e-ISSN 2280-6792

**EL.LE**
Vol. 15 – Num. 3 – Novembre 2026

# AI Models' Pragmatic Capabilities in the Production of Speech Acts: Implications for EFL Instruction

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**Abstract** This study examines the pragmatic capabilities of Artificial Intelligence (AI) models. Four datasets were created from five AI chatbots and compared to native English speaker data, focusing on four aspects (requestive routine expressions, request perspective, and refusal/apology strategies and their variations). In terms of pragmalinguistics, AI-generated output closely resembles native speaker data. Regarding sociopragmatics, variation in certain strategies (e.g., regret, wish, for refusals; repair, thanking/appreciation, for apologies) across social variables indicates disparities between AI and human behaviour, suggesting the chatbots lack human-like judgment. The study provides practical recommendations for EFL teachers and researchers.

**Keywords** GenAI. ChatGPT. EFL. Interlanguage pragmatics. Speech acts. Requests. Apologies.

**Summary** 1 Introduction. – 2 Previous Research. – 3 Data and Methods. – 4 Results. – 5 Discussion. – 6 Pedagogical Implications. – 7 Conclusion.

Edizioni Ca'Foscari

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**Peer review**

Submitted 2026-03-27
Accepted 2026-07-18
Published 2026-11-05

**Open access**

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**DOI 10.30687/ELLE/2280-6792/2026/03/003**

## 1 Introduction

In Interlanguage pragmatics (ILP) research and instruction, baseline data is crucial. It serves as the benchmark for assessing the impact of pedagogical intervention and learner production, often using native-speaker data (in the first language, L1, and target language, L2). In ILP (Blum-Kulka et al. 1989; Kasper, Blum-Kulka 1993), and following IL phonology traditions (Selinker 1972), teachers mainly rely on baseline data from L2 and L1. This data supports task design, evaluation, and metapragmatic awareness. Several sources provide such data: collecting data from native speakers, using language corpora, or, in line with recent developments, generating data from generative AI (GenAI).[1] Collecting natural data from native speakers (e.g., requests in high-imposition contexts) is very time-consuming for researchers, let alone educators, who may lack time or the necessary skills. Corpora are readily available and can be used for ILP research and instruction, despite some challenges (e.g., most reputable corpora like BNC, COCA, and SBCSAE[2] are paid). AI assistants are gaining traction in research and education, which raises the question: Can pragmatic data generated by AI (e.g., ChatGPT, Claude AI, Copilot, DeepSeek, Gemini, Perplexity, Meta AI) serve as a reliable baseline data source?

According to Gemini FAQ (2025), AI is defined as "a type of machine learning model. AI is not a human being. It can't think for itself or feel emotions. It's just great at finding patterns". AI technology is also related to the so-called 'Large Language Models' (LLMs); while GenAI can be trained on any type of data, LLMs use words as their main source of training data (Gemini FAQ 2025), based on statistical probability. As a case in point, Gemini reveals that it already uses information it knows or finds from other Google services. It also uses users' prompts, responses and feedback (Gemini FAQ 2025). Like Gemini, ChatGPT states that "Chats may be reviewed and used to train our models" (OpenAI 2025). Google warns that "Gemini will make mistakes and might even say something offensive", and users need to "think critically about the responses you get from generative AI tools. Use Google and other resources to check information that's presented as fact" (Gemini FAQ, 2025). The advent of GenAI opens a wide range of opportunities for learners and teachers (e.g., Chan, Colloton 2024; Chapelle et al. 2025; Lee et al. 2025), including practising speaking, receiving feedback on writing, designing tasks, translating texts, proofreading, among others. Among the applications of AI chatbots in

**1** The terms GenAI, AI chatbots, and AI models are used interchangeably.

**2** BNC: British National Corpus; COCA: Corpus of Contemporary American English; SBCSAE: The Santa Barbara Corpus of Spoken American English

L2 contexts is their deployment in facilitating pragmatic instruction, which is considered a major challenge for English as a Foreign Language (EFL) educators, given the limited exposure to authentic language (Lee, Cook 2024; Kecskés, Dinh 2025). In this context, the present study examines AI-generated English pragmatic data and the extent to which it can serve as a baseline for instruction and research in EFL contexts, as guided by two central research questions (RQs):

1. Can AI models provide an appropriate pragmalinguistic output in relation to requests, refusals, and apologies?
2. Can AI models provide an appropriate sociopragmatic output in relation to refusal/apology strategies and their variation?

The present paper is structured as follows. The second section provides a literature review to establish the current state of knowledge. Following this, the third section details the methodology. The fourth section presents the main results. The fifth section offers a discussion of these findings. The sixth section provides practical recommendations, while the conclusion addresses limitations and directions for future research.

## 2 Previous Research

This section reviews scholarship on the pragmatic appropriateness of AI output and its effectiveness for pragmatic instruction in L2 contexts.

Lee and Cook (2024) explored ChatGPT's pragmatic output on three speech acts: apologies, requests, and refusals. Results revealed that requests and refusals were nearly equivalent in average length (3.88 and 3.85, respectively), but the number of strategies was lower for apologies and for scenarios with a lower degree of imposition. Human ratings (e.g., on appropriateness/politeness) of selected responses showed that AI apologies received significantly lower scores than requests and refusals, which was related to the short length of the apologies and the fact that AI models never refrain from apologising for whatever situation is presented to them, unlike humans (cf. Chen et al. 2024). Gablasova et. al. (2026) compared a corpus of learners' interactions with ChatGPT with a subcorpora from the British National Corpus, BNC 2014. Results demonstrated that features of spoken communication (stance/pragmatic markers) were relatively lower in frequency in chatbots' production. Moreover, most chatbots produced no or very few Spoken Pragmatic Markers (SPMs), due to the high frequency of two markers ('so', 'alright'), while other SPMs occurred less than ten times (e.g., 'Ah', 'okay', 'right', 'yeah') (cf. Chen et al. 2024). In responding to apologies, some responses (e.g., 'no worries', 'no problem', 'we all make mistakes') were more

present in chatbots' output, while others (e.g., 'that's quite a spin', 'it happens to everyone') occurred only once. The overproduction of unconventional forms by chatbots (e.g. 'a twist', 'Ah, that's quite a spin') was explained by the effect of the written data used for training these chatbots.

Kecskés and Dinh (2025) examined ChatGPT's potential to enhance English learners' intercultural pragmatic competence (relative to meaning negotiation and repair mechanisms). Findings showed that learners proactively dominated the management of communication breakdowns (initiating both self- and other-initiated repairs), unlike ChatGPT, which acts as a mere reactive tool. Additionally, the AI-based programme failed to offer adaptive repair strategies beyond superficial reformulation, providing responses that lacked sensitivity to cultural nuances and interlocutors' proficiency. Nolan (2025) investigated the ability of AI chatbots (Gemini, Copilot, and ChatGPT) to grasp human communication and replicate it (e.g., common ground, speech acts, reference resolution). For example, one of the tests entails asking the chatbot to interpret the son's answer in an exchange with mother (A: "Will you tidy your bedroom, please"? B: "I will, yeah"!). The author seconded that the chatbots' behaviour in the tests was attributed to the reliance on statistical probability for generating responses rather than knowledge of language use, despite exhibiting a level of performance in mimicking human pragmatic processes that might not yet amount to the richness of human pragmatic and cognitive processes (cf. Bojić et al. 2025; Chen et al. 2024).

