language-learning experience".

The integration of ITS creates a collaborative classroom. The machine provides the tiered scaffolding and data-driven precision required for technical mastery, while the human teacher provides the creative and social framework for that mastery to be applied. This dual approach ensures that students receive a rigorous, individualized education that remains grounded in authentic communication.

IV. The Psychology of AI-Assisted Learning

The integration of Artificial Intelligence into language education transcends technical utility, fundamentally altering the psychological landscape of the classroom. As AI agents move from passive tools to active dialogue partners, they impact the learner's internal state—specifically their motivation, emotional regulation, and cognitive habits. This section explores the dual-edged nature of AI-assisted learning: its ability to lower barriers to entry while simultaneously risking the erosion of independent thought.

Motivation is the primary engine of successful language acquisition. AI tools leverage gamification—the application of game-design elements in non-game contexts—to maintain student engagement through dopamine-driven feedback loops.

Modern AI platforms utilize leaderboards, streaks, and immediate digital rewards to foster a sense of progress. According to Figueroa-Flores (2016), gamification in language learning satisfies the basic psychological needs of autonomy, competence, and relatedness.

When an AI provides a level-up notification or a badge after a successful conversation, it transforms the often-tedious process of vocabulary acquisition into a series of achievable micro-goals. This structural reinforcement is particularly effective for younger learners, who benefit from the clear, incremental markers of success that traditional semester-long courses often lack.

However, researchers warn of the "novelty effect—a short-term increase in effort or interest that results from the introduction of a new technology rather than from any inherent improvement in learning outcomes" (Kessler, 2018). As the newness of interacting with an AI wears off, motivation may plateau. To combat this, AI systems must move beyond superficial rewards and provide deep, intrinsic value through personalized storytelling and meaningful interaction. Without substantive pedagogical depth, gamified AI risks becoming a digital chocolate-covered broccoli—a tool that looks fun but fails to sustain long-term cognitive investment.

One of the most profound psychological shifts in AI-assisted education is the reduction of Foreign Language Anxiety (FLA). "In a traditional classroom, students often experience social evaluative anxiety, fearing that a mispronounced word or a grammatical slip will lead to judgment from peers or the teacher" (MacIntyre & Gardner, 1994).

AI provides a psychologically safe environment for experimentation. Because an AI lacks consciousness, social status, and emotions, the student perceives it as a neutral tool. This non-judgmental feedback loop allows the student to keep their Affective Filter low, ensuring that their cognitive resources are focused on language processing rather than anxiety management.

The AI serves as a rehearsal space. By mastering a conversation in a low-anxiety digital environment, students build a foundation of communicative self-efficacy. This confidence then transfers to human-to-human interactions. As noted by Lucas et al. (2017), the virtual agent acts as a transitional partner, bridging the gap between silent study and the high-pressure environment of live social communication.

Despite the motivational and emotional benefits, the integration of AI introduces a significant cognitive risk: over-dependency, often manifested as cognitive offloading. This occurs when a student uses technology to perform a task that they are capable of doing themselves, leading to a decline in long-term memory and skill retention.

In language learning, the danger lies in the shift from using AI as a translator to using it as a thinker. If a

student relies on an LLM to generate entire essays or responses, they bypass the essential mental effort required to construct meaning in the target language. "This bypasses the Desirable Difficulty principle, which suggests that learning is most effective when the brain has to work to retrieve and organize information" (Bjork & Bjork, 2011). When the AI does the heavy lifting of thought organization, the student's neural pathways for syntax and logic are not reinforced.

Much like how reliance on GPS can erode a person's natural sense of direction, over-reliance on AI writing assistants can lead to linguistic decline. Students may become proficient at prompting an AI to speak for them but remain unable to formulate an original thought during a spontaneous face-to-face encounter. "This creates a facade of proficiency—where the student's digital output is high, but their internal linguistic competence remains shallow" (Warschauer, 2023).

The psychology of AI in language learning is a balance of scaffolding and struggle. While AI is an unparalleled tool for increasing motivation through gamification and reducing the crippling effects of anxiety, it must be implemented with fading strategies to prevent cognitive offloading. Educators must ensure that AI remains a smart partner that supports the student's voice, rather than a competitor that replaces it. The ultimate goal is to use the AI to build the student's psychological resilience and independent capability, ensuring they are eventually prepared to step away from the screen and engage authentically with the world.

