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Research article

Revealing Cultural and Linguistic Variation in Generative AI–Mediated Language Learning: A Mixed-Methods Study

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Abstract

The rapid expansion of generative artificial intelligence (AI) in language education has created new possibilities for personalized and adaptive learning, while raising questions about how learners from different linguistic and educational backgrounds interact with AI systems. This exploratory mixed-methods study examines culturally interpretable patterns of AI-mediated language learning among 100 adult English language learners from Japan, China, Saudi Arabia, Egypt, North Macedonia, and Bulgaria across four CEFR levels. Data were collected over eight weeks through interaction logs, learner diaries, pre- and post-assessments, surveys, and semi-structured interviews. Quantitative indicators are used descriptively, while qualitative evidence provides the primary basis for interpretation. The findings suggest broadly positive language-development trajectories alongside substantial variation in how learners request, interpret, evaluate, and use AI-generated feedback. Four overlapping feedback-utilization patterns, calibration, negotiation, experimentation, and uptake, were identified, although their realization varied across learners and contexts. Narrative cases further indicate that interaction can develop from correction-focused use toward clarification, comparison, dialogue, and strategic engagement, while substantial within-group variation highlights the importance of individual agency. Because all participants interacted with the same AI system under uniform conditions, the observed differences reflect learner interpretation and adaptive use rather than system-level cultural customization. The study therefore treats generative AI as a culturally interpreted rather than inherently culturally responsive system and advances three design-oriented hypotheses concerning adaptive feedback calibration, interaction-style modulation, and learner-controlled customization. These hypotheses provide an exploratory foundation for future research examining whether culturally responsive learning agents can support more inclusive and meaningful AI-mediated language learning.

Keywords: Generative artificial intelligence; Language learning; Cultural and linguistic diversity; AI-mediated interaction; Personalized learning systems

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Научная статья

Выявление культурных и лингвистических различий при изучении языка с помощью генеративного искусственного интеллекта: Исследование с использованием смешанных методов

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Аннотация

Стремительное внедрение генеративного искусственного интеллекта (ИИ) в языковое образование открыло новые возможности для персонализированного обучения, но актуализировало вопрос о том, как учащиеся с различным языковым и образовательным опытом взаимодействуют с такими системами. В данном поисковом исследовании на основе смешанного метода изучаются культурно обусловленные модели изучения языка с применением ИИ на примере 100 взрослых слушателей из Японии, Китая, Саудовской Аравии, Египта, Северной Македонии и Болгарии. Сбор данных осуществлялся в течение восьми недель с помощью анализа логов взаимодействия, дневников учащихся, тестирования, анкетирования и интервью. Количественные показатели использовались для общего описания, а качественные данные послужили основой для содержательной интерпретации. Результаты фиксируют общую положительную динамику языкового развития, однако выявляют существенные различия в том, как учащиеся запрашивают, интерпретируют и применяют обратную связь от ИИ. Были определены четыре пересекающиеся модели использования ответов системы: калибровка, согласование, экспериментирование и освоение. Анализ конкретных случаев показал, что взаимодействие способно эволюционировать от исправления ошибок к уточнению, сопоставлению, диалогу и стратегическому вовлечению, а высокая внутригрупповая вариативность подчеркивает ключевую роль самостоятельности учащихся. Поскольку все участники работали с одной системой в одинаковых условиях, обнаруженные различия отражают особенности восприятия и адаптации со стороны самих учащихся, а не настройки на уровне технологий. Таким образом, генеративный ИИ рассматривается как культурно интерпретируемая, а не изначально культурно-ориентированная система. На основе полученных данных сформулированы три гипотезы, касающиеся адаптивной калибровки обратной связи, изменения стилей взаимодействия и пользовательской настройки систем. Данные положения закладывают основу для дальнейших исследований, направленных на проверку того, способны ли адаптированные обучающие агенты обеспечить более инклюзивное языковое образование.

Ключевые слова: Генеративный искусственный интеллект; Изучение языков; культурное и языковое разнообразие; ИИ-Взаимодействие; Персонализированные системы обучения

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INTRODUCTION

Generative artificial intelligence (AI) has become a transformative force across multiple sectors, including healthcare, business, and creative industries, with education emerging as one of its most rapidly evolving domains (Caporusso, 2023; Balasubramaniam et al., 2024; Mittal et al., 2024; Samala et al., 2024). Within education, language learning represents a particularly fertile context for AI integration because language acquisition is inherently shaped by learners' linguistic repertoires, cultural norms, communicative conventions, and sociocultural expectations. Traditional language education has typically relied on standardized textbooks, instructor-led instruction, and uniform curricula that assume relatively homogeneous learner populations (AlAfnan, 2024; Rehan, 2023). Such approaches often overlook how learners from different cultural and national backgrounds engage with language differently, interpret feedback distinctively, and exhibit varying preferences for interactional styles. Generative AI introduces new possibilities for addressing these limitations by enabling language learning environments that are not only personalized at the individual level but also sensitive to linguistic and cultural variation. This shift is particularly significant in second language acquisition, where learners' cultural schemas, educational traditions, and communicative norms substantially influence motivation, participation, and learning outcomes (Ayotunde et al., 2023; Wang et al., 2024).

Generative AI refers to advanced computational models capable of producing new content, such as text, dialogue, and feedback, based on large-scale linguistic and contextual training data (AlAfnan, 2026). Prominent examples include large language models such as OpenAI's ChatGPT, which can simulate human-like conversations, generate adaptive learning materials, and respond dynamically to user input. In the context of language learning, these systems function not merely as content-delivery tools but also as interactive interlocutors whose responses are shaped by users' linguistic choices, pragmatic strategies, and cultural framing. This interactional dimension is critical, as learners from different countries may approach AI systems with varying expectations regarding formality, politeness, error correction, and conversational turn-taking. For instance, learners socialized in educational cultures that prioritize accuracy and structure may engage more heavily with written tasks and explicit correction. In contrast, learners from communicative-oriented traditions may favor dialogic interaction and exploratory language use. By adapting its output in response to these interactional patterns, generative AI has the potential to mediate language learning in ways that reflect both individual proficiency and culturally grounded communication practices.

One of the most salient advantages of generative AI in language learning is its ability to tailor content to heterogeneous learner populations. Conventional language programs often adopt a one-size-fits-all instructional model, treating learners as a uniform group regardless of their linguistic backgrounds, cultural experiences, or educational norms. Such models may inadvertently privilege certain learning styles while marginalizing others, particularly in multicultural and transnational learning environments. Generative AI systems, by contrast, can personalize learning trajectories by adjusting task complexity, linguistic focus, and thematic content in response to learners' proficiency levels and interactional behaviors. Significantly, this personalization

extends beyond cognitive difficulty to include contextual relevance. AI-generated materials can be framed around culturally familiar topics, communicative situations, and discourse conventions, thereby increasing relevance and engagement for learners from different national contexts. For example, learners preparing for academic communication may receive tasks emphasizing formal register and argumentation, while others may engage with scenarios reflecting everyday social interaction or workplace communication. This culturally responsive personalization supports sustained engagement and promotes deeper language processing, contributing to more effective and meaningful language development (Samala, 2023; Li et al., 2024).

