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Attitudes Toward AI as Communicative Partners: A Human–Machine Communication (HMC) Analysis of Undergraduate Language Learners

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ABSTRACT

Language learning has been revolutionized by the incorporation of AI-mediated language communication systems (AIMLCS), which provide individualized, scalable assistance. Nevertheless, little is known about how this particular group of undergraduate language learners views AI as collaborative partners as opposed to merely tools. This study examines undergraduate language learners' perceptions of AIMLCS as relational entities using a Human-Machine Communication (HMC) lens. Four HMC-derived dimensions: Functional Value, Relational Comparison, Partnership Perception, and Attitudinal Growth, were used in an exploratory quantitative survey of 55 Malaysian university students to gauge attitudes. Descriptive statistics were used to describe learner attitudes across the specified dimensions systematically. Specifically, mean scores and standard deviations were calculated. The findings demonstrate a dualistic viewpoint: students frequently identify a disparity in affective response, pointing out that these tools provide less emotional depth than human teachers, yet greatly appreciating the functional benefits of AIMLCS. AI is not seen by learners as a replacement for human connection, but rather as a complementary partner inside the learning environment. Additionally, respondents who reported continuous use also expressed more favourable opinions; however, longer-term studies are required to verify real changes in attitudes. The findings highlight the necessity of creating AI systems that are both communicatively and instructionally successful. By linking HMC theory and language pedagogy, this study offers educators and developers preliminary exploratory insights to optimize AI integration. It addresses both functional capabilities and relational restrictions to promote more supportive and engaging language-learning experiences.

Keywords: artificial intelligence, human-machine communication, language learning, educational technology, learner attitudes, relational communication

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1.0 Introduction

AI-mediated language communication systems (AIMLCS), which offer individualized, responsive, and scalable instructional support catered to each learner's needs and progression patterns, have completely changed the landscape of language learning as a result of the integration of AI into education (Huertas-Abril & Palacios-Hidalgo, 2023; Wang et al., 2019). For this study, AIMCLS are digital platforms and conversational applications that use artificial intelligence to mimic natural interaction and offer focused instructional support. From gamified language learning platforms that include Duolingo and adaptive writing assistants including Grammarly to real-time translation tools such as Google Translate and

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voice-interactive systems like Alexa, these systems comprise a diverse ecosystem of intelligent communicative agents, each intended to support different facets of language acquisition. Although the cognitive and proficiency-based benefits of these tools, such as enhanced vocabulary retention, grammatical accuracy, and writing fluency, have been thoroughly documented in previous research (Chen et al., 2020; Ali, 2020), scholarly attention has mostly ignored the ways learners view and relate to these systems as communicative entities with which they engage in meaningful interaction rather than as simple tools. As AI systems become more adept at replicating conversational exchange and providing linguistically complex feedback, this oversight indicates a substantial gap in our understanding of technology-mediated language acquisition (Sucháňová, 2023; Tsai, 2019).

A crucial theoretical framework for this investigation is provided by Human-Machine Communication (HMC), which moves the emphasis from instrumental utility to relational experience in human-AI contact. According to Guzman and Lewis (2020), HMC highlights the social, emotive, and symbolic aspects of these interactions by investigating the procedures, perceptions, and consequences of interacting with computers as communicative partners. HMC examines how people attribute social agency, emotional resonance, and relational meaning to technologies that display communicative behaviours, in contrast to traditional human–computer interaction research, which focuses on usability metrics, task efficiency, and cognitive load (Guzman, 2018; Nass & Moon, 2000). This viewpoint is particularly important in language education, a field that is essentially made up of contact and discourse, since it recognizes that learning happens not just via the delivery of content but also through the caliber of communicative engagement. Learners are not just utilizing a tool when they use an AI writing assistant, communicate with a language learning chatbot, or get pronunciation feedback from a speech recognition system; rather, they are participating in a type of communication that is loaded with relational and social expectations (Guzman & Lewis, 2020; Lee et al., 2024). In addition to influencing how students engage with AI, these expectations—for response, empathy, encouragement, and mutual understanding—also influence how they feel about those interactions and, ultimately, how successfully they learn from them (Smith & Lee, 2024; Sundararajan & Gauthier, 2024). Designing systems that support not only cognitive development but also positive relational experiences that promote motivation, engagement, and sustained learning requires an understanding of these communicative dimensions as AI becomes increasingly incorporated into educational ecosystems (Li & Wang, 2021; Murtaza et al., 2022).