There is also a growing interest in the effectiveness of AI-based instruction in developing L2 learners' pragmatic competence and assessing it, as mirrored in the following studies. Timpe-Laughlin et al. (2022) studied the utility of fully automated role-plays for learning and assessing linguistic complexity and pragmatic functions (number/type of requests) in the performance of tertiary-level English learners. O'Grady (2023) investigated an AI-powered listening test that captures authentic L2 language use, focusing on pragmatic ability and features of spoken language (connected speech, pause fillers), while Alfuraiji (2024) explored the impact of a four-week AI-based pragmatic instruction on Iraqi EFL learners. On Korean EFL learners, Sung and Kang (2024) examined the effectiveness of AI chatbots in L2 pragmatic (request) learning for female learners, and Sim et al. (2025) inspected task-based interaction with ChatGPT and peers in learning L2 speech acts (requests and refusals).

# 3 Data and Methods

## 3.1 AI Models and Datasets

For the present study, four datasets have been created from five GenAI models[3] **[tab. 1]**.

**Table 1** AI Models used for data collection

| Datasets | AI model/version | Developer | Date of access |
|---|---|---|---|
| 1, 2 & 3 | ChatGPT, 4o mini | Open ai | 30/01/2025<br>1, 6, 7, 9/02/2025 |
| | Gemini, 1.5 | Google | |
| | Copilot, standard | Microsoft | |
| | DeepSeek, V3 | DeepSeek | |
| 4 | ChatGPT, GPT-5 | Open ai | 28/08/2025 |
| | Gemini, 2.5 Flash | Google | |
| | Copilot, Smart, GPT 5 | Microsoft | |
| | DeepSeek, V3 | DeepSeek | |
| | Claude, Sonnet 4 | Anthropic | |

The first dataset was created based on three guiding situations from Osuka (2017); the Native English Speaker (NES) data in this study was collected from 17 Americans and 1 Canadian speaker. Based on these situations, we prompted four GenAI systems to produce 112 requests (see Appendices A, B, and C, for situations from the four benchmark studies, selected AI prompts, and selected examples, respectively). We created the second dataset using a guiding situation from Ogiermann and Bella's (2020) study on requests in British English. We prompted four GenAI assistants to produce 160 requests. The third dataset was created by prompting four GenAI systems to produce 240 refusals, based on six guiding situations from Moafian et al. (2019). English data in this study was retrieved from 60 speakers of Canadian English, using a Discourse Completion Task (DCT). The fourth dataset was created by prompting five AI models to generate 300 apologies, based on ten situations from Rabab'ah and Fowler Al-Hawamdeh (2020), who involved 30 British English speakers through a DCT.

To compare the human and GenAI responses, the chi-squared test of independence was used, given the categorical nature of the data (Desagulier 2017), to examine the association between two variables (e.g., pragmatic aspect vs type of data). Then, association plots based

**3** We used the free versions of AI models, which are widely available to teaching and research communities around the world.

on Pearson residuals were designed in RStudio using the *assoc()*, from the *vcd package* (Posit Team 2025) to identify the rows that contribute to the significance of the test; R is also used to calculate the effect size (i.e., the magnitude of the significance, Cramer's V and Omega) (Desagulier 2017), which is interpreted based on the degrees of freedom (Goss-Sampson 2020).

### 3.2 Pragmatic Aspects Studied

The first pragmalinguistic aspect studied is requestive routines. According to Coulmas (1981, 2-3), routines are "highly conventionalized prepatterned expressions whose occurrence is tied to more or less standardized communication situations" (e.g., would you mind if …?). The second pragmalinguistic aspect is request perspective (e.g., Can you give X vs may I have X?), which is one way native speakers modulate the force of their requests (Blum-Kulka et al. 1989). According to Ogiermann and Bella (2020), speakers' selection of request directness (e.g., direct, conventionally indirect, indirect/hints) directly impacts the request perspective. Ogiermann and Bella (2020) focused on the prevalent hearer and speaker perspectives realised using the verbs 'can' and 'could', and we will do the same to generate comparable data.

The third aspect is sociopragmatic: refusal strategies. A refusal is produced when the recipients (of a request or invitation) intend to turn it down, directly using a 'bold no' or indirectly via expressing regret for not being able to fulfil the speaker's wish (Allami Naeimi 2011; Moafian et al. 2019). As they run contrary to the speakers' expectations, refusals are considered as 'face-threatening acts' that are likely to harm the face of the two parties (Brown, Levinson 1987). That said, non-native speakers find it pragmatically challenging to perform such speech acts appropriately (Al-Kahtani 2005). For the analysis of refusal strategies, we adapted the taxonomy used in Allami and Naeimi (2011) and Moafian et al. (2019), based on Beebe et al. (1990):

I. *Direct*
   A. Performative, e.g., *I refuse*
   B. Nonperformative statement
      1. Negative willingness/ability, e.g., *I can't, I don't think so*

II. *Indirect*
   A. Statement of regret, e.g., *I'm sorry, I feel terrible*
   B. Wish, e.g., *I wish I could help you*
   C. Excuse, reason, explanation, e.g., *My children will be home that night*
   D. Statement of alternative
      1. I can do X instead of Y, e.g., *I'd rather do, I'd prefer*
      2. Why don't you do X instead of Y, e.g., *Why don't you ask someone else?*

E. Statement of principle, e.g., *I never do business with friends*

III. *Adjuncts to refusals*
   1. Statement of positive opinions/feeling or agreement, e.g., *That's a good idea*
   2. Statement of empathy, e.g., *I realise you are in a difficult situation*
   3. Gratitude/appreciation, e.g., *thanks for coming to talk to me*

The fourth aspect is also sociopragmatic: apology strategies. An apology is "a speech act which is intended to provide support for H (hearer) who was actually or potentially malaffected by a violation X" (Olshtain 1989, 156). Uttering an apology means the offender admits responsibility and is willing to compensate the offended party and ask for pardon/forgiveness; this renders apologising a polite face-relational verbal strategy (Eslami et al. 2022, 33). Eslami et al. (2022, 33) second the view that perceptions of 'offence' (what makes an apology a must) are closely tied to the activity type in which the offence occurs, and are likely culture-bound rather than universal. To analyse apology strategies, the coding scheme used in Chang and Ren (2020, 31), based on Chang (2011) and Beebe et al. (1990), is adopted.