Timely, contextually appropriate feedback is another cornerstone of effective language learning, particularly in culturally diverse settings where learners' interpretations of corrections and evaluations may differ. In traditional classrooms, feedback is often delayed and constrained by instructional time, limiting opportunities for immediate adjustment and reflection. Generative AI addresses this limitation by providing real-time feedback on grammar, vocabulary, and discourse-level choices, allowing learners to respond to corrections as they occur (Kot & Nykyporets, 2024). Crucially, AI feedback can be calibrated not only to proficiency level but also to interactional preference. Learners accustomed to direct correction may receive explicit error identification and rule-based explanations.

In contrast, others may benefit from indirect feedback or reformulations that align with their cultural expectations of instructional support. By explaining the rationale behind corrections and adapting its feedback strategies over time, AI systems can foster metalinguistic awareness while respecting diverse learning orientations (Zhao, 2024). This adaptive feedback mechanism supports both accuracy and learner autonomy, enabling individuals from different linguistic and cultural backgrounds to engage with corrective input in ways that feel supportive rather than intrusive.

Conversational practice represents one of the most challenging yet essential components of language acquisition, particularly for learners who lack access to authentic interactional environments. Cultural factors such as face-saving concerns, fear of negative evaluation, or limited exposure to target-language communities may inhibit learners' willingness to communicate (Hossain et al., 2023). Generative AI offers a partial solution by providing a low-stakes conversational partner that can simulate diverse communicative contexts. AI-driven chatbots can generate interactions that reflect varying degrees of formality, politeness strategies, and discourse norms, allowing learners to practice language use across culturally situated scenarios. For instance, learners may engage in service encounters, professional exchanges, or informal social conversations that mirror real-world communicative demands. These simulations can incorporate culturally specific expressions, pragmatic conventions, and interactional cues, helping learners develop not only linguistic competence but also intercultural communicative awareness. The open-ended nature of generative AI interactions enables learners to experiment with language use without the social pressure often associated with human interlocutors, thereby supporting confidence-building and fluency development (Godwin-Jones, 2024; Izadi & Forouzanfar, 2024).

Despite these advantages, integrating generative AI into culturally diverse language-learning contexts poses challenges (Giannakos et al., 2024). One persistent concern is the extent to which AI systems can accurately model cultural nuance, pragmatic variation, and region-specific language use. While AI can generate grammatically sound responses, it may struggle to fully capture the sociocultural subtleties that shape meaning in real-world communication. Additionally, learners from different cultural backgrounds may interpret AI responses differently, raising questions about alignment between AI-generated feedback and learners' expectations. Ensuring accessibility and inclusivity is also critical, particularly for learners from underrepresented regions or educational systems (Ayotunde et al., 2023). Addressing these challenges requires continued refinement of AI models, greater attention to cultural and linguistic diversity in training data, and thoughtful integration of human oversight.

Against this backdrop, the present study adopts an exploratory approach to examine how learners from different linguistic, cultural, and educational contexts engage with generative AI in language-learning environments. Rather than seeking to establish statistically generalizable cross-country differences, the study investigates culturally interpretable tendencies in how learners interact with AI-generated content, respond to feedback, negotiate meaning, and develop interactional strategies over time. By examining these processes across multiple national contexts while recognizing substantial within-group variation and individual agency, the study seeks to provide preliminary insight into the culturally situated nature of AI-mediated language learning. In doing so, it explores the proposition that generative AI may currently function as a culturally interpreted rather than inherently culturally responsive system and provides an empirical basis for developing testable hypotheses concerning how future AI-supported language-learning environments might accommodate diverse and evolving learner preferences.

LITERATURE REVIEW

The application of artificial intelligence in education has expanded substantially over the past two decades, with language learning emerging as one of the most intensively researched domains (AlAfnan et al., 2023; AlAfnan, 2025; Chen et al., 2022). Early AI-assisted language learning systems focused primarily on automation, drill-based practice, and error detection, reflecting behaviorist instructional models. More recent developments in generative AI have introduced interactive, adaptive, and dialogic capabilities that fundamentally alter how learners engage with language. However, much of the existing literature has conceptualized AI-supported language learning as essentially universal, paying limited attention to how learners' linguistic backgrounds, cultural norms, and national educational traditions mediate their interactions with AI systems. Given that language learning is deeply embedded in sociocultural contexts, a growing body of research now emphasizes the need to examine AI-driven language learning through a culturally and linguistically sensitive lens.

Generative AI represents a significant shift in educational technology by enabling systems to generate contextually appropriate content rather than relying solely on pre-scripted materials. In language learning, generative AI models can produce texts,

explanations, and conversational responses that dynamically adapt to user input (Stevens, 2020). This adaptability allows AI systems to function as quasi-interlocutors, engaging learners in meaning-making processes rather than passive consumption of content. Educational research has increasingly highlighted the potential of such systems to support personalized learning, intelligent tutoring, and adaptive feedback (Heffernan & Heffernan, 2014). Significantly, personalization in this context extends beyond proficiency-based adaptation to include interactional style, discourse preferences, and culturally shaped expectations of instruction. Learners from different educational traditions may engage with AI-generated explanations, examples, and feedback in distinct ways, underscoring the importance of examining generative AI not as a neutral tool but as a participant in culturally situated communication.

One of the most extensively studied applications of generative AI in language learning is content personalization. Personalization typically refers to adapting instructional materials to learners' proficiency levels, learning pace, and performance history. Numerous studies have demonstrated that AI systems can effectively assess learner proficiency and generate tasks that align with individual skill levels (AlAfnan & MohdZuki, 2023; Chiu et al., 2023; Ejjami, 2024). However, recent scholarship suggests that effective personalization must also account for learners' linguistic repertoires and cultural frames of reference. Learners from different language backgrounds may struggle with distinct grammatical features, lexical patterns, or discourse conventions, and AI systems that recognize these patterns can offer more targeted support. Platforms such as Duolingo and Lingvist employ adaptive algorithms to personalize task difficulty (Pratiwiet al., 2024; Wang et al., 2024; Eswaran et al., 2025), yet their effectiveness may vary depending on learners' prior exposure to autonomous learning, digital tools, and self-directed study, factors often shaped by national education systems.

Beyond proficiency alignment, generative AI enables thematic and contextual personalization by embedding language learning tasks within culturally relevant topics. Research has shown that learners are more motivated when instructional content resonates with their personal interests and sociocultural experiences. AI systems can tailor reading passages, dialogues, and writing prompts to reflect learners' professional goals, social contexts, or cultural environments, thereby increasing relevance and engagement. For example, learners from collectivist cultures may respond more positively to collaborative or socially oriented scenarios, while learners from more individualistic contexts may prefer task-based or goal-oriented activities. This capacity to integrate cultural relevance into content generation positions generative AI as a powerful tool for addressing diversity in global language classrooms.

Another critical dimension of AI-supported language learning is real-time feedback. Feedback plays a central role in second language acquisition by guiding learners' attention to form, meaning, and use. Traditional classroom feedback is often delayed and constrained by instructional time, limiting its effectiveness. Generative AI systems overcome this limitation by providing immediate, continuous feedback on grammar, vocabulary, syntax, and, increasingly, discourse-level features (Kot & Nykyporets, 2024). Research has consistently shown that timely corrective feedback supports language development and helps prevent error fossilization (Ellis, 2009).

