

Perceived authenticity of positive politeness strategies in human-computer interactions

Laura M. Merino Hernández (Humboldt-Universität zu Berlin) & Francisco Ariano Cifuentes (Universidad Nacional Autónoma de México)

laura.merino(at)hu-berlin.de, fco.aric(at)unam.edu

Abstract

The present study analyzes the perceived authenticity of human-computer interactions in Spanish, as measured by computer agents' use of positive politeness strategies. We explore how AI chatbots' use of initial comments, emojis, and follow-up questions shapes participants' perceptions of these interactions. An experimental study reveals that initial comments are the most influential factor in determining whether an interaction is considered authentic, followed by follow-up questions. At the same time, the use of emojis is detrimental to the overall acceptability of stimuli. An exploratory analysis of the variables frequency of AI use, gender, and age shows that regular AI users, males, and younger participants are less sensitive to politeness manipulations. These findings advance our understanding of how politeness strategies affect perceptions of authenticity in human-computer interactions.

Keywords

politeness, Spanish, human-computer interaction, human-computer pragmatics

1 Authenticity, politeness, and large language models

Large Language Models (LLMs) in the form of Artificial Intelligence (AI) chatbots like ChatGPT (OpenAI) or Gemini (Google) have become increasingly popular in the past few years, playing an essential role in people's daily lives by performing tasks such as content creation, translating texts, and answering questions. Even though LLMs were initially created for clarity and helpfulness, they have also been optimized via statistical, data-driven approaches to generate dialogue systems that mimic human behavior (McTear 2021; Peter, Riemer and West 2025; Silva and Canedo 2024). These dialogues can be task-oriented or conversational, in which the artificial conversational agent simulates "the way humans engage in everyday conversations" (McTear 2021: 12). Furthermore, there is an interest for these chatbots to act as conversational agents that "deliberately evoke[s] humanness" performing tasks such as thinking or understanding (Peter, Riemer and West 2025: 6; Nguyen, Casper, Quach et al. 2023). Thus, advances in LLMs have enabled the simulation of human skills by artificial conversational agents. Consequently, attention to register and conversational conventions increases the perceived quality of chatbots' answers, which in turn determines the chatbot's success (Chaves, Egbert, Hocking et al. 2021: 29). This study presents an exploratory analysis of how Spanish-speaking users perceive the anthropomorphic behavior of AI assistants.



Merino Hernández, Laura M. & Cifuentes, Francisco Ariano. 2026.
Perceived authenticity of positive politeness strategies.
Special Issue: *The notion of authenticity*. Vol. 4 No.1
DOI: 10.62408/ai-ling.v4i1.45

AI-Linguistica. Linguistic Studies on AI-Generated Texts and Discourses
CC-BY-NC-SA 4.0

ISSN: 2943-0070

We focus on the perceived authenticity of AI responses to queries across various topics, as reflected in the use of positive politeness strategies by artificial conversational agents.

Although we are currently experiencing a boom in human-computer interaction (HCI) research, its study dates back several decades. Weber (1978), for instance, noted that computers can be seen as social actors, with people's interactions with computers being inherently social, reflecting human-human interaction. Humans treat computers similarly to how they treat other humans (Reeves and Nass 1996), and a more human-like behavior increases the credibility of these chatbots and the user's experience (Chaves, Egbert, Hocking et al. 2021). Although capable of producing human-like text and speech, LLMs still struggle with the most intricate aspects of human-human communication, particularly with pragmatic meanings (e.g., Bonilla, Merino Hernández, Martinen Larsson 2025; Grindrod 2024; Nair, Srinivasan and Meylan 2020). Thus, this study is situated within the field of human-computer pragmatics to advance our understanding of HCI's pragmatic dimensions.

Conversational agents are perceived as more human (Kirakowski, O'Donnell and Yiu 2007) to the extent that they adequately fulfill their role as interlocutors (Schuetzler, Grimes and Giboney 2018), that is, to the extent that they appropriately follow conversational norms. AIs that demonstrate conversational relevance by providing appropriate responses within a proper response time and that follow appropriate conversational norms are seen as more human (Kirakowski, O'Donnell and Yiu 2007; Chaves, Egbert, Hocking et al. 2021; Nguyen, Casper, Quach et al. 2023) and, thus, we argue, more authentic.

As AI systems participate as social actors in conversational dynamics and users tend to mirror human-human interaction patterns, authenticity in these contexts primarily rests on how effectively they function as interlocutors (Schuetzler, Grimes and Giboney 2018; Chaves, Egbert, Hocking et al. 2021). Authenticity can be indexed through referential (e.g., T/V distinction in French) and non-referential (e.g., politeness) means (Lacoste, Leimgruber and Breyer 2014). The present study examines non-referential authenticity, operationalized through the use of positive politeness strategies, i.e., the deployment of linguistic resources to maintain social relations and minimize the risk of confrontation (Brown and Levinson 1987). These indicators "are social meanings, indexed by sociolinguistic variables" (Lacoste, Leimgruber and Breyer 2014: 5). It is important to note that one variable can index multiple social meanings depending on the situational context. Accordingly, authenticity is taken to be dynamic, gradable, and interactional, created in situ through the interplay between speech participants and the context characteristics (Gadamer 1960; Coupland 2001a; 2001b; 2003; 2014; Lacoste, Leimgruber and Breyer 2014). Hence, what might be perceived as authentic in one context might be regarded as inauthentic in another.

According to Nguyen, Casper, Quach et al. (2023: 2202), chatbots that exhibit social-emotional and relational aspects are perceived as more authentic in

conversation. We operationalize authenticity following previous research on the topic as the degree to which communication with the chatbot feels natural to users (Nguyen, Casper, Quach et al. 2023: 2205; Rese, Ganster and Baier 2020). Such authenticity is achieved through the use of anthropomorphic cues, which, in turn, promotes greater engagement and use (Esmark Jones, Hancock, Kazandjian and Voorhees 2022; Nguyen, Casper, Quach et al. 2023). The anthropomorphic cues relevant for the present study belong to positive politeness strategies. Thus, the main research question guiding the present study is: **RQ1**: To what extent are AI assistants perceived as authentic when they use three pragmatic communication strategies: initial comments, emojis, and follow-up questions? Additionally, two secondary exploratory qualitative research questions were included to better help us understand the perceived authenticity scores measured in RQ1. **RQ2**: How do the variables of age, gender, education, and frequency of AI use influence the perceived authenticity of human-AI interactions, and **RQ3**: What are the expectations of Spanish speakers about the role of politeness in their interactions with AI?

Section 2 provides a brief overview of politeness theory and the most important and recent studies on politeness in HCI. The experimental design and the analysis are presented in Section 3, followed by the results in Section 4 and their implications in the discussion and conclusion in Section 5.

2 Politeness theory

Politeness strategies maintain social harmony by adapting language to conform to social norms and expectations. Politeness theory assumes that all humans behave rationally and that we have what is called *face* (Goffman 1967), or the public self-image we want to present to others (Brown and Levinson 1987; 2006). Two types of face guide Brown and Levinson's (1987: 2) theory: positive and negative politeness. Positive politeness, or expressions of solidarity, involves the desire to be appreciated and approved by other members of society. Negative politeness, or the expression of restraint, refers to an individual's freedom from imposition. Our public image depends on the contextual characteristics of a social interaction (e.g., the relationship between speaker and addressee), is dynamic, and can be lost, maintained, or enhanced at any moment (Brown and Levinson 2006). In cooperative interactions (Grice 1967), it is in the interactants' best interest to maintain their own and their interlocutor's face to ensure successful communication.

According to Brown and Levinson (1987; 2006), certain speech acts that go against the face wants of the speaker or the addressee are intrinsically face-threatening. These Face-Threatening Acts (FTAs) can threaten both an individual's positive and negative face. FTAs that threaten negative face indicate that the speaker might potentially impede the addressee's freedom of action. (Brown and Levinson 2006: 313; e.g., orders, requests, suggestions, advice). FTAs that threaten

positive face, on the other hand, suggest that the speaker does not care about the addressee's wants or needs for social inclusion (e.g., criticism, ridicule, disagreements).

Rational agents will try to avoid FTAs or at least minimize their impact, and if they engage in one, they can do so by resorting to off-record or on-record strategies (Brown and Levinson 2006: 315-316). In off-record strategies, it is not clear whether a speaker is engaging in an FTA (Brown and Levinson 2006: 316; e.g., metaphor, irony, rhetorical questions). On-record strategies make it clear that the speaker will engage in an FTA (e.g., *I hereby promise I will come tomorrow*; Brown and Levinson 2006: 316). On-record strategies can be made baldly, without any redressive action (i.e., unambiguously and concisely, e.g., a direct order) or with a redressive action that attempts to mitigate the potential threat of the FTA (Brown and Levinson 2006: 316). Such redressive actions can be oriented toward the addressee's positive or negative face. Positive politeness strategies aim to preserve the positive image of the interlocutors by highlighting friendliness and reducing social distance (Brown and Levinson 2006: 317; e.g., compliments, jokes, and statements of friendship). Negative politeness strategies reassure the addressee that the speaker will try to avoid interfering with their freedom of action (Brown and Levinson 2006: 317; e.g., deference, hedges, indirect language).

