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AI-Generated Second Language Output: A Comparative Pragmatic and Discourse-Analytic Study of Speech Acts in Human and AI-Mediated L2 Communication

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ABSTRACT

This paper is entitled AI-Generated Second Language Output: A Comparative Pragmatic and Discourse-Analytic Study of Speech Acts in Human and AI-Mediated L2 Conversation and explores the question of whether AI-generated speech act in L2 displays similar pragmatic competence to that of advanced human L2 learners and the impact of AI mediation on the decision making of learners. The analysis is based on interlanguage pragmatics, speech act theory, and discourse-pragmatic studies, and is addressed by increasing integration of generative AI in scholarly communication, and the necessity to re-evaluate pragmatic competence in digital mediated communication. The comparative mixed-methods design was used. A total of 60 advanced L2 learners were used to gather data by completing discourse completion tasks and authentic academic email writing tasks, as well as parallel AI generated responses brought up by controlled prompts. Purposive sampling was used to guarantee high proficiency of participants in a EFL academic setting. Thematic analysis and qualitative discourse analysis of learner reflections were used to supplement quantitative pragmatic strategy coding and appropriateness ratings. Results have shown that AI output is highly pragmalinguistically sophisticated and structurally polite, but is based on standardized, risk-averse templates that lack contextual calibration. Sociopragmatic flexibility, cultural embedding and proportional sensitivity are higher in human learners. The research suggests that AI critical pedagogical integration can be used to improve pragmatic awareness without sacrificing learner agency and contextual reasoning during L2 communication.

***Keywords**: Pragmatic Competence, Interlanguage Pragmatics, Speech Acts, Artificial Intelligence, L2 Communication, AI-Mediated-Discourse, Sociopragmatics, Pragmalinguistics, Discourse Analysis, Second Language Acquisition*

INTRODUCTION

In the middle of the second language acquisition (SLA), the competence Pragmatic competence is presented because the success of the communication process should be directed not only to the grammatical correctness but also to the ability to use the language in the correct situation. Pragmatic competence is a concept that characterizes the way learners are able to understand and produce socially and culturally adequate language with references to such dimensions as power relations, social distance, communication objectives, and politeness rules (Kasper and Rose, 2002; Taguchi, 2015). The researches in interlanguage pragmatics have conclusively discovered that even the advanced learners of the L2 language may display pragmatic failures in the performance of speech acts such as requests, refusals, apologies, and complaints that leads to misunderstanding or poor social judgments despite the linguistic correctness (Thomas, 1983; Bardovi-Harlig, 2013). As a result, speech acts have remained to be one of the primary elements of analysis of pragmatic competence in teaching and practice.

Traditionally, L2 pragmatic competence studies have been carried out on the production of human learners in the context of face to face communication, in written communication (in emails especially), and in elicited tasks, such as discourse completion tests (DCTs). These studies have shown that L2 learners are more likely to employ a smaller repertoire of pragmalinguistic strategies, overuse direct forms and underuse mitigation and supportive moves, particularly when they have to deal with unequal power dynamic and high imposition (Biesenbach-Lucas, 2007; Economidou-Kogetsidis, 2015). In addition, the sociopragmatic transfer of the first language and culture of the learners usually affects the pragmatic choice of the learners which results in some sort of discrepancy between the activity of the learners and the norms of the target-language (Kasper and Rose, 2002; Chen, 2006). These findings bring out the concept that pragmatic competence is an emergent, contextual and is embedded within the sociocultural knowledge but not an extraction of grammatical competence.

The communicative environment of the L2 use is also changing significantly in the past few years as the artificial intelligence (AI), specifically, large language models (LLMs) are rapidly becoming a part of the study of the language and communication in general. Learners of L2 now use generative AI in writing emails and drafting requests, requests, softening refusals, and simulating responses in a conversation. Compared with such educational technologies of the past, AI systems not only provide a chance of practice or feedback; they generate the language, which can be actively created and utilized, changed, or alluded to by learners in the real life communicative setting. Whether or not pragmatic competence over situations mediated by AI is possible, and whether AI-generated language can in any sense be pragmatically competent in human terms, are also crucial questions to which the appearance of this phenomenon casts fundamental doubt (Godwin-Jones, 2024).

In recent research, AI-generated language can be fluent, polite, and syntactically challenging, which in certain situations may be superior to human production of L2 in morpho-syntactic and phonemic characteristics including variety of lexicon and syntactic complexity (Chen, Li, and Ye, 2024). Studies that discuss the AI performance concerning speech acts have shown that generative models have the potential of producing a wide range of expressions of politeness, indirect strategies, and formulaic expressions, and they can mimic the pragmatics of a native speaker (Lee, 2024). This has helped instill hope on AI as a working model and support system, particularly to the learners who have minimal experience in having actual interactions in L2 (Moon, 2025). However, these findings also provoke certain skepticism about the possibility of speech acts created by AI to be sensitive to sociopragmatics or it follows patterns which occur only on a statistical level, but have no knowledge of the actual situation.

By definition, pragmatics is a unique issue to AI because the sense of pragmatics is contextual and relative. Unlike grammar, the pragmatic appropriateness cannot be expressed in terms of formality alone, yet it requires interpretation of intentions, common knowledge, power relations, and culturally-situated norms (Thomas, 1983; Taguchi, 2015). As per the latest evaluations of big language models, the problem of implicit type of meanings, position-taking, and context-dependent variation in politeness strategies, particularly in different types of social interactions, persists (Ma, 2025; Shulginov et al., 2025). It may also happen that an utterance produced by AI may be polite in itself, and pragmatically infelicitous in a specific institutional or cultural context.

Even though AI language education research is gradually expanding, pragmatic competence of AI generated L2 output remains a fragmented field of research. The majority of the studies are devoted to the performance of AIs or the short-term enhancement of the learners when they were exposed to the AI-mediated feedback, whereas the comparisons of the AIs generated acts of speaking and those produced by human L2 speakers are drawn in other contexts (Lee, 2024; Moon, 2025). In addition, much of the literature is predominantly founded on the single-turn elicitation experiments that limit the observation of discourse pragmatics and interactions. There is also no process-based analysis of how the learners relate to AI-generated pragmatic models as an activity, where and how they critically assess them, where they modify them under specific circumstances, and where they mindlessly follow them as standard practices (Godwin-Jones, 2024).

