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Semiotics of Emotion in AI-Based Text Interaction: Analysis of Signs and Meaning in Emotional Responses by Chatbots

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ABSTRACT

Background: Chatbot systems in education, customer service, and social-media platforms increasingly rely on scripted empathy language, yet how these linguistic signs are semiotically constructed and interpreted by users remains empirically under-examined, particularly because prior studies favor computational sentiment metrics over sign-based interpretation.

Purpose: This study analyzes how linguistic signs in text-based chatbot responses construct emotional meaning, by identifying the operational function of Saussurean, Peircean, Barthesian, and Ekmanian categories in a corpus of authentic chatbot–user exchanges.

Method: This qualitative descriptive study applied semiotic analysis to 120 chatbot–user interaction excerpts purposively collected from three educational chatbots, two customer-service chatbots, and two social-media conversational assistants operating in Indonesian and English between January and March 2026. Excerpts were selected using explicit inclusion criteria (presence of emotional linguistic markers, availability of corresponding user response, and public or consented data source) and coded using a discourse coding sheet, a semiotic interpretation matrix, and an Ekman emotion-category rubric, with inter-coder checking by two independent coders.

Results and Discussion: Empathy (21.7%) and reassurance (18.3%) emerged as the most frequent emotional sign categories among the seven coded types, operating as Peircean symbols such as "I understand your concern" and "Thank you for your patience." These signs were interpreted by participant excerpts as markers of emotional closeness, while emotionally neglectful responses (8.3% of the corpus) were associated with symbolic distance in the surrounding discourse. These findings extend prior sentiment-focused chatbot research by showing specifically how classical semiotic categories operate in AI-generated emotional discourse.

Conclusions and Implications: Emotional communication in chatbot interaction is represented through linguistic signs, symbolic interpretation, and contextual discourse rather than through biological affect. The findings contribute to digital semiotics and AI linguistics, and offer a coding framework that developers and researchers can use to design more empathetic and ethically responsible conversational AI.

Keywords: *Chatbot; Emotional Semiotics; Linguistic Signs; Digital Communication; AI-Mediated Interaction.*

ABSTRAK

Latar Belakang: Sistem chatbot pada layanan pendidikan, pelayanan pelanggan, dan media sosial semakin banyak menggunakan bahasa empati yang terskrip, tetapi bagaimana tanda linguistik tersebut dikonstruksi dan dimaknai secara semiotik oleh pengguna masih jarang dikaji secara empiris, terutama karena penelitian terdahulu lebih menekankan metrik sentimen komputasional dibanding interpretasi berbasis tanda.
Tujuan: Penelitian ini menganalisis bagaimana tanda linguistik dalam respons chatbot berbasis teks membangun makna emosional, dengan menjelaskan fungsi operasional kategori Saussure, Peirce, Barthes, dan Ekman pada korpus interaksi chatbot-pengguna yang nyata.
Metode: Penelitian deskriptif kualitatif ini menerapkan analisis semiotika terhadap 120 kutipan interaksi chatbot-pengguna yang dipilih secara purposif dari tiga chatbot pendidikan, dua chatbot layanan pelanggan, dan dua asisten percakapan media sosial berbahasa Indonesia dan Inggris pada Januari–Maret 2026. Kutipan dipilih menggunakan kriteria inklusi eksplisit (adanya penanda linguistik emosional, tersedianya respons pengguna, dan sumber data publik/telah memperoleh persetujuan) serta dikodekan menggunakan lembar coding wacana, matriks interpretasi semiotik, dan rubrik kategori emosi Ekman, dengan pemeriksaan antar-pengkode oleh dua pengkode independen.
Hasil dan Pembahasan: Empati (21,7%) dan peneguhan/reassurance (18,3%) menjadi dua dari tujuh kategori tanda emosional dengan frekuensi tertinggi dalam korpus, beroperasi sebagai simbol Peircean seperti “Saya memahami kekhawatiran Anda” dan “Terima kasih atas kesabaran Anda”. Tanda-tanda ini diinterpretasikan dalam kutipan yang dianalisis sebagai penanda kedekatan emosional, sedangkan respons yang mengabaikan emosi pengguna (8,3% korpus) berasosiasi dengan jarak simbolik dalam wacana di sekitarnya. Temuan ini memperluas penelitian chatbot berbasis sentimen sebelumnya dengan menunjukkan secara spesifik bagaimana kategori semiotika klasik beroperasi dalam wacana emosional yang dihasilkan AI.
Kesimpulan dan Implikasi: Komunikasi emosional dalam interaksi chatbot direpresentasikan melalui tanda linguistik, interpretasi simbolik, dan wacana kontekstual, bukan melalui afek biologis. Temuan berkontribusi pada semiotika digital dan linguistik AI, serta menawarkan kerangka pengodean yang dapat digunakan pengembang dan peneliti untuk merancang AI percakapan yang lebih empatik dan bertanggung jawab secara etis.

