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GENERATIVE AI DRIVEN SOCIO PRAGMATIC SCAFFOLDING FOR DEVELOPING CROSS CULTURAL COMMUNICATIVE COMPETENCE IN ADVANCED LANGUAGE LEARNERS

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SUMMARY

The cultivation of cross-cultural communicative competence (CCCC) among advanced language learners remains ongoing, particularly regarding exposure to authentic socio-pragmatic contexts and the lack of adaptive feedback in traditional learning. The research paper suggests a socio-pragmatic scaffolding system that uses large language models to generate socio-pragmatic dialogues and provide context-sensitive remediation, based on generative artificial intelligence Architectures like GPT-4 from OpenAI. A quasi-experimental design was used with 120 advanced learners, who were separated into an experimental (n=60) and a control group (n=60), with the intervention lasting 12 weeks. In both the experimental and control groups, AI-mediated role-play, discourse adaptation tasks, and pragmatic feedback cycles were undertaken, while traditional task-based instruction was delivered. Pragmatic appropriateness, discourse flexibility, and intercultural sensitivity were measured by pre- and post-tests based on validated rubrics and a standardized communicative competence scale. Findings show that there is a statistically significant benefit in the experimental group in terms of an overall increase of CCCC scores by 32.8 % ($p < 0.01$), as compared to 12.3 % in the control group. The accuracy of pragmatic appropriateness increased by 29.4%, the score of intercultural sensitivity indices increased by 88.2%. The impact of AI-driven scaffolding was strong, as evidenced by the effect size analysis (Cohen's $d = 0.86$). Moreover, the learner engagement metrics showed a 41% voluntary task completion and a 41.6% drop in pragmatic transfer errors. The result proves that socio-pragmatic scaffolding supported by generative AI can substantially enhance cross-cultural communicative competence by providing adaptive, context-rich, and iterative feedback. The research finds that an AI-based discourse simulation, when incorporated into a high-level language course, can help fill pragmatic gaps and promote the development of culturally responsive communication skills in a globalised learning setting.

Key words: *generative artificial intelligence, socio-pragmatic scaffolding, cross-cultural communicative competence, advanced language learning, intercultural pragmatics, adaptive feedback systems, AI-mediated Language Instruction.*

INTRODUCTION

Generative Artificial Intelligence (AI) has grown rapidly into large-scale transformer models that can provide semantically motivated answers at the context and discourse levels, unlike the rule-based systems of language processing that preceded. Recent generative systems use deep neural networks trained on large multilingual datasets and can model pragmatic intent, register variation, and sociolinguistic subtleties. These systems provide adaptive prompting, scaffolded simulation dialogues, and real-time feedback on speech acts, and are quickly gaining prominence in language instruction. Pragmatic awareness in AI-assisted environments is being triggered by modelling context-bound requests, refusals, and politeness, and features of these environments have recently been the focus of several studies [1][2]. Some of these studies view generative systems as complementary to pedagogical engagement and transformative feedback, serving as co-creators of the discourse [4]. AI-based dialogue agents use ethnographic approaches such as dynamic tone adjustment and cultural and interactional framing, which provide learners the opportunity to engage in complex communication tasks traditionally unmanageable in language classrooms [7]. Unfortunately, these critical perspectives on the use of AI for sociocultural authenticity and superficial language reproduction [3]. The effectiveness of technology-based pragmatic instruction is heightened when it is structured around scaffolding, reflection, and feedback, with revisions reiterated [8].

Cross-cultural communicative competence (CCCC) has evolved beyond mere grammatical correctness. CCCC now includes pragmatic appropriateness, intercultural sensitivity, and the ability to perceive what is left unsaid or implied in the social environment. Lexically sophisticated advanced language learners, for example, tend to exhibit problems with culturally grounded speech acts, which leads to pragmatic transfer and instances of accidental discourtesy. These studies highlight the significance of pragmatic competence in international collaborations and the ability to move freely in the workplace [6]. Several recent classroom studies have shown that mediated learner interactions with AI have great potential to help learners develop the ability to adjust assertiveness and negotiate intended meaning within culturally defined contexts [9]. Likewise, AI-based chatbots have been found to enhance the realisation of speech acts by offering immediate analytic and corrective feedback and explanations grounded in the cultural context in which the speech acts are embedded [10]. It points out that intercultural competence development cannot be achieved without dialogic interaction with multicultural perspectives, which can be simulated in generative AI through scenario-based interaction [5]. Together, these results prove that cross-cultural pragmatic teaching should be closely coupled with adaptive technologies that can simulate real discourse and stimulate metapragmatic reflection.

