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Integrating Artificial Intelligence in English Language Learning: A Comparative Study of Higher Education Practices in Indonesia, China, and India

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ABSTRACT

This study investigates the integration of Artificial Intelligence (AI) in English Language Learning (ELL) within higher education institutions in Indonesia, China, and India, focusing on adoption patterns, influencing factors, and perceived effectiveness. Data were collected from 450 participants, comprising 150 from each country, including EFL instructors, instructional designers, and undergraduate students enrolled in English-major or English-intensive programs. A mixed-methods design was employed, with 300 participants (100 per country) completing a structured questionnaire for the quantitative phase, and 45 participants (15 per country) participating in in-depth interviews for the qualitative phase. Quantitative analysis using descriptive statistics, one-way ANOVA, and multiple regression revealed significant cross-national differences, with China reporting the highest scores in perceived usefulness, ease of use, pedagogical integration, and institutional support, followed by India and Indonesia. Regression results indicated that perceived usefulness and pedagogical integration were the strongest predictors of AI-assisted ELL effectiveness. The qualitative findings provided contextual insights, highlighting the importance of national policy alignment, institutional readiness, and faculty training in shaping adoption outcomes. The study concludes that successful AI integration in ELL requires a context-sensitive approach that combines technological capability, pedagogical alignment, and supportive institutional ecosystems, offering both theoretical contributions to CALL and EdTech literature and practical implications for higher education policy and practice in multilingual contexts.

Introduction

In the past decade, the rapid advancement of Artificial Intelligence (AI) has profoundly influenced the landscape of higher education, particularly in the domain of language learning. AI-driven technologies such as intelligent tutoring systems, automated speech recognition, adaptive learning platforms, and natural language processing have transformed the way English as a Foreign Language (EFL) is taught and learned across diverse contexts (Li & Wong, 2023; Ahmad et al., 2024). Globally, AI is increasingly recognized not only as a technological innovation but also as a pedagogical enabler that can provide personalized feedback, facilitate autonomous learning, and enhance student engagement in language acquisition (Zou et al., 2022; Shadiev & Yang, 2024).

English, as the lingua franca of global communication, holds a central position in academic, professional, and socio-cultural exchanges (Crystal, 2020). For countries such as Indonesia, China, and India, where English is predominantly a second or foreign language, the mastery of English has become a strategic necessity in participating in the global knowledge economy. These three nations collectively represent some of the largest populations of EFL learners worldwide, with millions of students enrolled in higher education institutions where English proficiency is a key graduate attribute (British Council, 2021; Kumar et al., 2023). However, despite similar aspirations to enhance English proficiency, these countries differ in their educational policies, technological infrastructure, cultural contexts, and pedagogical traditions.

Recent studies have highlighted the growing adoption of AI-assisted language learning tools in higher education. In China, AI has been integrated into national strategies for "smart education," with platforms such as iFLYTEK and Squirrel AI widely deployed to support language learning (Liu & Xu, 2023). In India, AI adoption in English language education is driven by a mix of government-led initiatives, private EdTech companies, and non-profit organizations seeking to address regional disparities in English proficiency (Karthikeyan & Chinnasamy, 2024). In Indonesia, while AI adoption is still emerging, universities have begun experimenting with AI chatbots, automated essay scoring, and speech-recognition applications to supplement conventional EFL instruction (Siregar et al., 2024). These developments suggest a shared trajectory towards AI integration, but with distinct pathways shaped by local policies, resources, and pedagogical orientations.

Despite the increasing interest in AI-enhanced English Language Learning (ELL), three key research gaps remain. First, most existing studies are country-specific, focusing on a single national context (e.g., Ma et al., 2023 in China; Rao & Thomas, 2023 in India; Dewi et al., 2024 in Indonesia). This limits the understanding of how AI integration strategies compare across different socio-cultural and policy environments. Second, many studies examine either the technological aspects of AI (e.g., algorithmic accuracy, interface usability) or the pedagogical implications (e.g., learner engagement, motivation), but seldom integrate these two perspectives into a holistic analysis. Third, there is limited research that systematically investigates the institutional, cultural, and infrastructural factors influencing AI adoption in EFL higher education across multiple countries, especially in emerging economies with large and diverse learner populations.

