

EXPLORING EMOTIONALLY INTELLIGENT MACHINES: CAN AI TRULY UNDERSTAND HUMAN AFFECT?

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Abstract

Artificial intelligence systems now claim the ability to recognize human emotions. Many systems also claim to respond to these emotions appropriately. Researchers question whether such systems truly understand human affect. This study examined that question using a mixed-methods design. The researchers recruited 150 participants for the quantitative component. Participants interacted with three commercially available emotion-recognition AI systems. Each participant completed a structured questionnaire after the interaction. The questionnaire measured perceived accuracy, empathy, and trust. The researchers then conducted semi-structured interviews with twenty participants to explore their subjective experiences in greater depth. The researchers also analyzed system-generated logs. These logs recorded the emotional labels detected by each AI system. The researchers compared these labels against participants' self-reported emotional states. Results showed that AI systems detected basic emotions with reasonable accuracy. However, the systems failed to detect nuanced or mixed emotional states. Participants rated AI empathy lower than AI accuracy. Correlation analysis revealed a moderate relationship between accuracy and trust. Interview data showed that participants valued responsiveness over technical accuracy. Participants described their interactions as helpful but emotionally shallow. The study concludes that AI simulates emotional intelligence at a surface level. Genuine affective understanding remains beyond current AI capability. This finding carries implications for the design of future emotionally intelligent systems.

INTRODUCTION

Human emotion shapes almost every form of communication. Emotion guides decision-making. Emotion influences trust (Şengöz, 2024). Emotion affects how people interpret the words and actions of others (Fatima & Ahmad, 2025). For decades, researchers viewed emotional understanding as a uniquely human capacity

(Ahmad et al., 2025). Machines processed data. Humans felt and interpreted meaning. This distinction has recently come under pressure. Artificial intelligence systems now claim the ability to detect human emotions. Some systems analyze facial expressions. Other systems analyze vocal tone. Still other systems analyze written text for emotional content. These systems power virtual

assistants, customer service chatbots, mental health applications, and educational platforms. Developers market these systems as emotionally intelligent. This marketing raises an important question. Can a machine truly understand human affect, or does it merely simulate understanding (Finet et al., 2025)?

The field of affective computing emerged to address this question. Affective computing combines computer science, psychology, and linguistics. Researchers in this field design systems that detect emotional signals. These systems use algorithms trained on large datasets of human expression. Some algorithms detect a smile. Other algorithms detect a raised pitch in speech. Still other algorithms detect certain words associated with anger or joy. These detection methods have improved considerably in recent years (Pietikäinen & Silven, 2022). Detection accuracy for basic emotions now reaches high levels in controlled settings. However, detection is not the same as understanding. A system may correctly label an expression as angry. The system may still lack any genuine grasp of why the person feels angry. The system may also fail to grasp what that anger means within a broader social or cultural context (Hyvärinen, 2022).

This gap between detection and understanding forms the central problem of this study. Many AI systems now perform well on narrow emotional recognition tasks. Few systems demonstrate genuine comprehension of emotional meaning. Genuine comprehension requires context. It requires memory of prior interactions. It requires sensitivity to cultural norms. It requires an appreciation of individual variation in emotional expression (Younis et al., 2024). Current AI systems often lack these capacities. Systems trained primarily on Western datasets frequently misinterpret emotional expressions from other cultural backgrounds. Systems trained on adult speech patterns often misinterpret the emotional expressions of children or older adults. These limitations raise doubts about claims of genuine emotional intelligence in machines (Zibin et al., 2025).

The consequences of this gap extend beyond academic debate. Mental health applications

increasingly rely on AI to detect signs of distress. Customer service systems increasingly rely on AI to detect frustration (Boyd & Markowitz, 2026). Educational platforms increasingly rely on AI to detect confusion or disengagement among students. If these systems misread emotional signals, the consequences can be serious (Kumar et al., 2024). A mental health application might miss signs of genuine crisis. A customer service system might escalate a minor complaint unnecessarily. An educational platform might mislabel a student's boredom as confusion, or confusion as disinterest. These practical stakes make the question of genuine emotional understanding an urgent one for developers, policymakers, and users alike (Vicci, 2024).

Prior research has examined the technical accuracy of emotion-recognition systems in considerable depth. Fewer studies have examined how users themselves perceive these systems (Cant et al., 2024). Fewer still have connected technical accuracy with subjective user trust in a single, integrated study. This gap in the literature motivated the present research. The researchers designed this study to bridge technical measurement with human perception. The researchers measured how accurately AI systems detected emotions. The researchers also measured how users perceived that accuracy. The researchers explored, through interviews, what genuine emotional understanding meant to users themselves.

This study therefore examined artificial intelligence systems from two complementary angles. The first angle involved a quantitative assessment of system accuracy. The second angle involved a qualitative exploration of user experience. Together, these two angles offered a fuller picture than either approach alone could provide. The researchers hoped that this integrated picture would inform future design choices for emotionally intelligent systems. The researchers also hoped that the findings would inform public understanding of what current AI systems can and cannot achieve.