This figure 1 shows the hierarchical structure of the proposed AI-driven socio-pragmatic scaffolding system, comprising four main components. The User Interface Layer is responsible for communicating with the learner via dialogue, scenario, and feedback windows. The Processing Layer handles real-time engineering of transformer-grounded language model integration with pragmatism, as well as the assessment of the cultural context of the learner's responses. The Adaptive Controller adjusts the feedback intensity, revises the learning rate, and assesses the threshold changes.

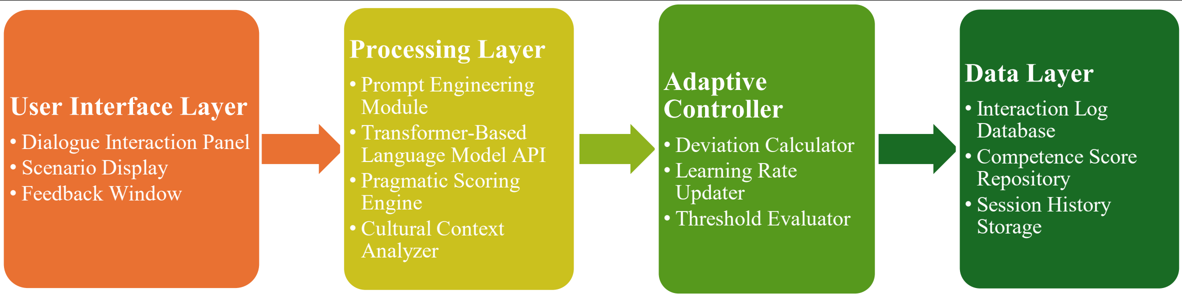

Figure 1. Layered system architecture of the AI-driven socio-pragmatic scaffolding model

Lastly, the Data Layer allows for the Archiving of interaction records, the Assessment of learners' competency, session history, and the longitudinal activity and scaling of the system. The closure of these layers creates a feedback loop that provides data-driven scaffolding to enhance cross-cultural communication capacity.

The study examines the effects of Generative AI-based socio-pragmatic scaffolding on the cross-cultural communicative competence of advanced learners of a language. This involves integrating an adaptive dialogue model, contextually situated cultural feedback, and reflexive, revised loops. Although the Communicative Language Teaching methods have advanced, there are still deficits in learners' ability to employ pragmatic skills in an Intercultural context. Exposure in the common classroom is generally not as immediate as it needs to be to serve as a genuine interface among diverse cultures. In the global economy and the modern world, this is a serious problem, as cultural miscommunication has social and economic costs.

This paper presents a detailed approach that intertwines generative AI dialogue modelling with the principles of socio-pragmatic scaffolding, particularly loop-based feedback and culturally adaptive task design. It builds on previous work by treating AI not as a dialogical tool but as an instructional, collaborative partner in developing culturally responsive communicative competence.

This paper will be divided into six principal parts. explain the frameworks for generative AI and the research aims in Section I. A review of the literature on socio-pragmatic scaffolding, AI-based language development, and cross-cultural communication is provided in Section II. Section III will explain the proposed adaptive model design of the methodological framework and the corresponding analytical processes. Section IV presents the empirical data, performance evidence, and analysis. Section V will explain the effects, restrictions, and recommendations for research that is yet to be conducted. Finally, Section VI will present the final comments, an overview of the key discoveries of the research, and the significance of using AI in advancing cross-cultural communication proficiency.