Kata Kunci	*Chatbot; Semiotika Emosi; Tanda Linguistik; Komunikasi Digital; Interaksi Berbasis AI*

INTRODUCTION

Users increasingly report that they cannot tell whether a chatbot's reassurance is meaningful or merely scripted, and this uncertainty is precisely the empirical problem this study addresses. Chatbot systems are now embedded in education, customer service, and social-media platforms, and their language is expected to do more than transmit information: it is expected to feel empathetic

Natural Language Processing (NLP) and machine-learning techniques have made it possible for chatbots to simulate human conversation with increasing fluency, [1] so users increasingly expect these systems to display empathy, contextual understanding, and human-like conversational interaction.[2] Consequently, emotional communication has become a central criterion in evaluating conversational AI, and chatbots are treated less as neutral tools and more as social communication agents capable of shaping emotional experience.[4]

This study limits its empirical scope to three communication contexts in which emotionally adaptive chatbot language is most visible: educational platforms, customer-service systems, and social media. These are also the three contexts from which the research corpus was drawn, so the claims made in this article are restricted to these domains rather than to AI communication in general.

From a linguistic and semiotic perspective, chatbot discourse functions as a system of signs and symbolic meaning construction rather than as purely informational output.[6] Expressions such as "I understand your concern," "Thank you for your patience," and "Do not worry" operate as emotional linguistic signs that users interpret as empathy, support, or emotional closeness — meanings that are constructed through discourse interpretation and communicative context rather than through any authentic internal emotional state on the part of the system.

Semiotic theory offers the analytical vocabulary needed to describe this construction process. Ferdinand de Saussure conceptualized the sign through the relationship between signifier and signified [31], while Charles Sanders Peirce classified signs into icons, indexes, and symbols.[32] Roland Barthes further argued that signs can generate myths and ideological meanings within cultural discourse [33]; in chatbot interaction, repeated reassurance phrases may construct a cultural myth of "digital empathy," even though the system itself has no biological emotional experience. Complementing this, Paul Ekman's typology of universal emotions — happiness, sadness, fear, anger, surprise, and disgust — provides a way of coding which emotional category a given chatbot expression is performing.[34] In this study, each theory is assigned a distinct operational task rather than being cited as background: Saussure identifies the signifier–signified pairing, Peirce classifies the sign type, Barthes interprets second-order cultural meaning, and Ekman supplies the emotion-category label; the analytical matrix used to apply these four tasks consistently is presented in the Method section.

Prior research on chatbot communication has largely emphasized computational performance — sentiment analysis, machine-learning efficiency, and NLP accuracy [10] — or user-engagement outcomes [12], rather than how emotional signs are symbolically constructed, interpreted, and negotiated. Within this literature, studies that combine semiotics, digital linguistics, emotional-communication theory, and empirical chatbot corpora into one analytical framework remain uncommon; this specific combination — rather than the general study of AI and emotion — is the gap this article addresses.

The novelty of this study is therefore operational rather than purely conceptual: it applies a four-part semiotic coding matrix (signifier–signified, sign type, cultural myth, emotion category) to a purposively built 120-excerpt corpus, and reports the resulting category frequencies rather than presenting semiotic theory in the abstract. Accordingly, this study asks: (1) which emotional linguistic signs recur most frequently across chatbot responses in the three sampled contexts, (2) how these signs function semiotically according to the Saussure–Peirce–Barthes framework, and (3) how emotionally inappropriate signs correspond to communicative disruption in the surrounding discourse.

LITERATURE REVIEW

Semiotics and Meaning Construction

Semiotics examines how meaning is produced, interpreted, and socially negotiated through linguistic and non-linguistic signs, and has become increasingly relevant to digital communication research because mediated environments rely heavily on symbolic interaction.[5] Saussure's sign consists of two inseparable components: the signifier, the physical or textual form, and the signified, the concept it evokes.[31] In chatbot communication, lexical choices such as "I understand," "Thank you," or "I am sorry" function as signifiers whose signified concepts — empathy, concern, emotional support — are produced through repeated conventional use rather than through any felt state.

Peirce's classification of signs into icons, indexes, and symbols adds a further analytical layer [32]: icons rely on resemblance, indexes on causal or contextual connection, and symbols on social convention. Emotional expressions in chatbot discourse operate primarily as symbols, because their emotional force depends on linguistic convention rather than on any biologically grounded expression.