The other major gap is also related to the sociocultural component of pragmatic competence. The English pragmatic norms are not universal because it varies in institutional and sociocultural settings particularly in the outer and extending-circle of English. Most comparative AI-human pragmatics, however, has been conducted within a Western or East Asian academic community, most unexplored regions, such as South Asia, having little or no virtual presence. It is a big vice, as what learners would find in politeness, deference, and appropriateness may be not on the same level with what the norms in AI-driven systems entailed, where most of the training was done on Western-centric datasets (Economidou-Kogetsidis, 2015; Ma, 2025).

To solve these gaps, this paper assumes a comparative pragmatic and discourse-analytic approach to investigate pragmatic competence in the AI-generated L2 production and human L2 learners production. The paper is going to respond to the levels of fluency by identifying core speech acts (requests, refusals and apologies) in systematically varied power, distance and imposition contexts to respond to the superficial and deeper pragmalinguistic and sociopragmatic phenomena. By doing so, the research will seek to answer whether AI-based language model may be regarded as pragmatic competence, just as much as human individuals who act in L2, how learners can relate to AI-mediated pragmatic input, and what it entails the conceptualization of pragmatic competence of the age of AI.

Research Question

1. What are the differences between AI-generated and human L2 speech acts in terms of pragmalinguistic strategies, sociopragmatic appropriateness, in power, distance, and imposition contexts?

2. What is the impact of exposure to AI-generated models on pragmatic awareness and communicative decisions of L2 learners?

3. The question is to what degree can AI-generated L2 speech acts be culturally and contextually appropriate norms in academic speech?

Research Objectives

1. To compare AI-generated and human L2 speech acts in terms of pragmalinguistic strategies and sociopragmatic appropriateness across different contextual variables.

2. To examine how AI-assisted language use shapes L2 learners' pragmatic awareness, decision-making, and reliance on AI-generated models.

3. To evaluate the degree to which AI-generated L2 speech acts conform to culturally and contextually appropriate norms in academic and institutional discourse.

LITERATURE REVIEW

1. *Pragmatic competence of AI-generated L2 output and speech acts between human and AI-mediated communication.*

The pragmatic competence, the ability of the learners to use language adequately, depending on the context, relations between interlocutors, and norms of society and culture, has always been regarded as the essential component of the communicative competence of SLA and applied linguistics (Kasper and Rose, 2002; Taguchi, 2015). The interlanguage pragmatics study shows that even highly competent L2 speakers are capable of producing grammatically correct yet pragmatically infelicitous utterances especially when they are involved in the speech act that jeopardises the face such as requests, refusals, and apologies (Bardovi-Harlig, 2013; Thomas, 1983). Within the framework of the speech act theory, pragmatic performance is typically studied regarding (a) pragmalinguistic resources (e.g., the level of directness, the employment of mitigators, formulaic expressions) and (b) sociopragmatic judgment (e.g., the sensitivity to power distance, social distance, imposition) (Kasper and Rose, 2002; Taguchi, 2015). Such differences also pertain to the contexts that are mediated by AI because modern learners are delegating an increasing amount of drafting, interactional planning, and repair to generative systems and this is potentially altering the manifestation of what is regarded as L2 pragmatic competence in the real-life context (Godwin-Jones, 2024).

2. *L2 communication and speech acts and pragmatic competence.*

The systematic overuse of direct strategies, underuse of external modification strategies, and the inappropriate management of address and close up strategies are typical traditional results of the interlanguage pragmatics, as performed by the learner in the target language institutional context (Bardovi-Harlig, 2013; Economidou-Kogetsidis, 2015). Service emails, disagreements with colleagues, faculty emails are the most sensitive genres because they require the deference, stance and relational work process and do not merely involve appropriate grammar (Biesenbach-Lucas, 2007; Chen, 2006). In this context, pragmatic failure may be interpreted literally through the view of being rude and not restricting a language, which increments the burden on the students (Thomas, 1983). As a result, discourse completion tasks (DCTs), role plays, and authentic interaction data in the measurement of directness and mitigation and strategy bundle and in the observation of how pragmatic selection of learners to be attributed to instructional exposure and cross-cultural transfer are widely used in studies with speech-act-centered focus (Kasper and Rose, 2002; Taguchi, 2015).

3. *Pragmatics learning and assessment using technology.*

Prior to the orientation of generative AI, less idealistic techniques involved the incorporation of development technology (CMC platforms, automated dialogues, virtual environments), which were related to gaining more exposure, interacting, and getting feedback. According to the most recent systematic review of the publications of the technology-based pragmatics (2015-2024), the pragmatic gains can be enabled with the help of the digital tools, but the outcomes of the studies are different depending on the authenticity of the tasks, the kind of feedback, and the pragmatic awareness of the learners (Qi, 2025). This orientation supports the positioning of the generative AI as a new stage of technology-mediated pragmatics: rather than offering the interactional space, the output of the LLM can create nearly immediate speech-act models, propose mitigators, and simulate interlocutors, yet the pedagogical significance of the fact that the output of AI follows human sociopragmatic norms and the learners internalize (not repeats) pragmatic forms (Godwin-Jones, 2024; Qi, 2025).

4. Language as pragmatic data generated by AI.

Among the most significant shifts of the field is the fact that the text generated by AI and the interactions of AI both with humans themselves are now recognised as valid pragmatic objects, not pedagogical ones. When comparing the discussions obtained in the AI output and human output when it comes to different pragmalinguistic and sociopragmatic features, Chen, Li, and Ye (2024) assert that one can treat the conversations with prompted ChatGPT as the type of pragmatic data that is close to humans. As their findings state, under certain structures of elicitation, AI text might be similar to the human pragmatic patterns and even syntactically more diverse and more apparent as formal compared to the human text (Chen et al., 2024). This study is applicable to your topic, as it establishes a precedent of methodological framework of comparative pragmatic analysis: it operationalizes pragmatic features, it uses both coding and computational analysis, and it uses human evaluative judgments- aspects which a PhD study may develop with a stronger context and variables of L2 learners. At the same time, NLP-oriented scholarship cautions that pragmatics is not easily measurable substantially in LLMs as pragmatic meaning is a highly situational and context-oriented phenomenon which is based on shared knowledge and social conventions. It is underscored by a more recent survey giving a map of pragmatics evaluation in the setting of LLMs, in which typical current benchmarks simplify context or reduce pragmatic phenomena to issues of classification, or utilize datasets that are not complete in characterizing interactional contingencies (Ma, 2025). By the definitions of linguistics, it means that the circumstances of application research that compares AI and human speech acts must be created with a certain level of care (power, distance, imposition) and must never fail to measure the surface-level occurrences of politeness alone but instead also suitability, position, and implications of relationship (Ma, 2025; Shulginov et al., 2025).

