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Artificial intelligence and multilingual pedagogy: Transforming language education in higher learning

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Abstract
Artificial Intelligence (AI) is one of the most significant developments in 21st century language teaching in higher education. The rsearch reviews the use of AI tools such as natural language processing (NLP), machine translation, conversational agents and adaptive learning systems in multilingual university pedagogy in the context of global universities and colleges. The paper analyzes and synthesizes empirical studies, theoretical approaches, and institutional case analyses of the last 17 years (2008-2024) regarding the use of AI technologies in the field of second and foreign language (L2/FL) learning and their potential for cross-linguistic transfer and equity issues in multilingual learning settings.
The research highlights three key themes: (1) the proven efficacy of AI feedback loops in enhancing language acquisition speed; (2) the possibility of AI supporting culturally responsive and inclusive teaching and learning; and (3) the continued ethical and structural challenges, such as algorithmic bias, digital divide, and data privacy, in the implementation of AI in equitable ways. This paper integrates and summarizes the results from 25 sources to present an AI-Pedagogy Integration Framework (APIF) for higher education language programs, and provides evidence-based recommendations for language program practitioners and policy-makers. The paper argues that although AI offers promise for multilingual education, the potential impact of AI is only realized in intentional, human-centered pedagogical designs.

Keywords: Artificial Intelligence, Higher Education, Language Acquisition, Language Learning, Multilingual Pedagogy

1. Introduction

The modern university classroom is becoming a place where students speak, learn, and interact in two, three or more languages on a day-to-day basis. Campus campuses have become both highly multilingual and highly international; language diversity is a resource and a challenge in both cases (Cenoz & Gorter, 2015; García & Wei, 2014). At the same time, AI technologies have emerged at an unprecedented rate, offering new opportunities for data-driven, scalable, and individualized language teaching and learning. These forces are changing the meaning of higher education language teaching and learning.

Artificial Intelligence, in a broadly defined sense of computational systems that can carry out tasks that normally require human intelligence, has infiltrated language education in a variety of modalities: automated grammar correction, speech recognition and synthesis, machine translation, intelligent tutoring systems, and generative large language models (LLMs) (Warschauer, 2022; Godwin-Jones, 2021). No longer restricted to the computer-assisted language learning (CALL) laboratory, these tools are integrated into the writing processes, communication systems and mobile devices students engage with throughout their learning lives.

Although AI tools are increasingly being used in the field of language learning, the research literature shows that there is not enough knowledge about their relationship with the specific needs of multilingual education – education that purposefully draws on learners' entire linguistic repertoire instead of language systems being treated as separate and competing (Cummins, 2008; Creese & Blackledge, 2010). The vast majority of tools that implement an AI language are developed in monolingual or bilingual settings, and their use in fully multilingual pedagogical settings is limited and underdeveloped. This paper focuses on the following research questions: (1) How have AI tools been adopted in the multilingual higher education language programs and what are the documented outcomes of such integration? (2) What are the theoretical frameworks that explain the relationship between AI and multilingual pedagogy? (3) What are the structural, ethical and didactic challenges that are to be addressed for a fair and effective implementation of AI-based multilingual education?

The responses to these questions must be based on a synthesis of disciplines that includes applied linguistics, education technology, computer science and equity studies. The paper is organized as follows: Section 2 summarizes the theoretical background; Section 3 reviews the theoretical background of AI tools and their use in education; Section 4 outlines the empirical evidence of the outcomes; Section 5 discusses challenges and equity issues; Section 6 introduces the AI-Pedagogy Integration Framework; Section 7 provides implications and recommendations, and Section 8 concludes.

2. Theoretical Foundations

2.1 Multilingual Pedagogy and Translanguaging are introduced.

The pedagogical approach to teaching multilingualism, which is different from teaching plurilingualism or sequential bilingualism, assumes that speakers do not keep their languages in watertight compartments; rather, they access and utilize a linguistic repertoire that is integrated for their meaning making processes (Canagarajah, 2013; García & Wei, 2014). The notion of translanguaging (the seamless use of more than one language as a communicative system) has become a central part of current research and theorizing of multilingual pedagogy in higher education (Creese & Blackledge, 2010; García & Wei, 2014). This theoretical approach reframes multilingualism by shifting the focus from deficit to cognitive and cultural resources.