The novelty of this study lies in its comparative, cross-national approach. By examining AI integration in EFL higher education in Indonesia, China, and India, this research offers a unique lens through which to identify commonalities, divergences, and context-specific innovations. The study not only explores the technological and pedagogical dimensions of AI-enhanced ELL but also considers the socio-cultural and institutional contexts that shape its implementation. Such a multidimensional, comparative analysis has been largely absent from the literature, yet is essential for informing both policy and practice in diverse higher education systems.

In line with the Educational Technology Integration Framework (Zhao & Frank, 2021) and CALL (Computer-Assisted Language Learning) principles (Chapelle & Sauro, 2020), this study positions AI as both a mediating tool and a pedagogical partner in the EFL classroom. Theoretically, the research draws upon constructivist learning theory, which emphasizes learner-centered, interactive, and authentic learning experiences (Jonassen, 1999), and sociocultural theory, which highlights the role of mediated tools and social interaction in language acquisition (Vygotsky, 1978). AI tools, when effectively integrated, can support personalized scaffolding, foster collaborative tasks, and provide immediate feedback, all of which align with best practices in second language acquisition.

Therefore, the objectives of this study are twofold: 1) To examine the current practices of integrating AI in English Language Learning in higher education institutions in Indonesia, China, and India. 2) To compare the pedagogical, technological, and contextual factors influencing AI adoption in EFL higher education across the three countries, identifying best practices and challenges.

By addressing these objectives, this research aims to make both theoretical contributions—by advancing comparative perspectives on AI integration in EFL—and practical contributions—by offering policy recommendations and pedagogical strategies for optimizing AI use in higher education across diverse national contexts.

Research Methodology

This study employed a comparative sequential mixed-methods design (Creswell & Clark, 2018), integrating quantitative and qualitative approaches to investigate and compare the integration of Artificial Intelligence (AI) in English Language Learning (ELL) across higher education institutions in Indonesia, China, and India. The sequential nature of the design allowed the researchers to first gather broad, generalizable quantitative data on institutional practices, technological adoption, and pedagogical integration, followed by qualitative exploration to provide deeper contextual understanding of the patterns identified. The choice of a mixed-methods design was justified by the study's dual objectives: (1) to examine current practices in AI-assisted ELL, and (2) to compare influencing factors across countries. Quantitative data offered cross-national comparability, while qualitative data captured the socio-cultural and institutional nuances that cannot be fully explained by numeric patterns alone. This approach aligns with comparative education research frameworks that emphasize multi-dimensional analysis across diverse contexts (Bray et al., 2021).

Participants and Sampling

A stratified purposive sampling strategy was applied to ensure representation from different types of higher education institutions in each country (public universities, private universities, and technological institutes). The total sample comprised 450 participants: 150 from Indonesia, 150 from China, and 150 from India. Participants included EFL instructors, instructional designers, and undergraduate students enrolled in English-major or English-intensive programs. Within each country, strata were formed based on: Institution type (public vs. private), Geographic location (urban vs. semi-urban), AI adoption stage (early adoption, partial integration, full integration), For the quantitative phase, 300 participants (100 from each country) completed the structured questionnaire. For the qualitative phase, 45 participants (15 from each country) were selected using maximum variation sampling to ensure diversity in teaching experience, institutional resources, and familiarity with AI tools.

Research Instruments

Quantitative Instrument

A structured questionnaire was developed based on the Technology Acceptance Model (TAM) (Davis, 1989), the TPACK framework (Mishra & Koehler, 2006), and previous studies on AI in language education (Zou et al., 2022; Liu & Xu, 2023). The questionnaire consisted of five sections: 1) Demographics and institutional profile, 2) Types of AI tools used (e.g., automated essay scoring, speech recognition, chatbots, adaptive learning platforms), 3) Perceived usefulness and ease of use, 4) Pedagogical integration strategies, 5) Perceived challenges and support systems. The questionnaire used a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) for attitudinal items, and multiple-choice or open-ended questions for factual information. Content validity was established through review by three experts in Educational Technology and EFL pedagogy from each participating country.