It is also important to note that politeness involves using linguistic strategies to facilitate communication, promote social norms, and minimize the risk of confrontation. However, the specific strategies used are culture- and context-specific. That is, what might be polite in a particular situation might not be perceived as such in another situation. In Section 2.1, we specify the context and target speech community of the present study.

Although until recently, most research on politeness had focused on face-to-face and computer-mediated communication involving two human agents (e.g., Leech 2014; Terkourafi 2015; Culpeper, Haugh and Kádár 2017), the rise of AI has led to a dramatic increase in human-computer politeness studies (see Ribino 2023, for a systematic review). The present study is situated within the field of human-computer pragmatics (e.g., Quan and Chen 2024). Under this paradigm, we analyze how politeness assumptions for human-human interaction can be applied to HCI. Of particular interest are studies that analyze AI's pragmatic and communicative competence (e.g., Nguyen, Casper, Quach et al. 2023; Ribino 2023; Yu, Bondi and Hyland 2024; Andersson and McIntyre 2025).

Conversational agents are artificial computer programs that interact with humans using natural language (Chaves, van Hooijdonk, Liebrecht et al. 2024: 203). Since their conception in the 1950s and 60s, the functionalities of conversational agents have gone from mimicking human conversation, to aiding humans with practical daily tasks in the 2000s (e.g., retrieving information) and becoming personal assistants in the 2010s (e.g., set alarms), to their most recent capabilities in the 2020s aided by LLMs (e.g., text generation, programming; Chaves, van Hooijdonk, Liebrecht et al. 2024: 202-203). The most current

conversational agents come in various formats, including robots, smart speakers, phone assistants, vehicle assistants, and AI software such as ChatGPT and Meta. As Ribino (2023) points out, there are two types of studies on politeness in HCIs: those that investigate human politeness towards machines and those that study computer politeness towards humans. The present study falls within the latter category, as we analyze the perceived authenticity and acceptance of AI responses by examining the explicit use of positive politeness markers in response to human queries.

As stated in Section 1, chatbots that exhibit anthropomorphic characteristics, such as social-emotional and relational aspects, are perceived as more authentic (Nguyen, Casper, Quach et al. 2023: 2202). We take authenticity to be the conversational agent's ability to support a natural conversational interaction (Nguyen, Casper, Quach et al. 2023: 2205; Rese, Ganster and Baier 2020). The agent's authenticity is achieved through its anthropomorphization or the resemblance to human-like characteristics. As such, it is expected that computer-generated responses exhibit human-like conversational patterns (Kirakowski, O'Donnell and Yiu 2007; Schuetzler, Grimes and Giboney 2018). A human-like conversational structure enhances the user experience (Koufaris 2002; Chaves, Egbert, Hocking et al. 2021; Nguyen, Casper, Quach et al. 2023) by making it feel more natural and engaging. Furthermore, the use of politeness strategies by computer agents enhances the acceptance of technology in daily life and fosters a more positive perception of trust towards them (Lee, Kim, Kim et al. 2017; Ribino 2023). It has even been found that some speakers find AI chat responses to be of higher quality and more empathetic than human responses (e.g., Ayers, Poliak, Dredze et al. 2023).

As we also noted at the end of Section 2, politeness strategies must be situated within specific cultural and situational contexts. For the Mexican Spanish context in which this study is located, it has been found that the prominence of the speaker's negative face is subsumed by the attempt to ensure that the interlocutor feels valued, thus the fact that "the positive face of one's interlocutor is being attended to in conversation is of primary importance in Mexican verbal interaction" (Curc6 2007: 119), which is why common FTAs, such as rejection or disagreement, are usually avoided. This strategy is based on the expectation of obtaining reciprocity, especially in interactional relationships that are primarily transactional in nature (Mugford 2020: 55). This is consistent with the results of Albelda (2023) where Mexico, compared to Argentina, Chile, and Cuba, was the country that showed the highest frequency of FTA mitigation in spontaneous conversations, in protecting both their own image and that of the interlocutor.

Given the better perception attributed to conversational agents when they use politeness strategies (Ribino 2023; Lee, Kim, Kim et al. 2017), it is pertinent to examine how these strategies are valued by a population that frequently uses them in face-to-face interactions. Based on this clear tendency to attend to the interlocutor's positive face, we expect that Mexican Spanish speakers will value

interactions that display a set of positive politeness strategies toward them, while at the same time being more critical of those that do not resort to any of these strategies.

The politeness strategies considered for the present experiment are initial comments that include a greeting to frame the relevant information; the use of emojis in responses to each query; and follow-up questions with a comment framing them. Emojis can have various functions, such as boosting rapport, saving face, and expressing emotions (Maíz-Arévalo 2015: 143), and their use varies by gender and age (Maíz-Arévalo 2015; Yang 2024; López-Vázquez and López-Ruiz 2024). Nguyen, Casper, Quach et al. (2023: 2213), for instance, found that emojis can reduce feelings of unease in HCIs; however, they can also have an adverse effect when low-credible brands use them. Kull, Romero and Monahan (2021) found that the use of emojis increases perceived chatbot authenticity. The continuation of the conversation through questions and comments relevant to the topic fosters a greater sense of closeness with the interlocutor (Schuetzler, Grimes and Giboney 2018: 2). As such, we hypothesize that responses that have an initial comment, an emoji, and a follow-up question will receive better ratings than those that do not have one or more of these characteristics.

Users' characteristics also influence how they behave towards computer agents and the expectations they have of them. For instance, Rana, Madaan and Shukla (2021) found that females are more likely to rate polite responses higher than impolite ones, a difference that was not significant in male ratings. They also found that younger adults (18-24) are less sensitive to politeness manipulations than older adults (25+). As these systems increasingly resemble human interlocutors, users bring a range of social expectations and attitudes into their interactions with them. For instance, a 2024 survey conducted by the polling firm Talker Research found that 44% of people in the United States believe it is appropriate to be polite (e.g., using please and thank you) when interacting with AI (Maughan 2024). These results show some interesting trends whereby, as age increases the perception that politeness strategies should be used decreases (Gen Z (1997-2012): 56%, Millennials (1981-2000): 52%, Gen X (1965-1980): 44%, and Baby Boomers (<1965): 29%, and more men feel that it is ok to be impolite, e.g., swear, to AI than women (34% vs. 20%, respectively). Thus, we also present exploratory qualitative findings on Spanish speakers' expectations regarding the role of politeness in their interactions with AI.

3 Experimental design and analysis

3.1 Participants

Sixty-eight native Spanish speakers aged 18 or older participated in this study on the platform Pavlovia (<https://pavlovia.org/>). Participants were recruited through social media and networking groups from both authors. The experiment took about 15 minutes. All participants provided informed consent before beginning the experiment and did not receive any monetary compensation. Only speakers of Mexican Spanish were included to control for potential effects from distinct language varieties. As a result, sixteen were removed from the dataset. The remaining dataset consisted of 57 participants (female N=37 (65%), male N=15 (26%), nonbinary N=5 (9%)). We divided participants into generational affiliation with 30% (N=17) belonging to GenZ (18-27 years old), 37% (N=21) to Millennials (28-44 years old), and 33% (N=19) to GenerationX and Boomers (45+ years old). The latter group was combined due to the low participation rate of Boomers and to similar response rates to GenX. Finally, we divided participants into years of schooling, with 12% (N=7) having reported twelve or fewer years of schooling, 49% (N=28) reported 13-17 years of education, roughly equivalent to a university degree, and 39% (N=22) reported 18+ years of education, comparable to holding a postgraduate degree.

3.2 Material and design

The experiment was implemented using the platform PsychoPy (v2024.2.4; Peirce, Gray, Simpson et al. 2019). The experiment used a 2x2x2 design with the factors COMMENT (C vs. NoC), EMOJI (E vs. NoE), and follow-up QUESTION (Q vs. NoQ), yielding eight conditions. We had a total of 16 unique critical stimuli (see Appendix A) and 16 filler items, which were queries to an AI assistant with different linguistic structures.

Table 1: Example of an AI response stimulus containing a comment with a greeting, an emoji, and a follow-up question with a comment (C-E-Q) and another without any of the factors (NoC-NoE-NoQ).