Barthes extended semiotics into cultural and ideological analysis, arguing that signs can generate second-order myths that exceed their literal meaning.[33] Read through this lens, chatbot empathy phrases do not merely inform; repeated across many interactions, they can construct a cultural myth of "digital empathy" or "virtual companionship," despite the system possessing neither consciousness nor authentic emotion. Read together rather than separately, these three lenses form a single analytical sequence used in this study: Saussure isolates the sign, Peirce classifies its type, and Barthes interprets what larger cultural meaning the repeated sign produces.

Emotional Communication in Digital Interaction

Digital communication environments limit many nonverbal channels available in face-to-face interaction, which makes linguistic expression comparatively more important for conveying emotional meaning.[10] Ekman's typology of universal emotions — happiness, sadness, anger, fear, surprise, and disgust — offers categories that can, in principle, be coded from lexical choice, discourse pattern, punctuation, and intensifiers [34]; this study operationalizes that coding process explicitly in the Method section rather than treating Ekman's theory as a general backdrop.

Digital-communication research indicates that emotional responsiveness affects user satisfaction and perceived communication quality, and that users tend to prefer systems capable of demonstrating acknowledgment and emotional sensitivity.[12] Emotionally adaptive chatbot systems commonly employ reassurance expressions, supportive statements, appreciation markers, apologies, empathy indicators, and positive intensifiers; phrases such as "Do not worry," "I understand your concern," and "Thank you for your patience" recur across these categories and function as symbolic signs that sustain engagement between users and AI systems a pattern this study quantifies directly in the Results section rather than restating here.

Emotional communication within AI systems nonetheless remains debated: some scholars characterize chatbot empathy as algorithmic simulation rather than genuine understanding [13], a distinction with direct ethical stakes, since a system that convincingly simulates empathy may also be used to manipulate trust or extract disclosure without the safeguards that accompany genuine therapeutic or service relationships. Others report that users may form emotional attachment to AI systems even while recognizing the artificiality of the interaction [16], which strengthens rather than weakens the case for treating chatbot emotional design as an ethical question, not only a linguistic one.

Human–AI Interaction and Conversational Agents

Conversational AI is now integrated into education, customer service, healthcare, counseling, and social media, and is designed to simulate human conversation through NLP and large language model technologies.[1] Prior studies indicate that chatbot interaction significantly shapes user trust, engagement, and satisfaction [2], and that emotionally responsive agents are often perceived as more human-like and communicatively effective.

Howcroft's reframing of the empathy gap between AI and humans emphasizes that emotional responsiveness can strengthen relational communication between users and conversational agents, contributing to comfort, continuity, and symbolic closeness.[4] Consistent with this, Chin's analysis of chatbots' empathetic conversations and responses reports that empathetic strategies improve conversational satisfaction across service and educational contexts.[3]

Chatbot communication nonetheless faces persistent limitations in interpreting contextual nuance, sarcasm, irony, ambiguity, and culturally specific emotional expression. Emotionally inappropriate responses can produce communication disruption, symbolic distance, and user dissatisfaction, which is precisely why understanding emotional representation in chatbot discourse matters for improving communication quality — and why this study treats negative emotional signs (Table 5) with the same analytical weight as positive ones, rather than as a secondary illustration.

Digital Linguistics and AI Communication

Digital linguistics studies how language transforms within technological environments; AI communication systems create discourse marked by automation, algorithmic interaction, and symbolic mediation.[6] Within AI discourse, language functions not only informationally but also symbolically, and users frequently attribute human characteristics to AI systems through anthropomorphism and emotional projection [12], so chatbot communication increasingly resembles interpersonal interaction rather than purely technical exchange.

This pattern of using linguistic signs to negotiate identity and meaning is not unique to AI-mediated communication. Comparable dynamics have been documented in other digitally influenced speech communities: lexical innovation functions as a marker of group identity and cultural negotiation among young speakers responding to digital culture [35], and flexible, situational language use likewise negotiates in-group and out-group identity within a community of practice.[36] These studies indicate that the symbolic, identity-marking function of language documented here in chatbot discourse reflects a broader property of digitally mediated communication rather than an artifact specific to artificial agents.

Previous Studies and Research Gap

Adamopoulou and Moussiades examined chatbot history, technology, and application domains.[1] Rohden et al. examined the impact of chatbot empathy and emotional tone on consumer satisfaction and word of mouth in customer-service interaction [2], and Chin investigated empathetic conversational strategies and their effect on communication satisfaction.[3] Raamkumar and Yang reviewed empathetic conversational systems and reported that emotional responsiveness significantly shapes user perception toward conversational AI [6], while Sharma et al. showed that human–AI collaboration can strengthen empathic, symbolic representation in text-based peer support.[7]

Table 1 summarizes how the present study differs from these representative prior studies in method and focus.