V. The Human-Centered Approach & Cultural Implications

As Artificial Intelligence becomes increasingly integrated into the linguistic landscape, a critical tension emerges between technical efficiency and cultural authenticity. Language is not merely a code to be decrypted or a set of grammatical rules to be mastered; it is a living breathing entity deeply intertwined with identity, history, and social context. A human-centered approach to AI in education asserts that while machines can process syntax, only humans can navigate the soul of a language.

Despite the remarkable capabilities of Large Language Models (LLMs), AI still struggles with the high-context nature of human communication. Authentic communication relies on more than literal translation; it requires an understanding of cultural nuance, idioms, and regional slang, which often bypass the logical structures of AI training data.

Idioms are cultural artifacts that often defy literal logic. For example, the English phrase "beating around the

bush" or the Japanese concept of *Kuuki wo yomu* (reading the air) involves social histories that AI can define but cannot always apply with appropriate social timing. Research by Thorne and Hellermann (2021) suggests that while AI can generate grammatically perfect sentences, it often lacks the pragmatic competence to know when a specific slang term is endearing versus when it is offensive in a specific subculture. AI tends to provide a standardized version of a language, which can lead to a sterile form of communication that lacks the grit and character of real-world dialects.

Furthermore, AI often struggles with sarcasm and irony, which are foundational to many cultures' communicative styles. Because AI models are trained on patterns of probability, they may miss the subtle vocal inflections or contradictory word choices that signal a speaker is saying the opposite of what they mean. "Without an understanding of these hidden cultural connotations understanding, a student relying solely on AI might master the mechanics of a language but remain culturally deaf to its social subtleties" (Chun, 2022).

The rise of smart digital assistants necessitates a radical shift in the professional identity of the language teacher. In an AI-enhanced classroom, the teacher's value lies in their ability to manage the human-in-the-loop model. While the AI handles the repetitive drills of verb conjugation and vocabulary building, the teacher facilitates complex social interactions. According to Kern (2021), for instance, if an AI provides a translation, the teacher asks, "In what social setting would this be considered too formal?" or "How would this change if you were speaking to an elder in a rural village?"

Teachers serve as the ultimate judges of sociolinguistic appropriateness. They provide the why behind the what. An AI might tell a student that a certain word is a synonym for another, but a teacher can explain the historical baggage or the emotional weight that word carries in a specific country. "This mentorship ensures that students do not just become fluent in a technical sense but become interculturally competent—able to navigate the sensitive boundaries of a different society" (Byram & Masuhara, 2013).

A significant risk of AI integration is the standardization of language. Because many AI models are optimized for clarity and safety, they often filter out regionalisms, non-standard dialects, or edgy cultural expressions, leading to a homogenization of the target language.

To ensure AI tools do not erase cultural richness, schools must implement strategies that prioritize linguistic diversity:

- **Diverse Training Data:** Educators should advocate for AI tools that are trained on diverse datasets, including African-American Vernacular English (AAVE), regional Spanish dialects (e.g., Rioplatense), or Québécois French.
- **Comparative Analysis:** "A powerful pedagogical strategy involves asking students to compare an AI-standardized response with a recording of a native speaker from a specific region. This highlights the gap between textbook language and lived language" (Ware & Hellmich, 2021).
- **The Local Expert Model:** Using AI to generate a baseline of text, which students then localize by interviewing native speakers or researching regional slang. This forces the student to use the AI as a draft rather than a final authority.

Finally, maintaining cultural relevance requires ensuring that AI does not reinforce the prestige of certain dialects over others. If AI tools only recognize standard accents, they unexpectedly tell students that regional identities are incorrect. "A human-centered approach requires teachers to explicitly validate regional variations, using the AI as a tool to explore these differences rather than suppress them" (Warschauer & Matuchniak, 2020).

The most effective language education occurs at the intersection of machine precision and human empathy. While AI provides the smart partner for structural mastery, the human mentor remains the indispensable cultural guide. By prioritizing authentic communication and resisting the urge to sanitize language through automation, educators can ensure that AI serves to enhance—rather than replace—the rich, messy, and beautiful complexity of human culture.

VI. Ethical Considerations & Implementation Challenges

The transition toward AI-mediated language education does not merely involve technical obstacles but a profound ethical undertaking. As schools move from experimental usage to systemic integration, they must navigate a landscape full of risks related to social equity, data sovereignty, and algorithmic integrity. Without a robust ethical framework, the smart partner of AI may inadvertently become a tool for exclusion and standardization.

One of the most pressing ethical concerns is the potential for AI to exacerbate the Digital Divide. While AI has the potential to universalize high-quality

tutoring, its current distribution model often favors those with significant financial resources.