Research Objectives

1. To examine the accuracy of AI systems in recognizing human emotional states.
2. To explore user perceptions of empathy and trust in AI-driven emotional interactions.
3. To identify the factors that distinguish genuine emotional understanding from simulated emotional response in AI systems.

Research Questions

1. How accurately do AI systems recognize human emotional states across different contexts?
2. How do users perceive the empathy and trustworthiness of emotionally responsive AI systems?
3. What factors do users and researchers associate with genuine emotional understanding, as opposed to simulated response, in AI systems?

Significance of the Study

This study offers practical insight for developers designing emotionally responsive AI systems. The findings inform decisions in mental health technology, education, and customer service. The study also contributes to theoretical debates on machine cognition and affect. Policymakers may use these findings to guide regulation of emotionally intelligent systems. The study ultimately bridges technical and human-centered perspectives on artificial emotional intelligence.

LITERATURE REVIEW

Affective computing emerged as a distinct field of inquiry in the mid-1990s (Mengoni et al., 2024). Early researchers in this field sought to give machines the ability to recognize and simulate human emotion. This early work focused primarily on facial expression analysis (Tuschling & Weber-Guskar, 2025). Researchers built systems that could classify facial images into discrete emotional categories. These categories typically included happiness, sadness, anger, fear, surprise, and disgust. This six-category model drew heavily on earlier psychological research into universal facial expressions. Later researchers expanded this work to include vocal tone analysis. Vocal tone analysis examines pitch, speed, and volume to infer emotional state. Still later

researchers expanded the field further to include text-based sentiment analysis. Text-based sentiment analysis examines written language for emotional cues. Together, these three approaches formed the technical foundation of modern emotion-recognition AI (Lee, 2023).

Subsequent research raised concerns about the accuracy of these methods across different populations. Several studies found that facial recognition systems performed less accurately on non-Western faces. Other studies found that vocal tone analysis struggled with speakers of different linguistic backgrounds (Guo et al., 2024). Text-based sentiment analysis faced similar challenges. Sentiment analysis systems trained on English-language datasets often misclassified emotional expressions in other languages. These findings pointed to a persistent bias problem in emotion-recognition technology. Researchers attributed this bias to imbalanced training datasets. Most large datasets used to train these systems drew heavily from Western, English-speaking populations. This imbalance limited the generalizability of many emotion-recognition systems (Ahmad et al., 2021).

A separate body of research examined the psychological theory underlying emotion-recognition technology. Some researchers relied on basic emotion theory. Basic emotion theory holds that a small set of emotions is universal across cultures. Other researchers favored dimensional models of emotion (Oppong). Dimensional models describe emotion along continuous scales, such as valence and arousal, rather than discrete categories. Still other researchers argued for constructionist theories of emotion (Barrett & Lida, 2024). Constructionist theories hold that emotional experience is shaped heavily by cultural and situational context, rather than fixed biological categories. This theoretical disagreement had direct implications for AI system design. Systems built on basic emotion theory tended to classify expressions into fixed categories. Systems built on dimensional or constructionist theories tended to produce more flexible, context-sensitive outputs. Researchers continue to debate which theoretical foundation

best supports genuine emotional understanding in machines (Barrett & Lida, 2024).

A growing body of literature also examined user trust in emotionally responsive AI. Several studies found that users trusted AI systems more when the systems responded appropriately to emotional cues. Other studies found that trust declined sharply after a single instance of emotional misinterpretation. This finding suggested that user trust in emotional AI was fragile (Riedl, 2022). Researchers found that users held different expectations for different application domains. Users expected higher emotional accuracy from mental health applications than from entertainment applications. Users tolerated occasional emotional misinterpretation in low-stakes contexts, such as music recommendation systems. Users showed far less tolerance for misinterpretation in high-stakes contexts, such as crisis intervention services (Kwilinski et al., 2024). Researchers have debated whether AI systems can achieve genuine emotional understanding, as opposed to mere simulation. Some scholars argued that understanding requires subjective experience. Machines lack subjective experience. Therefore, these scholars concluded that machines cannot achieve genuine emotional understanding, regardless of their technical sophistication. Other scholars took a more functionalist position (Matta, 2026). Functionalist scholars argued that understanding should be judged by behavior and outcome, not by internal experience. Under this view, a system that reliably produces appropriate emotional responses demonstrates a functional form of understanding. This theoretical divide remains unresolved in the current literature (Orsini, 2024).

Recent technological developments have intensified this debate (Gyamfi et al., 2022). Large language models now generate emotionally appropriate text with considerable fluency. These models can express apparent sympathy, encouragement, or concern in response to user input. Some researchers argued that this fluency represents genuine progress toward emotional understanding. Other researchers cautioned that fluent emotional language may create a false impression of understanding among users. This

concern, often described as the risk of emotional deception, has become a central theme in recent scholarship. Researchers increasingly call for transparency in how emotionally responsive AI systems are designed and marketed (Andleeb et al., 2025).