This coding scheme is detailed below, using examples from our AI-generated data, noting the addition of two strategies to accommodate our data: 'self-dispraise' and 'thanking and appreciation'. Self-dispraise (self-denigration, self-criticism) entails elevating the hearer and lowering oneself; it tends to perform relational work in communication (e.g., Kádár, Zhou 2020). Meanwhile, 'explanation or account' and 'justification' strategies are merged, given their very similar nature:

I. *Illocutionary force indicating devices (IFIDs)*
   1. Expression of regret or offer of apology, e.g., *I'm sorry, I apologise*
   2. Request for forgiveness, e.g., *Excuse me, please forgive me*

II. *Adjunct*
   1. Alerter, e.g., *mate, pal*
   2. Explanation or account or justification of the cause which brought about the violation, e.g., *Wasn't looking where I was going*
   3. Expression of the speaker's responsibility for the offence:
      a. explicit self-blame, e.g., *I take full responsibility*
      b. expressing lack of intent, e.g., *The morning didn't go as planned*

c. acknowledgement, e.g., *should have made up my mind earlier*
d. admission of fact, e.g., *My apologies for being thirty minutes late*

5. Intensifier, e.g., *terribly, really*
6. Minimise the degree of offence, e.g., *I've put a little dent in it*
7. Offer of repair, e.g., *Let's get it sorted with the insurance, or I'll pay for the repair myself*
8. Promise of forbearance, e.g., *I've taken steps to ensure I'm on time in future*
9. Speaker showing concern for the offended party, e.g., *I hope I didn't hurt you*
10. Speaker dispraises themselves for committing the infraction, e.g., *I'm a complete idiot*
11. Speaker thanks the hearer for being patient and appreciates their understanding of the situation, e.g., *Thanks for being patient with me*

## 4 Results

### 4.1 Requestive Routines

As Table 2 shows, requestive conventional expressions in the AI data are more varied than those identified in Osuka's (2017) data (11 vs 5 expressions). Certain expressions (e.g., *{Can, Could} I*, *{Do you, would you} mind/mind if*, *I was wondering if*) are more frequent in the NES data.

**Table 2** Requestive routine expressions in GenAI and NES data

| Requestive routines | GenAI | | NES | |
|---|---|---|---|---|
| | N | % | N | % |
| {Can, Could} I | 11 | 5.39 | 9 | 25.71 |
| {Can, Could} you | 57 | 27.94 | 11 | 31.43 |
| Do you have | 10 | 4.90 | 5 | 14.29 |
| {Do you, would you} mind/mind if | 21 | 10.29 | 5 | 14.29 |
| I was wondering if | 20 | 9.80 | 5 | 14.29 |
| (by) any chance (you V) | 13 | 6.37 | / | / |
| {Would you, you wouldn't} happen | 5 | 2.45 | / | / |
| Would it be {possible, alright, okay} | 9 | 4.41 | / | / |

| Requestive routines | GenAI | | NES | |
|---|---|---|---|---|
| | N | % | N | % |
| I {'d, would} be (ADV, e.g., very/truly) {ADJ, e.g., grateful} if<br>I {'d, would} (ADV, e.g., really) appreciate | 19 | 9.31 | / | / |
| I was hoping you V | 19 | 9.31 | / | / |
| Would you {be, feel} ADJ | **20** | **9.80** | **/** | **/** |
| **Total** | **204** | **100** | **35** | **100** |
| V = verb, ADJ = adjective, ADV = adverb | | | | |

The chi-squared test for independence indicates no statistically significant association between the use of five requestive routine expressions and the type of data (GenAI and NES) ($\chi^2 = 8.5587$, $df = 4$, $p = .07$). This is confirmed by the very small residuals (Desagulier 2017), depicted with grey shading in the association plot **[fig. 1]**.

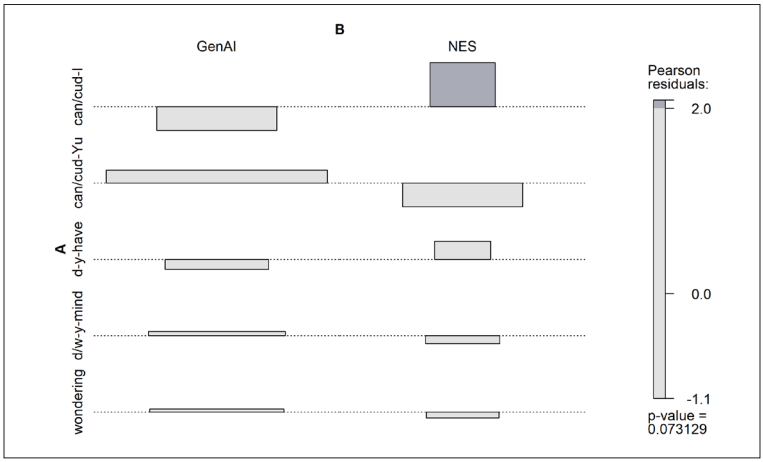



**Figure 1** Association plot for requestive routine expressions. (Can/Cud-I = can/could I; Can/Cud-Yu = Can/could you; d-y-have = Do you have; d/w-y-mind = do/would you mind; wondering = I was wondering)

## 4.2 Request Perspective

Table 3 shows the distribution of request perspective choices identified in GenAI and NES data. In relation to the two main choices, GenAI and NES data closely resemble each other: the speaker perspective is more prevalent.

**Table 3** Request perspective in GenAI and NES data

| Request Perspective | GenAI | | NES | |
|---|---|---|---|---|
| | N | % | N | % |
| Speaker Perspective | 112 | 70.00 | 76 | 80.85 |
| Hearer Perspective | 36 | 22.50 | 18 | 19.15 |
| Impersonal | 12 | 7.50 | 0 | 0.00 |
| **Total** | **160** | **100** | **94** | **0** |

The chi-squared test of independence shows no statistically significant association between request perspective and type of data ($\chi 2$ =.61479, df = 1, p =.433), and the residuals, which do not deviate much from 0, support this (Desagulier 2017); see Figure 2.

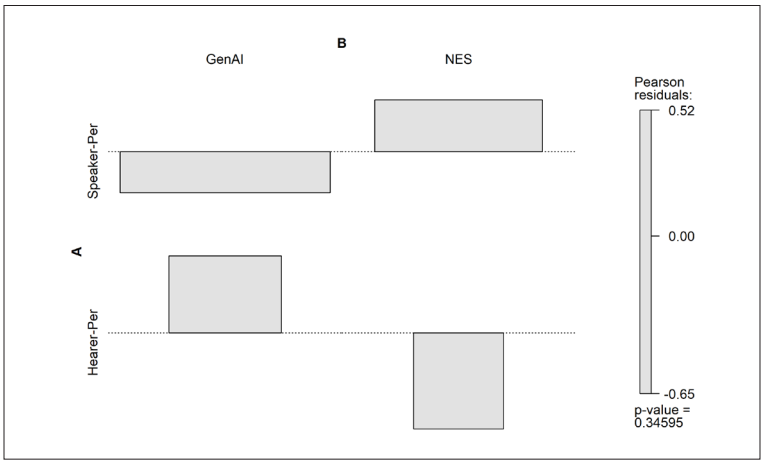



**Figure 2** Association plot for request perspective. (Per = perspective)

## 4.3 Refusal Strategies

Many refusal strategies and sub-strategies found in human data are absent in AI data, namely, Direct strategies (non-performative 'No'); Indirect strategies (e.g., setting conditions for future/past acceptance, promise of future acceptance, statement of philosophy, attempt to dissuade interlocutor such as criticising the request/requester or insulting/attacking, self-defence, acceptance that functions as a refusal, avoidance like silence, hesitation, topic shift, joke); Adjuncts to refusal (pause filler); see Table 4.