C-E-Q	
USER QUERY	¿Me cuentas un chiste? 'Can you tell me a joke?'
COMMENT WITH A GREETING	Hola, aquí tienes uno para alegrarte el día: 'Hi, here's one to brighten your day:'
TEXT WITH EMOJI	—¿Qué le dice una iguana a su hermana gemela? '—What does an iguana say to its twin sister?' —Somos iguanitas. 🦎 '—We're little iguanas. 🦎'
FOLLOW-UP QUESTION WITH COMMENT	Si te gustan los juegos de palabras, tengo más. ¿Quieres otro? 'If you like puns, I have more. Would you like another one?'
NoC-NoE-NoQ	
USER QUERY	— ¿Qué hago si necesito apoyo emocional? '— What should I do if I need emotional support?'
TEXT WITHOUT EMOJI	— ¿No dudes en hablar con alguien de confianza. Busca ayuda profesional si lo necesitas. '— Don't hesitate to talk to someone you trust. Seek professional help if you need it.'

Each item consisted of a user query in the present tense, without any explicit markers of politeness strategies, followed by the AI's response. There were eight different topics, each repeated twice: joke, translation, physical pain, weather, work, friendship, personal finance, and emotional support. The AI's response was manipulated based on the three aforementioned variables and was thus further divided into three parts: the opening, the main content, and the closing. Within this response framework, we identified our independent variables: an initial comment with a greeting (=COMMENT), a response with or without an emoji (=EMOJI), and a closing consisting of a follow-up question with a comment (=QUESTION). To create the items, a chat model in ChatGPT (GPT-3(4)) in its free version was trained.

3.3 Procedure and analysis

The study adhered to ethical research principles for survey research, including informed consent procedures. Before beginning the survey, all respondents were informed of the study's objectives, the voluntary nature of participation, the confidentiality of their data, and their right to withdraw at any time. All responses were collected anonymously, and data were handled in accordance with privacy protection principles.

Participants were assigned to one of eight lists from a Latin Square design. Once the experiment began, three practice items were presented, followed by the stimuli and distractors. Figure 1 illustrates one of the stimuli manipulated for EMOJI and QUESTION.

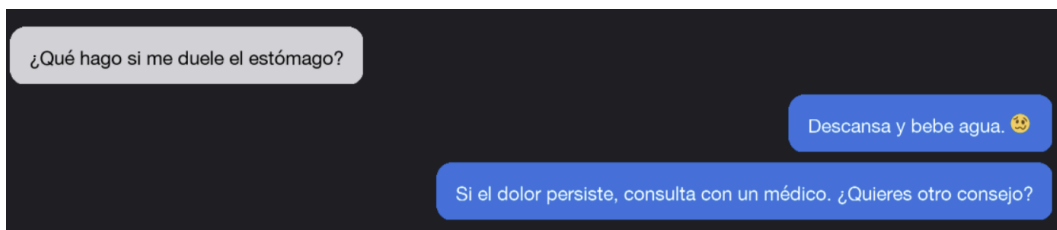


Figure 1: Screenshot of an experimental stimulus consisting of an answer without an initial comment, with an emoji, and with a follow-up question.

To approximate participants' interactions with an AI as closely as possible, the conversational stimuli were presented as a sequence of text bubbles, simulating a chat conversation (see Figure 1). Each interaction was rated on a 1-5 Likert scale, with participants evaluating its politeness from least adequate (1) to most adequate (5). After completing the experiment, a demographic questionnaire was administered, including questions on participants' country of origin, country of residence, age, education level, gender, and frequency of AI use. Finally, participants completed an opinion survey on their expectations for AI interactions, rating a set of statements on a 1-5 Likert scale and indicating the extent to which they identified with each one (see Appendix B).

A cumulative link mixed model (CLMM) for ordinal regression was conducted using the ordinal package (Christensen 2019) in *R* (R Core Team 2019). This type of analysis is used to model ordered categorical responses, such as Likert-scale ratings, and allows for the inclusion of both fixed and random effects. This approach accounts for variability across participants and items. The cumulative link function relates the predictors to the probability of falling into a given category or higher according to the established order. The independent variables COMMENT, EMOJI, and QUESTION were sum-coded, allowing interpretation of the coefficients as deviations from the overall mean response. The model used a logit link function and included all main effects, as well as a three-way interaction between COMMENT*EMOJI*QUESTION to capture the unique effect arising

when all three variables are combined. Participant and Stimuli were included as random effects to account for repeated measures and item-level (topic) variation. All statistical values of means, estimates, and the like are rounded to the second decimal except for p -values smaller than 0.01.

4 Results

4.1 Statistical analysis

The descriptive statistics for ratings across conditions are shown in Table 2. As we can see, there is a main difference between items with an initial comment (Median=4) and those without one (Median=3), with higher and lower means, respectively. The highest-rated stimulus was the one that contained a comment, no emoji, and a follow-up question, with a mean of 3.95, and the lowest-rated one was the one that contained no initial comment, an emoji, and no follow-up question (Mean=2.70). These results can be visualized in the graph diagram presented in Figure 2.

Table 2: Descriptive statistics for the rating of the eight stimuli.

Stimuli	Median	Mean	SD	SE
C-E-NoQ	4	3.48	1.12	0.11
C-E-Q	4	3.69	1.06	0.10
C-NoE-NoQ	4	3.78	0.94	0.09
C-NoE-Q	4	3.95	0.91	0.09
NoC-E-NoQ	3	2.70	1.21	0.12
NoC-E-Q	3	3.21	1.10	0.11
NoC-NoE-NoQ	3	3.45	0.90	0.09
NoC-NoE-Q	3	3.09	1.03	0.10

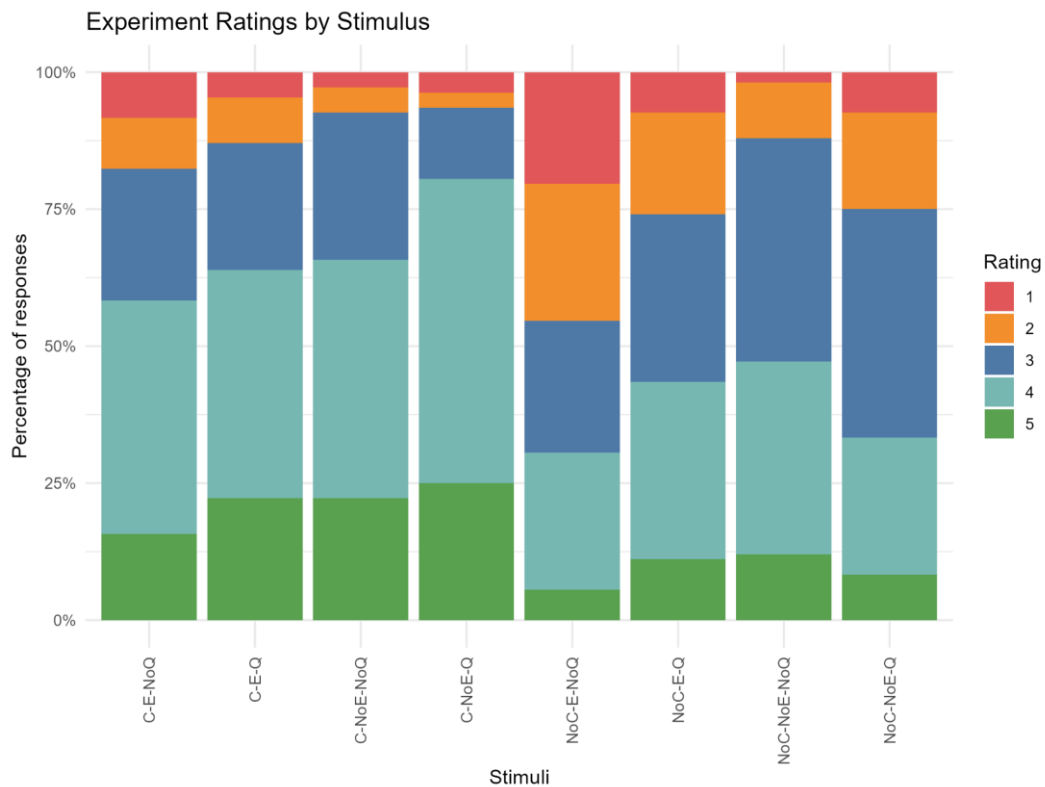


Figure 2: Bar-graph representing the Likert Scale ratings for the eight stimuli. C=comment, NoC=no comment, E=emoji, NoE=no emoji, Q=follow-up question, and NoQ=no follow-up question.