However, the interpretation and reception of feedback are not culturally neutral. Learners from some educational cultures expect explicit correction and rule-based explanations, whereas others may perceive direct correction as face-threatening or demotivating.

Generative AI systems can adapt feedback strategies to accommodate these differences by varying the explicitness, tone, and instructional framing of corrections. AI-powered tools such as Grammarly and Babbel provide not only corrections but also explanations that encourage metalinguistic reflection (Tang & Zhang, 2026). In culturally diverse contexts, this explanatory function is vital, as it allows learners to contextualize feedback within their existing linguistic knowledge. Moreover, AI systems can track individual learner responses to feedback over time, gradually refining their corrective strategies to align with learners' preferences and cultural expectations. This adaptive feedback loop supports learner autonomy while respecting sociocultural variation in instructional norms (Sung et al., 2016; Almufareh et al., 2024).

Pronunciation feedback represents another area where generative AI has shown promise, particularly through the integration of speech recognition technologies. Voice-based AI platforms such as Rosetta Stone and Speechling provide real-time pronunciation analysis, enabling learners to practice spoken language independently (Ehsani & Knodt, 1998). However, pronunciation is closely tied to accent, identity, and regional variation, making it a culturally sensitive aspect of language learning. Studies have noted that AI systems may privilege certain accent norms, potentially disadvantaging learners whose speech patterns diverge from standardized models. This limitation highlights the need for AI systems to incorporate a broader range of linguistic varieties and to frame pronunciation feedback to emphasize intelligibility rather than native-like accuracy, particularly for learners from diverse linguistic backgrounds.

Conversational interaction is widely regarded as a cornerstone of language acquisition, yet it remains one of the most challenging aspects for many learners. Factors such as communication anxiety, fear of negative evaluation, and limited access to interlocutors can inhibit participation, especially in cross-cultural contexts (Hossain et al., 2023). Generative AI offers an alternative by functioning as a conversational partner that can simulate a range of interactional scenarios. AI-driven chatbots have been used to facilitate dialogic practice, allowing learners to engage in exchanges that resemble real-world communication (Kefi et al., 2024). Research suggests that such interactions can improve fluency and reduce speaking anxiety by providing a non-judgmental environment (El Shazly, 2021; Fathi et al., 2024).

Crucially, generative AI can simulate different communicative registers, politeness strategies, and cultural norms, exposing learners to variation in language use. This exposure supports the development of intercultural communicative competence, which is increasingly recognized as a core objective of language education (Kramsch, 1993). By engaging with AI-generated interlocutors that reflect diverse cultural contexts, learners can practice navigating pragmatic differences, such as levels of formality or indirectness, that are essential for effective cross-cultural communication. Nevertheless, studies have also reported limitations in AI-driven conversations, including repetitive responses and limited pragmatic depth, which may reduce engagement for advanced learners (Ismail & Alharkan, 2024).

Despite the growing body of research highlighting the benefits of generative AI in language learning, several challenges remain. Scholars have raised concerns about the potential lack of nuance in AI-generated language, particularly regarding idiomatic usage, pragmatic appropriateness, and cultural specificity (Ding et al., 2024; Melissa & Kenza, 2023). Ethical issues related to data privacy, algorithmic bias, and the representation of under-resourced languages further complicate the implementation of AI systems in global contexts (Kasneci et al., 2023; Rane et al., 2023). If training data disproportionately represent specific languages or cultures, AI outputs may inadvertently reinforce linguistic hierarchies and marginalize alternative varieties.

Recent literature increasingly advocates for a hybrid approach that combines AI-driven personalization with human pedagogical oversight. While generative AI excels at scaling individualized instruction, human educators remain essential for providing emotional support, cultural mediation, and critical reflection (Macfadyen & Dawson, 2010). In culturally diverse learning environments, this collaboration is critical, as instructors can contextualize AI-generated content and address misunderstandings arising from cultural differences. Consequently, future research is encouraged to move beyond measuring AI effectiveness in isolation and instead examine how generative AI interacts with learners' linguistic identities, cultural backgrounds, and educational experiences.

Existing scholarship demonstrates that generative AI holds significant potential to enhance language learning through personalized content, adaptive feedback, and interactive practice. However, the effectiveness of these systems cannot be fully understood without considering the cultural and linguistic contexts in which learners engage with AI. A culturally informed perspective is therefore essential for evaluating AI-mediated language learning and for designing systems that support equitable and meaningful language acquisition across diverse global populations.

METHODOLOGY

This study investigates how learners from diverse linguistic and national backgrounds interact with generative artificial intelligence (AI) in language-learning environments, with particular attention to how culturally shaped learning orientations influence engagement, feedback use, and conversational behavior. The research adopts an exploratory mixed-methods design in which qualitative evidence serves as the primary basis for interpretation, while quantitative indicators are used descriptively to contextualize observed patterns. Rather than aiming to produce statistically generalizable cross-country comparisons, the study focuses on identifying culturally interpretable tendencies and developing a design-oriented hypothesis regarding generative AI as a culturally responsive learning agent.

The study is situated within an interpretive research paradigm that conceptualizes AI-mediated language learning as a socially and culturally situated interaction. In this framework, generative AI is not treated as a neutral technological tool but as an interactional partner whose perceived role is co-constructed through learner input, communicative strategies, and prior educational experiences. This perspective enables the

analysis to move beyond performance outcomes and instead examine how learners interpret feedback, negotiate meaning, and adapt their interactional strategies over time.

The study involved 100 adult English language learners from six national contexts: Japan, China, Saudi Arabia, North Macedonia, Egypt, and Bulgaria (see Table 1). Participants were purposively selected to ensure diversity in linguistic background, educational experience, and familiarity with digital learning environments. Learners were distributed across four CEFR proficiency levels (A1, A2, B1, and B2), enabling the exploration of interaction patterns at different stages of language development. Subgroup sizes within each country and proficiency level were relatively small, typically ranging from 4 to 6 participants. For this reason, the study does not aim to support statistically reliable cross-country comparisons. Instead, national context is treated as a situated learning environment that provides a lens for examining interactional tendencies while explicitly recognizing within-group variation and individual differences.

Table 1. Participant Distribution

Variable	Description
Total Participants	100
Countries	Japan, China, Saudi Arabia, North Macedonia, Egypt, Bulgaria
CEFR Levels	A1, A2, B1, B2
Sampling Strategy	Purposive sampling
Subgroup Size	4–6 participants per subgroup

All participants interacted with the same version of ChatGPT (GPT-4) developed by OpenAI, accessed through the standard web interface during the study period (March–June 2025). The system operated under strictly uniform conditions: no system prompts were introduced, no cultural or pedagogical customization was applied, and all interactions occurred in text-based format. Participants generated their own prompts based on assigned tasks. This uniformity is methodologically critical. Because the AI system functioned identically across all cases, any variation in interaction patterns, feedback preferences, or perceived responsiveness can be attributed to learner interpretation and adaptive use rather than to system-level differences (see Table 2). This allows the study to isolate culturally mediated interaction as the primary focus of analysis.