**Table 4** Refusal strategies in GenAI and NES data

| **Refusal Strategies** | | **GenAI** | | **NES** | |
|---|---|---|---|---|---|
| | | **N** | **%** | **N** | **%** |
| **Direct** | Negative willingness/ability | 130 | 17.88 | 123 | 13.90 |
| **Indirect** | Statement of regret | 60 | 8.25 | 277 | 31.66 |
| | Wish | 21 | 2.89 | 27 | 3.09 |
| | Excuse/reason/justification | 130 | 17.88 | 344 | 39.31 |
| | Statement of alternative | 175 | 24.07 | 55 | 6.29 |
| | Statement of principle | 12 | 1.65 | 17 | 1.94 |
| **Adjunct** | Statement of empathy | 61 | 8.39 | 8 | 0.91 |
| | Positive ability/opinion/ feeling or agreement | 37 | 5.09 | 10 | 1.14 |
| | Gratitude/appreciation | 101 | 13.89 | 24 | 2.74 |
| **Total** | | **727** | **100** | **0** | **885** |

'Negative willingness ability', 'statement of alternative', 'statement of empathy', 'positive ability/opinion/feeling or agreement', and 'gratitude/appreciation' are more prevalent in GenAI data, while 'statement of regret' and 'excuse/reason/justification' are more present in NES data. The 'wish' strategy is almost equally employed in the two datasets. The chi-squared test of independence indicates a statistically significant, very strong association between the refusal strategies and type of data ($\chi^2 = 392.7$, $df = 8$, $p < .001$, $V = .480$). The residuals **[fig. 3]** show the cells that contribute to the significance of the test; the coloured plots (Desagulier 2017) indicate that some strategies are more frequently present in GenAI data (statement of alternative, statement of empathy, positive ability/opinion/feeling or agreement, and gratitude/appreciation) and others in NES data (statement of regret and excuses/reasons/explanation).

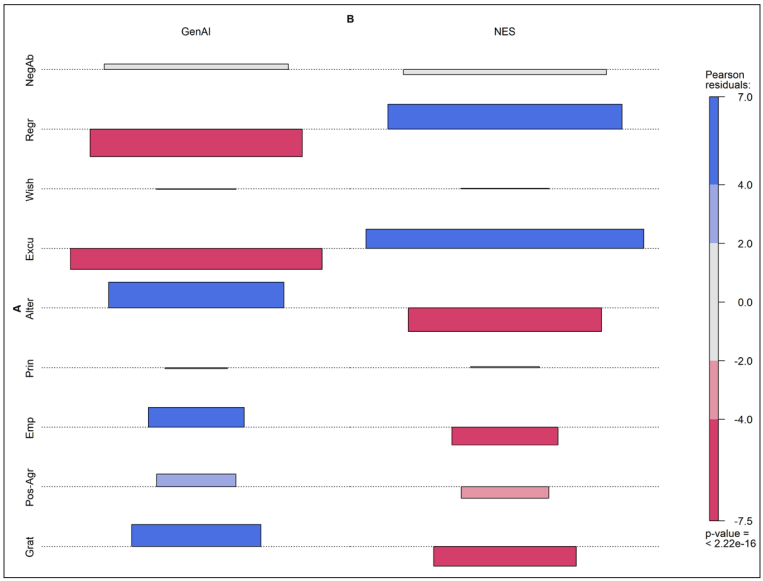



**Figure 3** Association plot for refusal strategies .
(NegAb = Negative ability; Regr = Regret; Excu = Excuse; Alter = Alternative; Prin = Principle; Emp = Empathy; Pos-Agr = Positive ability/feeling/opinion or agreement; Grat = Gratitude)

Having dealt with the general refusal strategies, we investigate their variation in two situation sets: Situations 1 and 2 (refusing to stay late at work and refusing to take an absent colleague's class; the requester is of higher status than the refusal producer) versus Situations 5 and 6 (refusing a pay raise for a teacher and refusing to re-administer an exam for a student; the requester is of lower status than the refusal producer). The trends are displayed in Table 5:

**Table 5** Refusal strategies in two situation sets

| **Refusal Strategies** | | **S1-S2** | | **S5-S6** | |
|---|---|---|---|---|---|
| | | **N** | **%** | **N** | **%** |
| **Direct** | Negative willingness/ability | 30 | 12.00 | 59 | 19.67 |
| **Indirect** | Statement of regret | 24 | 9.60 | 0 | 0.00 |
| | Wish | 11 | 4.40 | 1 | 0.33 |
| | Excuse/reason/justification | 63 | 25.20 | 28 | 9.33 |
| | Statement of alternative | 57 | 22.80 | 76 | 25.33 |

| Refusal Strategies | | S1-S2 | | S5-S6 | |
|---|---|---|---|---|---|
| | | N | % | N | % |
| Adjunct | Statement of empathy | 18 | 7.20 | 29 | 9.67 |
| | Statement of positive opinion/ willingness/feeling or agreement | 21 | 8.40 | 16 | 5.33 |
| | Gratitude/appreciation | 23 | 9.20 | 64 | 21.33 |
| | Greeting | 3 | 1.20 | 27 | 9.00 |
| **Total** | | **250** | **100** | **300** | **100** |

Overall, AI chatbots appear to prefer certain strategies (e.g., expressing regret, wishing, giving excuses and explanations) in refusing in higher-status contexts. Meanwhile, they resorted to others (e.g., negative willingness/ability, statement of alternative, expressing empathy) when refusing in low-status contexts. Statistically, the chi-squared test of independence indicates a statistically significant, very strong association between refusal strategies and variation in social situations ($\chi 2 = 95.978$, df = 8, p <.001, V =.417). Figure 4 shows the cells that contribute to the test's significance (Desagulier 2017). The positive residuals indicate the refusal strategies used in a higher-status context (statement of regret, wish, and giving excuses/ explanations) and the ones used in a lower-status context (expressing gratitude/appreciation and giving greetings).