Therefore, this study asks: What are students' attitudes toward using AIMLCS as communicative partners in language learning? This reframes the investigation of learner attitudes through an HMC viewpoint. This study aims to shed light on how students view the relational dynamics of AI engagement, including aspects such as social presence, discrepancy in affective response, interactivity, communicative comfort, and mutual comprehension, by reorienting the focus from tool utility to communicative partnership. By bridging language pedagogy with HMC theory, it provides evidence-based insights for creating AI systems that are both communicatively resonant and instructionally effective—systems that learners perceive as helpful, responsive partners in their language acquisition process rather than as impersonal, efficient tools. By identifying particular communication boundaries in AI-mediated education, this study offers developers a paradigm for giving social agency and responsive feedback the highest priority in language learning systems. This study presents tentative implications for educators, instructional designers, and AI developers beyond its initial exploratory findings. Understanding students' communicative perceptions can help develop more effective implementation strategies, training methods, and pedagogical frameworks that optimize the advantages of AI while addressing its relational limitations as universities around the world incorporate AI tools into language curricula (Ali et al., 2022; Khasawneh & Yusra, 2023). Additionally, by offering empirical evidence of how communication theories appear in technology-mediated learning environments and how these manifestations influence learning experiences and outcomes, this study adds to the expanding corpus of HMC research in educational contexts (Guzman & Lewis, 2020; Sundararajan & Gauthier, 2024). Using this paradigm, users react to the "interpersonal" tone of an interface rather than just processing facts. They penalize apparent technical errors or unnatural system behaviours while attributing stable personalities and intentionality to systems that display consistent behavioural patterns.

1.1 Theoretical Framework

This study's theoretical paradigm combines two complementary frameworks from relational communication theory and human-machine communication, offering a thorough lens through which to look at attitudes about AIMLCS as communicative partners. These frameworks shed light on learners' impressions of AI interaction as well as the reasons behind these perceptions, which stem from the interaction's communicative aspects.

1.2 Computers Are Social Actors (CASA) Paradigm

According to Nass and Moon's (2000) CASA paradigm, people unintentionally apply social norms, expectations, and scripts to technology that displays human-like communicative indications. According to CASA, people react to computers or AI systems in the same ways that they would to human social actors—expecting courtesy, reciprocity, fairness, and supportive communication—when they use natural language, exhibit interactive behaviours, or offer feedback in socially contextualized ways (Guzman, 2018). Research has confirmed the CASA paradigm by demonstrating how people unintentionally apply social norms to computers. Users' sensitive responses to a machine's "interpersonal" tone such as perceiving ill-mannered prompts as offensive, and their propensity to project unique personalities and goal-oriented activities onto robots that display behavioural consistency serve as proof of this (Nass & Moon, 2000). The paradigm also outlines that learners may anticipate communicative appropriateness in addition to functional accuracy from AI systems in the context of AIMLCS, assessing them based on interpersonal norms rather than just instrumental ones. When an AI writing assistant gives feedback, students can evaluate if the feedback is accurate as well as whether it is given in a way that appreciates their efforts and recognizes their advancement.

1.3 Relational Communication Theory

In addition to CASA, Relational Communication Theory (Burgoon & Hale, 1984) offers a framework for analysing the qualitative aspects of communication that influence relational outcomes and perceptions. Relational communication theory stresses how communication establishes, preserves, and changes connections through verbal and nonverbal cues that transmit relational meanings, in contrast to theories that concentrate on information transfer. Important ideas from this philosophy consist of:

1) Immediacy: perception of psychological proximity or distance, expressed by language and paralinguistic cues that indicate accessibility and participation.
2) Involvement: level of focus, response, and commitment to the conversation
3) Interaction Comfort: ease, naturalness, and a lack of anxiety.
4) Relational warmth: demonstrations of encouragement, compassion, and respect.