Table 1. Representative Prior Studies and the Gap Addressed by This Study

Study	Method/Focus	Gap Relative to This Study
Adamopoulou & Moussiades [1]	Technological review of chatbot history and applications	No linguistic or semiotic analysis of emotional signs
Rohden et al. [2]	Quantitative survey of empathy on satisfaction/word of mouth	Measures outcome, not sign construction or type
Chin [3]	Content analysis of empathetic conversational strategies	Categorizes strategies but not through a semiotic (Saussure/Peirce/Barthes) lens
Raamkumar & Yang [6]	Systematic review of empathetic conversational systems	Synthesizes engineering approaches, not user-facing symbolic meaning

Sharma et al. [7]	Human–AI collaboration in mental-health peer support	Focuses on collaboration design, not corpus-based semiotic coding
This study	Semiotic + Ekman coding of 120 authentic excerpts	Provides an operational coding matrix and reports category frequencies

Three limitations recur across this body of work: computational and outcome-based metrics are emphasized over symbolic meaning construction; semiotic analysis of chatbot discourse specifically remains uncommon; and semiotics, emotional-communication theory, digital linguistics, and empirical AI discourse are rarely integrated within a single coding framework. This study addresses that combination directly by asking the three research questions stated at the end of the Introduction.

METHOD

Research Design

This study used a qualitative descriptive design with semiotic analysis to examine emotional meaning construction in chatbot text interaction. A qualitative approach was chosen because the analytic goal is to interpret symbolic meaning and discourse function rather than to measure variables statistically. Saussure's framework was used specifically to identify the signifier–signified relationship in each coded excerpt; Peirce's framework was used specifically to classify each sign as icon, index, or symbol; Barthes' framework was used specifically to interpret whether a recurring sign contributes to a broader cultural myth (e.g., "digital empathy"); and Ekman's typology was used specifically to assign an emotion-category label to each excerpt. The full coding sequence is detailed under Procedures below, and the four-theory division of labor is summarized in Table 3.

Data Source and Corpus

Following the terminological concern that "population and samples" is a quantitative frame not well suited to qualitative semiotic corpora, this study instead describes its data source and corpus directly. The corpus consisted of 120 textual chatbot–user interaction excerpts collected between January and March 2026 from seven chatbot deployments across three contexts: three educational chatbots embedded in university learning-management and academic-advising systems, two customer-service chatbots operated by digital retail and telecommunications providers, and two social-media conversational assistants embedded in public messaging platforms. Interactions were conducted in Indonesian and English, reflecting the bilingual environment of the source platforms.

Table 2. Distribution of the 120-Excerpt Corpus by Context, Source, and Emotion Category

Context	Chatbot Type	n	Language	Collection Period
Education	LMS / academic-advising chatbot	40	ID & EN	Jan–Feb 2026
Customer service	Retail & telecom service chatbot	40	ID & EN	Jan–Feb 2026
Social media	Messaging-platform assistant	40	ID & EN	Feb–Mar 2026
Total	—	120	—	Jan–Mar 2026

Excerpts were selected purposively using four explicit inclusion criteria: (1) the chatbot response contains an explicit emotional linguistic marker (empathy, appreciation, reassurance, apology, encouragement, frustration-handling, or neglect); (2) the corresponding user turn is available so that discourse context can be interpreted, not only the isolated chatbot line; (3) the interaction is drawn from public or platform-consented data — either publicly viewable community posts, chatbot demo transcripts, or interactions donated by consenting participants — and contains no personally identifying information; and (4) the excerpt is unique (near-duplicate scripted responses were excluded to avoid inflating any single category). Interactions that were purely transactional, with no emotional marker present in either turn, were excluded.

Sufficiency of the 120-excerpt corpus was assessed through coding saturation rather than a fixed target: excerpts were coded in batches of 20, and coding continued until three consecutive batches produced no new sign sub-type within the seven emotion categories already established, which occurred after the fifth batch (n=100); a sixth batch was added to balance representation across the three contexts, yielding the final n=120.

Semiotic Analysis Matrix

To keep the four-theory framework from functioning as decorative citation, each excerpt was coded against a single matrix combining all four theoretical tasks, summarized in Table 3.