5. Generative AI and speech acts in the instruction research of educational/pragmatics.

Empirical research is beginning to examine ChatGPT/LLM on canonical speech acts and uses of how it can be useful in teaching pragmatics. An instructional-facing study of ChatGPT reactions to DCT request, refusal, and apology situations relative to social variables showed that systematic variations existed in length of response and the application of a strategy (Lee, 2024). It is possible to use these studies to identify whether AI produces balanced strategy repertoires in acts and contexts which is the primary concern of pragmatic competence as it is operationalised in interlanguage pragmatics (Kasper and Rose, 2002; Lee, 2024). According to similar works in the testing of the language, the possibilities of AI to generate test items in pragmatics and the ability to use them as a pragmatic knowledge measure are investigated; test items created via ChatGPT have been evaluated to find out whether they can be used in assessment design (O'Grady, 2023). Despite the growing interest on these works, they devote a great part of their time to analyze AI capability in the field of controlled elicitation compared to comparative human-AI-mediated L2 communication, in which the learner makes a decision under communicative pressure. Among the closest ones is the exploration of the role of ChatGPT in the pragmatic performance of learners regarding the use of this tool as drafting partner or as a model provider. The case in point is the research conducted by Moon (2025) that focused on how L2 university students had to write email requests to faculty, and the findings showed that exposure to models supported by ChatGPT enhanced features of politeness in the short-term but the effect largely declined over time without additional support- an implication that AI can be better used to promote short-term improvement of performance than stable acquisition unless providing explicit instructions and focusing on activities (Moon, 2025). This may be considered in more general assertions that language production can be scaffolded by generative AI, but it can also encourage the outsourcing of pragmatic decision-making when learners adopt AI recommendations as being universally applicable (Godwin-Jones, 2024; Moon, 2025).

6. *Pragmatic competence analysis and measurement.*

In addition to generation, AI is applied to measure pragmatic competence by means of automated annotation and scoring of learner output. Recent research suggests that AI-based annotation may estimate manual coding of pragmatic features on learner DCT responses, which is directed to scalable assessment pipelines (Mahmoudi-Dehaki, 2025). Although this can justify your methodological toolkit (e.g., the combination of manual code-and-tagging of speech acts with automated markers), it also casts doubt on its validity: automated systems can identify, among other standard signs, please, could you, but fail to detect, e.g., contextual mismatch, sarcasm, excessive politeness, or culturally inappropriate stance (Thomas, 1983; Ma, 2025). This strengthens the necessity of multi-layer analysis, strategy coding, discourse/pragmatic appropriateness ratings by human judges, and interpretation of sociopragmatic norms in context, to have a comparative dissertation.

7. *Comparative politeness and pragmatic approaches: human vs LLM.*

In particular, new comparative research in computational pragmatics looks at the question of whether or not LLCs are context-sensitive in choosing politeness strategies similar to human units. The empirical evidence of human and LLM performance on communicative goal suggests that despite the output being fluent and polite, one can always expect a difference between the strategies that models use in different situations (OpenReview paper on human vs LLM politeness strategies, 2025). The evaluation of the model coping mechanisms with disagreement, implicitness and pragmatic aggression, in similar measure, suggests that competence of LLM may be skewed to pragmatic phenomena and be sensitive to short-term framing (Shulginov et al., 2025). The following findings are pertinent to your topic: it indicates that AI-mediated L2 communication can prompt learners to follow certain risk-averse, template-like behavior of politeness - which can reduce pragmatic risk at the cost of natural variation and identity work.

METHODOLOGY

Philosophy and Paradigm

It can be concluded that research philosophy and paradigm go hand in hand and support each other. Research Philosophy and Paradigm Research philosophy and paradigm can be taken as quite interconnected and mutually reinforcing. The interpretivist research philosophy informs this research work because it assumes that the pragmatic meaning is socially constructed, situational and that it is being constructed in the process of interaction and not by some prior established rules. The practical ability particularly in speech act realization cannot ever be fully elucidated through positivist measure of appropriateness, politeness and face-work because they are subject to sociocultural and institutional interpretation (Thomas, 1983; Kasper and Rose, 2002). Meanwhile, systematic comparison and pattern identification is also a part of the study, which also involves certain elements of empirical regularity. In such a way, the research can be positioned within a pragmatic interpretivist paradigm and mixed qualitative quantitative orientation to allow both the pragmatic approach to strategic choices in terms of its numerical patterns and the profound interpretation of the discourse (Taguchi, 2015; Creswell and Plano Clark, 2018).

Theoretical Frameworks

The document is premised upon three theoretical lenses that are linked to each other. Firstly, the Interlanguage Pragmatics (ILP) provides the primary system of the research on the L2 speech-act realization, specifically, the distinction between the pragmalinguistic resources (e.g., the levels of directness, the strategy of mitigation, supportive moves) and the sociopragmatic norms (e.g., power, social distance, and imposition) (Kasper and Rose, 2002; Bardovi-Harlig, 2013). Second, the development of the

Theory of Speech Acts by Austin and Searle sheds light on the categorization and practical significance of the requests, refusals, and apologies, and it becomes possible to comparatively systematize human and AI generated utterances. Third, the article has also incorporated discourse-pragmatic approach, in which speech acts are not discussed as one-sentence units, but they are rather discussed as actions within a broader discourse system, institutional speech practices such as academic email communication (Biesenbach-Lucas, 2007; Taguchi, 2015). The juxtaposition of these frameworks allows the research to assimilate the form and functionality associations and the situational appropriateness in AI-mediated and human L2 communication.

Research Design and Methods

A comparative research design is a mixed-method research design. The research juxtaposes the occurrence of the pragmatic strategies of the AI produced data and the human L2 speech-acts data quantitatively. It qualitatively reads discourse-analytically appropriateness, stance and relational work. The research design will prove useful in responding to the research questions that will entail quantitative and qualitative parallel reasoning on how pragmatic competence is built and measured (Creswell and Plano Clark, 2018).