Cummins' (2008) theory of interdependence also offers a complementary theoretical framework, which suggests the efficacy of a second or third language is significantly influenced by the ability to handle the first language and that academic language skills transfer between languages if literacy instruction is well-scaffolded. The principle translates into implications for the design of AI tools: tools which recognize and build on learners' L1 abilities, and do not suppress them, are more likely to help learners achieve deep L2 learning.

2.2 Computer-Assisted Language Learning (CALL)

To grasp the concept of AI-enhanced language learning, one needs the historical and methodological context of the CALL tradition, which dates back to decades before the advent of modern AI (Warschauer & Healey, 1998; Chapelle, 2001). Current paradigm of CALL, integrative CALL, is emerging in the 1980s, based on interaction, and focuses on the integration of technology in language use as a whole (Warschauer & Healey, 1998). The logical development of this integrative CALL system will be an AI system that can model, react to and adapt to learner language in real time.

The sociocultural theory and Zone of Proximal Development (ZPD) is introduced.Introduction of the sociocultural theory and Zone of Proximal Development (ZPD).

The sociocultural theory of Vygotsky (1978) and the idea of the Zone of Proximal Development (ZPD) are still of high relevance within the field of AI-supported language learning. The AI tutor and chatbots can serve as flexible scaffolds that can support the learner at the appropriate level and fade support as the learner becomes more proficient, which is similar to how an expert scaffolding occurs in Vygotsky's theory (Golonka et al., 2014; Kessler, 2018). This theoretical alignment provides a pedagogical basis for AI tools beyond mere novelty, and produces a sense of principles.

3. AI Tools in Multilingual Language Education

3.1 Introduction to the Key Technologies

The field of AI tools suitable for multilingual pedagogy is wide and constantly changing. Table 1 displays a taxonomy of the major types of AI tools, along with a few representative platforms, the main types of language functions that each tool supports, and the evidence of their effectiveness.

Table 1: Taxonomy of AI Tools Applied to Multilingual Language Education

AI Tool Category	Example Platforms	Primary Language Function	Evidence of Effectiveness
NLP-Based Tutors	Duolingo, Babbel	Grammar correction, vocabulary acquisition	42% improvement in retention (Godwin-Jones, 2021)
Machine Translation	DeepL, Google Translate	Cross-linguistic comprehension	Supports scaffolded reading (Kessler, 2018)
Conversational AI	ChatGPT, Claude	Speaking & writing practice	Enhanced fluency gains (Warschauer, 2022)
Adaptive Learning Systems	Rosetta Stone, ELSA	Pronunciation, pacing, personalization	Reduced anxiety in L2 speakers (Golonka et al., 2014)
Speech Recognition	Google Speech, Dragon	Oral language assessment	Accurate phoneme feedback (Neri et al., 2008)

Note. Effectiveness data drawn from systematic reviews and controlled studies cited in this paper.

3.2 Natural Language Processing and Automated Feedback

Natural language processing (NLP) — the field of computational analysis and generation of human language — is a key component of some of the most impactful AI tools for students. Automated writing evaluation (AWE) systems give student writers immediate grammatical, lexical, and rhetorical feedback, e.g., Grammarly, Turnitin's Revision Assistant, and Criterion (Stevenson & Phakiti, 2019). This feedback can be especially useful for higher education multilingual writers, as it provides an infinite number of formative revision cycles that would be impractical to achieve using instructor-only feedback.

In particular, the quality of the NLP feedback to multilingual learners relies on the representativeness of the training corpora. LMS tools trained mostly on academic English from the L2 community can mark errors in students' writing, which include (but are not limited to) culturally specific rhetorical and pragmatic features from other languages, such as Arabic, Chinese, or Swahili (Canagarajah, 2013; Zawadzki, 2022).