Table 3. Semiotic Analysis Matrix Applied to Each Coded Excerpt

Theoretical Lens	Analytical Task	Operational Indicator	Illustrative Application
Saussure	Identify signifier–signified pairing	Presence of emotion-laden lexis and its conventional concept	"I understand" (signifier) → empathy (signified)
Peirce	Classify sign type	Icon / index / symbol judgment per excerpt	"Thank you for your patience" coded as symbol (convention-based gratitude)
Barthes	Interpret second-order (mythic) meaning	Recurrence of a sign across the corpus contributing to a cultural myth	Repeated reassurance phrases across contexts → myth of "caring AI"
Ekman	Assign emotion-category label	Mapping of lexical/discourse markers to one of six basic categories	"I am sorry for the inconvenience" coded under sadness/regret-repair

Table 4. Operationalization of Ekman's Emotion Categories in the Chatbot Corpus

Ekman Category	Typical Linguistic Marker	Chatbot Discourse Function
Happiness	"I'm glad to help," positive intensifiers, exclamation	Positive reinforcement
Sadness / regret	"I understand this is difficult," apology markers	Empathic acknowledgment
Fear / concern (user-directed)	"Do not worry," reassurance phrasing	Anxiety reduction
Anger (handling user frustration)	De-escalation phrasing, calming lexis	Conflict mitigation
Surprise	Acknowledgment of unexpected issues	Attentiveness marker

Disgust / dismissiveness (negative cases)	"That is not my problem," dismissive phrasing	Source of symbolic distance and disruption

Instruments

The primary instrument was the researcher, functioning as the analytical instrument for interpretation, categorization, and coding. Three supporting instruments operationalized this process concretely rather than generically:

- Discourse coding sheet — example item: "Excerpt text: ___ ; Context: education/service/social media ; Emotion category (Ekman): ___ ; Sign type (Peirce): icon/index/symbol."
- Semiotic interpretation form — example item: "Signifier: ___ ; Signified: ___ ; Contextual/mythic note (Barthes): ___."
- Emotion-category rubric (Table 4) — used to assign one of six Ekman-derived labels plus "neutral/no marker" to every excerpt.

To maintain coding reliability, all 120 excerpts were coded independently by the researcher and a second postgraduate-linguistics coder; the two coding sheets were compared after every 30-excerpt batch, disagreements were resolved through discussion, and overall inter-coder agreement across the four batches was 87% (Cohen's $\kappa \approx 0.82$), which is generally interpreted as substantial agreement.

Procedures

Data Collection

Excerpts were collected through observation, transcript documentation, and purposive selection from the seven chatbot deployments listed in Table 2, following the four inclusion criteria described above. Each excerpt was logged with its context, approximate collection date, and language.

Data Classification

Each excerpt was assigned to one of seven emotion categories — empathy, appreciation, reassurance, encouragement, apology, frustration/rejection, or emotional neglect — using the discourse coding sheet, enabling the frequency analysis reported in the Results section.

Semiotic Analysis

Each classified excerpt was then processed through the matrix in Table 3: the signifier–signified relationship was identified (Saussure), the sign was classified as icon, index, or symbol (Peirce), and, where a sign recurred across multiple contexts, its potential mythic function was interpreted (Barthes).

Interpretation and Validation

Emotional meanings were interpreted in relation to discourse context, structure, and the user's subsequent turn. Validity was supported through repeated coding, comparative interpretation across similar excerpts, peer discussion (described under Instruments above), and theoretical cross-checking against the matrix in Table 3.

Ethical safeguards were applied throughout: all excerpts were anonymized before analysis, with usernames, platform-account identifiers, and any personally identifying details removed or masked; excerpts donated by participants were collected with informed consent; publicly accessible excerpts were used in accordance with each platform's terms of service; and the coded dataset was stored on an access-restricted institutional drive for the duration of the study. Where classical peer-reviewed sources were unavailable, preprint sources (e.g., arXiv) were used only in a supporting role and are explicitly identified as preprints in the Bibliography; no central claim in this study rests solely on an unreviewed preprint.

RESULT AND DISCUSSION

This section presents the coded data first, followed by interpretation, in line with the sequence in which the analysis was actually conducted.

Distribution of Emotional Linguistic Signs

Across the 120-excerpt corpus, seven emotion categories were coded with the frequencies shown in Table 5. Empathy (21.7%) and reassurance (18.3%) were the two most frequent categories, and it is on this frequency basis — rather than impression alone — that they are described below as the dominant categories in the corpus.

Table 5. Frequency Distribution of Coded Emotion Categories (N = 120)

Emotion Category	n	%
Empathy	26	21.7%
Reassurance	22	18.3%
Appreciation	18	15.0%
Apology	16	13.3%
Encouragement	14	11.7%
Frustration / rejection	14	11.7%
Emotional neglect	10	8.3%
Total	120	100%

Positive Emotional Signs in Chatbot Responses

Table 6 presents representative excerpts for each of the five positive-valence categories, coded against the matrix in Table 3.