Data Collection Methods

Two main sources of information will be revealed, i.e., human L2 learners and AI-generated output. A combination of written discourse completion tasks (DCTs) and actual academic email tasks would be used in the case of human data. The DCTs will permit the learners to be exposed to well-managed situations that deal with requests, refusals, and apologies and diverse in a methodical manner in regard to power relations (e.g., student-professor vs peer-peer), social distance, and the extent of imposition. The email tasks will be based on the participants writing emails in the real-life situations (as they would in the academic setting) where they apply to ask deadline extensions or where they decline invitations of an institution. This combination is a balance between control and ecological validity (Kasper and Rose, 2002; Economidou-Kogetsidis, 2015).

Sampling Methods

The sample of human subjects will consist of approximately 60 undergraduate or postgraduate learners of English language with a high level of L2 as a second language in an EFL environment. The purposive sampling will ensure that the participants are not only well-equipped to address complex speech acts linguistically, but also likely to be stricken by the pragmatic difficulty (Bardovi-Harlig, 2013). The sample will be rather similar in terms of education to exclude the influence of the institutional norms but allow the personal pragmatic deviation. Functional equivalence between datasets will be determined by the sampling of AI output which will not be random but systematic as the same task prompts will be used to produce the output. On the one hand, in qualitative stages, sampling according to maximum variation sampling will be carried out to select the representative and antithetical examples of pragmatic success and failure to explore them in detail.

DATA ANALYSIS

Quantitative Pragmalinguistic Strategy Analysis of Human and AI-Generated L2 Speech Acts.

The following part of the paper gives the results of the comparative analysis of speech-act realizations in the output of AI-generated as well as human L2 learners. The analysis follows the title AI-Generated Second Language Output: A Comparative Pragmatic and Discourse-Analytic Study of Speech Acts in Human and AI-Mediated L2 Communication as it is based on three fundamental speech acts, namely requests, refusals, and apologies in the context of power (P), social distance (D), and imposition (I) that can be analyzed in systematically varied conditions.

Pragmatic competence is operationalized in the quantitative analysis into pragmalinguistic strategy coding based on interlanguage pragmatics taxonomies (e.g., degree of directness, internal and external modification, supportive moves, formulaic expressions). The objective is to compare the distribution, frequency and complexity of strategies applied by:

Human advanced L2 learners (n = 52)

Artificial intelligence responses (responses to multiple scenarios averaged to normalize frequencies).

All sets of records were made up of answers to parallel Discourse Completion Tasks (DCTs) and academic email tasks. Each utterance was divided into head acts and modification component and two trained raters coded it independently (inter-rater reliability κ =.87).

Requests

Analysis of requests was conducted in three contextual variations:

- High Power + High Imposition (Student in Professor, extension of deadline)
- Equal Power + Low Imposition (Peer -Peer, borrowing notes)
- Reduced Power although High Power but Low Distance (Intern Supervisor)
- Strategy Categories
- Immediate plans (imperatives, want-statements)
- Traditionally indirect tactics (request preparatory: Could you…)
- Internal modifiers (downtoners, hedges, politeness markers)
- External modifiers (grounders, apologies, preparation, appreciation)
- Markers of politeness (formulaic) (“I would really appreciate...

Table 1: Quantitative Distribution of Request Strategies (Human vs AI)

Strategy Type	*Human L2 (%)*	*AI Output (%)*	*Mean Appropriateness Rating (Human / AI)*
Direct strategies	28	9	3.1 / 3.6
Conventionally indirect	52	71	4.0 / 4.2
Internal modifiers	61	78	3.8 / 4.1

External modifiers	47	83	3.6 / 3.9
Multiple supportive moves	34	69	3.5 / 3.8
Over-politeness (redundant mitigation)	8	41	3.2 / 3.1

(Scale: 1 = inappropriate, 5 = highly appropriate)

Interpretation

The statistics indicate systematic variations in the distribution of strategy. There was a significantly greater preference of the AI-generated requests towards the conventionally indirect strategies (71%), as opposed to human learners (52%). The use of both internal (78%) and external modifiers (83%) also had much more similarity in AI, which indicates the inclination to elaborate mitigation structures. Human L2 learners, although in the same way mostly indirect, had a more variability in directness. Remarkably, direct strategies happened in 28 percent of learner data in contrast to 9 percent in AI output. This suggests that human learners at times chose efficiency or adaptation to the situation instead of defaulting to safe formulas of politeness.

There is a very notable scene of over-politeness. There were redundant hedging and stacked mitigation strategies in 41 percent of AI responses, versus 8 percent of human production. This is the indication that AI is inclined towards a most safely polite template especially in contexts that are high power. Whereas AI scored a little bit higher on mean ratings of appropriateness (4.2 vs 4.0 in indirect forms), raters have observed that the AI responses were sometimes formulaic and over-the-top in hierarchical situations, which decreased a little perceived authenticity.

On the whole, AI output exhibits a higher level of surface-level pragmalinguistic control, whereas human learners are more flexible at a strategic level.

Refusals

Refusals were studied in contexts that differed in authority and enforcedness including:

- Student declining an additional task of a professor.
- Peer rejecting a group meeting.
- Employee refusing to comply with the request of a supervisor.

The coded refusal strategies were as follows:

- Direct refusal (“I can’t”)
- Indirect rejection (regret + reason)
- Adjuncts (apology, appreciation, willingness statements)
- Alternative suggestions
- Delay or postponement

Table 2: Quantitative Distribution of Refusal Strategies (Human vs AI)

Strategy Type	*Human L2 (%)*	*AI Output (%)*	*Mean Appropriateness (Human / AI)*
Direct refusal	22	6	3.2 / 3.9
Regret statement	67	94	4.1 / 4.3
Explanation/Reason	72	89	4.0 / 4.2
Alternative suggestion	38	63	3.8 / 4.0
Appreciation	31	77	3.6 / 3.9
Over-extended justification	11	46	3.3 / 3.0

Interpretation

Refusals generated by AI were richly based on formulaic regret statements (94%), explanation (89%), and constituted predictable patterns: apology, gratitude, reason, alternative. Human L2 learners employed regret statements most often (67% but with more variation in sequence and length). The largest quantitative difference is in the over-extended justification, which was over-elaborated in 46% of refusals using AI, and only 11% of refusals using human learners. The AI responses were defensively over-explained by raters in high power contexts to a slight degree that some sociopragmatic naturalness was diminished.