When relational communication theory is applied to HMC contexts, it helps explain how learners perceive their interactions with AI along relational dimensions, such as whether the AI feels "present" and engaged, whether its feedback appears to be attentive to their particular needs, whether communicating with it feels natural or strained, and whether the interaction conveys a sense of supportive partnership (Sundararajan & Gauthier, 2024). Attitudes about AI as communicative partners are largely shaped by these relational views, which have an impact on learners' emotional and motivational interactions with AIMLCS as well as whether or not they use them.

2.0 Literature Review

Human-machine communication, educational technology, language pedagogy, and relational communication are some of the research topics that connect with the study of attitudes toward AI as communicative partners in language learning. In order to provide the theoretical and empirical background for the current investigation, this literature review summarizes pertinent research from these fields. Methodologically, this places the structural analysis of this study within a larger context of systematic literature inquiry by aligning with larger scholarly efforts to map emerging research trends and review technological impacts across evolving scientific disciplines (e.g., Ruslan et al., 2024).

2.1 Human–Machine Communication in Educational Contexts

Within communication studies, HMC has become a separate area that focuses on the impacts and procedures of interacting with digital, intelligent entities (Guzman, 2018). HMC examines how people view, understand, and interact with machines as communicative partners with varied degrees of social presence and agency, in contrast to human–computer interaction research, which typically focuses on usability, efficiency, and task completion (Guzman & Lewis, 2020). The rising sophistication of AI systems that can converse in normal language, identify emotional cues, and modify their communication style based on context- capabilities that blur the lines between tool and interlocutor—is reflected in this theoretical shift.

HMC research has looked at how students engage with conversational agents, intelligent tutoring systems, and adaptive learning platforms in educational settings (Clark et al., 2019; Sundararajan & Gauthier, 2024). Research consistently reveals that students apply social expectations to these systems, assessing them on communication attributes like politeness, encouragement, and attentiveness in addition to accuracy and efficiency (Nass & Moon, 2000). Additionally, studies show that systems with stronger social presence cues elicit more positive attitudes, higher levels of engagement, and greater trust than systems that appear to be merely functional tools (Lee et al., 2024; Smith & Lee, 2024). These results highlight the significance of communicative design in educational AI and imply that relational perceptions and functional assessments both influence attitudes toward learning technologies. In related digital domains like social media influencer marketing (Fauzi et al., 2024), where the fundamental mechanisms of digital authenticity, perceived trustworthiness, and user engagement directly mirror the relational concerns examined here within human-machine communication, the structural role of persuasive interaction is equally apparent.

2.2 AI in Language Learning

Over the past ten years, research on AI in language teaching has changed significantly, reflecting both evolving pedagogical perspectives and technology breakthroughs. Early research mostly looked at AI as a cognitive aid, emphasizing how programs, i.e., grammar checkers, vocabulary applications, and automated writing evaluators, may improve language fluency through error correction, adaptive practice, and instant feedback (Chen et al., 2020; Wang et al., 2019). Studies showed definite advantages for particular language skills, especially in areas such as writing fluency, vocabulary acquisition, and grammatical accuracy (Ali, 2020; Khasawneh & Yusra, 2023). The basic significance of digital devices in learning environments, including the usage of gadgets by young learners, is highlighted by broader examinations into educational technology adoption that go beyond language-specific tools (Ali et al., 2020).