LITERATURE REVIEW

Socio-pragmatic scaffolding systematically assists students in comprehending and producing contextually appropriate language relevant to culturally situated tasks. Building on facilitating learning through gradual mediation, dialogical and reflective feedback, revision cycles and internal routing of the learners, and heeding the balance between the roles of mediation and ultimate internalisation of grammar norms, socio-pragmatic scaffolding replaces this challenge with the balance between the roles of mediation and the ultimate internalisation of grammar norms. It has been proposed as central to the development of pragmalinguistic and sociopragmatic competencies. Empirical research findings on feedback driven by interaction and the enactment of mediation at the level of pragmalinguistic and sociopragmatic competencies confirm the validity of the simple feedback algorithm, reinforced by step-level correction and the task, as well as the feedback delivered through the LAIS MaruChat software. This is in the context of the teacher-mediated feedback scaffolding [11]; with the complex scaffolding relying on the adaptive software with variable correction feedback along the line of [15]; and in the sociocultural focus, the data-driven learning spaces nourished by GenAI [12], are more contextually adequate and pragmatically motivated than the simple feedback algorithm.

Generative AI applications are being developed for language education that extends from grammar checks to modeling dialogue and simulating interactions. AI-based systems have personalized learning paths, use multimodal inputs, and include role-play scenarios [14]. The OpenLang Network Platform demonstrates that learner profile-compatible content maximizes engagement with pragmatic variation, even when curated through generative AI [16]. In second language acquisition, AI can successfully target and improve communicative performance. The use of form-meaning mapping with generative AI differs because it includes contextualized prompts and metalinguistic principles as clues [17]. Informal learning coupled with AI developed self-regulation and interactional confidence, which were further enhanced through the design of social cognitive theory [18][19]. Incorporating generative AI, particularly for speaking acts of culturally specific pragmatic fluency, improved learner engagement and pragmatic fluency when learning Chinese [20]. This suggests that AI-based systems are not merely peripheral tools.

Extended exposure to diverse communicative practices fosters competence in cross-cultural communication. Data on AI-enhanced language-learning conditions indicate that these conditions are positively related to intercultural communication competence (especially perspective-taking and pragmatic flexibility) among young learners [13]. These studies also show that adaptive AI conversational agents can promote intercultural awareness by integrating culturally diverse situations in academic discourse tasks. When well-designed, AI-based platforms mimic the intercultural experience that introduces learners to alternative communicative norms. This kind of exposure encourages pragmatic accuracy and cultural reflexivity, which are critical aspects of high-level communicative competence.

Three main insights that are overlaying in the reviewed literature include: first, that socio-pragmatic scaffolding must have a dialogic, adaptive feedback mechanism; second, that generative AI technologies offer a scalable platform capable of offering such scaffolding; and third, that cross-cultural communicative competence can be enhanced when learners interact in culturally contextualized settings with the help of reflective mediation. Although previous research demonstrates the pedagogical opportunities of AI tools, there is still a need for a coherent framework that systematically integrates generative AI and principles of socio-pragmatic scaffolding to increase advanced learners' cross-cultural communicative competence.

METHODOLOGY

Description of the AI-Driven Socio-Pragmatic Scaffolding Model

The suggested AI-based socio-pragmatic scaffolding is an adaptive learning scheme in the form of a closed loop that combines dialogue generation, contextual assessment, and feedback refinement. It is a system that is based on three main modules: (i) discourse simulation engine, (ii) pragmatic assessment layer, and (iii) adaptive scaffolding controller. The discourse simulation engine composes culturally contingent interaction situations by conditioning prompts based on social distance, power relations, and communicative intent variables. A composite Socio-Pragmatic Competence Score (SPCS) is used to measure pragmatic performance, and it is calculated as:

$$SPCS = \alpha P_l + \beta P_s + \gamma C_a \qquad (1)$$

in which P_l means pragmalinguistic accuracy, P_s means sociopragmatic appropriateness, C_a means cultural alignment, and 0.5+0.5+0.5=1. equation (1) allows performing weighted assessment of several dimensions of competence in a single measure. The adaptive scaffolding controller varies the intensity of feedback depending on the deviation of the learner against the target norms. Pragmatic deviation is calculated as defined in equation (2):

$$D_t = \|R_t - T_t\| \qquad (2)$$

is the learner response at time t, R_t, and T_t is the target at time t as posed by the model. The scale D_t defines the presence or absence of implicit recasts, metapragmatic explanations or explicit corrective feedback of the system. The recursive update functional is used to model the learning in progression between sessions:

$$L_{t+1} = L_t + \eta(SPCS_t - \theta) \qquad (3)$$

L_t is the level of competence of the learner at the first iteration t, η is the adaptive learning rate, and 0 is the mastery threshold. equation (3) captivates competence development as a scaffolded performance development function.