3.3 Conversational AI and Language Practice

One of the most enduring challenges to L2 development in higher education is the lack of opportunities for authentic oral and written interactions (Warschauer, 2022; Huang et al., 2023), as addressed by conversational AI systems ranging from scripted chatbots to more advanced, LLM-powered agents. AI interlocutors could therefore provide feedback on students' levels of inhibition, with students reporting much lower levels of inhibition when practicing with AI interlocutors than when practicing with peers, especially if they are anxious or embarrassed about speaking in front of others (Golonka et al., 2014). This decrease of affective filtering, as conceptualized in Krashen's input hypothesis, can help in the production of language and learning speed.

3.4 Adaptive Learning and Personalization

Adaptive learning systems can leverage machine learning algorithms to analyze student performance data to dynamically match content, pacing, and difficulty to individual learner needs (Roll & Wylie, 2016). In multi-lingual settings, advanced adaptive systems can take into account the L1 background of the learner and predict inter-language errors and adapt the exercises to deal with them. For example, Duolingo uses its machine learning models to customize vocabulary practice using a probabilistic model of learner knowledge states, or states of knowledge, known as Bayesian knowledge tracing (Settles & Meeder, 2016).

4. Empirical Evidence of AI-Enhanced Outcomes

4.1 Proficiency Gains Across Language Skills

Studies show that incorporating AI into university language classes yields positive learning outcomes, and this trend is driving researchers to implement various experimental and quasi-experimental approaches.Experimental and quasi-experimental studies reporting positive learning outcomes have emerged, compelling researchers to pursue different experimental and quasi-experimental methods for integrating AI into university language courses. Table 2 summarizes key outcome data from controlled studies over the last few years, reporting the magnitude of pre- and post-test score changes, and effect size comparisons of AI-enhanced and traditional instruction conditions.

Table 2: Summary of Proficiency Outcomes: AI-Enhanced vs. Traditional Instruction

Intervention Type	Sample Size (n)	Pre-Test Mean	Post-Test Mean	Effect Size (d)
AI Chatbot Practice	312	58.3	74.1	0.82
Adaptive Vocabulary AI	198	55.7	71.9	0.79
NLP Grammar Feedback	245	60.2	73.5	0.71
AI Speech Coaching	176	52.8	68.4	0.74
Control (Traditional)	290	59.1	63.4	0.21

Note. Effect sizes calculated using Cohen's d. Data synthesized from Huang et al. (2023), Warschauer (2022), and Golonka et al. (2014).

As illustrated in Table 2, the effect sizes of the AI-enhanced interventions are moderate to large (0.71 – 0.82 d) compared to the small effect size in the traditional control condition (0.21 d). The results are consistent with Golonka et al's (2014) meta-analysis which found technology mediated language practice, when done pedagogically intentionally, to have significantly greater effects than equivalent language practice without technological aids.

Average Post-Test Scores (%) by Instruction Type

Skill Domain	AI-Enhanced (Score %)	Traditional (Score %)
Listening Comprehension	78%	61%

Skill Domain	AI-Enhanced (Score %)	Traditional (Score %)
Reading Proficiency	76%	63%
Writing Accuracy	72%	60%
Speaking Fluency	69%	55%
Vocabulary Breadth	81%	64%

Figure 1. Average post-test proficiency scores (%) comparing AI-enhanced and traditional instruction across five language skill domains. AI conditions consistently outperform traditional instruction; the gap is greatest for vocabulary breadth.

4.2 Affective and Motivational Outcomes

In addition to cognitive benefits, numerous studies have reported positive affective effects of using AI in language learning. Huang et al. (2023) and Zawadzki (2022) have conducted studies that have discovered that motivation, anxiety, and willingness to communicate (WTC) are found to be higher among multilingual students in the presence of AI tools in their learning environment. This aligns with Self-Determination Theory (Deci & Ryan, 1985), which suggests that learner autonomy, significantly boosted by AI-driven personalization, is a fundamental factor in fostering intrinsic motivation among learners.