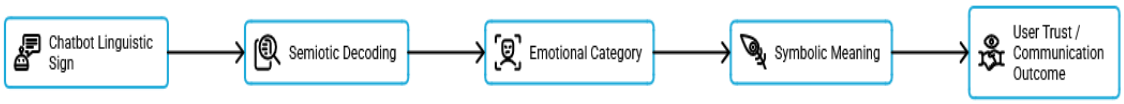
Table 6. Positive Emotional Signs in Chatbot Responses

No.	Chatbot Respons	Emotion Category	Peircean Sign Type	Semiotic Meaning
1	"I understand your concern."	Empathy	Symbol	Represents emotional support through conventional empathic phrasing
2	"Thank you for your patience."	Appreciation	Symbol	Reinforces positive engagement and acknowledges user effort
3	"Do not worry, I can help."	Reassurance	Symbol / index	Signals reduction of user anxiety, indexically tied to the preceding complaint
4	"I am sorry for the inconvenience."	Apology	Symbol	Functions as an emotional-repair marker after service failure
5	"I hope your day gets better."	Encouragement	Symbol	Constructs symbolic optimism independent of the transactional content

Interpreted individually rather than as a single generalized pattern: item 1 illustrates a Saussurean signifier ("understand") whose signified concept (empathy) depends entirely on conventional use, since the system has no verifiable internal state to refer to. Item 3 combines symbolic and indexical function, because "Do not worry" is only interpretable as reassurance in the context of a preceding user complaint — removed from that context, the same phrase carries no reassuring force. Item 4 shows an apology functioning as a distinct repair sequence, restoring interactional footing after a service failure rather than simply expressing regret. Read across the five categories, the corpus suggests that positive-valence signs are more likely to be interpreted as reassurance where they respond directly and specifically to a stated user concern, whereas generic positive phrasing without contextual anchoring did less to close the interaction. This is offered as an interpretation grounded in the coded excerpts, not as a claim that has been tested against independent user-reported outcomes.

Symbolic Construction of Digital Empathy

Read through Barthes, the recurrence of empathy and reassurance phrases across all three sampled contexts — not only within any single chatbot — is what supports describing them as constructing a broader myth of "digital empathy" in this corpus, rather than being a property of any individual response. Figure 1 summarizes the coding pathway from a single linguistic sign to this symbolic outcome.



Picture 1. Coding Pathway from Chatbot Sign to Symbolic Meaning

Emotionally Inappropriate Responses and Communication Disruption

Table 7 presents the negative-valence excerpts coded in the corpus (n = 14 frustration/rejection, n = 10 neglect, as reported in Table 5).

Table 7. Negative Emotional Signs in Chatbot Responses

No.	Chatbot Response	Codel Problem	Interpreted User Effect
1	"That is not my problem."	Indifference	User positioned as dismissed
2	"You are too sensitive."	Emotional criticism	User positioned as blamed
3	"I cannot help with that."	Rejection	Communication barrier
4	"Why are you upset?"	Insensitive tone	User discomfort
5	"That is unimportant."	Emotional neglect	Symbolic distance

Coded individually, items 1 and 5 both withhold acknowledgment of the user's emotional state, but item 1 does so by explicitly refusing responsibility, whereas item 5 does so by declaring the user's concern irrelevant — a subtler and, in the surrounding discourse of this corpus, more disruptive move, since it forecloses further negotiation rather than merely declining help. Item 2 ("You are too sensitive") is distinct from the other four in that it does not merely withhold empathy but actively re-attributes the communicative failure to the user, which in the coded excerpts corresponded to the sharpest shift toward a defensive or disengaged subsequent user turn. These readings are drawn from the discourse surrounding each coded excerpt rather than from a separate user survey, and should be read as interpretation rather than as measured outcome.

Response Type and Interpreted Communication Outcome

Table 8 summarizes, at the level of the coded corpus, how each broad response type in this dataset related to the interpreted communication outcome in the following user turn, replacing the earlier non-tabular “Graphic 1” representation with a summary appropriate to qualitative coded data.