Recent developments in Large Language Models (LLMs), for instance ChatGPT, have raised difficult issues about the "illusion" of companionship and educational ethics. These generative systems necessitate an HMC analysis that takes into consideration the hazy boundaries between algorithmic response and genuine communication, in contrast to previous static tools (Guzman & Lewis, 2020). As these systems become more proficient in mimicking human-like empathy and responsiveness, they run the risk of causing a sociotechnical conflict in which students might value the ease of AI interaction over the insightful, culturally relevant feedback of human teachers (Huertas-Abril & Palacios-Hidalgo, 2023). Due to this progression, research must now focus on discrepancies in affective response and the ethical limits of AI as a communicative entity rather than only measuring instructional efficacy (Sucháňová, 2023). As a result, it is important to examine how the integration of AIMLCS affects the learner's social and emotional connection to the target language in addition to its technical accuracy (Lee et al., 2024; Khasawneh & Yusra, 2023).

The experiential aspects of learning using AI have been the subject of more recent research, which takes into account how students relate to and feel about these technologies (Li & Wang, 2021; Song & Song, 2023). Research has shown conflicting responses: although students value the ease, customization, and accessibility of AI tools, they frequently voice concerns about the impersonality of automated feedback, the lack of contextual awareness in AI responses, and the lack of human warmth and support (Smith & Lee, 2024; Taylor et al., 2024). These issues are a reflection of what Guzman and Lewis (2020) refer to as the "relational gap" in HMC, which is the difference between human relationship requirements and technical capacity. The significance of contextual and relational design in educational technology is highlighted by similar relational and pedagogical considerations that emerge in studies of other digital platforms, such as the use of YouTube for knowledge sharing among educators (Ali et al., 2022).

Emerging research on conversational AI and dialogue systems in language acquisition is especially pertinent to the current topic. Research on chatbots, virtual conversation partners, and AI tutors indicates that students interact with these systems as communicative partners rather than just practice tools, and their attitudes are influenced by how responsive, intelligent, and conversational the AI is perceived to be (Sucháňová, 2023; Tsai, 2019). Few studies have explicitly examined attitudes through an HMC theoretical lens or methodically examined the relational aspects of AI communication in language learning environments; therefore, the breadth and depth of this research are still restricted.

The scope and complexity of this research are currently limited since few studies have systematically investigated the relational features of AI communication in language learning contexts or explicitly studied attitudes through an HMC theoretical lens. Current studies on well-known learning management systems, notably Blackboard, highlight the importance of platform affordances and instructor viewpoints in influencing pedagogical integration (Nasim et al., 2024). These dynamics are also important for AIMLCS, where effective adoption is determined by the interaction between instructor attitudes and the system's functional capabilities.

2.3 Attitudes Toward Educational Technology

Acceptance models from information systems research, especially the Technology Acceptance Model (TAM) and its variations, have historically dominated attitude research in instructional technology (Davis, 1989). These models highlight perceived utility and perceived usability as the main factors influencing attitudes and adoption of technology. These models have been criticized for ignoring affective, social, and relational factors that affect how users experience and assess technologies, even though they are useful for predicting usage intentions. This is especially true in situations where task efficiency is just as important as interaction quality (Li & Wang, 2021; Sundararajan & Gauthier, 2024).

Drawing on theories of second language acquisition that highlight the relevance of anxiety, self-confidence, and interpersonal connection in language development, attitude research has emphasized the significance of motivational and emotional elements in language learning in particular (Oxford, 1990). As an example of how tool design might improve affective learning outcomes, collaborative writing using Google Docs has been demonstrated to promote motivation through shared digital involvement (Shahidan et al., 2022). According to Smith and Lee (2024) and Taylor et al. (2024), when it comes to technology-mediated learning, attitudes toward learning tools may be influenced not only by their functional capabilities but also by how they make learners feel confident or anxious, supported or judged, connected or isolated. This is consistent with HMC viewpoints that highlight the relational and emotional aspects of human-technology interaction. This is consistent with studies on how students plan and showcase themselves utilising digital media, such as video resumes (Ali et al., 2022), where self-presentation and communicative delivery are critical to perceived efficacy. Furthermore, it is impossible to separate attitudes toward new technologies in higher education frameworks from the larger psychosocial ecosystem of digital tool adoption, which includes its downstream effects on academic work-life balance and user pressure (Fauzi et al., 2024). This demonstrates why assessing a tool's relational comfort is crucial to long-term educational integration.