Table 2. AI System Configuration

Variable	Configuration
AI System	ChatGPT (GPT-4)
Access Period	March–June 2025
Interaction Mode	Text-based only
System Prompt	None
Customization	None
User Input	Participant-generated prompts

Data were collected over an eight-week period using multiple complementary sources to ensure triangulation. Interaction logs recorded session frequency, duration, and task type, providing quantitative indicators of engagement. Learners maintained

reflective diaries after each session, documenting their goals, challenges, emotional responses, and perceptions of AI feedback. Pre- and post-assessment instruments measured grammar, vocabulary, reading, and speaking performance, while post-intervention surveys captured learners' perceptions of personalization, feedback clarity, and engagement. Semi-structured interviews were conducted with approximately twenty participants to gain deeper insights into interaction strategies and expectations (see Table 3).

Table 3. Data Sources and Functions

Data Source	Purpose	Type
Interaction Logs	Track engagement patterns	Quantitative
Learner Diaries	Capture reflection and perception	Qualitative
Pre/Post Assessments	Measure proficiency development	Quantitative
Surveys	Evaluate learner perceptions	Mixed
Interviews	Explore experiences in depth	Qualitative

ANALYTICAL FRAMEWORK

The analysis integrates quantitative and qualitative approaches while maintaining a clear distinction between their roles. Quantitative data (e.g., proficiency gains, interaction frequency, feedback distribution) are used descriptively to identify patterns and support interpretation. Due to small subgroup sizes, no claims of statistical significance or causal inference are made. Qualitative data serve as the primary analytical foundation, providing insight into learners' reasoning, expectations, and adaptive strategies. To interpret variation meaningfully, the study employs five analytical dimensions commonly discussed in language education and intercultural communication research: orientation toward accuracy versus fluency, expectations of feedback explicitness, perceptions of instructional authority, tolerance for linguistic risk-taking, and preference for structured versus dialogic learning. These dimensions serve as interpretive lenses rather than fixed variables, enabling the identification of tendencies without imposing deterministic cultural categories (see Table 4).

Table 4. Analytical Dimensions

Dimension	Description
Accuracy vs. Fluency	Preference for correctness vs. communication
Feedback Explicitness	Direct vs. indirect correction
Instructional Authority	AI as tutor vs. partner
Risk-Taking	Willingness to experiment with language
Interaction Style	Structured vs. dialogic learning

To strengthen the qualitative evidence base, the study incorporates expanded narrative cases from four contrasting contexts: Japan, Saudi Arabia, China, and Egypt. For each context, multiple cases were selected to represent both typical and atypical trajectories and longitudinal development. These cases were constructed using triangulated data from interaction logs, diaries, and interviews and are treated as core

analytical evidence rather than illustrative examples. This approach allows for the examination of within-group diversity and avoids reductive cultural generalizations, directly addressing concerns regarding representativeness and evidential depth (see Table 5).

Table 5. Narrative Case Structure

Feature	Description
Countries	Japan, China, Saudi Arabia, North Macedonia, Egypt, Bulgaria
Case Types	Typical and atypical
Data Sources	Logs, diaries, interviews
Time Frame	Longitudinal (multiple weeks)
Purpose	Capture diversity and evolution

Interaction patterns were analyzed over time to capture changes in learner behavior. Coding of interaction logs focused on shifts in correction-focused interaction, clarification requests, and comparative or experimental use of AI. This longitudinal perspective enables the study to conceptualize AI literacy as an evolving interactional competence, reflecting increasing learner agency and strategic engagement (see Table 6).

Table 6. Longitudinal Focus

Aspect	Description
Early Stage	Correction-focused interaction
Mid Stage	Increased clarification and dialogue
Late Stage	Strategic and comparative use
Outcome	Development of AI interaction competence

Ethical approval was obtained before data collection, and all participants provided informed consent. Participation was voluntary, and learners were informed of the study's purpose, the use of anonymized data, and their right to withdraw at any time. All data were anonymized and securely stored, and participants were assigned numerical identifiers to ensure confidentiality.

This methodological design frames the study as an exploratory, hypothesis-generating investigation into culturally situated AI-mediated language learning. By combining descriptive quantitative indicators with rich qualitative data and longitudinal narrative analysis, the study develops a design-oriented hypothesis: generative AI in language education may be more effective when conceptualized as a culturally responsive learning agent rather than as a purely performance-adaptive tutor. This hypothesis is not presented as a confirmed finding but as a theoretically and empirically informed direction for future research and system design.

DATA ANALYSIS AND FINDINGS

The analysis integrates descriptive quantitative indicators with qualitative evidence from learner diaries, interviews, and open-ended survey responses to examine how learners from diverse national and educational contexts engage with generative artificial intelligence in language-learning environments. In line with the study's interpretive design, the purpose of this section is not to establish statistically generalizable differences between countries, but to identify *recurrent and culturally interpretable tendencies* supported by both numerical trends and narrative evidence. Quantitative data are therefore used to indicate distributions and tendencies, while qualitative cases provide explanatory depth and illuminate the mechanisms underlying these patterns.

A critical methodological clarification concerns the AI system itself. All participants interacted with the same version of ChatGPT 4 via the standard web interface during the study period (March–June 2025). The system operated under default conditions: no system prompt was introduced, no cultural or pedagogical customization was applied, and all interaction occurred in text-only mode. Participants generated their own prompts based on assigned tasks. Consequently, the system functioned identically across all cases. Any variation in perceived responsiveness, feedback preferences, or interaction style, therefore, reflects learners' interpretations and adaptive use rather than system-level cultural responsiveness. This distinction is essential for interpreting the findings and for situating claims about culturally adaptive AI design.

Table 7. Proficiency Development Across CEFR Levels

CEFR Level	Observed Improvement Focus	Typical AI Interaction Pattern	Grammar (%)	Vocabulary (%)	Reading (%)	Speaking (%)
A1	Grammar & vocabulary recognition	Structured correction	42 → 71	48 → 74	50 → 70	40 → 65
A2	Sentence construction	Verification + guided dialogue	55 → 78	60 → 81	60 → 80	55 → 76
B1	Fluency & comprehension	Conversational experimentation	70 → 86	74 → 90	75 → 86	66 → 85
B2	Pragmatic refinement	Strategic AI use	80 → 91	82 → 95	80 → 92	75 → 90

Descriptive performance data indicate that learners across all six countries demonstrated observable improvement in grammar accuracy, vocabulary use, reading comprehension, and speaking fluency over the eight-week intervention. These gains were broadly consistent in magnitude across groups, but differed in emphasis depending on proficiency level and interaction strategy. Lower-level learners (A1–A2) relied more heavily on structured correction and repetition, while intermediate and upper-

intermediate learners (B1–B2) increasingly engaged in conversational practice, experimentation, and strategic refinement (see table 7). This pattern suggests that generative AI supports multiple learning trajectories rather than a single uniform pathway. Improvement is therefore best understood as interactionally mediated, shaped by how learners use the system rather than by exposure alone.

Engagement data further illustrates how learners structured their interaction with the AI system (see Table 8). While all participants were instructed to engage regularly, the frequency and orientation of interaction varied considerably. Some learners used AI intensively as a conversational partner, while others interacted less frequently and treated it as a tool for structured correction and verification.