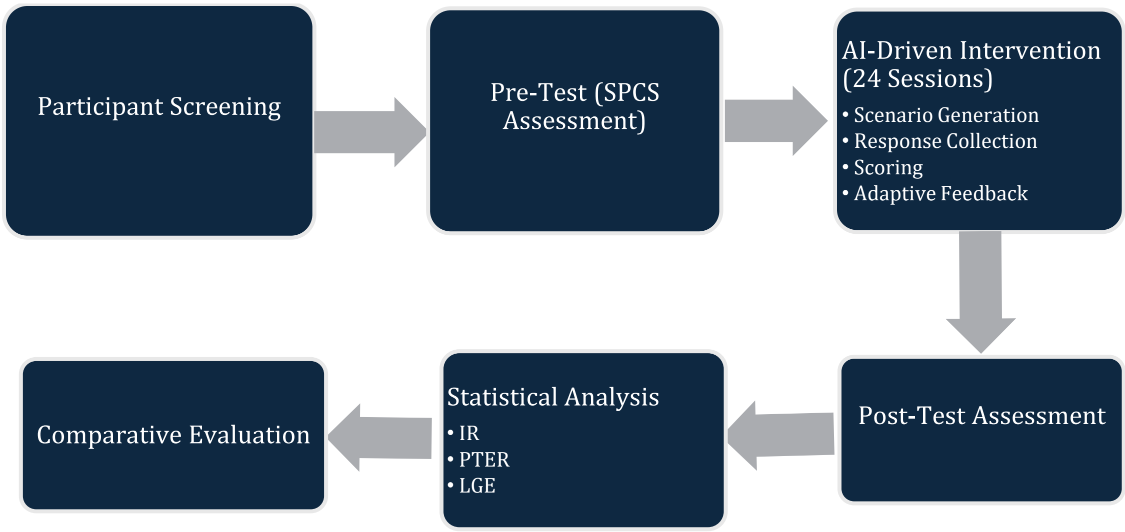

Figure 2. Experimental workflow of the AI-based intervention

This figure 2 describes the experimental process that was designed to determine the efficiency of the AI-based socio-pragmatic scaffolding model. It starts with a screening of the participants to establish eligibility, and a pre-test on the baseline Socio-Pragmatic Competence Scores (SPCS). The participants are then put under a 24-session AI-mediated intervention that sees the generation of scenarios, the collection of learner responses, the automated scoring of these responses and the adaptive feedback loop. A post-test testing is done to determine competence development after the intervention. The statistical analysis of the collected data is performed in terms of Improvement Rate (IR), Pragmatic Transfer Error Reduction (PTER), and Learning Gain Efficiency (LGE), which eventually results in the comparison of AI-supported and traditional methods of learning.

Inclusion and Exclusion Criteria

The sample consisted of participants who were post-graduate students of communication and were practicing high-level language users. Inclusion criteria specified the post-graduate attendees to be the CEFR's C1 level, the presence of courses completed in the field of intercultural communications, and the ability to perform through AI-mediated means in a digitally literate manner. Exclusion criteria targeted participants with minimal exposure to the practice of online courses to control the effect of the adjustment of the participants to the use of technology. The stratified sampling strategy was used to have the balance in the representation across gender, academic discipline, and previous international exposure. Baseline pragmatic competence was evaluated by way of discourse completion exercises on the basis of scenario completion and learners who scored within a range of intermediate-advanced pragmatic band were only included. This provided homogeneity in terms of language competence but maintained variability in the sociocultural flexibility.