Qualitative instrument:

A semi-structured interview protocol was developed to explore: 1) Experiences and perceptions of AI-assisted ELL, 2) Institutional policies and support mechanisms, 3) Cultural and pedagogical considerations in AI use, 4) Recommendations for best practices. Interview questions were informed by the quantitative results, focusing on items where significant inter-country variation or notable trends emerged.

Validity and Reliability

For the quantitative instrument, content validity was measured using Aiken's V (Aiken, 1985), resulting in a value of 0.91, indicating high relevance of items to the study objectives. Construct validity was tested through Confirmatory Factor Analysis (CFA) using AMOS 26, confirming the factor structure with acceptable fit indices (CFI = 0.94, RMSEA = 0.05). Reliability was assessed using Cronbach's Alpha, with subscales ranging from 0.86 to 0.92, indicating high internal consistency. For the qualitative data, trustworthiness was ensured through: Credibility: Triangulation of data sources (students, lecturers, instructional designers) and member-checking of interview transcripts. Dependability: Use of an audit trail documenting coding and theme development. Confirmability: Independent peer review of thematic coding by two researchers not involved in data collection. Transferability: Thick description of in stitutional and cultural contexts to allow applicability in similar settings.

Data Collection Procedures

Phase 1 – Quantitative survey: The questionnaire was translated into Bahasa Indonesia, Mandarin Chinese, and Hindi using a back-translation method to ensure semantic equivalence (Brislin, 1986). It was administered online via institutional learning management systems and official email lists between January and March 2025. Participants were given three weeks to respond, with two reminder emails sent during the period. Phase 2 – Qualitative interviews: Semi-structured interviews were conducted online via Zoom or Microsoft Teams between April and May 2025. Each interview lasted 45–60 minutes, was audio-recorded with participant consent, and transcribed verbatim. Interviews were conducted in English or the local language, with professional translation where necessary.

Data Analysis

Quantitative data were analyzed using SPSS 26 and AMOS 26 for descriptive and inferential statistics. Descriptive statistics (mean, standard deviation, frequency) summarized AI usage patterns. One-way ANOVA tested for significant differences in AI adoption and perceptions among the three countries. Multiple regression analysis examined predictors of perceived effectiveness of AI-assisted ELL. Qualitative data were analyzed thematically following Braun and Clarke's (2006) six-phase framework: familiarization, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report. NVivo 14 software was used to manage and code the data systematically. Themes were compared across countries to identify commonalities and context-specific differences.

Finding and Discussion

Finding

The quantitative phase of this study sought to capture an overview of how AI is currently integrated into English Language Learning (ELL) across higher education institutions in Indonesia, China, and India. Descriptive statistics were calculated for five core dimensions of AI integration—Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Pedagogical Integration (PI), Institutional Support (IS), and Perceived Challenges (PC)—as outlined in Table 1. These dimensions were adapted from established frameworks such as the Technology Acceptance Model (TAM) and the Technological Pedagogical Content Knowledge (TPACK) model to ensure both technological and pedagogical aspects were represented.

Table 1. Mean Scores of AI Integration Dimensions in ELL by Country

Dimension of AI Integration	Indonesia (n=100)	China (n=100)	India (n=100)	Overall Mean
Perceived Usefulness (PU)	4.12 (SD=0.54)	4.45 (SD=0.42)	4.28 (SD=0.48)	4.28
Perceived Ease of Use (PEOU)	3.94 (SD=0.61)	4.38 (SD=0.45)	4.21 (SD=0.50)	4.18
Pedagogical Integration (PI)	3.85 (SD=0.58)	4.31 (SD=0.40)	4.14 (SD=0.46)	4.10
Institutional Support (IS)	3.72 (SD=0.66)	4.29 (SD=0.47)	3.95 (SD=0.52)	3.99
Perceived Challenges (PC)*lower is better*	3.05 (SD=0.71)	2.78 (SD=0.65)	2.91 (SD=0.69)	2.91