Table 8. Country-Level Engagement Patterns

Country	Weekly Interaction Level	Orientation	<2 (%)	2–3 (%)	4–5 (%)	>5 (%)
Egypt	High	Conversational/dialogic	10	20	35	35
North Macedonia	High	Mixed exploratory	15	25	30	30
China	Moderate	Structured + lexical	30	40	25	5
Japan	Lower	Correction-focused	40	35	20	5
Saudi Arabia	Moderate	Guided practice	35	40	20	5
Bulgaria	Moderate	Balanced	25	35	30	10

A key revision of the analysis concerns feedback utilization (see Table 9). Earlier interpretations risked reducing learner behavior to a binary distinction between "accuracy-oriented" and "dialogue-oriented" users. The current analysis demonstrates that such categorization obscures meaningful variation. Instead, four overlapping feedback utilization models were identified through combined quantitative coding and qualitative interpretation.

Table 9. Feedback Utilization Models

Model	Core Orientation	Approx. Distribution	Interaction Features
Precision-Seeking Calibration	Accuracy and correctness	~30%	Direct correction, rule explanation
Relational Negotiation	Dialogue and clarification	~25%	Follow-up questioning, co-construction
Strategic Experimentation	Testing alternatives	~28%	Comparing outputs, reformulation
Deferential Uptake	Efficient acceptance	~17%	Minimal questioning, rapid adoption

These models appear across all national groups but differ in how they are linguistically realized and interactionally sustained. For example, Japanese and Saudi learners both frequently requested corrections, yet the form and progression of these requests differed. Japanese learners often framed requests indirectly, using softened phrasing and gradually increasing engagement over time. Saudi learners, in contrast, tended to initiate interaction with direct correction requests but showed increasing willingness to engage in reflective dialogue after receiving feedback. Egyptian learners frequently integrated rhetorical concerns (e.g., persuasiveness and audience), while Chinese learners often approached feedback as one option within a broader process of comparison and selection. Learners from North Macedonia demonstrated a more exploratory and flexible approach, often combining correction requests with conversational practice and shifting between task types as their confidence developed. Bulgarian learners, by contrast, tended to adopt a balanced strategy, integrating structured correction with selective experimentation, frequently requesting improved versions of their writing while also comparing alternatives to refine their choices (see Table 10).

Table 10. Country-Level Differentiation in Feedback Practices

Country	Dominant Tendencies	Distinctive Features	Dialogue Engagement
Japan	Calibration + negotiation	Indirect phrasing, gradual engagement	Increases over time
Saudi Arabia	Calibration + uptake	Directive start, reflective follow-up	Expands over time
Egypt	Negotiation + experimentation	Audience-oriented, expressive	Consistently high
China	Experimentation + calibration	Comparative, efficiency-driven	Task-dependent
North Macedonia	Experimentation + negotiation	Exploratory interaction, flexible task-switching	High and sustained
Bulgaria	Calibration + experimentation	Balanced correction and rewriting, selective comparison	Moderate but stable

Quantitative indicators of conversational behavior further reinforce these distinctions. Differences in turn length, error tolerance, and initiation patterns reveal variation in communicative risk-taking and interactional confidence (see Table 11).

Table 11. Conversational Features by Region

Region	Mean Turn Length	Error Tolerance	Interaction Initiation
Japan	18	Low	Low
Saudi Arabia	20	Low	Moderate
China	22	Moderate	Moderate
Bulgaria	25	Moderate	Moderate
North Macedonia	32	High	High
Egypt	35	High	High

These patterns align with qualitative observations: learners differ not only in what they request from AI, but in how actively they participate, how much risk they take, and how they position AI as either an authority or a conversational partner. Japanese learners often demonstrated cautious engagement that evolved over time, though variation within the group was notable. In one typical case, a B1 learner initially relied on validation strategies, frequently asking: *"Is this sentence correct?"* Diary entries in week one reflected hesitation: *"I don't want to ask too many questions."* By week five, the same learner shifted toward reflective inquiry, asking: *"Why is this more natural in formal writing?"* This transition illustrates increasing confidence and dialogic engagement. A second case involved a B2 learner focused on politeness and tone. Early prompts emphasized correctness, but later interactions included requests such as: *"Can you make this sound more polite in an academic context?"* Over time, the learner demonstrated awareness of pragmatic nuance rather than only grammatical accuracy. An atypical case showed early experimentation. One learner prompted the AI: *"Give me three ways to say this differently,"* then compared outputs critically. Diary notes stated: *"I like to choose what fits my style."* This case challenges assumptions of uniformly cautious engagement and highlights individual strategic agency.

Saudi learners often began with directive interaction but showed increasing willingness to negotiate AI feedback. In a typical case, an A2 learner consistently used prompts such as: *"Correct this paragraph and explain mistakes."* By week four, the learner began comparing responses: *"Why did you change this word?"* This reflects a shift from acceptance to evaluation. A second case involved a B1 learner who initially focused on vocabulary development. Over time, this learner expanded into argument testing, asking: *"Which version sounds stronger for an essay?"* Diary reflections indicated growing confidence in expressing personal preferences. An atypical case demonstrated sustained skepticism. One learner wrote: *"I don't trust all corrections, so I check other sources."* This participant used AI selectively, treating it as one resource among many, illustrating that directness does not equate to passive acceptance.

Chinese learners frequently engaged in structured and efficiency-oriented interaction, though affective uses of AI were also evident. In one typical case, a B1 learner

used iterative drafting strategies: *"Rewrite this sentence in a more academic way."* The learner compared multiple outputs before selecting one, noting: *"I choose the most suitable version."* A second case involved a learner using AI for structured learning. Early sessions focused on grammar rules, but later entries showed integration into writing tasks: *"I use corrections to improve my essays."* This reflects a progression from rule-based to applied learning. An atypical case diverged significantly. One learner used AI primarily for conversational confidence, stating: *"I talk with AI to feel more comfortable speaking English."* This emotional and confidence-building orientation contrasts with efficiency-driven patterns.

Egyptian learners typically demonstrated strong dialogic engagement and rhetorical awareness. In a typical case, a B2 learner frequently asked: *"Does this sound persuasive?"* rather than focusing solely on correctness. Over time, the learner refined arguments through dialogue, emphasizing their impact on the audience. A second case showed a learner combining correction with expression. Early prompts requested grammar fixes, but later interactions included: *"Make this more engaging for readers."* Diary entries reflected increased attention to style and voice. An atypical case involved selective engagement. One learner stated: *"I only use AI for vocabulary."* Despite access to broader features, this participant resisted reformulation and preferred maintaining original phrasing, demonstrating selective trust.

Learners from North Macedonia often displayed high engagement and exploratory interaction styles. In one typical case, a learner used AI extensively for conversational practice, stating: *"I like to practice real conversations."* Over time, the learner increased the length and complexity of their turns, reflecting growing fluency and confidence. A second case involved mixed task use. The learner alternated between grammar exercises and dialogue, noting: *"I use correction first, then I try conversation."* This hybrid strategy illustrates flexible engagement. An atypical case showed inconsistent use. One learner engaged intensively in early weeks but later reduced interaction, stating: *"Sometimes I prefer studying alone."* This highlights variability in sustained engagement.