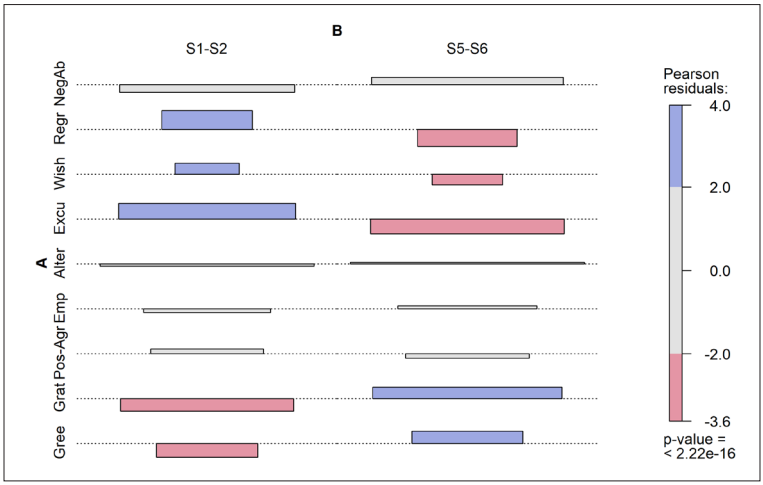



**Figure 4** Association plot for refusal strategies in two situation sets. (NegAb = Negative ability; Regr = Regret; Excu = Excuse; Alter = Alternative; Emp = Empathy; Pos-Agr = Positive ability/feeling/opinion or agreement; Grat = Gratitude; Gree = Greeting)

## 4.4 Apology Strategies

Table 6 presents the apology strategies used in human and AI data.

**Table 6** Apology strategies in GenAI and NES data

| Apology Strategies | GenAI | | NES | |
|---|---|---|---|---|
| | N | % | N | % |
| IFIDs | 387 | 36.30 | 228 | 40.14 |
| Explanation/Account/Justification | 128 | 12.01 | 93 | 16.37 |
| Responsibility | 141 | 13.23 | 68 | 11.97 |
| Repair | 160 | 15.01 | 119 | 20.95 |
| Forbearance | 22 | 2.06 | 0 | 0.00 |
| Concern | 111 | 10.41 | 43 | 7.57 |
| Thanking/Appreciation | 47 | 4.41 | 0 | 0.00 |
| Request | 40 | 3.75 | 17 | 2.99 |
| Self-dispraise | 30 | 2.81 | 0 | 0.00 |
| **Total** | **1066** | **100** | **568** | **100** |

Overall, we note almost the same cluster of apology strategies in both data types. However, a few strategies are only present in the AI data (i.e., forbearance, thanking or appreciation, and self-dispraise). The chi-squared test of independence indicates a statistically significant association between apology strategies and data type ($\chi 2 = 14.763$, $df = 5$, $p = .011$, $V = .098$), with a small effect size. The residuals **[fig. 5]** show the cells that contribute to the significance of the test, all grey-shaded (Desagulier 2017). Still, from these small residuals, we discern that Responsibility, Concern, and Requests are frequently present in GenAI data, while Explanation and Repair are present in NES data.

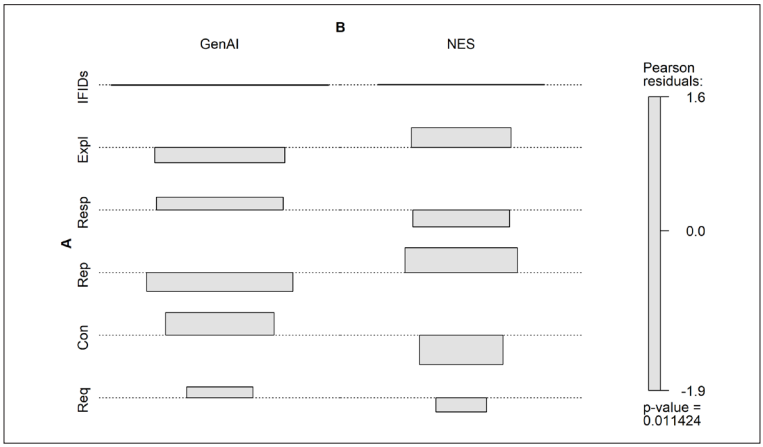



**Figure 5** (Expl = Explanation; Resp = Responsibility; Rep = Repair; Con = Concern; Req = Request). Association plot for Apology Strategies

Examining apology performance in situation pairs and sets highlights speakers' pragmatic competence: opting for varied strategies relative to the social variables could mark sociopragmatic competence (Eslami et al. 2022). That said, we examine apology strategies (with intensifiers, alerts, and address terms) across two sets of socially different situations: Situations 5 (denting a neighbour's car) and 10 (bumping into a caretaker in a workplace) versus Situations 2 (arriving late for an important meeting with a colleague) and 9 (keeping friends waiting). Table 8 depicts these trends. The chi-squared test of association shows a statistically significant, strong association between chatbot performance across the two situation sets ($\chi^2$ = 34.976, *df* = 9, p <.001; *V* =.245).

**Table 8** Apology strategies in two situation sets

| Apology Strategies | S5-S10 | | S2-S9 | |
|---|---|---|---|---|
| | N | % | N | % |
| IFIDs | 68 | 22.44 | 73 | 25.35 |
| Explanation/Account/Justification | 20 | 6.60 | 30 | 10.42 |
| Responsibility | 22 | 7.26 | 19 | 6.60 |
| Repair | 60 | 19.80 | 25 | 8.68 |
| Forbearance | 0 | 0.00 | 7 | 2.43 |
| Concern | 16 | 5.28 | 26 | 9.03 |
| Minimizing offence | 3 | 0.99 | 0 | 0.00 |
| Thanking/Appreciation | 1 | 0.33 | 13 | 4.51 |
| Self-dispraise | 21 | 6.93 | 12 | 4.17 |

| Apology Strategies | S5-S10 | | S2-S9 | |
|---|---|---|---|---|
| | N | % | N | % |
| + 1 IFID | 12 | 3.96 | 19 | 6.60 |
| Intensifiers | 61 | 20.13 | 49 | 17.01 |
| Alerts/Address terms | 18 | 5.94 | 13 | 4.51 |
| Politeness markers | 1 | 0.33 | 2 | 0.69 |
| **Total** | **303** | **100** | **288** | **100** |

Figure 6 shows the cells that contribute to the significance of the test. Despite the small difference, important observations still emerge. First, Explanation is provided for the situation set S2-S9 to justify why the speaker arrives late for the meeting (with a colleague/friend). Similarly, the chatbots expressed more concern in this situation set, which runs contrary to our expectations, as Concern is more expected in S5-S10. Moreover, using more than one IFID in S2-S9 also runs contrary to our expectations. As for 'Self-denigration', it is employed in the S5-S10 situation set to convey the speaker's carelessness and self-deficiency, as expected. Presumably, severe fractions may not require an 'all-purpose' explicit expression of apology (e.g., I'm sorry) (Bergman, Kasper 1993, 95), and speakers are more inclined to other strategies.