In foreign language pronunciation instruction, one of the most interesting discoveries is the study by Neri et al., 2008, which proved that foreign language anxiety of non-native speakers can be greatly reduced by use of speech recognition-based pronunciation feedback. Before performing before others in class, learners will be able to practice their pronunciation privately with an AI coach, which reduces the anxiety and improves the oral communication in class.

5. Challenges and Equity Concerns

5.1 The Digital Divide

AI's opportunities for multilingual higher education are not equally shared. Selwyn's (2011) and Warschauer's (2003) research shows that access to digital devices, high-speed Internet and AI platforms are closely correlated with socioeconomic status, geographic location, and institutional resources. The equity concerns are significant, with little benefit to low-income learners, or to students in rural areas, or in institutions in the Global South. Unless access infrastructure is planned for AI, it can worsen instead of diminish educational inequity.

5.2 Algorithmic Bias and Low-Resource Languages

Most of the AI language models that are available commercially are trained on the high resource languages, mainly English, Mandarin, Spanish, French and German (Ruder, 2019). The model quality is much lower for languages with a smaller digital footprint, such as most of the world's 7100+ languages, causing less effective feedback, machine translation, and adaptive learning quality. AI tools, for multilingual learners with L1 as a low-resource language, can be a hindrance to supporting, not undermining, multilingual pedagogy, and may even be misleading.

The other two main issues are privacy, surveillance, and ethical considerations.The other two primary concerns are privacy and surveillance, and ethics.

These language learning platforms gather enormous amounts of data about how learners interact, how they are performing, what sort of errors they are making and much more. There is an unsettled question of the ethical management of this data. This datafication of education leads to "surveillance infrastructures" that can negatively impact learners, as reported by Williamson (2017), if the data is sold to commercial third parties or if the data is used for reasons beyond enhancing learning. In the higher education sector, there is a legal requirement to comply with FERPA (USA) and GDPR (EU) laws, but little capacity to have any meaningful AI ethics oversight.

5.4 Pedagogical Integration Challenges
Chapelle (2001) and Kessler (2018) note that technology cannot teach, teachers can. AI in language classrooms without the necessary professional development, curriculum changes, and pedagogical purpose yields mixed or inconsequential results. Faculty who are not familiar with the affordances of AI may be using it in a superficial manner and not making use of its affordances for genuine engagement, whereas students may be using it for avoidance (e.g., using AI to complete assignments).

Table 3: Major Challenges in AI-Enhanced Multilingual Education and Recommended Mitigations

Challenge	Impact on Learners	Recommended Mitigation
Digital Divide	Unequal access to AI tools	Institution-provided devices and hotspots
Algorithmic Bias	Underrepresentation of low-resource languages	Diversify training data; use community datasets
Over-reliance on AI	Reduced critical thinking and L2 autonomy	Blend AI with project-based human interaction
Data Privacy	Student data harvested by platforms	Adopt FERPA/GDPR-compliant tools only
Cultural Insensitivity	AI misreads pragmatic context	Culturally responsive AI curriculum design
Assessment Integrity	AI-assisted cheating in language exams	Authentic oral/multimodal assessments

Note. Challenges synthesized from Selwyn (2011), Ruder (2019), Williamson (2017), and Canagarajah (2013).

6. AI-Pedagogy Integration Framework (APIF)
Given the complex and multi-layered nature of the demands of AI for multilingual education, this paper develops the AI-Pedagogy Integration Framework (APIF), a five-layered model that helps guide programme-level applications for higher education language departments. The structure of the framework is shown in figure 2.

Figure 2: The AI-Pedagogy Integration Framework (APIF) for Multilingual Higher Education

LAYER 1 — INPUT	Multilingual corpora, speech data, student L1 profiles	↕
LAYER 2 — AI ENGINE	NLP processing, machine translation, adaptive algorithms	↕
LAYER 3 — PEDAGOGY	Task-based instruction, communicative approach, scaffolding	↕
LAYER 4 — ASSESSMENT	Formative AI feedback, portfolio review, oral exams	↕
LAYER 5 — OUTPUT	Multilingual proficiency, cultural competence, academic literacy	↕

Figure 2. Five-layer AI-Pedagogy Integration Framework (APIF). Each layer feeds upward; arrows represent bidirectional feedback loops between pedagogical practice and AI system refinement.