The disparity between Free and Premium AI models creates a layered educational system. Premium models (such as GPT-4 or specialized proprietary Intelligent Tutoring Systems) offer significantly higher complexities in feedback, better support for low-resource languages, and more sophisticated conversational flow. "Students in well-funded private institutions or high-income households can afford these platinum tutors, while students in underfunded public sectors may be relegated to older, glitchier, or advertisement-heavy models" (Warschauer, 2023).

Beyond software costs, AI integration requires high-speed internet and modern hardware. In many multilingual settings—particularly in developing nations or rural areas—unreliable connectivity renders cloud-based AI unusable. As noted by Reich and Ito (2020), technology often enhances existing inequalities rather than fixing them. If mastery of a second language becomes dependent on access to high-end AI, the language gap between socio-economic groups will likely widen, limiting the upward mobility that language proficiency is supposed to provide.

The effectiveness of an AI partner depends on its ability to collect and analyze massive amounts of student data. However, the integration of these tools into non-transparent AI ecosystems raises significant concerns regarding Data Privacy and Security.

When a student interacts with a conversational AI, their voice recordings, writing samples, and personal progress metrics are often stored on servers owned by private corporations. Many of these companies use User Generated Content to further train their models. This creates a conflict of interest: is the tool serving the student, or is the student's data serving the company's product development? According to Lupton and Williamson (2017), the datafication of childhood and education risks turning students into permanent data points without clear right to be forgotten protocols.

Educational institutions are increasingly targets for cyberattacks. A breach in an AI tutoring platform could expose sensitive student information, including linguistic disabilities, learning speeds, and personal identifiers. "Schools must demand Privacy by Design, ensuring that AI tools use edge computing (processing data on the device) or anonymization techniques to protect the vulnerable multilingual populations they serve" (Holmes et al., 2022).

AI is not a neutral authority; it is a reflection of its training data. Algorithmic Bias in language education

can lead to the reinforcement of linguistic hegemony—where certain dialects or accents are treated as the correct standard while others are marginalized.

Automatic Speech Recognition (ASR) systems are often trained primarily on standard accents (e.g., General American English or Peninsular Spanish). Studies have shown that "these systems have higher error rates for non-native speakers or individuals with regional dialects" (Koencke et al., 2020).

If an AI tool consistently fails to understand a student from Singapore or Nigeria, it sends a powerful psychological message that their version of the language is broken. This reinforces a narrow, Eurocentric or Anglo-centric view of language that ignores the reality of Global Englishes.

Furthermore, LLMs may unintentionally generate content that reflects cultural stereotypes found in their training data. For example, an AI might consistently associate certain languages with "specific low-wage professions or social roles. Educators must be vigilant in audit-testing AI responses to ensure they are providing an inclusive and diverse representation of the target culture" (Bender et al., 2021).

To navigate these ethical minefields, schools must move away from ad-hoc adoption toward a Phased Integration Strategy.

Phase 1: Initial Trials and Audits

Before full-scale adoption, institutions should conduct Pilot Trials with a diverse subset of the student population. These trials should specifically monitor for bias—checking if the tool performs equally well across different accents and socio-economic backgrounds. Schools should also perform a Data Privacy Audit to ensure the tool complies with local regulations like General Data Protection Regulation GDPR or Children's Online Privacy Protection Act COPPA.

Phase 2: Teacher Training and Literacy

Integration is only as effective as the educators behind it. "Schools must invest in AI Literacy for teachers, moving beyond how to use the tool to how to critically evaluate the tool" (Luckin, 2017). Teachers need to be trained to spot algorithmic bias and taught how to use AI as a scaffold rather than a crutch for their students.

Phase 3: Full-Scale Adoption and Continuous Monitoring

Once a tool is implemented, the work is not finished. Schools must establish a Feedback Loop where students and teachers can report errors or biased responses. Implementation should follow a "Hybrid Model, where AI-assisted exercises are always paired

with human-led discussions, ensuring that the human mentor remains the ultimate authority on cultural and ethical matters" (Selwyn, 2019).

A successful integration of AI in language education requires more than just technical proficiency; it requires moral courage. By addressing the digital divide, protecting student privacy, and actively fighting algorithmic bias, educators can ensure that AI serves as a truly smart partner. The goal is an inclusive future where technology does not homogenize language, but rather provides every student—regardless of their background—with the tools to find their own unique voice in a multilingual world.

CONCLUSION

The move toward using Artificial Intelligence in language education is ultimately about finding a better way to teach that keeps the human experience at its center. This dual approach ensures that students get a personalized education that focuses on both technical skills and the ability to communicate in the real world.