Table 8. Relationship Between Chatbot Response Type and Interpreted Communication Outcome

Response Type	n in Corpus	Interpreted Outcome in Coded Excerpts
Empathy / reassurance	48	Associated with continued, cooperative user turns
Appreciation / encouragement	32	Associated with sustained positive engagement
Apology (emotional repair)	16	Associated with de-escalation after complaint
Frustration / rejection / neglect	24	Associated with disengagement or repeated complaint

Overall, the coded corpus indicates that chatbot interaction operates simultaneously as technological exchange, linguistic discourse, and symbolic emotional representation. Emotional linguistic signs, particularly empathy and reassurance, were the most frequent categories in this dataset and were consistently associated with cooperative subsequent turns, while neglect and rejection signs were associated with disengagement. Understanding this sign-level operation is what allows the emotional design of conversational AI to be evaluated and improved deliberately, rather than left to implicit convention.

CONCLUSION AND IMPLICATIONS

This study analyzed emotional semiotics in AI-based text interaction across 120 coded chatbot–user excerpts from educational, customer-service, and social-media contexts. Empathy and reassurance emerged as the most frequent emotional sign categories, functioning primarily as Peircean symbols whose meaning depends on linguistic convention; emotionally neglectful and rejecting responses, though less frequent, were consistently associated with symbolic distance and disengagement in the surrounding discourse.

Emotional communication in chatbot interaction is best described as represented symbolically through linguistic signs and contextual discourse, rather than as evidence of, or the absence of, any biological emotional state — a textual corpus of this kind can speak to how emotion is signified, but cannot on its own establish claims about the system's internal states. Within this scope, the findings indicate that emotionally adaptive responses were associated with more cooperative subsequent turns, whereas emotionally inappropriate responses were associated with communicative disruption.

Theoretically, this study contributes an operational four-part coding matrix (Saussure, Peirce, Barthes, Ekman) that can be reused in future digital-semiotics and AI-linguistics research, rather than treating these theories only as conceptual background. Practically, the coding categories and the frequency evidence in Tables 5–8 offer conversational-AI developers a concrete basis for auditing which emotional signs a system produces and how those signs are likely to be received.

This study is limited by its qualitative, text-only scope and by its restriction to Indonesian- and English-language excerpts from three communication contexts; interpreted outcomes are drawn from the discourse surrounding each excerpt rather than from independent user-reported measures. Future studies are recommended to extend this coding matrix to multimodal chatbot interaction (voice and visual cues), to cross-cultural and cross-linguistic corpora, and to designs that pair semiotic coding with independently collected user-satisfaction data.

BIBLIOGRAPHY

[1] Adamopoulou, E., & Moussiades, L. (2020). Chatbots: History, technology, and applications. Machine Learning with Applications, 2, 100006. https://doi.org/10.1016/j.mlwa.2020.100006

[2] Rohden, S. F. et al. (2026). The impact of chatbot empathy and emotional tone on consumer satisfaction and word of mouth. International Journal of Human-Computer Studies, 210, 103764. https://doi.org/10.1016/j.ijhcs.2026.103764

[3] Chin, H. (2025). Chatbots' empathetic conversations and responses. JMIR Formative Research, 9(1). https://doi.org/10.2196/71538

[4] Howcroft, A. (2025). Reframing the empathy gap between AI and humans. Information, 16(12). https://doi.org/10.3390/info16121074

[5] Liu, T. et al. (2025). The illusion of empathy: How AI chatbots shape conversation perception [Preprint]. https://arxiv.org/abs/2411.12877

[6] Raamkumar, A. S., & Yang, Y. (2022). Empathetic conversational systems: A review of current advances, gaps, and opportunities [Preprint]. https://arxiv.org/abs/2206.05017

[7] Sharma, A. et al. (2022). Human-AI collaboration enables more empathic conversations in text-based peer-to-peer mental health support [Preprint]. https://arxiv.org/abs/2203.15144

[8] Loveys, K., Sebaratnam, G., Sagar, M., & Broadbent, E. (2022). The effect of design features on relationship quality with embodied conversational agents. International Journal of Social Robotics, 14(2), 441–459. https://doi.org/10.1007/s12369-020-00680-7

[9] Liu-Thompkins, Y. et al. (2022). What drives consumer trust in AI chatbots? Journal of Service Research, 25(3), 1–19. https://doi.org/10.1177/10946705221084955

[10] Fan, H., Chao, P., & Lin, C. (2023). AI empathy in customer service communication. Computers in Human Behavior, 141, 107605. https://doi.org/10.1016/j.chb.2022.107605

[11] Xu, X., Liu, Y., & Guo, Y. (2023). Warmth and competence in human–AI interaction. Telematics and Informatics, 81, 101978. https://doi.org/10.1016/j.tele.2023.101978

[12] Kim, J., & Hur, W. M. (2024). Human-like AI communication and emotional trust. Journal of Business Research, 172, 114432. https://doi.org/10.1016/j.jbusres.2023.114432