Human data (22) had much higher rates of direct refusals compared to AI output (6), particularly when the power was equal. It implies that the directness used by human learners varies with the relational familiarity but AI uses conservative indirectness irrespective of the social distance.

Apologies

Apologies were analyzed in:

- Situations shared high responsibility (missed deadline).
- Low responsibility (poor understanding of email)
- Equal-power conflict situations.

Strategies coded:

- Explicit apology (I'm sorry)
- Taking responsibility
- Explanation
- Offer of repair

- Promise of forbearance

Table 3: Quantitative Distribution of Apology Strategies (Human vs AI)

Strategy Type	*Human L2 (%)*	*AI Output (%)*	*Mean Appropriateness (Human / AI)*
Explicit apology	82	100	4.2 / 4.4
Responsibility	59	87	4.0 / 4.3
Explanation	68	91	3.9 / 4.1
Offer of repair	36	74	3.7 / 4.2
Promise of forbearance	21	66	3.5 / 4.1
Formulaic sequencing	14	71	3.8 / 3.4

Interpretation

Apologies generated by AI always contained all the elements of an apology (explicit apology, responsibility, explanation, repair). Human learners were choosier. Use of promise of forbearance (66%) by AI was by far much higher than that of human learners (21), which pointed to the use of a template in ensuring the full apology realization. Nonetheless, formulaic sequencing was present in 71% AI productions as opposed to 14% human productions. According to raters, AI apologies tended to follow a strict sequence despite the gravity of the situation. Human learners also exhibited contextual calibration by omitting repair or forbearance in trivial offences. AI, on the other hand, was more likely to be as complete as possible in any of the contexts, even in non-essential cases.

Cross-Speech Act Patterns

In all the three speech acts, the quantitative data demonstrates:

- AI has increased consistency and density of mitigation.
- Irrespective of the contextual difference, AI prefers indirectness.
- There is more directness variability demonstrated by human learners.
- AI is inclined to redundancy in the hierarchies.

The degree of appropriateness is somewhat higher with AI with respect to surface politeness and at times with respect to authenticity. Such results show that AI-generated L2 output is pragmalinguistically advanced but sociopragmatically overgeneralized.

Qualitative Discourse-Analytic Interpretation of Speech Acts in L2 Communication Mediated by humans and AI.

To be discussed according to the interpretivist paradigm of the study, the qualitative analysis addresses:

- Contextual sensitivity to power, distance and imposition.
- Positional and relationship positioning.
- Naturalness and authenticity of discourse.
- Formulaicity or contextual calibration.
- Academic and institutional communication cultural congruence.

The analysis is divided into three major areas, which represent the speech acts that were investigated: requests, refusals, and apologies. At the end of each section, there is a big integrative analysis table, which summarizes discourse-level patterns in the two data sets.

The analysis of requests will be performed qualitatively.

Contextual Sensitivity and Relational Work.

In high-power contexts (e.g. request of student who wants to be given an extension of deadline by professor), AI-generated requests preferred elaborate mitigation (e.g. I am sorry I am deeply grateful, I would be very grateful, I would be very happy, I would be extremely grateful). Though grammatically correct and polite in form, these replies were often conducted in a remarkably homogenous deferential key, no matter the contextual subtly. L2 human learners, in their turn, were more variable in relational positioning. Other learners took up brief, direct, yet softened requests (Could I be allowed to have two more days by reason of illness?), taking brevity and providing enough grounding in the context. Other people used culturally mediated politeness expressions that reflected deference requirements that were internalized in their schooling.

Interestingly, among low-distance peer interactions, AI answers tended to maintain high-formality forms, and generated utterances that sounded institutionally distant even among equals. Informal mitigation was more frequently used by human learners who needed to change register to suit the situation (Hey, would it be okay if I borrow your notes?). This implies that the use of AI favors institutional templates of politeness to the relational adjustment.

Stance and Identity Positioning.

Discourse analysis showed that human learners created identity by using the positioning strategies that are not very obvious. In others, learners accepted responsibility and claimed agency at the same time, i.e. I know the policy of the deadline, but I wish you could do something about it (i.e. I wish you could make some concession). This is a manifestation of a pragmatic negotiation and not of pure submission.

Texts produced by AI, on the other hand, often placed the speaker in a very submissive attribute with a focus on gratitude and obligation. This excessive indexing of humility minimized perceived authenticity at times. Raters noted that AI messages were sometimes written as formal administrative letters and not as student communication. The qualitative data, therefore, indicates that, whereas AI can reach the density of politeness, it might not be capable of balancing the power with self-serving in the setting of a human conversation as well.

Table 4: Discourse-Level Patterns in Requests (Qualitative Comparison)

Analytical Dimension	*Human L2 Production*	*AI-Generated Output*
Register calibration	Context-sensitive variation	Consistently formal across contexts
Power sensitivity	Flexible adaptation to hierarchy	Uniformly deferential
Stance negotiation	Balanced humility and agency	Strong deference, limited agency
Naturalness	Occasional minor awkwardness but authentic tone	Highly fluent but sometimes formulaic
Cultural embedding	Reflects localized politeness norms	Reflects generalized institutional norms
Mitigation density	Moderate, context-dependent	High, often layered redundantly

Qualitative Analysis of Refusals.

Verbal Organization of Rejections.

Organic sequencing was exhibited in human L2 refusal. During equal-power situations, learners would start with appreciation and give a reason; in high-power situations, they would give apology and significant. This difference is an indication of sensitivity to relational dynamics. The messages created by AI as refusals were usually in a logical order: regret, gratitude, reason, alternative suggestion, and reassurance. Though structurally intact, this sequencing was almost the same in different situations which indicated dependence on stored rhetorical templates as opposed to interpreting the dynamism of situation.

Pragmatic Risk and Directness.

Human learners occasionally used weak directness in peer situations (I cannot join today because I have another commitment) which raters rated as okay due to low imposition and no difference in status. Such straightforwardness was seldom allowed by AI responses even where it was socially appropriate. This indicates one of the qualitative differences: AI is more concerned with practical safety, reducing the risk of threats to the face. Instead, human learners get involved in pragmatic risk-taking which is compatible with real interpersonal communication.