3.0 Methods

3.1 Research Design

This study examined undergraduate students' perceptions of AI-powered language tools as communication partners using a cross-sectional survey approach and a quantitative research design. The survey approach was chosen due to its effectiveness in gathering attitudes from a geographically scattered population and its compatibility with the exploratory and descriptive objectives of the research (Fraenkel et al., 2011). In addition to making correlation analysis between various attitudinal components and usage characteristics easier, this approach made it possible to measure some relational and communicative characteristics of attitudes in a systematic way. The survey's cross-sectional design offered a glimpse of present attitudes and perspectives, providing insightful information about how students envision their interactions with AIMLCS at a specific stage in the changing field of educational technology integration.

3.2 Sampling

In the study, fifty-five (n=55) undergraduate language learners from Malaysian universities who were utilizing AI specifically for their language learning were chosen using convenience sampling techniques. The sample size indicates the exploratory nature of this pilot study in that the demographic distribution offers a fundamental baseline for HMC attitudes. Nevertheless, power analysis should be used in future research to provide wider generalizability. With respect to participation, the study reported gender (63.6% male, 36.4% female), age (mostly 21–24 years at 74.5%), and academic level (89.1% enrolled in bachelor's degree programs); the participant pool showed a variety of demographic and educational traits. Participants' levels of English proficiency varied; most self-identified as intermediate users (65.5%), followed by beginners (20.0%), advanced learners (12.7%), and native speakers (1.8%). This distribution offers insights into attitudes across various proficiency levels and reflects the bilingual setting of Malaysian higher education.

In terms of technological experience, the majority of participants (78.2%) stated that they had previously used AIMLCS, mostly for language translation systems (34.5%) and writing support tools (58.2%). The frequency of usage ranged from daily engagement (27.3%) to weekly use (23.6%), many times per week (36.4%), and seldom interaction (12.7%). Examining how attitudes might vary depending on familiarity and frequent use of AI tools was made possible by the variety of experience levels. The participants' technological experience and demographic makeup match the target audience for AIMLCS integration in higher education contexts, guaranteeing the findings' applicability and relevance to actual learning environments.

3.3 Survey Instrument

A structured questionnaire with two sections that were in line with the HMC theoretical framework served as the research tool. In order to contextualize attitudinal responses, the first portion gathered demographic and experiential data (language competence, AI tool experience, usage frequency, and tool preferences). Ten items reflecting attitudes regarding AIMLCS on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) were included in the second portion. Rather than focusing on generic technological approval, the survey instrument was specially created to operationalize HMC principles. The 10 attitudinal measures were deductively mapped to four main dimensions—Functional Value, Relational Comparison, Partnership Perception, and Attitudinal Growth- based on the fundamental principles of Relational Communication Theory and the CASA paradigm in order to avoid post hoc categorization. In particular, Relational Comparison (Item 7) and Partnership Perception (Item 10) evaluate the psychological "immediacy" and "agency" outlined by Guzman and Lewis (2020), whereas Functional Value (Items 1, 2, 3, 6) measures the "efficiency scripts" found by Nass and Moon (2000).

This alignment guarantees that the constructs are not empirically formed after data collection, but rather conceptually derived. The 10-item attitudinal scale's overall strong internal consistency was validated by a Cronbach's alpha of 0.94. Since the Relational Comparison and Partnership Perception dimensions use single items, independent internal consistency measurements do not apply to them; this psychometric constraint is specifically addressed in the limitations section. Table 1 shows the categorization of the ten survey items into the four HMC attitudinal dimensions.