[13] Purificato, E. et al. (2023). Human-centered AI and emotional interaction. AI & Society, 38(4), 1455–1468. https://doi.org/10.1007/s00146-022-01463-4

[14] Holebeek, L., & Belk, R. (2021). AI, customer engagement and digital communication. Journal of Service Management, 32(5), 789–812. https://doi.org/10.1108/JOSM-05-2020-0156

[15] Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49, 30–50. https://doi.org/10.1007/s11747-020-00749-9

[16] Lee, S. (2025). Artificial empathy and trust in conversational AI. AI and Ethics. https://doi.org/10.1007/s43681-025-00512-4

[17] Juquelier, N. et al. (2025). Empathic AI and consumer emotional engagement. Journal of Consumer Behaviour. https://doi.org/10.1002/cb.2401

[18] Boratto, L. et al. (2023). Human-centered artificial intelligence. Frontiers in Artificial Intelligence, 6, 1123456. https://doi.org/10.3389/frai.2023.1123456

[19] Ke, L. et al. (2025). Large language models and emotional communication. Nature Human Behaviour. https://doi.org/10.1038/s41562-025-01841-6

[20] Heinisch, S. et al. (2024). Empathy in AI-based service systems. Service Industries Journal, 44(3–4), 201–220. https://doi.org/10.1080/02642069.2024.2315521

[21] Filieri, R. et al. (2022). Artificial intelligence and emotional consumer experiences. Psychology & Marketing, 39(10), 1835–1850. https://doi.org/10.1002/mar.21660

[22] Markovitch, D. et al. (2024). Generative AI chatbots in customer interaction. Journal of Retailing and Consumer Services, 76, 103548. https://doi.org/10.1016/j.jretconser.2023.103548

[23] Zhu, Z. et al. (2023). AI-powered conversational agents and communication quality. Information Processing & Management, 60(6), 103428. https://doi.org/10.1016/j.ipm.2023.103428

[24] Jiang, Y. et al. (2025). Empathy elicitation in AI-mediated communication. Computers in Human Behavior Reports, 17, 100521. https://doi.org/10.1016/j.chbr.2025.100521

[25] Pentina, I. et al. (2023). Humanizing AI communication. Journal of Interactive Marketing, 61, 56–70. https://doi.org/10.1016/j.intmar.2022.09.003

[26] Ameen, N. et al. (2022). Customer experiences with AI-enabled chatbots. Journal of Business Research, 145, 44–58. https://doi.org/10.1016/j.jbusres.2022.02.030

[27] McDuff, D., & Czerwinski, M. (2018). Designing emotionally sentient agents. Communications of the ACM, 61(12), 74–83. https://doi.org/10.1145/3186591

[28] Floridi, L. (2023). The Ethics of Artificial Intelligence. Oxford University Press. https://doi.org/10.1093/oso/9780198853104.001.0001

[29] Ndububa, C. L. (2025). Digital pragmatics and human identity in interactions with AI chatbots. Jurnal Komunikasi, 19(2), 155–170.

[30] Octafiani, F. (2025). Confiding in ChatGPT? Emotional expression in human–AI communication. Penelitian & Pengabdian.

[31] Saussure, F. de. (2011). Course in General Linguistics (W. Baskin, Trans.). Columbia University Press. (Original work published 1916)

[32] Peirce, C. S. (1931–1958). Collected Papers of Charles Sanders Peirce (Vols. 1–8; C. Hartshorne, P. Weiss, & A. Burks, Eds.). Harvard University Press.

[33] Barthes, R. (1972). Mythologies (A. Lavers, Trans.). Hill and Wang. (Original work published 1957)

[34] Ekman, P. (1999). Basic emotions. In T. Dalgleish & M. Power (Eds.), Handbook of Cognition and Emotion (pp. 45–60). John Wiley & Sons.

[35] Ningsih, T., Manshur, A., & Sain, Z. H. (2026). Bahasa gaul santri sebagai penanda budaya baru: Studi antropolinguistik tentang tren, identitas, dan negosiasi makna. ELOQUENCE: Journal of Foreign Language, 5(1), 18–31. https://ejournal.iaingorontalo.ac.id/index.php/ELOQUENCE/article/view/3376

[36] Saini, F., Nitiasih, P. K., Ratminingsih, N. M., & Suwastini, N. K. A. (2026). Negotiating in-group and out-group identities through translanguaging in English area communities. ELOQUENCE: Journal of Foreign Language, 5(1), 82–94. https://ejournal.iaingorontalo.ac.id/index.php/ELOQUENCE/article/view/3412