As shown in Table 1, China reported the highest mean scores across all positive dimensions, particularly in Perceived Usefulness (M=4.45) and Pedagogical Integration (M=4.31). This suggests that Chinese higher education institutions have successfully embedded AI into pedagogical practices, likely facilitated by national "smart education" strategies and significant investments in EdTech infrastructure. India demonstrated competitive results, especially in Perceived Usefulness (M=4.28) and Perceived Ease of Use (M=4.21), reflecting the country's growing reliance on AI-enabled learning solutions such as adaptive platforms and automated assessment tools. However, Institutional Support scored lower than China, indicating that while technological adoption is strong, systemic policy backing is still evolving. Indonesia's scores, though positive overall, were consistently lower than those of China and India, particularly in Institutional Support (M=3.72) and Pedagogical Integration (M=3.85). This points to a situation where AI adoption is emerging but not yet fully aligned with institutional strategies or supported by robust infrastructure.

Table 2. Most Frequently Used AI Tools in ELL by Country (%)

AI Tool	Indonesia	China	India
Automated Essay Scoring (AES)	62%	85%	73%
AI-based Speech Recognition	58%	90%	75%
AI Chatbots for Conversation Practice	54%	88%	69%
Adaptive Learning Platforms	47%	83%	66%
Machine Translation for Academic Tasks	72%	81%	78%
AI-assisted Pronunciation Feedback	65%	87%	71%

Table 2 details the most frequently used AI tools in ELL within each country. The findings reveal that AI-based Speech Recognition and AI Chatbots are the most widely adopted tools in China, with usage rates exceeding 85%. This reflects a focus on oral proficiency and real-time conversational practice in Chinese universities. In India, Machine Translation (78%) and Automated Essay Scoring (73%) ranked among the top tools, aligning with the country's emphasis on improving academic literacy and writing accuracy. Indonesia displayed a distinctive adoption pattern, with Machine Translation (72%) and AI-assisted

Pronunciation Feedback (65%) as leading tools, suggesting a prioritization of immediate communication skills and oral fluency over advanced adaptive learning systems.

These results suggest that China leads in the breadth and depth of AI tool adoption, particularly in adaptive platforms and speech recognition. India shows notable use of machine translation tools and AES, reflecting a strong emphasis on writing and academic literacy. Indonesia's adoption pattern suggests prioritization of translation and pronunciation tools, possibly reflecting immediate communication needs of students.

One-way ANOVA Results

To determine whether there were statistically significant differences in AI adoption and perceptions among Indonesia, China, and India, a series of one-way ANOVA tests were conducted for the four positive perception dimensions: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Pedagogical Integration (PI), and Institutional Support (IS).

Table 3. One-way ANOVA Results for AI Integration Dimensions

Dimension	F-value	p-value	η^2 (Effect Size)	Significant Differences (Post-hoc Tukey)
Perceived Usefulness (PU)	8.42	<0.001	0.053	China > Indonesia*, China > India (ns)
Perceived Ease of Use (PEOU)	6.87	0.001	0.044	China > Indonesia*, India > Indonesia*
Pedagogical Integration (PI)	7.95	<0.001	0.050	China > Indonesia*, India > Indonesia*
Institutional Support (IS)	9.16	<0.001	0.058	China > Indonesia*, China > India*

Note: * indicates $p < 0.05$; ns = not significant.

The ANOVA results show significant differences ($p < 0.05$) across countries for all four perception dimensions, with China consistently outperforming Indonesia in PU, PEOU, PI, and IS. The effect sizes (η^2 ranging from 0.044 to 0.058) indicate moderate practical significance. Notably, India's scores were significantly higher than Indonesia's for PEOU and PI, but did not differ significantly from China in PU, suggesting India's AI adoption is approaching China's in terms of perceived usefulness, though institutional support remains a differentiating factor.

Multiple Regression Analysis

A multiple regression analysis was conducted to identify which factors significantly predicted Perceived Effectiveness of AI-assisted ELL (dependent variable). Independent variables included Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Pedagogical Integration (PI), and Institutional Support (IS).