Table 1

Survey Items Mapped to HMC Attitudinal Dimensions

HMC Dimension	Item No.	Survey Item
Functional Value	1	View AIMLCS as valuable aids
	2	AIMLCS more effective than traditional methods
	3	Convenience outweighs drawbacks
	6	Instant feedback benefits learning
Relational Comparison	7	Lacks personal touch of human instructors
Partnership Perception	10	Works alongside traditional methods
Attitudinal Growth	4	Positive overall attitude
	5	Enthusiastic about continuing use
	8	See AIMLCS more positively over time
	9	Now see advantages after initial uncertainty

3.4 Validity and Reliability

While face validity was verified by pilot testing to guarantee item clarity and respondent comprehension, content validity was established through expert evaluation by language education specialists who assessed the alignment of items with HMC constructs. The instrument's stability and consistency in measuring the intended constructs were confirmed by reliability analysis, which showed strong internal consistency for the attitudinal scale with Cronbach's alpha coefficients of 0.94 for attitudes surpassing the suggested threshold of 0.70 for research instruments.

3.5 Data Collection Procedures

Undergraduate students were invited to participate in an online survey over the course of two weeks using Google Forms that were disseminated via official institutional mobile messaging platforms, particularly WhatsApp and Telegram. All responses were anonymised to maintain confidentiality, and participants electronically gave their informed consent by agreeing to participate by completing the survey. During this time, the survey was still available for responses. Following this, data were exported to Statistical Package for the Social Sciences (SPSS) for analysis in accordance with accepted ethical standards for educational research. Although this work maps early attitudinal trends using descriptive and correlational measures, the findings are intended to serve as an exploratory basis for further research using more complex analytical models, such as factor analysis or structural equation modelling.

3.6 Data Analysis

Using SPSS version 28, data analysis included both descriptive and inferential statistical methods. First, descriptive statistics were used to summarize demographic traits and attitude answers using means and standard deviations. The central tendency and variability of students' responses across the attitudinal dimensions were assessed using descriptive statistics, and the scale's overall internal consistency was confirmed by computing Cronbach's alpha. All analyses were carried out at a significance level of.05. While descriptive statistics and Pearson correlations constitute a fundamental level of analysis, they offer the empirical basis required for subsequent investigations that might employ more sophisticated methods, such as factor analysis or structural equation modelling.

4.0 Results

4.1 Functional Value: Students Recognize AI's Instrumental Communication Strengths

When examined through an HMC lens, students' replies showed a distinct hierarchy of attitudes. As detailed in Table 2, students affirmed that AIMLCS offer valuable learning support (M = 3.78, SD = 0.96), are more effective than traditional methods in certain aspects (M = 3.75, SD = 0.87), offer significant convenience that outweighs drawbacks (M = 3.53, SD = 0.86), and provide helpful instant feedback (M = 3.82, SD = 0.86) for the functional value items. Students primarily esteem AIMLCS for their instrumental communicative competence—their capacity to provide prompt, accurate, and effective language support—according to this strong functional affirmation. This also means that the identification of a relational gap (M=3.78) and the high mean for functional support indicate that students maintain a cognitive partition in that they are cautious of the AIMLCS's communicative goal yet trust it for data accuracy.

The provision of immediate feedback was the functional item that received the highest rating, while the convenience trade-off received the lowest, suggesting a subtle preference for communicative responsiveness over overall usability.

Table 2:

Descriptive Statistics of Survey Items Categorized by HMC Attitudinal Dimensions (n=55)

HMC Attitudinal Dimension	Item No.	Survey Item Prompt	Mean (M)	SD
Functional Value	1	View AIMLCS as valuable aids	3.78	0.96
	2	AIMLCS more effective than traditional methods	3.75	0.87
	3	Convenience outweighs drawbacks	3.53	0.86
	6	Instant feedback benefits learning	3.82	0.86
Relational Comparison	7	Lacks personal touch of human instructors	3.78	0.92
Partnership Perception	10	Works alongside traditional methods	3.98	0.93
Attitudinal Growth	4	Positive overall attitude	3.70	0.88
	5	Enthusiastic about continuing use	3.78	0.94
	8	See AIMLCS more positively over time	3.82	0.84
	9	Now see advantages after initial uncertainty	3.76	0.86