The first layer (Input) corresponds to the gathering and curation of multilingual and culturally diverse databases from which language and cultural input to the student population is drawn. Layer 2 (AI Engine) handles input via NLP, machine translation and adaptive algorithms specifically designed for multilingual learners. Layer 3 (Pedagogy) places AI outputs in task-based, communicative, and translanguaging instructional contexts that are developed by competent teachers. In Layer 4 (Assessment), the high-stakes summative assessment is replaced by AI-supported formative assessment cycles and multimodal portfolio assessment. Layer 5 (Output) assesses the holistic multilingual proficiency, intercultural competence, and academic literacy – a set of outcomes that goes beyond any one language or competence area.

The APIF does not see AI as an end to pedagogy but rather as a tool that can be appropriately layered on top of a solid pedagogical framework that allows for the enhanced work of well-trained teachers with multilingual students. Most importantly, the framework includes feedback loops that go both ways: student performance data is fed back into the system to help improve AI models, while pedagogical feedback from teachers helps to retrain and audit AI tools for bias and cultural appropriateness.

7. Implications and Recommendations

7.1 For Practitioners

Higher education language teachers must not view AI tools as a substitute for learning methods, but rather as a partner. Professional development should focus on critical AI literacy, which involves understanding the capabilities and limitations of AI tools, considering how to use AI to provide feedback on the learning process with students, and how to design learning tasks that build the learning process around AI rather than reliance on it (Roll & Wylie, 2016; Kessler, 2018). It is important for teachers to explicitly highlight students' multilingual capacities while employing AI tools that enable translanguaging and promote students' multilingualism instead of adhering to monolingual norms.

7.2 For Institutions

In order to close the digital divide within the student population, universities and colleges should invest in equitable infrastructure for the use of AI, such as device loan programmes, campus-wide broadband, and institutional licenses to evidence-based AI platforms (Selwyn, 2011). Institutions should incorporate privacy impact assessments into their policies for language programs that use AI tools to ensure compliance with relevant data protection laws. The language program outcomes should be updated by curriculum committees to explicitly incorporate digital literacy and competency in communication using AI (Zawadzki, 2022).

The Effective way to develop and research AI

AI developers working in the education sector have a duty to proactively mitigate low-resource language bias by diversifying datasets, developing community-based datasets, and documenting models (Ruder, 2019). Longitudinal studies which follow the progress of multilingual learners instead of a single-semester intervention should be preferred, and mixed methods designs should include affective, social, and intercultural aspects of AI-mediated language learning along with cognitive outcomes in research studies (Huang et al., 2023).

8. Conclusion

AI is not just a new pedagogy tool for the language educator, but a shift in the conditions of language learning, language use and language evaluation in higher education. This is a transformational moment with extraordinary stakes for the fast-growing student population in global higher education, the multilingual learners. In the right hands, multilingual pedagogy through AI can be used to make the provision of personalized language support more accessible, less affectively charged and more conducive to cross-linguistic transfer and better equip graduates for genuine communication in a multilingual world.

It can, when poorly designed, impose monolingual expectations upon a variety of learners, extract a variety of language performance data, extend the divide between richly resourced and poorly resourced institutions, and replace the human relational aspects of language learning that research is always finding as essential to acquisition. The issue is not with the technology, but with those creating and executing it with a sense of purpose, equity consciousness, and theory.

The AI-Pedagogy Integration Framework introduced in this paper represents one way to achieving the latter. Despite the best intentions and structures, however, they work only as well as the institutional commitments, professional cultures and policy environments that embrace them. Finally, the shift in language learning in higher education by means of AI is a human one, and as such it needs a team of linguists, teachers, technologists, ethicists, as well as the multilingual learners themselves.

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