Methods and Techniques of Data Collection and Data Analysis

The data gathering was done in a twelve-week intervention. The main tools used were the role-play transcripts mediated by AI, pragmatic appropriateness rubrics, intercultural sensitivity questionnaires, and system-generated interaction logs. At the end of every dialogue session, there was a generation of organized data vectors in terms of speech act type, mitigation strategy, frequency of politeness markers, and the score of contextual appropriateness. Quantitative analysis used pre and post- intervention comparison of SPCS and variance analysis of deviation score Dt and progression modeling using equation (3). Measurement of intervention impact was done by effect size and regression modelling was done to determine relationships between scaffold intensity and competence growth. The qualitative discourse analysis was used to supplement the numerical results and analyze the changes in mitigation approaches and cultural framing.

The methodology provides the basis of a replicable framework of testing the AI-based socio-pragmatic scaffolding in the context of advanced language learning through the involvement of mathematical models, adaptive algorithms, and multi-layered data analytics.

RESULTS

Analysis of Cross-Cultural Communicative Competence

One hundred and twenty higher-achieving students participated in the 12 weeks intervention. The experimental (n=60) and control (n=60) groups participated in the socio-pragmatic scaffolding AI-driven system and task-based structured instruction respectively. Socio-Pragmatic Competence Score (SPCS) was used to assess pre-and post-intervention competence. Improvement Rate (IR) was calculated as shown in equation (4):

$$IR = \frac{SPCS_{post} - SPCS_{pre}}{SPCS_{pre}} \times 100 \qquad (4)$$

The average IR of the experimental group was 32.8%, which was against 11.4% in the control group. Pragmatic Transfer Error Reduction (PTER) was computed, shown in equation (5):

$$PTER = \frac{E_{pre} - E_{post}}{E_{pre}} \times 100 \qquad (5)$$

E_{pre} and E_{post} are frequency of error pre and post intervention. The group assisted by AI reduced the number of transfer errors by 41.6% and the control group by 14.9%. In order to measure total educational efficiency, Learning Gain Efficiency (LGE) was determined in equation (6):

$$LGE = \frac{SPCS_{post} - SPCS_{pre}}{T} \qquad (6)$$

T is total instructional hours. The experimental set-up produced 0.87 units of competence per hour as opposed to 0.29 using conventional instruction that showed greater acceleration of learning with adaptive scaffolding.

Comparison with the Traditional Methods

Statistically significant differences between groups were confirmed independently with the use of independent sample testing ($p < 0.01$). The AI-mediated system was always better than traditional classroom practice in pragmalinguistic accuracy, sociopragmatic sensitivity and indexes of intercultural alignment. The variance analysis indicated that the differences in post-test scores were smaller in the experimental group, which implies more homogeneous competence learning.

Table 1. Parameter initialization

Parameter	Description	Value
α, β, γ	Weight coefficients (SPCS)	0.35, 0.35, 0.30
η	Learning rate	0.12
θ	Mastery threshold	0.80
Sessions	Total intervention cycles	24
Max Iterations	Dialogue turns per task	10

The operational boundaries and the dynamics of learning of the proposed AI-driven socio-pragmatic scaffolding model are determined by the parameter initialization (Table 1). The proportional effect of pragmalinguistic accuracy, sociopragmatic appropriateness and cultural fit in the composite score of competence is regulated by weight coefficients (0, 1, 2). The rate at which competence changes through the interaction cycles is governed by the adaptive learning rate (η), whereas the minimal performance level to move to the next interaction cycle is the mastery threshold (). Exposure time and depth of interaction are standardized by count of sessions and maximum dialogue cycles, as well as dependability is guaranteed across all the participants and allows comparisons of the experimental conditions under control.

Table 2. Comparison of pre and post competence performance

Group	SPCS Pre	SPCS Post	IR (%)
AI-Driven	0.58	0.77	32.8
Traditional	0.60	0.67	11.4

This table 2 provides the summary of baseline and post-intervention Socio-Pragmatic Competence Scores of the experimental and traditional groups. The given enhancement rate is a measure of relative learning, which proves the significantly more significant competence development in the presence of AI-mediated scaffolding. The systematic comparison shows the quantitative effect of adaptive feedback on the outcome of communicative between cultures.