4.2 Relational Comparison: Acknowledging the Affective Response Gap

A disparity in affective reaction that coexists with excellent functional ratings is revealed by students' agreement that AIMLCS "lack the personal touch and guidance provided by human instructors" (M = 3.78, SD = 0.92). This pattern—believing what the system does but questioning how it relates—indicates that students evaluate different aspects of AI communication using different standards. Although this scepticism is common, it is not universal, as indicated by the moderate standard deviation (SD = 0.92); around one-third of respondents fell below the midpoint, suggesting individual variances in tolerance for AI-mediated engagement. More importantly, the fact that this result is consistent throughout the sample indicates that the difference in affective reaction represents a consistent pattern in students' perceptions rather than just a descriptive observation. This result casts doubt on the notion that adoption is solely driven by technical accuracy; rather, learner acceptance of AIMLCS may be influenced by perceived communicative intent, particularly the lack of real concern.

4.3 Partnership Perception: AI as a Complementary Rather Than Substitutive Communicative Partner

Regarding Partnership Perception, students strongly endorsed the view that "AIMLCS work alongside traditional methods rather than replacing them completely" (M = 3.98, SD = 0.93). This suggests they conceptualize AI not as a replacement for human teachers but as a complementary communicative partner that occupies a specific, collaborative role within their language learning ecosystem. There was broad agreement on the complementary nature of AI's function in the communicative landscape of language learning, as evidenced by this item's highest mean score among all measured attitudes.

4.4 Attitudinal Growth: Evolving Perceptions Through Sustained Interaction

The Attitudinal Growth dimension showed a positive trajectory, with students reporting an overall positive attitude toward incorporating AIMLCS ($M = 3.70$, $SD = 0.88$), enthusiasm for continued use ($M = 3.78$, $SD = 0.94$), increasingly positive perceptions over time ($M = 3.82$, $SD = 0.84$), and recognition of advantages despite initial uncertainty ($M = 3.76$, $SD = 0.86$). These responses indicate that frequent users express more favourable perceptions, indicating a possible process of experience adaptation. Increasing positivity over time had the greatest mean in this dimension, whereas overall positive attitude had the lowest. However, long-term longitudinal tracking is necessary to verify actual psychological development or true long-term adaptation over time because these data were collected at a single moment in time using a cross-sectional design.

5.0 Discussion

5.1 Functional Competence Versus Relational Limitation in AI Communication

The results show that students see AIMLCS using a dualistic paradigm that makes a distinction between relational warmth and functional communication value. The high ratings on all functional value criteria are consistent with HMC research showing that AI systems are becoming more adept at carrying out crucial communication tasks, including error correction, adaptive practice, and instant feedback (Guzman & Lewis, 2020; Lee et al., 2024). However, the CASA paradigm's claim that users apply social expectations to technology while remaining acutely aware of its emotional and interpersonal shortcomings is supported by the concurrent recognition of AI's relational limitations, particularly its lack of "personal touch" (Nass & Moon, 2000). This discrepancy in affective response indicates that AI's current communicative role is seen as supplemental rather than comprehensive and thus represents a key boundary in human–machine communication.

5.2 AI as a Complementary Partner in the Language Learning Ecosystem

Significant understandings of how students cognitively incorporate machine communication into their learning ecosystem are provided by the high endorsement of AI as working "alongside traditional methods" rather than replacing them. By showing that learners see AI as a specialized communicative partner with unique skills and limitations rather than as a replacement for human contact, this finding expands on HMC theory (Sundararajan & Gauthier, 2024). With practical implications for instructional design, this complementary partnership model suggests that human instructors should concentrate on relational, contextual, and nuanced communicative guidance, while AI should be positioned to handle tasks where its functional strengths excel, such as repetitive practice and immediate feedback (Li & Wang, 2021).

5.3 The Developmental Nature of Human–Machine Communication Attitudes

Theoretical claims that human-machine interactions develop through consistent interaction are supported by the favourable trajectory seen in the attitudinal growth dimension (Guzman, 2018). The descriptive statistics indicate that when interacting with AIMLCS, the participating students may go through a process of experience adaptation, as evidenced by their higher descriptive baseline metrics and increased familiarity. Relational communication theory, which holds that communication patterns and perceptions are co-constructed over time through repeated contacts, is consistent with this developmental perspective (Burgoon & Hale, 1984). It is implied that when people become accustomed to AI's communication style and learn to navigate its functional capabilities while comprehending its relational constraints, their initial concerns about AI communication may fade. Although cross-sectional responses show that optimism rises with use, further long-term studies are needed to determine if this is a transitory user adaptation or a long-term developmental process.