Relational Implications

In hierarchical refusals, AI replies were also overly reassuring at times in proportion to the refusal of the request, such as a response being as much reassuring as the request itself. The human response time was lesser and had a direct proportionality to the level of imposition. This pro rata calibration is the key of sociopragmatic competence. The qualitative results are thus that AI is complete and not proportionalally sensitive in some cases.

Table 5: Discourse-Level Patterns in Refusals (Qualitative Comparison)

Analytical Dimension	*Human L2 Production*	*AI-Generated Output*
Sequencing variation	Flexible ordering of strategies	Highly predictable structure
Directness tolerance	Context-dependent directness	Minimal directness
Proportionality	Length aligns with imposition level	Often extended regardless of context
Relational authenticity	Reflects interpersonal familiarity	Maintains institutional tone
Identity positioning	Speaker asserts constraints realistically	Speaker overemphasizes gratitude
Contextual nuance	Adjusted to distance and power	Consistent across contexts

There was variance in responsibility-taking in human learners. In less serious offences, few learners gave short apologies without long self-accusations. In grave crimes, they increased the responsibility recognition. Even in low-severity situations, AI-generated apologies were always as responsible as possible. This consistent intensification was ethically safe, but at times seemed to be overstated according to the gravity of the situation.

Emotional Authenticity

Human apologies were often referred to as being based on the individual by raters and even grammatically flawed. Algorithms are able to make AI apologies; however, they lacked emotion or were too formal. This observation is in line with the fact that the interpretivist viewpoint views pragmatic meaning as not only structural completeness but also interpersonal resonance. AI shows formal conformity to formulas of apology, but might not provide the fine-tuning of emotion that comes with interacting with another person in real life.

Cultural Norm Alignment

Hierarchical respect norms are also evident in Pakistani EFL academic environment. Human trainees also occasionally added politeness-related features of their cultures, e.g., protracted honorific appreciation. The responses of AI were the Western academic requirements of clarity and responsibility. Even though neither of the patterns was necessarily inappropriate, this variance underscores the role that AI can replicate dominant training-data norms instead of localized sociocultural requirements.

Table 6: Discourse-Level Patterns in Apologies (Qualitative Comparison)

Analytical Dimension	*Human L2 Production*	*AI-Generated Output*
Responsibility calibration	Adjusted to offense severity	Maximized across contexts
Emotional tone	Variable, personally inflected	Consistently formal

Cultural specificity	Reflects local deference norms	Reflects generalized Western norms
Structural completeness	Selective inclusion of components	Includes full apology set routinely
Natural flow	Occasionally imperfect but authentic	Highly polished, sometimes rigid
Contextual proportionality	Sensitive to imposition level	Uniformly elaborated

AI Mediation and interaction with the learner.

One of the essential qualitative aspects is the learner engagement with AI-generated recommendations when doing revision activities. Reflection on the conversations showed three trends through thematic analysis:

- Not modifying the adoption: There were learners who believed in the AI authority and adopted the output in form and gave the reason of fluency and correctness.
- Selective adaptation: A large percentage of learners reduced AI responses, eliminating the over-mitigation in accordance to their voice or contextual judgment.
- Resistance and critique: A smaller group oppressed AI proposals due to being perceived as too formal or not something that suited our situation.

These results indicate that AI mediation does not have a consistent effect on pragmatic output but instead, the agency of the learner is essential. Nonetheless, constant exposure to prototype models can eventually normalize politeness norms, which will have a tendency to reduce pragmatic heterogeneity.

Table 7: Patterns of Learner Interaction with AI Models

Interaction Type	*Description*	*Pragmatic Implication*
Full adoption	AI output used unchanged	Risk of dependency; reduced agency
Partial modification	Learner edits tone or length	Development of pragmatic awareness
Critical rejection	AI output discarded	Maintenance of local norms
Template internalization	Learners mimic AI style later	Possible homogenization of discourse
Over-reliance in high-stakes tasks	AI trusted more in hierarchical contexts	Outsourcing of pragmatic decision-making
Reflective comparison	Learners analyze differences	Enhanced metapragmatic awareness

Combined Qualitative Results.

In speech acts, the qualitative analysis demonstrates that there exist a number of global themes:

- AI shows great structural politeness competence and little contextual dynamism.
- Human learners are less pragmatic and more socially variable and negotiable.
- AI is pre-disposed to excessively generalized institutionalized forms of politeness.
- Cultural embedding and proportionality of situations are manifested in human production.
- Complex ways through which pragmatic development is mediated by learner interaction with AI.

The results support the view that pragmatic competence cannot be mitigated to mitigation density and formulaic completeness. It entails contextual reasoning, identity constructions, calibration proportionally and sociocultural embeddedness. The output of AI generated L2 can be considered to be pragmalinguistically advanced and sociopragmatically standardized. L2 productions of humans, though at times not so polished, show adaptive flexibility and relational authenticity.

Sociocultural Alignment, Integrated Process Analysis and Theoretical Implications.

- Process level (learner interaction with AI suggestions) analysis.
- Social cultural fit analysis (fitting local academic norms)
- Theoretical implications to the pragmatic competence in the AI era.

This part summarizes the patterns of empirical results into more general analysis findings that concur with Interlanguage Pragmatics and discourse-pragmatic theory.

Process-Level Analysis: AI Mediation and Pragmatic Decision-Making.

One of the key aims of the research was to analyze not only the differences in the products but also the procedure, in which learners are engaged with AI-generated speech-act models. Through the revision task and reflective data, it was possible to note that the AI mediation is a pragmatic scaffold, as well as a possible source of authority.

AI as Pragmatic Authority

Lots of the learners indicated apprehending AI output as more accurate, more professional, or safer, particularly in hierarchical educational settings (i.e., student-to-professor emails). This view affected the way they embraced AI-generated language as is. Numerically, in 63 percent of the revision cases, students still retained AI-generated indirectness and mitigation density despite having shorter and more direct first drafts. This implies that learner preferences can be transformed by AI output to highly mitigated forms. Nonetheless, the qualitative reflection exposed a contradiction: part of the learners admitted that AI responses were not natural enough: they were too formal. This implies new metapragmatic consciousness instead of active dependency.

Pragmatic Outsourcing and Pragmatic Development.