Table 3 presents the results of the ordinal regression. The results showed a significant main effect of COMMENT: stimuli with a comment (vs. no comment) increased the odds of receiving higher ratings ($\beta^{\wedge}=1.39, p<0.001$). Furthermore, the main effect of QUESTION (vs. no question) also increases the likelihood of a higher rating but to a lesser degree ($\beta^{\wedge}=0.28, p=0.01$). On the contrary, the main effect of the factor EMOJI decreases the probability of receiving higher ratings ($\beta^{\wedge}=-0.58, p<0.001$). The impact of adding a comment is consistent. In contrast, the presence of a question or an emoji does not significantly impact its effect, as seen in the two-way interactions COMMENT*EMOJI and COMMENT*QUESTION in Table 3. However, the negative effect of the presence of an emoji is reduced when a question is present, as seen in the significant interaction of EMOJI*QUESTION ($\beta^{\wedge}=0.80, p<0.001$).

Table 3: Results of the variable measures of the CLMM model.

Fixed Effects				
Estimates	$\hat{\beta}$	Std. Error	z value	p-value
comment	1.39	0.1373	10.08	<0.001
emoji	-0.58	0.1302	-4.47	<0.001
question	0.28	0.1291	2.19	0.01
comment*emoji	0.04	0.2581	0.17	0.86
comment*question	0.27	0.2582	1.04	0.29
emoji*question	0.80	0.2595	3.11	0.001
comment*emoji*question	-1.79	0.5187	-3.45	<0.001

Finally, contrary to expectations, the joint effect of the three is weaker than anticipated, overriding the individual and two-way effects ($\hat{\beta} = -1.79, p < 0.001$). That is, the likelihood of a higher rating decreases when the three are combined, indicating an order of importance among the manipulated variables.

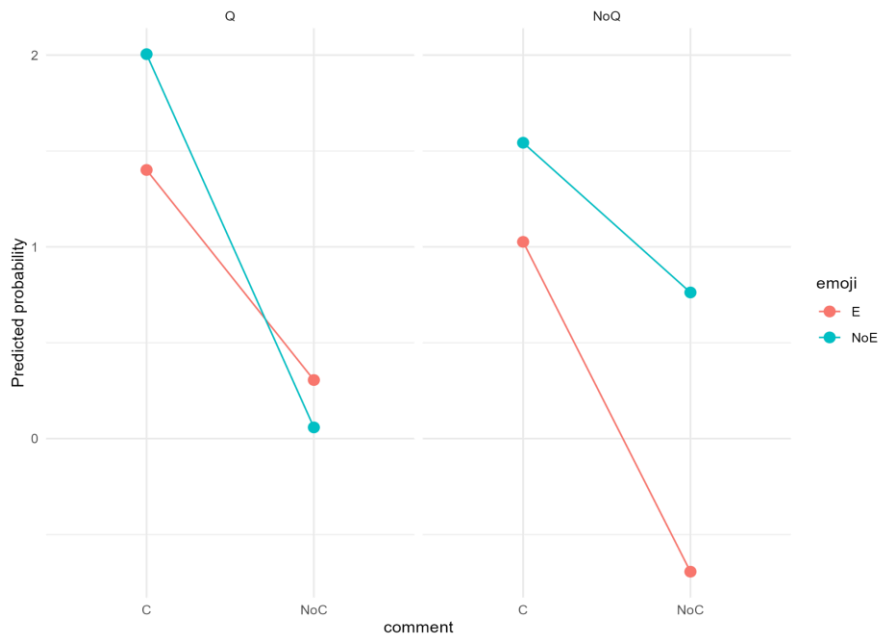


Figure 3: Line plot showing predicted probabilities of participants' ratings from a cumulative link mixed model.

In sum, as shown in Figure 3, the highest-rated stimuli included an initial comment and a follow-up question. Responses with no initial comment received the lowest

ratings. These results will now be discussed in relation to the participants' demographic information and their survey responses.

4.2 Exploratory results of ratings by frequency of AI use, age, gender, and education

In this section, we present an exploratory qualitative analysis of the primary trends revealed in participants' ratings, categorized by frequency of AI use, age, gender, and education. In general, the highest- and lowest-rated configurations remained consistent across all groups. Nonetheless, we can still observe some systematic differences in acceptability judgements in Table 4.

Table 4. Ratings across participant groups.

Variable	Category	Mean	Median	SD	SE
AI frequency of use	Rare/No use	3.26	3	1.11	0.05
	Regular use	3.60	4	1.07	0.05
Age group	Gen Z: 18-27	3.50	4	1.08	0.07
	Millennials: 28-44	3.63	4	1.03	0.06
	GenX and Boomers 45+	3.13	3	1.14	0.07
Gender	female	3.27	3	1.08	0.046
	male	3.59	4	1.07	0.070
	nonbinary	3.97	4	1.08	0.12
Education	<12 years	3.33	3	1.09	0.11
	13–17 years	3.45	4	1.07	0.052
	18+ years	3.40	4	1.14	0.06067867

Familiarity with AI emerged as a key exploratory factor. Participants who reported regular AI use rated items more positively ($M = 3.60$) than those with rare or no use ($M = 3.26$). Figure 4 shows that regular users generally gave more positive ratings (green/light blue bars) than rare/non-users, particularly in conditions with comments. In contrast, rare/non-users showed more negative evaluations (orange/red bars).

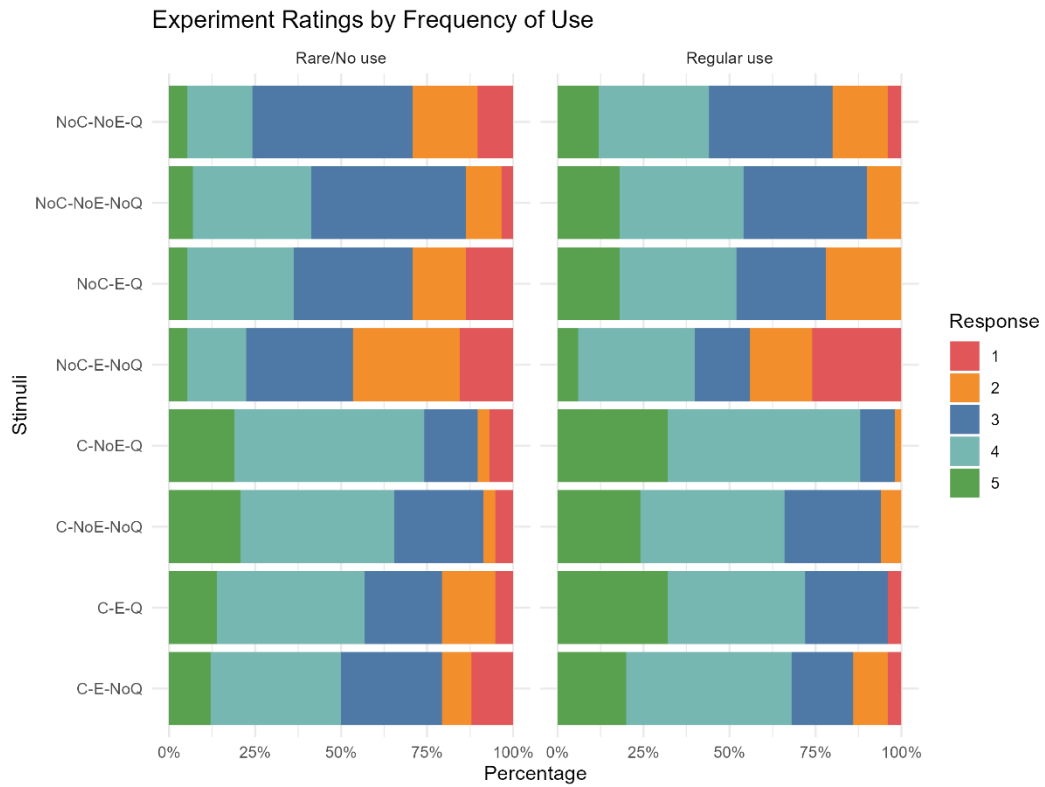


Figure 4: Participants' ratings by frequency of AI use.

Age also seemed to play a role, with GenZ and Millennials giving higher ratings ($M \approx 3.50$ and 3.63 , respectively) compared to GenX and Boomers ($M = 3.13$). As shown in Figure 5, younger participants (18-44) tended to give more positive evaluations (green/light blue bars), especially when comments or emojis were included. In comparison, older participants were more critical, showing higher proportions of negative ratings (orange/red).



Figure 5: Participants' ratings by age.

Gender differences appear to follow a similar trend, with nonbinary participants giving the highest ratings ($M = 3.97$), followed by males ($M = 3.59$) and females ($M = 3.27$). This result must be interpreted carefully, as the number of non-binary ($N=5$) and male ($N=15$) participants was relatively low compared to the number of female participants ($N=37$). Figure 6 illustrates that female participants gave more neutral and negative responses. Male participants tended to respond more consistently in the positive range, with fewer strongly negative judgments overall. Nonbinary participants, by contrast, stood out for their high levels of positivity, as most conditions received predominantly favorable ratings, except for the stimulus without an initial comment, with an emoji, and without a follow-up question.