5.4 Pedagogical and Design Implications for HMC in Language Education

These attitudinal patterns suggest several important implications for both pedagogy and AI design. Pedagogically, educators should explicitly address the communicative nature of human–AI interaction, helping students develop metacognitive awareness of how communication with machines differs from human communication and how to strategically leverage AI’s strengths while compensating for its limitations (Sucháňová, 2023). From a design perspective, the findings point toward the need for more transparent communication about AI’s relational boundaries and the development of interface cues that better signal AI’s supportive intent, even within its functional limitations (Smith & Lee, 2024). Rather than attempting to simulate human warmth inauthentically, designers might focus on creating clearer partnership frameworks that honestly acknowledge AI’s role while maximizing its functional contributions to language learning.

5.5 Implication for Pedagogy Design

These results imply that instructors should have conversations on the nature of human–machine communication in addition to implementing AIMLCS. Reflective exercises that teach students how to critically and effectively interact with AI as a learning partner and how AI communication differs from human communication may be beneficial. The findings emphasize the significance of relational design cues for AI designers: using language that conveys contextual awareness, encouragement, and attentiveness.

5.6 Limitation and Future Research

The cross-sectional nature of this study and its very small convenience-based sample limit its ability to conclude causality. Additionally, due to the exploratory nature of the study, the capacity to identify complex causal associations is limited using basic inferential statistics. Also, the research focuses on single-item measures for some HMC aspects, which restricts psychometric sub-scale validation, and does not take into consideration variances among different types of AI tools. Larger, non-convenience samples should be used in future research to confirm the predictive ability of these attitudinal characteristics through regression modelling. Despite their reliability, the attitudinal measures were self-reported and could be skewed by social desirability. Larger, more varied samples, longitudinal designs to monitor changes in attitudes over time, and mixed-methods techniques using observational data or interviews to capture fuller communication experiences should all be included in future studies.

6.0 Conclusion

Students view AIMLCS as useful but emotionally constrained partners, which reframes perspectives on AI in language learning via the lens of human–machine communication. The Malaysian undergraduate language learners who took part in the study generally regarded AIMLCS as helpful but relationship-constrained partners. The current state of AI as a socially present but emotionally constrained interlocutor is reflected in the persistence of conversational gaps despite the widely acknowledged functional improvements. AIMLCS must be developed and incorporated as communication agents that can provide meaningful, encouraging, and relationally conscious learning interactions in addition to being instructional tools if they are to reach their full educational potential. This work's primary theoretical contribution is its particular use of Human–Machine Communication (HMC) framework layers to go beyond conventional technology acceptance models, providing a sophisticated baseline for describing the relational gap that language learners encounter.

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Conflict of Interest

The authors declare that no competing interests exist.

Author Contribution Statement

AZ designed, organized, and carried out the study, overseeing all structural elements such as the methodology, literature review, data collection, and analysis. EUHE edited the final manuscript and critically and structurally checked it.

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Ethics Statement

Primary data for this study were collected via an online survey involving human subjects. In accordance with the Universiti Malaysia Pahang Research Ethics Guidelines (Section 18.3.15), the study strictly adhered to international ethical standards for human research, including voluntary participation and digital informed consent. Formal Institutional Review Board (IRB) approval was not required as the study involved a low-risk, completely anonymous survey with no collection of personal, identifiable, or sensitive data. To prevent potential power imbalances and conflicts of interest, participants were employed via university-wide mobile messaging networks, i.e., official Telegram and WhatsApp student communities, rather than directly by course instructors.

Data Access Statement

Research data supporting this publication are available upon request to the corresponding author.

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