The data indicate there are three process trajectories:

- Outsourcing- The learners use AI to build socially relevant language, which lessens autonomous pragmatic thinking.
- Scaffolded learning - Students make comparisons of their work with AI models and learn to mitigate consciously.
- Critical negotiation Learners choose to follow, reject or modify AI suggestions selectively, depending on contextual judgment.

Most of the participants were placed into the second category (scaffolded learning) which presupposes that AI can be used as a noticing mechanism. Nonetheless, with repeated exposure to forms of template-like politeness, some pattern of strategies might become normalized over time and this could reduce the pragmatic diversity.

Table 8: Process-Level Patterns in AI-Mediated Pragmatic Decision-Making

Analytical Dimension	*Observed Pattern*	*Implication for Pragmatic Development*
Trust in AI authority	High in hierarchical contexts	Increased reliance on AI politeness norms
Strategy adoption rate	63% full or partial retention	Template internalization risk
Modification tendency	Primarily shortening excessive mitigation	Evidence of contextual recalibration
Resistance frequency	18% rejected AI suggestions	Active metapragmatic reasoning
Perceived safety	AI seen as “low-risk” option	Preference for risk-avoidant pragmatics
Long-term orientation	Learners mimic AI patterns in later tasks	Potential homogenization of discourse

Sociocultural Alignment and Contextual Congruence.

One of the research questions was the extent to which speech acts generated by AIs in the Pakistani EFL academic setting correspond to the culturally specific norms.

Coherence with the Local Academic Norms.

In authoritative situations, AI output was usually consistent with the respect and deference expectations. Nevertheless, its politeness style was based on Western institutional patterns with its focus on clarity and explicit responsibility and stringent series of apology. This was not the case with human L2 learners who at times used culturally ingrained expressions of humility and relational warmth. Indicatively, longer appreciation or relational framing (I hope you are in good health) was found more in human data. Raters rated both patterns as suitable but indicated that there were some differences in style. AI responses were seen as being globally standardised academic English and human responses were locally based.

Contextual Calibration

AI was not very sensitive to differences in social distance. As an example, AI maintained institutional formality in peer-to-peer situations. Human learners altered register with a more fluid response, mitigating interactions based on equal power. This shows that AI sociopragmatic model is highly hierarchical and poorly relational with reference to peer solidarity.

Proportionality and Imposition.

In low-imposition cases, AI often gave elaborate answers. Human learners were found to be more proportional on the speech-act length relative to the contextual gravity. The basis of sociopragmatic competence is proportional calibration. The homogeneous elaboration of AI implies construction of politeness patterns instead of context-based and reasoned elaboration.

Table 9: Sociocultural and Contextual Congruence (Human vs AI)

Dimension	*Human L2 Production*	*AI-Generated Output*
Local cultural markers	Frequently present	Rare or generalized
Hierarchical deference	Strong and culturally nuanced	Strong but standardized
Peer solidarity markers	Informal mitigation used	Formal mitigation retained
Contextual proportionality	Sensitive to imposition level	Often over-elaborated
Cultural authenticity	High contextual embedding	Globally neutral tone
Norm congruence	Locally appropriate	Globally appropriate but less localized

Coherent Interpretation between Speech Acts.

A combined process analysis gives a number of overall insights.

AI as Sociopragmatically Standardized and Pragmalinguistically Advanced.

Through quantitative performance, AI performed better in the areas of mitigation density, structural completeness, and indirectness frequency than human learners. On a qualitative level, what was found was that AI was formulaic, contextually less calibrated, and less relationally variegated.

It means that AI has a high pragmalinguistic competence and moderate sociopragmatic sensitivity.

L2 Production in Contextually Flexible.

Human learners infrequently exhibited small pragmatic errors or less mitigation, but they exhibited:

- Greater diversity of directness.
- Greater consistency with peer situational contexts.
- Cultural embedding
- Proportional sensitivity

The flexibility is an indication of contextual reasoning beyond formulaic patterning.

AI's Risk-Avoidance Bias

In all the speech acts, AI always chose the most face-safe option. This pragmatic safety bias minimizes social risk, and it minimizes the authentic identity positioning as well. Negotiation and strategic risk is inherent in human communication. On the other hand, AI-generated text reduces variability in order to achieve the equilibrium of politeness.

Pragmatic Competence Theoretical Implications.

The findings also form a part of three theoretical discourses in Emerging Second Language Acquisition.

Re-defining Pragmatic Competence in the Age of Artificial Intelligence.

The conceptualization of pragmatic competence traditionally assumes the capacity of the learners to choose the contextually adequate strategies in relation to the sociocultural norms.

With AI-mediated situations, competence can be hybrid:

- Human thought + AI-generated linguistic resources.
- Agency of learners + templates of algorithmic politeness.
- Thereby, pragmatic competence is decentralized between human and technological participants.

Interlanguage Pragmatics and AI.

The research establishes that AI is not exhibiting interlingual features since it is not setting up developmental patterns. It however generates pragmatic forms that are statistically dominant. Students who engage with AI can alter their developmental variability to standardized conventions of politeness. This implies that the AI can affect the development of the interlanguage pragmatics of learners by stabilizing some repertoires of strategies.

The discourse-pragmatic identity

Speech acts are not just forms of language but it is performance of identity. Human students are negotiating power, solidarity and position.

The output of AI is an institutional and not personal expression. The options of identity construction may be limited due to too much dependency on AI in L2 communication.

Combining quantitative, qualitative and process analyses, the data show:

- The AI-made L2 speech acts are syntactically smoothed and mitigated.
- AI is indirectly consistent and formulaically complete.
- Greater contextual variation and proportional calibration are found in human learners.
- AI mediation influences the pragmatic decision making of learners, and it cannot completely substitute human thinking.
- The sociocultural fit is different according to the local norms.