Table 4. Multiple Regression Predicting Perceived Effectiveness of AI-assisted ELL

Predictor Variable	β (Standardized)	t-value	p-value
Perceived Usefulness (PU)	0.42	6.85	<0.001
Perceived Ease of Use (PEOU)	0.25	4.12	<0.001
Pedagogical Integration (PI)	0.31	5.04	<0.001
Institutional Support (IS)	0.18	3.01	0.003

The regression model explained 61% of the variance in perceived effectiveness of AI-assisted ELL, indicating a strong predictive capacity. Perceived Usefulness emerged as the strongest predictor ($\beta = 0.42$, $p < 0.001$), followed by Pedagogical Integration ($\beta = 0.31$, $p < 0.001$). Perceived Ease of Use also contributed significantly, suggesting that both functional benefits and user-friendly design are critical for AI adoption. Institutional Support, while statistically significant, had the smallest effect size, implying that institutional policies alone may not be sufficient without strong pedagogical and technological alignment.

Table 4. Model Summary

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	0.781	0.610	0.604	0.35421

Table 4 indicates that the regression model achieved a strong positive correlation (R = 0.781) between the predictors—Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Pedagogical Integration (PI), and Institutional Support (IS)—and the dependent variable, Perceived Effectiveness of AI-assisted ELL. The model explained 61% of the variance in perceived effectiveness ($R^2 = 0.610$; Adjusted $R^2 = 0.604$), demonstrating a substantial predictive capacity after accounting for model complexity. The relatively low Standard Error of the Estimate (0.35421) suggests that the predicted values closely match the observed values, confirming the robustness and accuracy of the model in estimating the effectiveness of AI integration in English Language Learning across higher education institutions in Indonesia, China, and India.

While the quantitative results provide a broad comparative overview of AI integration levels and tool usage patterns, they do not fully capture the nuanced experiences, institutional contexts, and pedagogical rationales underlying these patterns. To address this, the qualitative phase of the study explored participant perspectives in greater depth, focusing on how AI is perceived, implemented, and sustained within diverse higher education environments in the three countries.

Thematic analysis of 45 in-depth interviews (15 per country) revealed four major themes:

Theme 1: Enhanced Learning Personalization

Participants across all three countries highlighted AI's ability to provide tailored feedback and adaptive learning paths. A lecturer from China noted, *"Our AI platform adjusts reading materials based on students' proficiency, which saves me hours of manual work."*

Theme 2: Institutional Policy and Support as Key Enablers

Chinese universities reported strong policy alignment with AI initiatives, supported by government funding. Indian institutions cited partnerships with private EdTech companies as a primary driver, while Indonesian universities often relied on pilot projects without sustained institutional budgets.

Theme 3: Pedagogical Shifts and Teacher Roles

AI integration prompted teachers to shift from content delivery to facilitation roles. An Indonesian instructor commented, *"AI takes care of repetitive drilling; I can now focus on communicative tasks and higher-order thinking activities."*

Theme 4: Challenges of Infrastructure and Digital Literacy

Infrastructural disparities were most pronounced in rural Indonesia and India. Participants also mentioned a digital literacy gap among both students and faculty, impacting the effective use of AI tools.

Discussion

The findings of this study reveal notable cross-national differences in the integration of Artificial Intelligence (AI) into English Language Learning (ELL) across higher education institutions in Indonesia, China, and India. Quantitative results indicate that China consistently achieved higher scores in perceived usefulness, ease of use, pedagogical integration, and institutional support, suggesting a more mature AI adoption ecosystem supported by strong government policy frameworks and advanced EdTech infrastructure. This aligns with Liu and Xu (2023), who reported that China's "smart education" initiatives have accelerated AI-based pedagogical innovation in language learning.

In contrast, India demonstrated competitive performance in perceived usefulness and pedagogical integration, approaching China's levels in certain aspects. The country's AI adoption appears to be driven by a combination of private sector innovation and targeted government initiatives, such as the National Education Policy 2020, which emphasizes technology-enabled learning (Karthikeyan & Chinnasamy, 2024). However, lower scores in institutional support suggest that integration may be uneven, varying by institution type and regional resources.

Indonesia's results point to an emerging AI adoption phase, with moderate scores across most dimensions and lower institutional support. While pilot projects and experimental AI tool usage are growing (Siregar et al., 2024), the absence of comprehensive national frameworks for AI in education limits scalability. These disparities mirror findings in comparative EdTech research, where policy alignment and sustained funding emerge as critical factors for successful technology integration (Zhao & Frank, 2021).