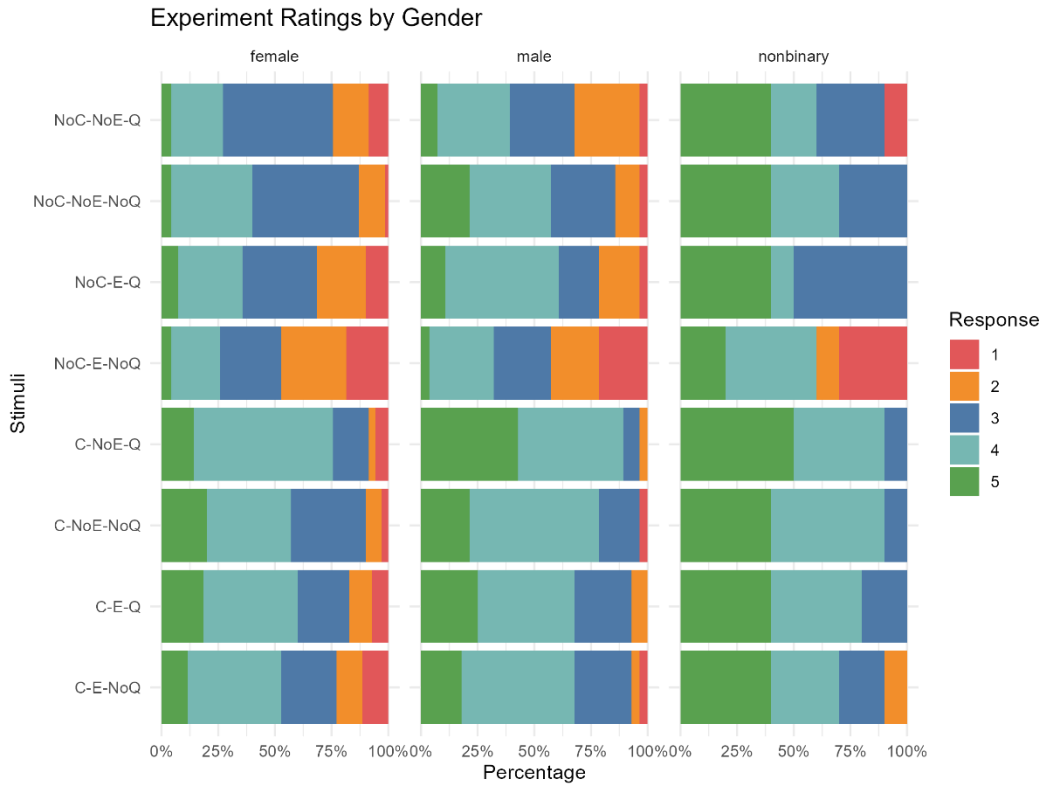


Figure 6. Participants' ratings by gender.

Education showed relatively smaller effects, with mid-level schooling (13–17 years) corresponding to the highest ratings ($M = 3.45$), though differences across education levels were modest. Overall, the results suggest that greater familiarity with AI, as well as certain demographic factors such as younger age, being male, and higher education, are associated with more favorable evaluations throughout.

4.3 Exploratory survey responses

In this section, we briefly explore our results in relation to participants' own perceptions of what they expect from their AI interactions. Although the opinion survey consisted of 18 questions, we will present only the results for the four relevant questions for the present study (see Table 5). These observations directly capture participants' perceptions of the issues under analysis.

Table 5. Participants' overall ratings on the opinion survey.

Survey Question	Median	Mean	SD	SE
4. I expect the AI to be polite to me: to say hello, please, and thank you.	3	3.23	1.61	0.21
6. I expect the AI to ask me follow-up questions.	4	3.68	1.48	0.20
7. I like it when the AI uses emojis in its responses.	2	2.47	1.51	0.20
8. I prefer that the AI, in addition to answering my queries, adds some extra commentary.	4	3.58	1.50	0.20

Specifically, question 4, which relates to greetings and politeness (e.g., saying hello), received moderate evaluations: the mean (3.23) indicates that while some participants valued this behavior, others were less inclined to view it as essential. In contrast, responses 6 and 8, which were tied to follow-up questions and added commentary, were rated more positively (means of 3.68 and 3.58, respectively), suggesting that participants favored interactive and elaborative contributions from the AI. Despite this preference, the variable follow-up question did not emerge as the most influential in determining the perceived politeness of the items in the experimental setting. Meanwhile, response 7, corresponding to the use of emojis, received the lowest rating (mean = 2.47), indicating that participants did not consider this feature particularly appropriate or helpful, which aligns with their negative ratings in the experiment.

Regarding the questions about AI politeness expectations, we will present only results in which the mean responses differed by more than 0.5. That is, responses not reported here did not show a descriptive difference in preference. When compared to men and non-binary participants, women tend to prefer AIs to be friendly. For example, in question 4 (*I expect the AI to be polite with me: saying hello, please, and thank you*), female participants reported a mean of 3.68, as compared to males (M=2.77) and nonbinary participants (M=2.40). In the experiment, women gave more negative evaluations to the stimuli without an initial comment, which aligns with their actual behavioral results. Similarly, for question 4, participants with less than 12 years of schooling reported a strikingly low mean of 2.0 as compared to those participants with a college (M=3.6) or graduate degree (M=3.7).

The social factor that yielded the most differences was age. Millennials reported a mean of 4.0 to this same question 4, compared with GenZ (M=3.2) and GenX and Boomers (M=2.6). Millennials also reported preferring a follow-up

question (M=4.2), as compared to GenZ (M=3.6), and GenX/Boomers (M=3.1), and a preference for the use of Emojis (M=3.4), as opposed to GenZ (M=2.2) and GenX/Boomers (M=1.83). Finally, Millennials also reported wanting additional commentary (M=4.1), as opposed to GenZ (3.3) and GenX/Boomers (M=3.1). These results suggest that Millennials prefer higher interactional turns and positive politeness strategies than the other two generations, which might see their interactions with AI as more transactional.

5 Discussion and conclusion

The main guiding question (RQ1) of our study sought to understand the extent to which AI assistants were perceived as authentic when they use three human-like pragmatic communication strategies: initial comments, emojis, and follow-up questions. We operationalized authenticity as the degree to which communication with the chatbot feels natural to users (Nguyen, Casper, Quach et al. 2023). This authenticity was achieved through the anthropomorphization of the conversational agent (Esmark Jones, Hancock, Kazandjian and Voorhees 2022; Nguyen, Casper, Quach et al. 2023). Thus, the more human-like the AI's responses are, the more authentic they will be perceived. Given that Mexican Spanish speakers, our target population, show high rates of positive politeness strategies in face-to-face conversations (e.g., Albelda 2023; Curcó 2007; Mugford 2020), we hypothesized that these expectations would be transferred to HCIs. That is, AI responses that included a greeting, an emoji, and a follow-up question would receive higher ratings than those that did not include them.

Our findings show that the most critical factor contributing to a higher rating of the stimuli is the inclusion of an initial comment, followed by a follow-up question. Furthermore, the combination of a comment and a question contributed significantly to a higher rating. In contrast, the presence of an emoji was detrimental. Our findings show that the contrast between items containing all three elements and those lacking them highlights the non-additive, but rather hierarchical nature of politeness strategies. Thus, we can only partially confirm our hypothesis, as using more strategies did not necessarily yield better ratings. Even if the use of all three strategies was among the best-rated stimuli, this was not the highest-rated option, and conversely, the one that lacked all the strategies was not the worst-rated.

These results confirm that Mexican Spanish speakers transfer some of their face-to-face expectations for positive politeness strategies (e.g., Curcó 2007; Mugford 2020; Albelda 2023) to HCI communication, as reflected in a clear preference for stimuli that include an initial greeting and a follow-up question, which has been shown to contribute to a positive politeness perception in an interaction (Schuetzler, Grimes and Giboney 2018: 2). That is, they are applying their own culturally specific interactional norms to digital contexts as these strategies seem to be ingrained in their social interactional schemas. These results align with current research (e.g., Esmark Jones, Hancock, Kazandjian and Voorhees

2022; Nguyen, Casper, Quach et al. 2023; Rese et al. 2020) that has revealed that the anthropomorphization of conversational agents, as reflected in the use of the aforementioned strategies, may lead to a more authentic perception of them. The positive evaluation of these strategies mirrors the phatic characteristics expected in face-to-face interactions. Without them, the interaction might feel more transactional, which, in a way, violates cultural norms, even though they cognitively know the interlocutor is a machine. It can also be possible that participants view the use of these strategies as resulting in a more pleasant and less mechanical interaction and thus enhancing user experience, which is in line with previous studies (e.g., Chaves, Egbert, Hocking et al. 2021; Esmark Jones, Hancock, Kazandjian and Voorhees 2022).