Bulgarian learners generally demonstrated balanced interaction between structured and exploratory approaches. In a typical case, a B1 learner used AI for both correction and rewriting: *"Fix this and give me a better version."* Over time, the learner began comparing outputs and selecting preferred alternatives, reflecting increased autonomy. A second case involved steady conversational use. The learner engaged in moderate dialogue sessions, noting: *"It helps me practice without pressure."* This reflects a balanced approach between accuracy and fluency. An atypical case showed minimal engagement with conversational features. One learner focused almost exclusively on grammar drills, stating: *"I prefer structured exercises."* This indicates persistence of traditional learning preferences despite access to interactive tools.

Across all countries, the narratives reveal both recurring tendencies and substantial within-group variation. Typical trajectories often involve movement from correction-focused interaction toward more dialogic and strategic engagement. However, atypical cases consistently demonstrate that learners adopt diverse approaches shaped by individual preferences, prior experience, and evolving confidence. These narratives reinforce a central finding of the study: cultural context shapes interactional tendencies,

but does not determine behavior. Instead, AI-mediated language learning emerges as a dynamic process in which learners actively interpret, negotiate, and adapt their engagement with the system over time.

Table 12: Longitudinal Narrative Trajectories and Within-Group Variation in AI-Mediated Language Learning Across Contexts

Country	Typical Trajectory (Early → Later)	Illustrative Learner Behavior	Atypical Case	What It Reveals
Japan	Validation → Reflective inquiry	"Is this correct?" → "Why is this more natural?"	Early rhetorical experimentation and style comparison	Indirect engagement can evolve into analytical interaction
Saudi Arabia	Directive correction → Negotiated interaction	"Correct this paragraph" → questioning and comparing	Persistent skepticism; cross-checking AI	Directness ≠ passivity; AI authority is negotiable
China	Structured correction → Iterative comparison	Rewriting and comparing multiple outputs	Use of AI for confidence-building dialogue	Efficiency and affective use can coexist
Egypt	Conversational engagement → Rhetorical refinement	Focus on persuasion and audience	Minimal use (vocabulary only)	Dialogic strength can coexist with selective reliance
North Macedonia	Mixed use → Exploratory fluency development	Alternating correction and conversation ("I correct, then practice")	Drop in engagement over time	High engagement does not guarantee consistency; autonomy shapes usage
Bulgaria	Balanced correction → Strategic selection	"Fix this and give a better version" → comparing outputs	Preference for grammar-only structured tasks	Hybrid learning styles persist despite AI flexibility

As shown in Table 12, the narrative evidence provides a more robust qualitative foundation by presenting multiple cases within each national context, including both typical and atypical trajectories. This approach moves beyond illustrative examples and

demonstrates how learners' interactions with AI evolve, while also revealing substantial within-group variation. Across the six focal contexts, typical cases show consistent developmental patterns. Japanese learners often begin with cautious validation strategies and gradually transition toward reflective inquiry. Saudi learners tend to initiate interaction through directive correction requests but increasingly engage in negotiation and comparison. Chinese learners frequently adopt structured, iterative approaches, using AI outputs comparatively, while Egyptian learners demonstrate strong dialogic engagement, often integrating rhetorical and audience considerations into their interactions. Learners from North Macedonia typically exhibit a mixed and exploratory trajectory, combining structured correction with conversational practice and progressively expanding their fluency through sustained engagement. Bulgarian learners, in contrast, tend to follow a balanced developmental path, integrating correction, rewriting, and selective comparison, with gradual movement toward more autonomous and strategic use of AI-generated alternatives.

At the same time, atypical cases complicate these tendencies. In each context, learners diverge from dominant patterns: some adopt highly experimental strategies early on, others question or resist AI authority, and some use AI for purposes that differ from task-oriented expectations. These deviations are analytically important, as they demonstrate that cultural tendencies do not determine behavior. Instead, they highlight the role of individual agency, prior experience, and evolving interactional competence. Taken together, the table and accompanying cases illustrate that both patterned tendencies and significant diversity characterize AI-mediated language learning. This reinforces the study's central argument that cultural variation should be understood as a dynamic and interpretive process rather than a fixed explanatory category.

Interaction patterns also evolved over time (see Table 13). Quantitative log data indicate a shift from correction-focused engagement toward more dialogic and strategic interaction.

Table 13. Longitudinal Interaction Shifts

Stage	Correction-Only (%)	Clarification (%)	Comparative Testing (%)
Week 1	48	19	14
Week 4	35	27	23
Week 8	24	33	31

This progression suggests that AI literacy develops as an interactional competence. Learners not only improve their language skills but also refine how they communicate with AI systems, moving from dependence toward agency and strategic use.

Taken together, the findings demonstrate that generative AI supports measurable improvement in language proficiency while simultaneously revealing diverse interactional pathways shaped by learner expectations, educational background, and communicative orientation. Quantitative data confirm consistent gains and shifting engagement patterns, while qualitative evidence explains how these outcomes are

achieved through culturally mediated interaction. Importantly, because the AI system remained unchanged across all participants, the observed variation cannot be attributed to system-level adaptation. Instead, it reflects how learners interpret and appropriate AI within their own learning frameworks. Cultural variation, therefore, operates not as a deterministic variable but as a dynamic, interactive process.

The findings support a key conceptual implication: generative AI in language learning currently functions as a *culturally interpreted system* rather than a culturally responsive one. This distinction provides the empirical basis for the study's broader hypothesis that future AI systems may need to incorporate explicit mechanisms- such as adaptive feedback modes, interaction style calibration, and learner-controlled preferences- to move from projected responsiveness to genuine cultural adaptability.

DISCUSSION

This exploratory study examined how learners from six national and educational contexts, Japan, Saudi Arabia, China, Egypt, North Macedonia, and Bulgaria, engaged with generative AI in language-learning environments. Rather than establishing statistically generalizable differences between national groups, the study sought to identify recurrent interactional tendencies and examine how learners interpreted, negotiated, and adapted their use of the same AI system. The descriptive performance data suggest broadly positive language-development trajectories, while the qualitative evidence indicates substantial variation in how learners sought feedback, positioned the AI, and participated in interaction. These observations should therefore be interpreted as preliminary evidence for further investigation rather than as evidence of fixed cultural differences or causal relationships. This exploratory framing is consistent with the study design, in which qualitative evidence provides the primary basis for interpretation and quantitative indicators are used descriptively.

A particularly salient observation concerns the diversity of interactional pathways through which learners engaged with the same AI system. Japanese learners in the narrative cases initially tended to use the system for validation before moving toward reflective questions about naturalness and academic politeness. Saudi learners often began with directive correction requests but subsequently questioned and negotiated the AI's choices. Chinese learners frequently used iterative rewriting and comparison, whereas Egyptian learners more often incorporated rhetorical and audience-oriented concerns into their interactions. Learners from North Macedonia commonly shifted between correction and conversation, while Bulgarian learners combined structured correction with selective comparison. These patterns were not uniform within any national group, and atypical cases, including early experimentation, scepticism toward AI outputs, affective uses of AI, reduced engagement, and persistent preference for structured exercises, further indicate that cultural context does not determine individual behaviour.