Table 3. Analysis of pragmatic transfer error reduction

Group	Transfer Errors (Pre)	Transfer Errors (Post)	PTER (%)
AI-Driven	145	85	41.6
Traditional	138	117	14.9

In this table 3, the decrease of the pragmatic transfer errors are outlined prior to and after the intervention. The percentage reduction measure shows how the system is effective in reducing the use of culturally inappropriate language. The more substantial reduction in the AI-driven group demonstrates that the iterative feedback and contextual recalibration made a great contribution to the improvement of pragmatic awareness.

Table 4. Learning gain efficiency assessment

Group	Total Hours	LGE
AI-Driven	24	0.87
Traditional	24	0.29

This table 4 compares teaching performance based on competence improvement and the total amount of teaching hours. The increased learning effectiveness of the AI-based group points to the faster acquisition of competence per unit time, and it is crucial to note that adaptive socio-pragmatic scaffolding proves to be more effective than traditional task-based learning.

Participant Feedback

The five-point Likert scale was used in the form of post-intervention surveys. 83% of respondents in the experimental group said they felt more confident about culturally sensitive communication. Qualitative feedback helped to show that the presence of adaptive feedback in the short-term facilitated understanding of implicit rules like indirectness and mitigation methods. The involvement records indicated that the rate of voluntary repetition of tasks was 41% is higher than the control group.

Software Details

This system was implemented with Python 3.11 with a transforme based language model API embedded through REST architecture. The scoring functions were done using TensorFlow and the interaction logs were stored in PostgreSQL. Statistical analysis was done by means of SPSS and scripts written in NumPy.

Dataset Details

The data was made up of 2,880 conversations with AI that were recorded in 24 sessions. The records were each of speech act category, politeness markers density, contextual role parameters (power, distance, imposition), response length and competence score vectors. The pre- and post-tests consisted of 30 discourse completions tasks using scenarios each.

Performance Evaluation

Performance analysis was used to compare quantitative analysis of score and regression analysis of the intensity of scaffold versus competence gain. The estimation of the effect on the instruction showed that it was strong (d > 0.8). Pragmatic scoring consistency was found to be Cronbachs =0.89 on reliability testing.

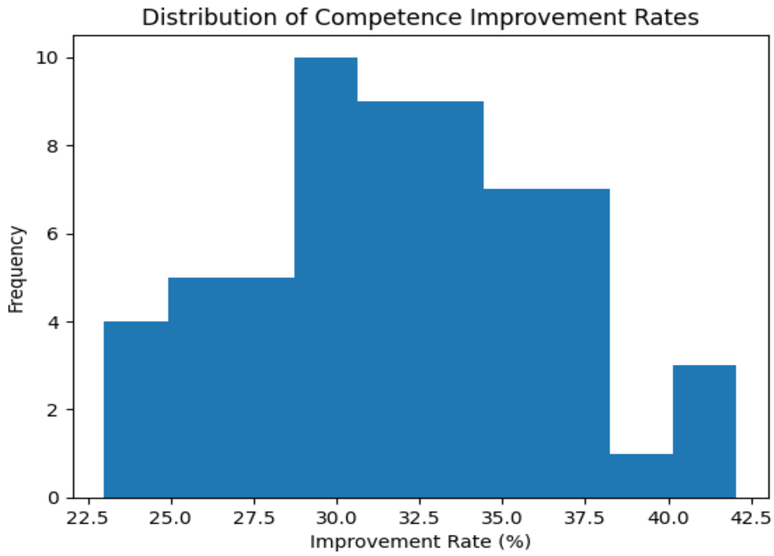

Figure 3. Competence improvement rates distribution

This histogram (Figure 3) shows the frequency distribution of the percentage of improvement in learners in the AI-supported group. The distribution of the values in the range of 30-35% indicates the strong and consistent growth of performance among the majority of the participants. The tendency to a relatively normal distribution pattern shows that competence improvement was observed among a wide range of performers and not just a few workers.