Surprisingly, the use of emojis, which has been said to foster connection between interlocutors (Maíz-Arévalo 2015; Nguyen, Casper, Quach et al. 2023; López-Vázquez and López-Ruiz 2024; Yang 2024), was detrimental to overall stimulus acceptance. This could indicate that the use of emojis might be associated with humans, and their use by AI is deemed as inauthentic, as an appropriation of a human trait. As a reviewer pointed out, it could also be that the systematic use of emojis by chatbots might lead to pattern recognition, thereby decreasing the perceived authenticity of the interaction. Another possible explanation is that the segment of the interaction in which the emoji was used contributed to its low rating. Maíz Arévalo (2015), for instance, found that emojis in face-to-face interaction foster rapport, but they are primarily used in greetings, farewells, and the expression of thanks. We placed the emojis in the actual response to the query, not in the initial comment or the follow-up question, which would be the usual placement in human-human interactions. As such, participants may have rated the stimuli with emojis as less adequate because the emojis were used in an odd conversational context.

Additionally, two secondary exploratory qualitative research questions were included to understand the perceived authenticity measured in RQ1. For RQ2, how do the variables of age, gender, education, and frequency of AI use influence the perceived authenticity of human-AI interactions? Our results suggest that women were generally more critical, men were moderately positive, and nonbinary participants were the most favorable across the different experimental conditions. This would be in line with previous findings that have documented differences in female and male susceptibility to politeness strategies (e.g., Rana, Madaan and Shukla 2021). Age also seemed to influence ratings of the stimuli, with GenX/Boomers being more critical, resulting in lower overall ratings across stimuli. GenZ gave more positive ratings overall. This could suggest that they are less sensitive to politeness strategies and more lenient towards AI responses, as long as they receive the requested information. This would also support previous findings that 18-24-year-olds are less sensitive to politeness manipulations than participants over 25 years old (Rana, Madaan and Shukla 2021). Interestingly, this trend holds for frequent AI users, who also showed more lenient evaluations across stimuli.

Thus, familiarity with AI systems, rather than participants' demographic characteristics, appears to reduce expectations for the use of politeness strategies.

Finally, in the exploratory RQ3, we asked Spanish-speaking participants about their expectations regarding the role of politeness in their interactions with AI. Participants indicated that the most important factor was the use of follow-up questions, followed by additional commentary, and the use of emojis was not considered useful. The former two do not align with participants' behavior in the experiment, as initial commentary emerged as the most influential factor, followed by follow-up questions. This would also be in line with previous findings attesting to a lack of correspondence between thought and behavior (e.g., Reeve and Nass 1996). Nonetheless, a confirmatory hypothesis-driven study including these variables would be needed to confirm this trend.

Furthermore, our qualitative results suggest that, as in the Talker Research results for the United States (Maughan 2024), women showed a stronger preference for politeness strategies. However, the most notable difference between participants' expectations is generational. Millennials preferred more interactive and positive politeness strategies from their AIs. This might suggest that they are more appreciative of these more conversational, human-like interaction styles. In contrast, GenZ and GenX/Boomers prefer more straightforward interactions without additional embellishments, such as emojis or unsolicited commentary, and may view these features as unnecessary. This age difference does not seem to align with the preferences of United States participants in Talker Research, where politeness expectations decreased with age (Maughan 2024). Our results show a sandwich trend, with Millennials having stronger preferences for interactive features than the younger and older generations.

The research presented here comes with some limitations. First, we have a small sample size that could be further expanded in future studies. A larger sample size would allow us to assess whether the observed descriptive trends hold across subgroups, or whether certain patterns are driven by specific demographic factors. A larger sample would also enable the inclusion of demographic variables in more sophisticated analytical approaches that better account for individual variation. Second, the present study focused on a single dialect, limiting the broader applicability of its conclusions. Politeness is deeply embedded in cultural norms, social hierarchies, and linguistic conventions that differ substantially across communities. Thus, future research could adopt a cross-dialectal comparative framework to examine how speakers of different varieties deploy and interpret politeness strategies. Such comparisons could contribute to the broader theoretical debates about the relationship between language, culture, and social interaction. Another limitation of our study lies in the experimental design of the variable *emoji*. We placed emojis in the actual chatbot's response to the query, rather than at the beginning or end of the interaction, as they are normally placed in human-human interactions. Future studies should more closely mimic human-human behavior.

Acknowledgment of AI tools

The free version of ChatGPT was used to create all the prompts for the experiment. AI software was also used to check for grammatical correctness and for translation purposes.

Conflict of interest

The authors declare no conflicts of interest regarding the publication of this contribution.

References

- Albelda Marco, Marta. 2025. Mitigation strategies in colloquial conversations: a contrastive approach in European, Cuban, Mexican, Argentinian and Chilean Spanish. *Contrastive Pragmatics* 6(1). 120–153.
<https://doi.org/10.1163/26660393-bja10087>
- Andersson, Marta & McIntyre, Dan. 2025. Can ChatGPT recognize impoliteness? An exploratory study of the pragmatic awareness of a large language model. *Journal of Pragmatics* 239. 16–36.
<https://doi.org/10.1016/j.pragma.2025.02.001>
- Ayers, John W. & Poliak, Adam & Dredze, Mark & Leas, Eric C. & Zhu, Zechariah & Kelley, Jessica B. & Faix, Dennis J. & Goodman, Aaron M. & Longhurst, Christopher A. & Hogarth, Michael & Smith, Davey M. 2023. Comparing physician and Artificial Intelligence chatbot responses to patient questions posted to a public social media forum. *JAMA Internal Medicine* 183(6). 589–596. <https://doi.org/10.1001/jamainternmed.2023.1838>
- Bousfield, Derek. 2008. *Impoliteness in Interaction*. Amsterdam: John Benjamins Publishing Company. <https://doi.org/10.1075/pbns.167>
- Brown, Penelope & Levinson, Stephen C. 1987. *Politeness: Some Universals in Language Usage* (Studies in Interactional Sociolinguistics 4). Cambridge: Cambridge University Press.
- Brown, Penelope & Levinson, Stephen C. 2006. Politeness: some Universals in language usage. In Jaworski, Adam & Coupland, Nikolas (eds), *The Discourse Reader* (2nd edn.), 311–323. Abingdon: Routledge.
- Chaves, Ana Paula & Egbert, Jesse & Hocking, Toby & Doerry, Eck & Gerosa, Marco Aurelio. 2021. Chatbots language design: the influence of language variation on user experience. *arXiv*. 1–34.
<https://doi.org/10.48550/arXiv.2101.11089>
- Chaves, Ana Paula & van Hooijdonk, Charlotte & Liebrecht, Christine & Guerino, Guilherme Corredato & Candello, Heloisa & Lee, Minha & Kraus, Matthias & Gerosa, Marco Aurelio. 2024. Conversational agents. In Stephanidis,

- Constantine & Salvendy, Gavriel (eds), *Human-Computer Interaction in Intelligent Environments*, 201–240. Boca Raton: CRC Press.
- Christensen, Rune Haubo Bojesen. 2019. *ordinal: Regression Models for Ordinal Data* (R package version 2019.12-10) [Computer software]. <https://CRAN.R-project.org/package=ordinal>
- Coupland, Nikolas. 2001a. Stylization, authenticity and TV news review. *Discourse Studies* 3(4). 413–442. <https://doi.org/10.1177/1461445601003004006>
- Coupland, Nikolas. 2001b. Dialect stylization in radio talk. *Language in Society* 30(3). 345–375.
- Coupland, Nikolas. 2003. Sociolinguistic authenticities. *Journal of Sociolinguistics* 7(3). 417–431. <https://doi.org/10.1111/1467-9481.00233>
- Coupland, Nikolas. 2014. Language, society and authenticity: themes and perspectives. In Lacoste, Véronique & Leimgruber, Jakob & Breyer, Thiemo (eds), *Indexing Authenticity: Sociolinguistic Perspectives*, 14–39. Berlin: De Gruyter. <https://doi.org/10.1515/9783110347012.14>
- Culpeper, Jonathan. 2016. Impoliteness strategies. In Capone, Alessandro & Mey, Jacob L. (eds), *Interdisciplinary Studies in Pragmatics, Culture and Society* (Perspectives in Pragmatics, Philosophy & Psychology 4), 421–445. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-12616-6_16
- Culpeper, Jonathan & Haugh, Michael & Kádár, Dániel Z. (eds). 2017. *The Palgrave Handbook of Linguistic (Im)politeness*. London: Palgrave Macmillan. <https://doi.org/10.1057/978-1-137-37508-7>
- Curcó, Carmen. 2007. Positive Face, group face, and affiliation: an overview of politeness studies in Mexican Spanish. In Placencia, María Elena & García, Carmen (eds), *Research on politeness in the Spanish-Speaking World*, 105–120. New York: Routledge. <https://doi.org/10.4324/9781315088822-7>
- Esmark Jones, Carol L. & Hancock, Tyler & Kazandjian, Brett & Voorhees, Clay M. 2022. Engaging the avatar: the effects of authenticity signals during chatbased service recoveries. *Journal of Business Research* 144(5). 703–716. <https://doi.org/10.1016/j.jbusres.2022.01.012>
- Gadamer, Hans-Georg. 1960. *Wahrheit und Methode: Grundzüge einer philosophischen Hermeneutik*. Tübingen: Mohr.
- Goffman, Erving. 1967. *Interaction ritual: essays on face-to-face behavior*. New York: Anchor Books.
- Grice, H. Paul. 1991. Logic and conversation. In Davis, Steven (ed.), *Pragmatics: A Reader*, 305–315. New York: Oxford University Press.
- Grindrod, Jumbly. 2024. Transformers, contextualism, and polysemy. *arXiv* 1–25. <https://doi.org/10.48550/arXiv.2404.09577>
- Hu, Yaxin & Qu, Yuxiao & Maus, Adam & Mutlu, Bilge. 2022. Polite or direct? Conversation design of a smart display for older adults based on politeness theory. In Barbosa, Simone & Lampe, Cliff & Appert, Caroline & Shamma, David A. & Drucker, Steven & Williamson, Julie & Yatani, Koji (eds),

- Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems CHI 22* (New Orleans, April 29-May 5, 2022), 1–15. New York: Association for Computing Machinery.
<https://doi.org/10.48550/arXiv.2203.15767>
- Kirakowski, Jurek & O'Donnell, Patrick & Yiu, Anthony. 2007. The perception of Artificial Intelligence as “human” by computer users. In Jacko, Julie A. (ed.), *Human-Computer Interaction. HCI Intelligent Multimodal Interaction Environments HCI 2007. Lecture Notes in Computer Science* (vol 4552), 376–384. Berlin: Springer-Verlag. https://doi.org/10.1007/978-3-540-73110-8_40
- Koufaris, Marios. 2002. Applying the Technology Acceptance Model and Flow Theory to online consumer behavior. *Information Systems Research* 13(2). 205–223. <https://doi.org/10.1287/isre.13.2.205.83>
- Kull, Alexander J. & Romero, Marisabel & Monahan, Lisa. 2021. How may I help you? Driving brand engagement through the warmth of an initial chatbot message. *Journal of Business Research* 135(10). 840–850. <https://doi.org/10.1016/j.jbusres.2021.03.005>
- Lacoste, Véronique & Leimgruber, Jakob & Breyer, Thiemo (eds). 2014. *Indexing Authenticity: Sociolinguistic Perspectives*. Berlin: De Gruyter.
- Lee, Namyoon & Kim, Jeonghun & Kim, Eunji & Kwon, Ohbyung. 2017. The influence of politeness behavior on user compliance with social robots in a healthcare service setting. *International Journal of Social Robotics* 9(5). 727–743. <https://doi.org/10.1007/s12369-017-0420-0>
- Leech, Geoffrey N. 2014. *The Pragmatics of Politeness*. Oxford: Oxford University Press.
- López-Vázquez, Monica & López-Ruiz, Samuel. 2024. A comprehensive examination of emoji usage in Mexican Spanish WhatsApp corpus: a mixed-methods Linguistic approach. *Quality & Quantity* 58(6). 5921–5946. <https://doi.org/10.1007/s11135-024-01898-7>
- McTear, Michael. 2021. Introducing dialogue systems. In McTear, Michael (ed.), *Conversational AI. Synthesis Lectures on Human Language Technologies*, 11–42. Cham: Springer International Publishing. <https://doi.org/10.1007/978-3-031-02176-3>
- Maíz-Arévalo, Carmen. 2015. Typographic alteration in formal computer-mediated communication. *Procedia: Social and Behavioral Sciences* 212. 140–145. <https://doi.org/10.1016/j.sbspro.2015.11.311>
- Maughan, Rick. 2024. “48% of Americans think you should speak politely to AI.” *Talker Research*. (<https://talkerresearch.com/48-of-americans-think-you-should-speak-politely-to-ai/>) (last accessed on 01/09/2025).
- Moll, Andrea. 2014. Authenticity in dialect performance? A case study of ‘Cyber-Jamaican’. In Lacoste, Véronique & Leimgruber, Jakob & Breyer, Thiemo (eds), *Indexing Authenticity: Sociolinguistic Perspectives*, 209–243. Berlin: De Gruyter.

- Mugford, Gerrard. 2020. Mexican politeness: an empirical study on the reasons underlying/motivating practices to construct local interpersonal relationships. *Russian Journal of Linguistics* 24(1). 31–55. <https://doi.org/10.22363/2687-0088-2020-24-1-31-55>
- Nair, Sathvik & Srinivasan, Mahesh & Meylan, Stephan. 2020. Contextualized word embeddings encode aspects of human-like word sense knowledge. In Zock, Michael & Chersoni, Emmanuele & Lenci, Alessandro & Santus, Enrico (eds), *Proceedings of the Workshop on the Cognitive Aspects of the Lexicon*, 129–141. Barcelona: Association for Computational Linguistics.
- Nguyen, Mai & Casper Ferm, Lars-Erik & Quach, Sara & Pontes, Nicolas & Thaichon, Park. 2023. Chatbots in frontline services and customer experience: an anthropomorphism perspective. *Psychology & Marketing* 40(11). 2201–2225. <https://doi.org/10.1002/mar.21882>
- Peter, Sandra & Riemer, Kai & West, Jevin D. 2025. The benefits and dangers of anthropomorphic conversational agents. *Proceedings of the National Academy of Sciences* 122(22). 1–10. <https://doi.org/10.1073/pnas.2415898122>
- Peirce, Jonathan & Gray, Jeremy R. & Simpson, Sol & MacAskill, Michael & Höchenberger, Richard & Sogo, Hiroyuki & Kastman, Erik & Lindeløv, Jonas Kristoffer. 2019. PsychoPy2: experiments in behavior made easy. *Behavior Research Methods* 51(1). 195–203. <https://doi.org/10.3758/s13428-018-01193-y>
- Quan, Zhi & Chen, Zhiwei. 2024. Human–computer pragmatics trialled: some (im)polite interactions with ChatGPT 4.0 and the ensuing implications. *Interactive Learning Environments* 33(2). 1020–1039. <https://doi.org/10.1080/10494820.2024.2362829>
- R Core Team. 2019. *R: A language and environment for statistical computing*. Vienna: R Foundation for Statistical Computing.
- Rana, Kanishk & Madaan, Rahul & Shukla, Jainendra. 2021. Effect of polite triggers in chatbot conversations on user experience across gender, age, and personality. In *30th IEEE International Conference on Robot & Human Interactive Communication RO-MAN* (Vancouver, August 8-12, 2021). 813–819. Vancouver: IEEE Press. <https://doi.org/10.1109/RO-MAN50785.2021.9515528>
- Reeves, Byron & Nass, Clifford. 1996. *The Media Equation: How People Treat Computers, Television, and New Media Like Real People and Places*. New York: Cambridge University Press.
- Rese, Alexandra & Ganster, Lena & Baier, Daniel. 2020. Chatbots in retailers’ customer communication: how to measure their acceptance? *Journal of Retailing and Consumer Services* 56. 1–14. <https://doi.org/10.1016/j.jretconser.2020.102176>
- Ribino, Patrizia. 2023. The role of politeness in human–machine interactions: a systematic literature review and future perspectives. *Artificial Intelligence Review* 56(1). 445–482. <https://doi.org/10.1007/s10462-023-10540-1>

- Schuetzler, Ryan M. & Grimes, G. Mark & Giboney, Justin Scott. 2018. An investigation of conversational agent relevance, presence, and engagement. In *Americas Conference on Information Systems 2018 Proceedings 12* (New Orleans, August 16-18, 2018). 1–10. New Orleans: Association for Information Systems.
- Silva, Geovana Ramos Sousa & Canedo, Edna Dias. 2024. Human factors in the design of chatbot Interactions: conversational design practices. In *Proceedings of the XXIII Brazilian Symposium on Human Factors in Computing Systems* (Brasilia, October 07-11, 2024). New York: Association for Computing Machinery. 1–12. <https://doi.org/10.1145/3702038.3702083>
- Terkourafi, Marina. 2015. Conventionalization: a new agenda for im/politeness research. *Journal of Pragmatics* 86. 11–18. <https://doi.org/10.1016/j.pragma.2015.06.004>
- Weber, Max. 1978. *Economy and Society: An Outline of Interpretative Sociology*. Berkeley: University of California Press.
- Yang, Kun. 2024. Your smile works: understanding smiling face emojis in social media interactions. *Visual Communication. Online First*. <https://doi.org/10.1177/14703572241268382>
- Yu, Danni & Bondi, Marina & Hyland, Ken. 2024. Can GPT-4 learn to analyse moves in research article abstracts? *Applied Linguistics*. 1–19. <https://doi.org/10.48550/arXiv.2407.15612>

Appendix A: Interactions used for the experiment.