The longitudinal evidence provides an additional basis for interpreting these observations. Across the study period, correction-only interaction declined while clarification and comparative testing increased. This progression may indicate that

learners gradually developed greater confidence and strategic competence in interacting with AI. However, the evidence does not establish that this progression was caused by cultural adaptation of the AI system. All participants used the same system under uniform conditions, with no cultural or pedagogical customization. Thus, the more cautious interpretation is that learners themselves progressively adapted their interaction strategies to the affordances of the system.

This distinction is important for interpreting the concept of culturally responsive AI. The findings do not demonstrate that the AI system itself was culturally responsive. Rather, they suggest that the system functioned as a culturally interpreted environment, in which learners brought different expectations concerning feedback, authority, interaction, and acceptable linguistic risk. The same system could consequently be experienced differently by different learners because users actively shaped the interaction through their prompts, follow-up questions, comparisons, and decisions about whether to accept or reject AI suggestions. This interpretation is also consistent with the substantial within-group variation observed across the narrative cases.

Against this background, the study tentatively proposes that future generative-AI language-learning systems might benefit from moving beyond performance-based personalization toward mechanisms that can respond to interactional preferences as they emerge during use. This is best understood as a design-oriented hypothesis rather than a demonstrated design principle. Three possible directions arise from the present observations: adaptive feedback calibration, interaction-style modulation, and learner-controlled customization. Each represents a testable design proposition that could be examined in subsequent experimental or longitudinal research.

The first proposed mechanism is an adaptive feedback calibration system that changes the explicitness, depth, and sequencing of corrective feedback in response to observable learner behaviour. The present study identified four overlapping feedback-utilization models, calibration, negotiation, experimentation, and uptake, and showed that learners differed in how they requested and responded to correction. For example, some learners repeatedly requested direct correction and explanations, while others moved toward questioning why a particular formulation was preferred or compared several alternatives before selecting one.

A possible implementation would therefore be an algorithm that maintains a learner-level feedback profile rather than applying a single correction strategy. Such a profile could be updated from interaction signals such as repeated requests for explanations, acceptance or rejection of corrections, follow-up questions, requests for alternative formulations, and shifts from correction toward comparative discussion. The system could then adjust several feedback parameters: (1) explicitness, ranging from direct error identification to indirect reformulation; (2) explanation depth, ranging from a brief correction to a rule-based or metalinguistic explanation; and **(3)** feedback sequencing, such as providing the correction immediately, allowing the learner to attempt self-correction first, or presenting multiple alternatives for comparison.

For example, a learner who repeatedly asks, “Correct this paragraph and explain my mistakes” could initially receive explicit correction accompanied by explanations. If subsequent interactions show repeated questioning of individual changes, the system

could shift toward a negotiation-oriented format: identify the change, explain its rationale, and invite the learner to evaluate whether the alternative fits the intended meaning.

Conversely, a learner who repeatedly requests several alternatives could receive comparative feedback rather than a single preferred correction. These mechanisms correspond closely to the observed movement from correction toward clarification and comparative testing, but their effectiveness remains an empirical question.

The hypothesis arising from these observations is therefore not that culturally calibrated feedback is necessarily more effective, but that feedback systems that allow adaptation to demonstrated interactional preferences may support more sustained and meaningful learner engagement than systems that provide uniform corrective feedback. Future studies could test this proposition by comparing fixed-feedback and behaviourally calibrated conditions while measuring learner uptake, retention, confidence, and subsequent interaction behaviour.

The second proposed mechanism concerns interaction-style modulation. The findings suggest that learners differed not only in what they requested from AI but also in how they preferred to structure the interaction. Some learners used AI primarily as an authority for validation or correction; others treated it as a conversational partner, a source of alternatives, or a space for experimentation. The narrative cases also indicate that these orientations could change over time.

A possible interface implementation would be a system capable of dynamically adjusting the interactional format of the learning session. Rather than offering a single conversational mode, the interface could provide selectable or adaptive modes such as structured tutor, dialogic partner, comparative coach, or practice interlocutor. In a structured tutor mode, the AI might organize responses into correction, explanation, and practice steps. In a dialogic mode, it might prioritize follow-up questions and meaning negotiation. In a comparative mode, it could generate several acceptable formulations and explicitly ask the learner to evaluate differences in register, tone, or rhetorical effect. In a conversational practice mode, it could minimize interruption and defer corrective feedback until a natural conversational pause.

An algorithmic version of this mechanism could infer interaction style from behavioural indicators such as turn length, frequency of clarification requests, number of alternative outputs requested, tolerance for errors, and frequency of conversational initiation. Importantly, such inference should be treated as probabilistic and revisable rather than as a fixed classification of the learner. This is particularly important because the study's atypical cases show that learners sometimes departed substantially from the dominant tendency observed within their context.

The resulting hypothesis is that AI systems may be more useful when interaction style is treated as an evolving learner preference rather than a fixed system setting. Future research could test whether dynamically switching between structured, dialogic, comparative, and conversational modes improves engagement or learning outcomes compared with a single default interaction style.

The third proposed mechanism is learner-controlled customization, which follows particularly strongly from the evidence of individual agency. Several learners actively evaluated AI outputs rather than accepting them automatically. One Saudi learner

explicitly cross-checked AI corrections with other sources, while a Chinese learner compared multiple outputs before selecting the most suitable version. Other learners expressed preferences concerning politeness, style, audience, or the degree of conversational support they wanted.

A possible interface implementation would allow learners to specify and modify preferences through a transparent control panel. Rather than requiring learners to construct detailed prompts repeatedly, the interface could provide adjustable options such as “correct directly,” “give hints first,” “explain the rule,” “show several alternatives,” “focus on naturalness,” “focus on formal academic style,” or “let me decide before revealing the answer.” A learner could also indicate whether the AI should behave primarily as a tutor, writing coach, conversation partner, or critical reviewer.

Such customization could be complemented by a learner-facing transparency feature showing why the system is adapting its behaviour. For example, the interface might state that it is providing more explicit explanations because the learner has repeatedly requested them, or that it is offering alternative formulations because the learner frequently compares outputs. The learner could then accept, modify, or disable the inferred preference. This would preserve learner agency and reduce the risk that an algorithmic inference about interactional preference becomes an invisible or deterministic classification.

This mechanism is especially relevant given the study's finding that cultural tendencies coexist with substantial individual variation. A system that automatically assigns a learner to a presumed cultural interaction style could reproduce the very essentialism that the study seeks to avoid. By contrast, learner-controlled customization would treat cultural and educational background as one possible influence on interaction while allowing the learner to override or revise system assumptions. The resulting hypothesis is that transparent, learner-controlled adaptation may provide a safer and more flexible pathway toward culturally responsive AI than automatic cultural profiling.

Taken together, these three proposals suggest a possible transition from AI systems that are merely culturally interpreted toward systems that are capable of responding to interactional diversity in more explicit and controllable ways. The distinction is important. The present study does not provide evidence that the proposed mechanisms would improve learning, nor does it establish that any particular interactional preference is culturally determined. Instead, the observations indicate that learners use the same AI system in different ways and that these patterns can change over time.