However, making this future work for everyone requires more than just good technology; it requires us to be careful and fair. We must make sure that AI doesn't accidentally make the gap between rich and poor students wider or turn language into something generic and boring. By protecting student privacy and making sure we celebrate different cultures and accents, we can ensure that technology supports the student's voice rather than replacing it. When used correctly, AI isn't there to take over the classroom; it's there to help every student find their own unique way to speak to the world.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest.

Funding

The authors received no financial support for this book review.

Human Participants

This paper does not involve human participants.

Originality Note

The authors confirm that the manuscript is their original work, and if others' works are used, they are properly cited/quoted.

REFERENCES

1. Abdi, S., Khosravi, H., Sadiq, S., & Gasevic, D. (2020). A multivariate approach for predicting student outcomes in adaptive learning systems. *International Journal of Artificial Intelligence in Education*, 30(4), 564–594.

2. Aleven, V., McLaughlin, E. A., Glenn, R. A., & Koedinger, K. R. (2016). Instruction based on adaptive learning technologies. *Handbook of research on learning and instruction*, 2, 522–560.
3. Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency*, 610–623.
4. Bjork, E. L., & Bjork, R. A. (2011). Making things hard on yourself, but in a good way: Creating desirable difficulties to enhance learning. *Psychology and the Real World: Essays Illustrating Fundamental Contributions to Society*, 2(1), 55–64.
5. Brandl, K. (2023). *Communicative Language Teaching in the Age of AI*. Cambridge University Press.
6. Byram, M., & Masuhara, H. (2013). *Intercultural Competence in Foreign Language Education*. Routledge.
7. Children's Online Privacy Protection Act of 1998, 15 U.S.C. 6501–6506 (1998).
8. Chiu, T. K., Xia, Q., Zhou, X., Lau, N. S., & Cheng, G. J. (2023). Systematic literature review on opportunities, challenges, and future research directions of generative AI in education. *Computers and education: artificial intelligence*, 4, 100152.
9. Chun, D. M. (2022). Review of "Artificial Intelligence in Language Education." *Language Learning & Technology*, 26(1), 1-5.
10. European Parliament and Council of the European Union. (2016). Regulation (EU) 2016/679 (General Data Protection Regulation).
11. Figueroa-Flores, J. F. (2016). Gamification and Game-Based Learning: Two Strategies for the 21st Century Learner. *World Journal of Education*, 6(2), 50–62.
12. Gass, S. M. (2017). *Input, Interaction, and the Second Language Learner*. Routledge.
13. Godwin-Jones, R. (2021). Evolving technologies for language learning: From computer-assisted to AI-enhanced. *Language Learning & Technology*, 25(3), 6–27.
14. Heift, T. (2010). Developing an intelligent tutoring system for foreign language learning. *Language Teaching*, 43(4), 441–462.
15. Heift, T., & Schulze, M. (2007). *Errors and Intelligence in Computer-Assisted Language Learning: Parsers and Pedagogy*. Routledge.
16. Holmes, W., Persson, J., Binns, R., & Tamre, M. (2022). Ethics of AI in Education: Towards a Community-Wide Framework. *International Journal of Artificial Intelligence in Education*.
17. Horwitz, E. K., Horwitz, M. B., & Cope, J. (1986). Foreign language classroom anxiety. *The Modern Language Journal*, 70(2), 125–132.
18. Kern, R. (2021). *Language, Literacy, and Technology*. Cambridge University Press.
19. Kessler, G. (2018). Technology and the future of language learning. *Foreign Language Annals*, 51(1), 205–218.
20. Khadivi, S., & Behrouzi, M. (2021). The role of AI chatbots in reducing foreign language speaking anxiety. *Journal of Artificial Intelligence in Education*, 31(2), 245–268.
21. Koenecke, A., Nam, A., Lake, B., Nudell, J., Quartey, M., Mengesha, Z., ... & Goel, S. (2020). Racial disparities in automated speech recognition. *Proceedings of the national academy of sciences*, 117(14), 7684–7689.
22. Krashen, S. D. (1982). *Principles and Practice in Second Language Acquisition*. Pergamon Press.
23. Knutsson, O., Blåsjö, M., Hållsten, S., & Karlström, P. (2012). Identifying different registers of feedback in an online writing environment. *The Internet and Higher Education*, 15(4), 235–246.
24. Levis, J., & McCrocklin, S. (2021). Reflective and transformative practice in pronunciation teaching. *Journal of Second Language Pronunciation*, 7(2), 153–172.
25. Levy, M. (1997). *Computer-Assisted Language Learning: Context and Conceptualization*. Oxford University Press.
26. Loewen, S., & Isbell, D. R. (2022). Pronunciation instruction and AI: The frontier of feedback. *Language learning & technology*, 26(1), 1-15.
27. Lucas, G. M., Gratch, J., Cheng, L., & Marsella, S. (2017). When the fortune teller is a rapport-building virtual agent: The role of nonverbal behavior and anxiety. *International Conference on Intelligent Virtual Agents*, 245–254.
28. Luckin, R. (2017). *Towards Artificial Intelligence in Education: Democratizing Knowledge*. UCL Press.
29. Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence Unleashed: An argument for AI in Education*. Pearson.
30. Lupton, D., & Williamson, B. (2017). The datafied child: The dataveillance of children and implications for their rights. *New Media & Society*, 19(5), 780–794.
31. MacIntyre, P. D., & Gardner, R. C. (1994). The subtle effects of language anxiety on cognitive processing in the second language. *Language Learning*, 44(2), 283–305.
32. McCrocklin, S. (2019). Pronunciation tools: The role of visualization in learner autonomous practice. *CALICO Journal*, 36(1), 40-58.
33. Reich, J., & Ito, M. (2020). *From Feedback to Feedback Loops: The Potential for AI in Education*. MIT Press.
34. Rezaei, S., & Ludwig, C. (2023). *Artificial Intelligence in Language Education: Practice and Theory*. Springer Nature.
35. Richards, J. C., & Rodgers, T. S. (2014). *Approaches and Methods in Language Teaching*. Cambridge University Press.
36. Schmidt, T., & Strasser, T. (2022). Artificial intelligence in foreign language learning and teaching: A review of recent developments. *Fremdsprachen Lehren und Lernen*, 51(1), 165-182.
37. Selwyn, N. (2019). *Should Robots Replace Teachers?* Polity Press.
38. Shute, V. J., & Rahimi, S. (2017). Review of computer-based assessment for learning in elementary and secondary education. *Journal of Computer Assisted Learning*, 33(1), 1–19.
39. Stockwell, G. (2022). *Mobile-Assisted Language Learning: Concepts, Contexts and Challenges*. Cambridge University Press.
40. Sweller, J. (2011). Cognitive load theory. *Psychology of Learning and Motivation*, 55, 37–76.
41. Thorne, S. L., & Hellermann, J. (2021). Sociocognitive perspectives on language use and language learning. *The Routledge Handbook of Second Language Acquisition and Corpora*. Routledge.
42. Vygotsky, L. S. (1978). *Mind in Society: The Development of Higher Psychological Processes*. Harvard University Press.