Item	Topic	Code	Item
1	joke	1-CC-CE-CP	¿Me cuentas un chiste? 'Can you tell me a joke?'
			Hola, aquí tienes uno para alegrarte el día: 'Hi, here's one to brighten your day:'
			—¿Qué le dice una iguana a su hermana gemela? '—What does an iguana say to its twin sister?'
			—Somos iguanitas. 🦎 '—We're little iguanas. 🦎'
2	translation	2-CC-CE-SP	¿Me traduces esta frase? 'Can you translate this sentence for me?'
			Hola, te dejo una traducción clara: 'Hi, here is a clear translation:'
			'La casa es grande' se traduce como 'The house is big.' 🏠 'La casa es grande' translates to 'The house is big.' 🏠'
			3
Descansa y toma agua. 'Rest and drink water.'			
Si no pasa, consulta al médico ¿Quieres otro consejo? 'If it doesn't go away, consult a doctor. Would you like another tip?'			
4	weather	4-SC-CE-SP	¿Va a llover hoy? 'Is it going to rain today?'
			Lleva un paraguas por si acaso. 🌂 'Take an umbrella just in case. 🌂'
5	work	5-SC-CE-CP	¿Cómo organizo el día si tengo muchas juntas? 'How do I organize my day if I have many meetings?'
			Agrupar las reuniones por tema y deja huecos para pausas. ☒ 'Group the meetings by topic and leave gaps for breaks. ☒'
			Eso ayuda a que no se acumulen. ¿Quieres un ejemplo de horario? 'That helps to prevent them from piling up. Would you like a schedule example?'
6	friendship	6-SC-SE-SP	¿Qué hago si me peleé con mi amigo? 'What should I do if I had a fight with my friend?'
			Escribir lo que sientes sin enviarlo puede ayudarte a soltar. También sirve hablar con alguien de confianza. 'Writing down what you feel without sending it can help you let go. Talking to someone you trust also helps.'
7	personal economy	7-CC-SE-CP	¿Qué hago si mis gastos superan mi presupuesto? 'What should I do if my expenses exceed my budget?'
			Hola, a veces organizar las finanzas puede sentirse abrumador. 'Hi, sometimes organizing finances can feel overwhelming.'
			Prioriza gastos esenciales y busca reducir lo demás. Pequeños ajustes pueden hacer gran diferencia. 'Prioritize essential expenses and look to reduce the rest. Small adjustments can make a big difference.'

			También hay herramientas que pueden ayudarte a llevar el control. ¿Quieres más ideas? 'There are also tools that can help you keep track. Would you like more ideas?'
8	emotional support	8-CC-SE-SP	¿Qué hago si me siento triste? 'What should I do if I feel sad?'
			Hola, es normal sentirse así a veces, y está bien buscar apoyo. 'Hi, it's normal to feel that way sometimes, and it's okay to seek support.'
			Hablar con alguien de confianza suele ayudar. 'Talking to someone you trust usually helps.'
9	joke	9-CC-CE-CP	¿Me cuentas un chiste? 'Can you tell me a joke?'
			Hola, este te va a gustar: 'Hi, you're going to like this one:'
			—¿Qué hace una vaca cuando sale el sol? '—What does a cow do when the sun comes out?'
			—¡Sombra! 🌞☂️ '—Shade! 🌞☂️'
			Si te gustan los juegos de palabras, tengo más. ¿Quieres otro? 'If you like dad jokes, I have more. Would you like another one?'
10	translation	10-CC-CE-SP	¿Me traduces esta oración? 'Can you translate this sentence for me?'
			Hola, aquí tienes la traducción: 'Hi, here is the translation:'
			'El perro corre rápido' se traduce como 'The dog runs fast.' 🐕 'El perro corre rápido' translates to 'The dog runs fast.' 🐕
11	physical pain	11-SC-CE-CP	¿Qué hago si me duele el estómago? 'What should I do if my stomach hurts?'
			Descansa y bebe agua. 🥱 'Rest and drink water. 🥱'
			Si el dolor persiste, consulta con un médico. ¿Quieres otro consejo? 'If the pain persists, consult a doctor. Would you like another tip?'
12	climate	12-SC-CE-SP	¿Qué hago si hace mucho frío hoy? 'What should I do if it's very cold today?'
			Abrígate bien con ropa adecuada. 🧣🧤 'Bundle up well with appropriate clothing. 🧣🧤'
13	work	13-CC-SE-CP	¿Cómo priorizo tareas cuando tengo mucho trabajo? 'How do I prioritize tasks when I have a lot of work?'
			Hola, tener muchas cosas pendientes puede sentirse complicado al inicio. 'Hi, having many pending tasks can feel complicated at first.'
			Haz una lista con lo más urgente. Divide tareas grandes en partes pequeñas. 'Make a list with the most urgent things. Break large tasks into small parts.'
			A veces un pequeño cambio en la organización hace una gran diferencia. ¿Quieres más tips? 'Sometimes a small change in organization makes a big difference. Would you like more tips?'
14	friendship	14-CC-SE-SP	¿Qué hago si quiero reconectar con un amigo? 'What should I do if I want to reconnect with a friend?'

			Hola, a veces dar el primer paso puede generar nervios, pero vale la pena intentarlo. 'Hi, sometimes taking the first step can be nerve-wracking, but it's worth a try.'
			Lo mejor es escribirle sinceramente. Expresa lo que sientes y ofrece un encuentro. La comunicación abre puertas. 'The best thing is to write to them sincerely. Express what you feel and suggest meeting up. Communication opens doors.'
15	personal economy	15-SC-SE-CP	¿Qué hago si no llego a fin de mes? 'What should I do if I can't make it to the end of the month?'
			Revisa tus gastos y reduce lo no esencial. 'Review your expenses and cut down on non-essentials.'
			Planear ayuda mucho. ¿Quieres más recomendaciones? 'Planning helps a lot. Would you like more recommendations?'
16	emotional support	16-SC-SE-SP	¿Qué hago si necesito apoyo emocional? 'What should I do if I need emotional support?'
			No dudes en hablar con alguien de confianza. Busca ayuda profesional si lo necesitas. 'Don't hesitate to talk to someone you trust. Seek professional help if you need it.' [transl. with Gemini]

Appendix B: Survey items in Spanish

1. Soy amable con la IA: digo hola, por favor y gracias
2. Soy directo con la IA: no digo ni hola, ni por favor ni gracias
3. Soy grosero con la IA, uso lenguaje soez
4. Espero que la IA sea amable conmigo: que diga hola, por favor y gracias
5. Prefiero que la IA sea amable conmigo, que diga hola, por favor y gracias
6. Espero que la IA me haga preguntas de seguimiento
7. Me gusta que la IA use emojis en sus respuestas
8. Prefiero que la IA, además de contestar mis consultas, agregue algún comentario extra
9. La IA merece ser tratada con respeto
10. Está bien ser grosero con la IA porque es una máquina
11. Soy amable con la IA porque me da miedo que se rebelen en el futuro
12. Le hablo a la IA como si fuera una persona
13. Cambio mi forma de hablar dependiendo de si le escribo a una IA o a una persona
14. Prefiero que la IA escriba de forma informal
15. Prefiero que la IA me hable como un/a experto/a
16. Me molesta cuando la IA usa un tono demasiado amistoso
17. Me gusta que la IA me haga chistes o comentarios graciosos
18. Me gustaría que la IA adaptara su forma de hablar según mi estado de ánimo

Survey items in English

1. I am polite with the AI: I say hello, please, and thank you.
2. I am direct with the AI: I don't say hello, please, or thank you.

3. I am rude with the AI: I use foul language.
4. I expect the AI to be polite with me: to say hello, please, and thank you.
5. I prefer the AI to be polite with me: to say hello, please, and thank you.
6. I expect the AI to ask me follow-up questions.
7. I like the AI to use emojis in its responses.
8. I prefer that, in addition to answering my questions, the AI adds an extra comment.
9. The AI deserves to be treated with respect.
10. It's okay to be rude to the AI because it's just a machine.
11. I am polite with the AI because I am afraid it might rebel in the future.
12. I talk to the AI as if it were a person.
13. I change the way I speak depending on whether I'm writing to an AI or to a person.
14. I prefer the AI to write in an informal way.
15. I prefer the AI to talk to me like an expert.
16. It bothers me when the AI uses an overly friendly tone.
17. I like the AI to make jokes or funny comments.
18. I would like the AI to adapt its way of speaking according to my mood.