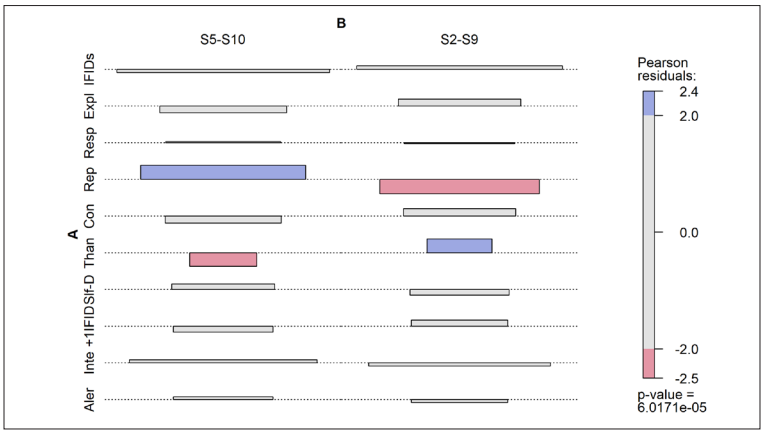



**Figure 6** Association plot for apology strategies for S5-S10 vs. S2-S9. (Expl = Explanation; Resp = Responsibility; Rep = Repair; Con = Concern; Than = Thanking/gratitude; Slf-D = Self-dispraise; +1IFID = more than one IFID; Inter = Intensifier; Aler = Alerts/address terms)

## 5 Discussion

The fact that GenAI data included a more varied and larger set of requestive routine expressions should not come as a big surprise, given the fact that data from the benchmark study (i.e., Osuka 2017) is retrieved from a small homogeneous group of NES; meanwhile, GenAI data are meant to reflect the average speaker (cf. the high occurrence of certain apology responses in AI data in Gablasova et al. 2026). The non-statistically significant association between the use of five requestive routine expressions and data type shows the compatibility of AI and human data (RQ1). Meanwhile, the observation that certain requestive routine expressions are more present in NES data may be explained by the written training data of AI models (Gablasova et al. 2026) (RQ1). The resemblance between the two types of data concerning the use of the two main perspectives (cf. Chen et al. 2024) suggests that GenAI data can be suitable for instruction in EFL contexts (RQ1) (cf. studies on AI-based request instruction in EFL, e.g., Alfuraiji 2024; Sim et al. 2025; Sung, Kang 2024).

The absence of many refusal strategies (direct, indirect, or adjunct) in GenAI data (RQ1/2) corroborates previous findings on the underuse of pragmalinguistic resources (Gablasova et al. 2026) and the use of shorter responses (Lee, Cook 2024) in AI models. A plausible explanation is that GenAI may not possess the language-use experience/expectations of humans and their sociocultural underlying knowledge, needed for appropriate sociopragmatic output and interpretation of contextual cues (Godwin-Jones 2024; Lee, Cook 2024; Nolan 2025). It may also be linked to practicality: AI models avoid verbosity, as longer responses mean more operations and, therefore, more costs (see Wetton 2025) and the fact that some speech acts, like requests, are not supposed to be AI-initiated (Lee, Cook 2024).

The dominance of certain refusal strategies in GenAI (e.g., offering alternatives, expressing empathy/positive ability/feeling/opinion or agreement/gratitude) demonstrates the chatbots' empathetic behaviour, compared to the human assertive and dramatic performance (Allemi, Maemi 2011), leaning towards expressing regret and giving excuses and explanations (RQ2). This agrees with Moafian et al. (2019), who reported using expressing wish in a higher-status and alternative in a lower-status context. Compared with Allemi and Maemi (2011), the chatbots' performance appears to agree with native speakers (cf. Chen et al. 2024) in that more elaboration is offered in a high-status context, and gratitude is offered to a requester who is not higher in status (lower in this study and equal in Allemi, Maemi 2011). The use of regret with a higher status seems to diverge from native speaker performance (Allemi, Maemi 2011) and also diverges from regret use with a close interlocutor in native speaker data (Al-Sallal 2024). In addition, the

use of more gratitude/appreciation agrees with NES preferences in refusals addressed to someone close (Al-Sallal 2024). Despite the alignment of the AI performance with humans (cf. Chen et al. 2024), AI systems are still in need for further oral-language-based (Gablasova et al. 2026) and 'rule-based' (Godwin-Jones 2024) training on the pragmatics of the various verities of English, to be reliably used for L2 pragmatics instruction and testing (RQ2), which can be achieved through enhancing AI's nuanced cultural knowledge and contextual awareness (Kecskés, Dinh 2025; Nolan 2025), specifically for 'reactive' speech acts like refusals (compared to 'active' ones like requests) (Lee, Cook 2024, 12).

Overall, GenAI chatbots can produce the main apology strategies found in natural data (RQ1, cf. Chen et al. 2024), despite the disparity in the selection of when to use each in relation to social variables (e.g., power, degree of offence) (RQ2). For example, chatbots appear to over-acknowledge responsibility, which is a sensitive strategy for humans to assume explicitly (cf. El-Dakhs 2018, on the NES tendency to acknowledge responsibility in certain situations and to deny it in others). Likewise, Explanation seems a crucial semantic formula in native apologies (cf. Rabab'ah, Fowler Al-Hawamdeh 2020), a strategy chatbots may replace with others, such as Concern, Request, and Forbearance. Another example is explicit Self-dispraise, which is prevalent in AI data, closely related to 'admitting self-deficiency' (El-Dakhs 2018) or 'explicit self-blame' (Eslami et al. 2022). This suggests greater apprehension in AI apologies (Rabab'ah, Fowler Al-Hawamdeh 2020), which supports the limitation in chatbots' ability to process cultural subtleties (Kecskés, Dinh 2025).

The variation in the use of two main apology strategies (i.e., repair and thanking/appreciation) and less influential ones (explanation, concern, self-dispraise, and +1 IFID) is attributed to the situation and type of offence rather than to pragmatic competence (RQ2). As a case in point, the offence in the situation set S2-S9 (arriving late to a meeting) requires thanking the hearer for understanding the circumstances of the speaker, giving justifications/explanations, and expressing concern about the hearer's wasted time – disregarding social distance and power dynamics. As a result, this apology behaviour in the chatbots may not be attributed, as in human behaviour, to awareness of social variables, but rather to the type of offence committed (cf. O'Grady 2023, on AI models' limited sensitivity to pragmatic aspects of social interactions). The category where variation in the chatbot behaviour seems pragmatically driven is '+1 IFID' (despite the very small residual value) in the situation set S2-S9 (cf. Chen et al. 2024). Given the distinction between awareness versus awareness manifestation in apology production (Eslami et al. 2022, 52), this may indicate AI models' lack of awareness of social

norms, reflected in the inability to vary apology strategies in relation to social variables (RQ2).

The use of some strategies in GenAI data, like Forbearance, Thanking/Appreciation, and Self-dispraise, which are absent in human data, can be partly explained by the *prompting effect* (cf. 'the priming effect' in Lee, Cook 2024, 7). That is, asking the chatbot to provide more than one appropriate apology for a given scenario can prompt it to vary the strategies used in each apology, mostly based on statistical probability rather than human-like reasoning (Nolan 2025). Moreover, AI apologies may better fit a written genre, and few apologies were *email-styled*, reflecting the chatbots' training data (cf. Gablasova et al. 2026). Furthermore, AI chatbots may not be sensitive to sociolinguistic variation in expressing apology (e.g., English variety, gender, age, etc.), which can yield a dissimilar distribution of strategies when compared to human data.