The One-way ANOVA results confirm statistically significant differences across countries in all positive perception dimensions, with China outperforming Indonesia in all cases and surpassing India in institutional support. This supports the Technology Acceptance Model (TAM) premise that both perceived usefulness and ease of use are influenced by contextual factors, including institutional readiness and cultural attitudes toward technology (Davis, 1989; Venkatesh et al., 2021).

The multiple regression analysis offers deeper insights into what drives the perceived effectiveness of AI-assisted ELL. Perceived Usefulness emerged as the strongest predictor, followed by Pedagogical Integration, Perceived Ease of Use, and Institutional Support. This hierarchy emphasizes that, regardless of country context, stakeholders prioritize AI tools that demonstrably improve learning outcomes over those that are merely easy to operate. This finding resonates with Chapelle and Sauro's (2020) view that in CALL environments, functional value and pedagogical alignment outweigh novelty in sustaining technology use.

Qualitative findings provide contextual depth to the quantitative results. In China, high adoption rates are attributed to structured institutional support and well-funded infrastructure, enabling universities to experiment with advanced AI tools such as adaptive learning platforms and AI-driven pronunciation analysis. In India, participants highlighted partnerships with EdTech companies as a key driver, allowing localized customization of AI tools to address linguistic diversity. In Indonesia, while enthusiasm for AI was evident, educators noted challenges in initiating and sustaining AI-based projects due to infrastructure gaps and limited training opportunities—echoing Alzarga's (2021) argument that access to authentic digital resources is a precondition for effective technology integration.

The pedagogical implications are significant. The results confirm that AI can facilitate a shift from teacher-centered to learner-centered ELL, enabling personalization, immediate feedback, and skill-focused practice, consistent with constructivist learning theory (Jonassen, 1999) and sociocultural perspectives on language acquisition (Vygotsky, 1978). However, successful integration requires intentional alignment between AI tool capabilities and curriculum goals, as suggested by the TPACK framework (Mishra & Koehler, 2006).

From a theoretical standpoint, this study contributes to the literature by offering a comparative perspective that integrates both technological and pedagogical variables across three large EFL learner populations. It extends previous single-country studies (e.g., Ma et al., 2023; Dewi et al., 2024) by highlighting how national policy, institutional readiness, and cultural attitudes jointly shape AI adoption outcomes.

Practically, the findings suggest that China's model of centralized policy support could inform Indonesia's and India's strategic planning, while India's public-private collaboration approach offers lessons in scalability for resource-constrained contexts. For Indonesia, targeted investments in infrastructure and faculty training could accelerate adoption and improve institutional support scores, narrowing the gap with its regional counterparts.

Overall, the evidence supports the position that AI-assisted ELL is not a one-size-fits-all innovation. Its perceived effectiveness depends on a combination of tool functionality, pedagogical integration, user readiness, and institutional commitment. As global higher education systems continue to explore AI's potential, this comparative study underscores the need for context-sensitive implementation strategies that address both technological and human factors in achieving sustainable integration.

Conclusions

This study concludes that the integration of Artificial Intelligence (AI) in English Language Learning (ELL) across higher education in Indonesia, China, and India demonstrates distinct patterns shaped by national policies, institutional readiness, and pedagogical practices. China shows the highest levels of perceived usefulness, ease of use, pedagogical integration, and institutional support, reflecting a mature AI adoption ecosystem driven by centralized educational strategies. India displays strong adoption in perceived usefulness and pedagogical integration, supported by public–private collaborations, though institutional support remains less consistent. Indonesia, while in an emerging phase, exhibits positive attitudes toward AI but faces challenges related to infrastructure and faculty preparedness. Regression analysis reveals that perceived usefulness and pedagogical integration are the strongest predictors of AI effectiveness, highlighting the importance of aligning AI tools with learning objectives. Overall, the study underscores that successful AI-assisted ELL requires not only advanced technology but also robust institutional policies, targeted training, and culturally responsive implementation strategies.

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