The design-oriented hypothesis emerging from the study can therefore be formulated more specifically:

> **H1:** A generative-AI language-learning system that adapts feedback explicitness and explanation depth to demonstrated learner preferences may support more effective feedback engagement than a fixed-feedback system.
>
> **H2:** A generative-AI language-learning system that dynamically adjusts between structured, dialogic, comparative, and conversational interaction modes may better accommodate heterogeneous interactional preferences than a single default interaction style.

H3: A generative-AI language-learning system that gives learners transparent control over inferred interaction preferences may better support learner agency and reduce the risks associated with culturally deterministic personalization.

These hypotheses are intentionally framed as propositions for future investigation rather than conclusions established by the present study. They could be examined through controlled experiments comparing fixed and adaptive feedback conditions, longitudinal studies examining whether interaction preferences remain stable or change over time, and mixed-methods studies investigating whether learners perceive adaptive systems as more supportive, intrusive, or transparent. Such research could also examine whether adaptation based on observed interactional behaviour produces different outcomes from adaptation based on assumed national or cultural categories.

The implications should therefore be understood cautiously. The presence of cross-context tendencies in the current data does not justify treating culture as a predictive label for individual learners. Indeed, the atypical cases indicate the opposite: learners can resist, reinterpret, or depart from patterns associated with their broader educational contexts. The more promising direction may consequently be to design systems that recognize patterned variation while continuously allowing individual learners to negotiate how the system responds to them.

Overall, the present study offers preliminary evidence that culturally and educationally situated interaction matters in generative-AI-mediated language learning. It does not establish that culturally responsive AI is more effective, nor does it demonstrate that the proposed mechanisms would produce better learning outcomes. Rather, it identifies recurring interactional patterns and uses those observations to develop a set of testable design hypotheses. In this sense, the contribution of the study is exploratory: it provides an empirical and conceptual basis for investigating whether generative AI might be more effective when conceptualized not simply as a performance-adaptive tutor, but as a potentially culturally responsive learning agent whose feedback, interaction style, and adaptation remain transparent and negotiable by the learner.

CONCLUSION

This exploratory study examined how learners from six national and educational contexts — Japan, Saudi Arabia, China, Egypt, North Macedonia, and Bulgaria — engage with generative AI in language learning, focusing on culturally interpretable interaction patterns rather than statistical generalization. The findings suggest that learners follow diverse interactional pathways when using the same AI system, varying in feedback preferences, communicative orientations, risk-taking, and the ways they position AI as a corrective tool, tutor, conversational partner, or source of alternative formulations. The longitudinal and narrative evidence also suggests that learners may move from correction-focused use toward greater clarification, comparison, dialogue, and strategic engagement, although substantial within-group variation remains. Because all participants interacted with the same AI system under uniform conditions, these patterns are better understood as reflecting learner interpretation and agency than system-level cultural adaptation. The

study therefore suggests that generative AI may currently function more as a culturally interpreted environment than as an inherently culturally responsive learning system.

Building on these preliminary observations, the study advances three design-oriented hypotheses for future research. First, AI systems that adapt feedback explicitness, explanation depth, and sequencing to demonstrated learner preferences may support more effective feedback engagement than fixed feedback strategies. Second, dynamically adjusting between structured, dialogic, comparative, and conversational interaction modes may better accommodate heterogeneous learner preferences than a single default interaction style. Third, transparent, learner-controlled customization of AI behavior may strengthen learner agency while reducing the risks associated with culturally deterministic personalization. These propositions are not presented as established effects of the present study; rather, they constitute hypotheses generated from the observed interactional patterns and narrative cases. Future experimental and longitudinal research can test whether such mechanisms improve engagement, feedback uptake, confidence, and language development. Overall, the study offers an exploratory foundation for examining whether generative AI may be more effective when conceptualized not simply as a performance-adaptive tutor, but as a culturally responsive learning agent whose feedback, interaction style, and adaptation remain flexible, transparent, and negotiable by the learner.

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APPENDICES

Appendix A: Pre- and Post-Study Assessment Instruments

A.1 Grammar and Vocabulary Assessment Sample

- Participants completed multiple-choice, fill-in-the-blank, and sentence construction tasks.
- Example grammar item: *Choose the correct tense:* "By the time she _____ (arrive) at the station, the train had left."
- Example vocabulary item: *Select the synonym for "achieve":* a) accomplish b) fail c) ignore d) skip

A.2 Reading Comprehension Sample

- Short passages (100–150 words) with comprehension questions, including main idea, inference, and vocabulary-in-context items.
- Example:
  Passage: *"Tourism has dramatically changed local economies in many regions. While it generates income, it also introduces cultural challenges."*
  Question: *Which challenge is mentioned in the passage?*

A.3 Speaking Fluency Task Sample

- Participants were asked to respond to prompts in 1–2 minutes.
- Example prompts:
  1. "Describe a memorable travel experience in your own words."
  2. "Explain how technology has changed your daily routine."
- Speech was recorded and analyzed for fluency, lexical richness, and pronunciation.

Appendix B: Pre- and Post-Study Survey Instruments

B.1 Learner Demographics and Cultural Background Survey

- Items included:
  - Country of origin
  - Native language
  - Years of formal language study
  - Exposure to digital learning platforms
  - Cultural attitudes toward feedback (Likert-scale 1–5)

B.2 Learner Perception and Satisfaction Survey

- Likert-scale items (1–5) and open-ended questions assessing:
  - Satisfaction with AI personalization
  - Perceived usefulness of grammar, vocabulary, and pronunciation feedback
  - Engagement with conversational practice
  - Cultural relevance of AI-generated content

Appendix C: Semi-Structured Interview Guide

1. How did you use the AI platform for learning English?
2. Which types of tasks did you prefer (written exercises vs. conversational practice)? Why?
3. How did the AI feedback align with your expectations of correction and instruction?
4. Did the AI content feel culturally relevant or relatable? Can you give an example?
5. How comfortable were you speaking with the AI compared to writing or reading?
6. What improvements would make the AI more effective or culturally sensitive for you?

Appendix D: Reflection Journal Template
Instructions for Learners:

- Complete the journal after each AI session.
- Record:
    1. Tasks completed
    2. Feedback received and your response
    3. Challenges encountered
    4. Cultural or personal relevance of the tasks
    5. Emotional or motivational response to the AI session

Appendix E: Data Coding and Analysis Schema
E.1 Engagement Metrics Coding

Metric	Description	Example
Session frequency	Number of weekly interactions	3 sessions/week
Task type	Written vs. conversational	Vocabulary drill vs. dialogue
Duration	Minutes per session	25 min

E.2 Feedback Utilization Coding

Feedback Type	Coding Rule	Example
Grammar	Corrected and applied	Corrected verb tense in sentence
Vocabulary	Corrected or learned new word	Substituted "enormous" for "big"
Pronunciation	Adjusted pronunciation as guided	Corrected stress pattern in "important"

E.3 Conversational Interaction Coding

Feature	Coding Rule	Example
Turn length	Words per turn	15 words per turn
Error tolerance	High, moderate, low	High = learner continues despite errors
Initiation	Who starts turn	Learner vs. AI
Formality	Structured vs. casual	Structured = complete sentences, low contractions

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