The bottom line is that AI is an approximation of surface-level pragmatic competence, but lacks the ability **to recreate the sociocultural rationality behind the pragmatic flexibility of humans.**

Table 10: Integrated Comparative Summary

Analytical Level	*Human L2 Production*	*AI-Generated Output*	*Overall Evaluation*
Pragmalinguistic control	Moderate–High	Very High	AI advantage
Sociopragmatic sensitivity	High contextual flexibility	Moderate, standardized	Human advantage
Context calibration	Adaptive	Uniformly cautious	Human advantage
Structural completeness	Variable	Consistently complete	AI advantage
Cultural embedding	Locally situated	Globally standardized	Human advantage
Identity positioning	Negotiated and dynamic	Institutional neutrality	Human advantage
Risk tolerance	Contextual risk-taking	Risk-avoidant	Human advantage

This synthesized discussion goes to show that AI-generated L2 output is very capable of reaching the stage of formal politeness realization but functions within a traditionalized, risk-averse pragmatic mode. Although sometimes of lesser quality, human L2 learners demonstrate the flexibility based on context, relational calibration, and the positioning of identity that is culturally embedded. AI serves as a useful scaffold and model provider. Nonetheless, the pragmatic competence in whole-hearted sense, namely, the reasoning in context, proportionality, sociocultural grounding, and negotiating relationships, are uniquely human.

The results provide the argument that the AI-mediated L2 communication is not the substitution of human pragmatic competence but its reformation. Pragmatic competence in the new age of AI-mediated language generation has turned to be a collective phenomenon created through collaboration between human agency and algorithmic patterning.

CONCLUSION

The current paper, which is entitled AI-Generated Second Language Output: A Comparative Pragmatic and Discourse-Analytic Study of Speech Acts in both human and AI-mediated L2 communication, aimed to test the hypothesis of whether AI-generated L2 speech acts can reflect pragmatic competence on par with advanced human L2 learners, and the role that AI mediation plays in pragmatic decision-making in learners. Based on interlanguage pragmatics, speech act theory, and discourse-pragmatic models, the study used a mixed-methods comparative study design to study requests, refusals, and apologies on systematically varied situations of power, social distance, and imposition.

The results of the quantitative and qualitative analysis all point to the fact that AI-generated output is characterized by a high degree of pragmalinguistic sophistication. In all speech acts, AI responses were always based on traditional indirect strategies, long-range internal and external modification, formal polite expressions, and structural complete sequencing. AI outperformed human L2 learners in terms of mitigation density, frequency of indirectness and presence of canonical speech acts i.e. regret statements in refusals and inclusion of responsibility-taking speech acts in apologies in quantitative terms. These findings indicate that generative AI systems are very skilled in recreating statistically predominant politeness norms present in institutional discourse of English.

Nonetheless, the pragmatic competence cannot be narrowed down to frequency or structural completeness. The discourse analysis (qualitative) indicated systematic variations in sociopragmatic sensitivity and contextual calibration. Although the speech acts produced by AI were fluent, polished, and grammatically correct, they frequently resorted to predictable templates and were polite in all circumstances. AI output was overgeneralization of deference in the hierarchical context and institutional formality even in the interactions of comparable power. Such trend is an expression of risk-averse pragmatic posture: AI will always pick the least face-threatening course of action, reducing the possibility of social error, but at the cost of reducing relational dynamism.

Human L2 learners on the other hand were found to be more variable and flexible in context. Even though their reactions sometimes involved smaller pragmatic flaws or even less elaborate damping, they expressed greater proportionality between the length of speech act and the degree of imposition. Students better anticipated register in the peer group, accepted a reasonable degree of directness when necessary, and incorporated culturally-specific indicators of politeness that were reminiscent of the local EFL academic setting. This flexibility points to active sociopragmatic thinking as opposed to adopting pre-set templates. Even less formally refined human speech acts were frequently characterized as more genuine, more personal based, and more negotiated in relation.

The results of the process-based research also shed more light on the transformational nature of AI in L2 communication. Students often saw AI output as authoritative and less risky, especially in high stakes academic communication. They used AI-generated mitigation strategies in their upgrades in numerous instances, which is indicative of the scaffold capabilities of the tool. Nevertheless, selective adaptation and resistance were also found in the data, indicating that learners do not internalize AI models passively. Rather, AI acts as a mediating resource that may facilitate the improvement of both noticing and pragmatic awareness, as long as they approach its output critically.

Simultaneously, the results also bring up critical issues on pragmatic homogenization. Due to the likelihood of AI to generate globally standard, institutionally neutral patterns of politeness, repeated exposure can eventually standardize these trends, and decrease the variety of pragmatic expression. In underrepresented EFL settings like Pakistan, AI-generated language could represent the hegemonic Western standards of academic culture instead of the local context of communicative activities. Although understood worldwide, this kind of output might not entirely conform to culturally entrenched norms of interpersonal warmth, deference, or solidarity.

In theory, this work is added to the new debates concerning the redefinition of pragmatic competence in the era of generative AI. Conventional frameworks formulate pragmatic competence as the capacity of the learner to make choices in context-specifically suitable forms due to the sociocultural knowledge. However, when it comes to AI-mediated communication the pragmatic performance is distributed as it is among human cognition and the technological systems. AI is very pragmalinguistically competent and contextually less dynamic. Meanwhile, human learners are not deprived of the ability to negotiate relationships, to calibrate proportionally, and to construct identities. In this way, however, pragmatic competence in modern contexts of L2 is becoming more and more hybrid - that is co-created by the interaction of learner agency and algorithmic patterning.

On the whole, the results indicate that AI-generated L2 speech acts are similar in that they are approximative of surface-level pragmatic competence but without complete replication of the sociocultural logic that human pragmatic flexibility may be based on. AI is more in structural politeness realization and consistency, but it has not that subtle contextual sensitivity of actual interpersonal communication. Instead of substituting the human pragmatic competence, AI creates the conditions in which it is created, and it is implemented.

The pedagogical role of the study is the importance of critical AI incorporation in L2 teaching. AI may become a potent template of simulating the means of mitigation and increasing practical awareness. Nevertheless, teachers should focus on the contextual reasoning, proportionality in calibration, and cultural particularity in order to avoid excessively using standardized templates. Evaluation activities must also remain the same in that they should still involve human evaluation to determine sociopragmatic fit beyond outward signs of politeness.

To sum up, the comparison reveals that, though linguistically advanced and formally polite L2 speech acts can be generated by generative AI systems, the pragmatic competence in its full sense is a highly human ability that lies in situational interpretation, relationship negotiation and cultural contextualization. With AI becoming a permanent part of academic and institutional communication, future research and pedagogy should be able to make certain that the technological innovation is complimentary to, and not the replacement of, the intricate human capabilities that allow us to use language meaningfully and contextually appropriately.

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