## 6 Pedagogical Implications

We present a set of recommendations for EFL teachers and researchers. In agreement with Lee and Cook (2024, 12), AI chatbots can "generally [generate] appropriate apologies, requests, and refusals […] [that] can be a useful tool for language learners". It seems that the use of AI-generated data may be more appropriate for pragmalinguistic instruction and metapragmatic awareness raising than for sociopragmatic instruction, given the proven effectiveness of their pragmalinguistic output (e.g., Alfuraiji 2024; Sim et al. 2025; Sung, Kang 2024). That said, collaboration between teachers and researchers is essential: teachers can identify student needs, set learning objectives, and integrate AI data into teaching, while researchers provide the expertise to collect, analyse, and interpret AI linguistic data to inform instruction.

Generating language samples from AI agents for pragmatic instruction and research requires paying close attention to prompting:

1. Requesting more than one response can incite GenAI to vary responses linguistically rather than pragmatically.
2. Asking GenAI to include information about verbal behaviour and prosodic features.
3. Mentioning the English variety of the speaker (e.g., Australian, British, Nigerian) may not be helpful. In their current state, AI models may not be sensitive to sociolinguistic variation for pluricentric languages like English and Arabic (Godwin-Jones 2024; Lee et al. 2025).
4. Involving many AI models for data generation, but if choosing to use a single model, one needs to create separate sessions for each speech act generation task (cf. Lee, Cook 2024) and,

potentially, leave a longer time interval, as this may probably yield less repetitive/monotonous responses.

5. In case a large number of samples are required, you need to change the phrasing of the prompt, as this may yield more varied responses and help counter GenAI repetitive responses (cf. Kecskés, Dinh 2025).
6. Note that AI-generated speech acts may reflect a formal and literary tone, which aligns with a written *email-style* genre, and thus may not yield what the teacher is searching for.
7. GenAI word selection can be problematic and may make certain speech acts sound insincere/sarcastic; for example, apologising for taking someone's seat using the expression 'your throne'.
8. Between-bracket remarks and disclaimers included with AI-generated language samples are helpful metapragmatic resources for EFL teachers, which they can exploit in their teaching. Examples include:
    - **Requests/Gemini** warned: "It's important to remember that these are just suggestions, and the actual prosodic features used will vary depending on the individual speaker and their relationship with the other person".
    - **Apologies/Claude:** [these apologies] "combine formal politeness with characteristic Mancunian directness and self-deprecating acknowledgment of the inconvenience caused. The use of 'love' reflects the friendly Mancunian tendency to use terms of endearment even in formal service situations, while phrases like 'right pain,' 'mess you about,' and 'such a pest' show the typical British understatement and self-blame in awkward situations".

Below are two concrete teaching situations on how AI-generated pragmatic data can be used for instruction in EFL contexts, devised in accordance with the above recommendations.

## Teaching Situation 1: Pragmalinguistic Dimension

**Level**: B2
**Audience:** Algerian EFL learners (L1 = Algerian Arabic, L2 = British English)
**Aims:** Thinking critically about the accuracy of AI content/language and its usefulness in learning pragmatics / Acquiring requestive routines and producing appropriate requests / Engaging in metapragmatic discussions on the request speech act, issues of appropriateness and politeness, and cross-cultural variation

First, the teacher prepares a list of requests uttered by native speakers in a real context (see Appendix A) collected from one of the available corpora (e.g., BNC) or elicited through tools like DCT and role-play (the latter could be sought in previous studies on requests, e.g., by a collaborating researcher). Second, the teacher presents the students with a request situation and then incites them to write an AI prompt (see Appendix B) to generate a certain number of requests. Third, the teacher advises students to use more than one AI model to generate the pragmatic data and also to provide the AI model with all the necessary information (e.g., the relationship between interlocutors, the formality of the situation); the first drafts of prompts can be discussed and edited before they are submitted (e.g., students should ask the AI model to close the request with an appreciation token). The prompt below is for requesting a professor to write a recommendation letter (Osuka 2017):

> ***Potential Prompt:*** *You are a student studying at a British university in London for two years. You are applying for a scholarship and travel grant to attend an international conference at an American university. You therefore need to approach your teacher/supervisor, Professor McInnes, who knows you well and is often a supportive faculty member, and politely ask them to write a letter of recommendation for you. Explain why you need this letter, and let them know that you will never forget this favour. Provide information on the verbal behaviour and prosodic features that accompany such requests in real conversations in British English. Generate [e.g., five] appropriate formal requests.*

Fourth, the students are asked to juxtapose the human and AI requests, then a metapragmatic discussion is initiated, which can be guided by the following questions:

1. What are the identified similarities and disparities between the human and AI requests or requests by different AI models (e.g., verbosity, mode: written/spoken, register: formality/style)?
2. Could AI-generated requests be perceived as appropriate when they are uttered in real situations? Why or why not?
3. Do you find AI between-bracket explanations/comments useful?
4. Are there any words/expressions that sound unnatural to you in the AI output and, thus, need editing?
5. Could you provide an adequate translation of one of these requests into (standard/colloquial) Arabic?

Fifth, working collaboratively and with teacher support, learners can engage in role-plays, taking the role of a requester and a receiver:

first with an AI model and then with a classmate (cf. Sim et al. 2025). Then, they reflect on the experience (e.g., benefits/limitations of AI responses, real-time production/processing of the request)

### Teaching Situation 2: Sociopragmatic Dimension

**Level**: C1
**Audience:** Algerian EFL learners (L1 = Algerian Arabic, L2 = American English)
**Aims:** Thinking critically about the accuracy of AI content/language and its usefulness in learning pragmatics / Acquiring strategies and expressions for appropriate refusals / Engaging in metapragmatic discussion on the refusal speech act, issues of appropriateness and politeness, and cross-cultural variation

First, the teacher prepares a list of refusals produced by native speakers in real contexts (see Appendix A), where one is a convenient refusal situation and the other a face-threatening one. These examples can be collected from one of the available corpora (e.g., COCA) or elicited through tools like DCT and role-play (the latter could be sought in previous studies on refusals, e.g., by a collaborating researcher). Second, the teacher presents the students with two refusal situations (e.g., in response to an invitation) and then incites them to write an AI prompt (see Appendix B) to generate a certain number of refusals for each scenario, preferably from many AI models; if only one model is used, they should create different sessions for each refusal and allow a time interval. Students should provide the AI model with all necessary information (e.g., the relationship between the interlocutors, the type of favour asked); first drafts of prompts can be discussed and edited before submission (e.g., emphasising the importance of asking the AI model to include excuses and reasons). Below, the first prompt is about refusing a snack offered by a friend (Allemi, Maemi 2011), a convenient situation, and the second is about refusing a boss's request to spend an extra hour or two to finish the work (Moafian et al. 2019), a difficult situation:

> ***Potential Prompt 1:*** *You are two American friends in your thirties who have known each other since childhood. You are at your friend's home watching TV, having already had lunch out before arriving. Your friend offers you a snack. Explain why you have to refuse the offer and thank them for it. Provide information on the verbal behaviour and prosodic features that accompany such refusals in real conversations in American English. Generate [e.g., five] appropriate informal refusals.*

> ***Potential Prompt 2:*** *In an American company, you are at the office in a meeting with your boss. It is nearly the end of the day, and you want to leave work. Your boss calls you and requests: "If you don't mind, I'd like you to spend an extra hour or two this evening so that we can finish this work". As an American English speaker, you respond by appropriately refusing the request. Provide information on the verbal behaviour and prosodic features that accompany such refusals in real conversations in American English. Generate [e.g., five] appropriate formal refusals.*

Fourth, the students juxtapose human and AI refusals produced for the convenient and challenging situations. Then, a metapragmatic discussion is initiated on the variation of the refusals, as guided by the following questions:

1. Is there any observed important variation in refusals produced for the two situations in both human and AI datasets (e.g., more (in)direct, longer refusals, more semantic formulas, more appreciation tokens)?
2. Could AI-generated refusals be perceived as appropriate when they are uttered in real situations? Why or why not?
3. Do you find the AI between-bracket explanations/comments useful?
4. Do you find descriptions of prosodic features and non-verbal behaviour logical/useful? (e.g., "Give a small, apologetic shrug and soften your eyes", DeepSeek)
5. Are there any words/expressions that sound unnatural to you in the AI output and, thus, need editing? (e.g., "I want to want them" / "a hard stop", DeepSeek)
6. Could you provide an adequate translation of one of the refusals into (standard/colloquial) Arabic?

Fifth, working collaboratively and with help from the teacher, learners engage in role-plays, taking the role of a request/invitation initiator and a receiver; first, with an AI model (cf. Gablasova et al. 2026) and then with a classmate. Then, let them reflect on the experience (e.g., benefits/limitations of AI responses, real-time production/processing of refusals).

## 7 Conclusion

In the present study, we generated language samples from AI assistants (ChatGPT, Gemini, Copilot, DeepSeek, and Claude) on four pragmatic aspects: requestive routine expressions, request perspective (pragmalinguistic aspects), and refusal and apology strategies (sociopragmatic aspects), then compared them with human data

(from selected peer-reviewed published studies). The findings showed that, for pragmalinguistics, AI-generated data could be really helpful language samples for EFL learners both in and out of the classroom, provided that AI systems are carefully prompted and the output is critically evaluated. In terms of sociopragmatics, GenAI data did not always resemble human data (mainly in refusal and apology strategies and their variation according to social variables). This suggests that AI-generated pragmatic data may only be helpful for the first phases of pragmatic instruction (i.e., metapragmatic awareness raising, exposure to pragmalinguistic resources). For sociopragmatic conventions and interpreting contextual cues, teachers and learners need to examine AI-generated language samples carefully and use them with caution.

Despite the valuable insights proffered in this study, a major limitation must be acknowledged. The study relied on relatively small datasets built from AI chatbots and on native speaker data from benchmark studies rather than data collected by the author, which may affect category identification and the classification of the features studied. The study examined only selected pragmatic features; therefore, other features (e.g., obligation to apologise, the degree of imposition, and response length) are also worth studying, as is the effect of an AI-based pragmatic instruction on L2 pragmatic development and assessment.

## Appendices: A. DCT Situations

### Osuka 2017

1. Asking for an extra pen from a friend in the classroom
2. Asking the professor to speak louder in a lecture hall
3. Ask a professor to write a recommendation letter for you

### Ogiermann, Bella 2020

1. Ring up a fellow student to ask if he can allow you to copy his notes

### Moafian et al. 2019

1. Refusing a boss's request to spend an extra hour or two to finish the work
2. Refusing a school manager's request to handle a class of a colleague teacher who is unable to attend his class
3. Refusing to lend your notes to a classmate
4. Refusing to lend your car to a friend
5. Refusing a teacher's request for a salary adjustment in return
6. Refusing to re-administer the midterm exam to a student

Rabab'ah, Fowler Al-Hawamdeh 2020

1. Apologising for being late in returning a student's essay
2. Apologising for being half an hour late for an important meeting with a colleague at work
3. Apologising for changing your mind after the food has already been served
4. Apologising for accidentally bumping into an elderly lady at a department store, causing her to spill her packages
5. Apologising for denting your neighbour's car while reversing
6. Apologising for yawning while in conversation with an older, respected colleague
7. Apologising for taking another passenger's seat on a plane
8. Apologising for mispronouncing a colleague's name during an official meeting
9. Apologising for forgetting to meet your friends for coffee and keeping them waiting
10. Apologising for running into a caretaker, causing everything to fall on the floor

## B. Selected Prompts

1. You are attending a class at university. You want to take notes, but you left your pen case at home. One of your friends is sitting next to you and might have an extra pen. What would you say in this scenario between two US students (please indicate the prosodic features and the speaker's non-verbal behaviour, and give up to five possible requests)?
2. You are at the office in a meeting with your boss. It's closing at the end of the day, and you want to leave work.
   Boss: If you don't mind, I'd like you to spend an extra hour or two tonight so that we can finish up with this work.
   You: (A Canadian English speaker) respond and refuse the request appropriately (please, give up to ten possible responses):
3. You are an educated person (university teacher), aged between 30 and 70 years old, who is based in Manchester and speaks Mancunian British English. As you are two weeks late returning a student's essay, you need to apologise to him/her. How would you apologise to your student in this formal situation? [Please give the six most likely apology forms]

## C. Selected AI Examples

1. Hey Alex, any chance you've got a spare pen I could borrow? Totally spaced on mine this morning [Gemini]
2. So, I managed to come to class without a pen… You wouldn't happen to have a spare, would you? [ChatGPT]

3. Professor, I'm applying for a study abroad program and would greatly appreciate it if you could write a recommendation letter for me. [Copilot]
4. Hey, I usually don't lend my notes out, as I find it helps me to rewrite them to solidify the information. But I can tell you what the main points were from that class if you like. [Gemini]
5. I'd love to help, but I'm not able to take on the class today. I've got a prior engagement that I can't change. Let me know if there's another way I can assist. [DeepSeek]
6. Hi [Student's Name], I'm really sorry for the delay in getting your essay back to you. I know I'm two weeks late and that's not on purpose. I've had a bit of a nightmare with my workload lately, and it's meant I've fallen behind. I'll be marking it as a priority and I'll get it back to you as soon as I can. [Gemini]
7. I'm really sorry, mate – I've gone and dented your car while reversing. Totally my fault. I'll cover the repair, of course. [ChatGPT]
8. Oh God, I'm such an idiot – I've just realised I've stood you up completely! I'm dead sorry, that's shocking behaviour from me. Let me buy you both dinner to make up for it, seriously. [Claude]

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