43. Ware, P., & Hellmich, E. A. (2021). Call for papers: Digital technology and social justice in language learning. *Language Learning & Technology*, 25(2), 1-7.
44. Warschauer, M. (2023). *The Digital Classroom: AI, Equity, and the Future of Learning*. Oxford University Press.
45. Warschauer, M., & Matuchniak, T. (2020). New technology and digital worlds: Analyzing evidence of equity in access, use, and outcomes. *Review of Research in Education*, 34(1), 179-225.

About the author

Jihan Bayram is a highly experienced professional with over 10 years of expertise in monitoring, evaluation, accountability, and learning (MEAL), specializing in the collection and analysis of both quantitative and qualitative data. Based in Aleppo, Syria, she has held key roles, including MEAL Officer at Caritas (INGO), where she designed comprehensive MEAL frameworks and managed beneficiary feedback mechanisms to strengthen program quality and accountability. Her background also includes work as a Regional Coordinator and Administrative Reporter, collaborating with major international agencies such as UNHCR, UNFPA, and UNICEF to supervise

implementation and produce timely reporting on essential community projects. Alongside her humanitarian career, Jihan is an accomplished academic and educator. She holds a BA in English Literature and completed an MA in Literary Studies at the University of Aleppo (2025). She has been a dedicated English language instructor since 2011, delivering lessons and structured learning plans to students of different levels through online platforms. Jihan is fluent in Arabic, English, and Kurdish, and brings strong technical proficiency in MS Office, Kobo, and Google Forms, supported by certifications in advanced Excel and project management.



This is an open access article distributed under the terms of the [Creative Commons Attribution-NonCommercial 4.0 International](https://creativecommons.org/licenses/by-nc/4.0/) (CC BY-NC 4.0) which allows reusers to distribute, remix, adapt, and build upon the material in any medium or format for noncommercial purposes only, and only so long as attribution is given to the creator.