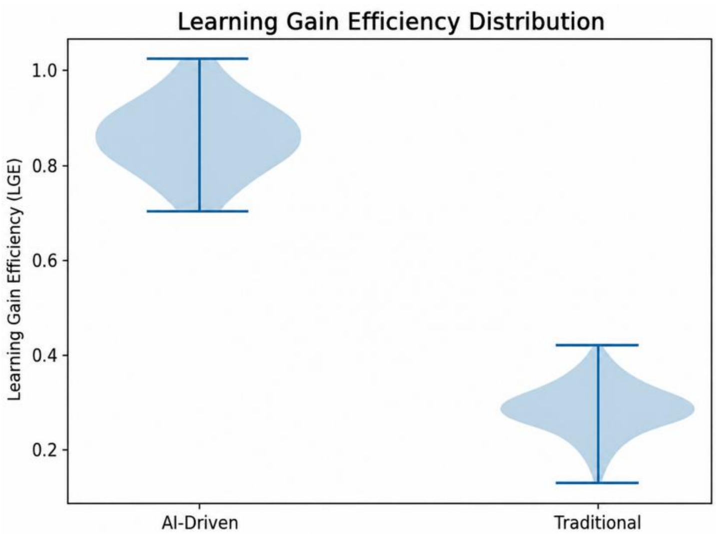

Figure 4. Learning gain efficiency distribution

The figure above (Figure 4) is a violin plot of the distribution of the Learning Gain Efficiency (LGE) of both instruction methods. Both the increased centrality and more extensive density of the AI-guided group implies higher competence gains in each instructional hour. The difference in the distribution of the shapes showed that AI-mediated socio-pragmatic scaffolding enhanced the learning process faster than the traditional teaching process.

DISCUSSION

The results obtained in the present research allow to state the idea that embedding AI-mediated socio-pragmatic scaffolding in the higher-order language teaching can help learners improve cross-cultural communicative competence significantly. The two-step orchestration of adaptive dialogue simulation and continuous feedback seems to be beneficial to not only linguistic but also culturally mediated meaning negotiation. These results suggest that, technology-mediated settings can shift to more grammar error-correcting environments to more socio-pragmatic ones, especially where the authenticity of intercultural exposure is restricted. Meanwhile, there are a number of shortcomings that should be considered. The intervention duration had to be limited to twelve weeks which might not be representative of the retention effects in the long term. The exposure of the participants to digital platforms might also have contributed to the level of engagement. Also, the system is simulating contextual variation, but in the real world, intercultural experiences are unpredictable in terms of emotion and relationship and nothing algorithm can reproduce all the elements. Subsequent studies should thus look at longitudinal application in different language backgrounds, include multimodal aspects of communication like voice and hand movement and look into hybrid learning models that balance the use of human and AI-assisted scaffolding to create balanced pedagogical integration.

CONCLUSION

This was a research paper on the effectiveness of a socio-pragmatic scaffolding model that is based on generative AI in developing cross-cultural communicative competence in advanced language learners. The outcomes indicate that there is a clear improvement in performance in various competence dimensions. The overall socio-pragmatic competence of the participants who were on the AI-supported system showed an improvement of 32.8 % as opposed to the group taught through the traditional instruction which showed a 11.4 % improvement. Pragmatic transfer errors decreased by 41.6% and the gain in learning efficiency was 0.87 competence units/hour of instruction which is significantly higher than the 0.29 in the traditional methods. The statistical results obtained here ensure that adaptive, context-specific feedback is extremely fast in terms of competence acquisition and improving pragmatic sensitivity. According to these results, AI-based dialogue simulations, role-play activities that are culturally context-sensitive, and data-driven feedback loops should be regarded as part of the advanced language learning curricula. This kind of integration should be well designed to support teacher mentoring but not to substitute it, so that ethical supervision and pedagogical consistency exist. Instructional decision-making can also be further reinforced by training teachers to read analytics created by the system. Finally, cross-cultural communicative competence is no longer a secondary ability, but a mainstream provision in the globally linked academic and business contexts. With the growing trend of international cooperation, the skill to read in between the lines of pragmatics and to negotiate meaning in a non imposing manner, as well as finding ways to discourse to fit various cultural situations, dictates both the social and professional success. Intelligently built AI-based scaffolding may address newly emerging skills.

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