Despite this substantial body of research, few studies have combined technical accuracy measurement with in-depth exploration of user perception within a single study. Most existing research favors either a purely technical approach or a purely user-centered approach. This gap limited researchers' ability to connect measured system accuracy with the lived experience of users interacting with these systems (Suhraab et al., 2024). The present study addressed this gap through a mixed-methods design, combining structured measurement of accuracy with in-depth interviews exploring user perception of empathy, trust, and genuine understanding.

RESEARCH METHODOLOGY

This study adopted a mixed-methods research design to examine the extent to which artificial intelligence systems could accurately recognize, interpret, and respond to human emotional states. The researchers selected this approach because it allowed for both quantitative measurement of AI performance and qualitative exploration of user perceptions regarding emotional authenticity in machine responses.

Research Design and Sample

The researchers employed a sequential explanatory design. The researchers first gathered quantitative data. The researchers then followed this with qualitative data collection to explain the numerical findings in greater depth. For the quantitative component, the researchers selected a sample of 150 participants who interacted with three commercially available emotion-recognition AI systems. Participants were selected through purposive sampling based on their prior exposure to conversational AI tools.

Data Collection

The researchers collected data using two primary instruments. First, participants completed a

structured questionnaire. This questionnaire measured perceived emotional accuracy, empathy, and trustworthiness of the AI systems on a five-point Likert scale. Second, the researchers conducted semi-structured interviews with 20 participants drawn from the larger sample. These interviews provided deeper insight into participants' subjective experiences. Additionally, the researchers analyzed system-generated logs. These logs allowed the researchers to compare AI-detected emotional labels against participants' self-reported emotional states.

Data Analysis

The researchers analyzed quantitative data using descriptive and inferential statistics. The researchers used correlation analysis to determine the relationship between AI accuracy and user trust. The researchers used SPSS software for this purpose. The researchers transcribed qualitative interview data. The researchers then analyzed this

data thematically, following Braun and Clarke's six-step framework. The researchers identified recurring themes related to emotional authenticity, misinterpretation, and user expectations.

Ethical Considerations

The researchers obtained informed consent from all participants before data collection began. The researchers ensured anonymity throughout the study. The researchers obtained ethical approval from the relevant institutional review board before the research commenced.

RESULTS AND DATA ANALYSIS

This chapter presents the findings of the study. The chapter first presents quantitative results drawn from the structured questionnaire and system logs. The chapter then presents qualitative themes drawn from the semi-structured interviews.

QUANTITATIVE RESULTS

Table 1: Participant Demographics (N = 150)

Category	Subgroup	Frequency	Percentage
Gender	Male	78	52.0%
Gender	Female	72	48.0%
Age Group	18–25 years	46	30.7%
Age Group	26–35 years	61	40.7%
Age Group	36 years and above	43	28.6%
Prior AI Experience	Frequent user	89	59.3%
Prior AI Experience	Occasional user	61	40.7%

Table 1 presents the demographic composition of the study sample. The sample included a near-equal distribution of male and female participants. Most participants fell within the 26 to 35 age group. A majority of participants reported frequent prior use of AI systems. This profile

suggested a sample reasonably familiar with conversational AI tools. Familiarity with AI tools likely shaped participants' expectations during the study. The researchers considered this balance adequate for the quantitative analysis.

Table 2: Perceived Accuracy, Empathy, and Trust Scores (5-point Likert Scale)

Variable	Mean	Standard Deviation
Perceived Emotional Accuracy	3.42	0.68
Perceived Empathy	2.87	0.79
Perceived Trustworthiness	3.15	0.71

Table 2 presents mean scores for the three core variables measured in the questionnaire. Perceived emotional accuracy received the highest mean score among the three variables. Perceived empathy received the lowest mean score, falling below the scale midpoint. Perceived

trustworthiness fell between accuracy and empathy in overall rating. This pattern suggested that participants viewed the AI systems as reasonably accurate. However, participants did not view these systems as genuinely empathetic. This gap pointed toward the central concern of this study.

Table 3: AI-Detected Emotion versus Self-Reported Emotion (System Log Analysis)

Emotion Category	AI Detection Accuracy
Happiness	84.6%
Anger	79.2%
Sadness	71.3%
Fear	65.8%
Mixed or Ambiguous Emotion	38.4%

Table 3 compares AI-detected emotional labels against participants' self-reported emotional states. AI systems detected happiness with the highest accuracy among all categories. Anger and sadness followed with moderately high accuracy rates. Fear detection showed a lower accuracy rate than the previous three categories. Detection accuracy

dropped sharply for mixed or ambiguous emotional states. This decline indicated a clear limitation in current emotion-recognition technology. AI systems performed well on singular emotional expressions but poorly on the complex emotional states common in everyday life.

Table 4: Correlation Between Perceived Accuracy and Trust

Variable Pair	Pearson Correlation (r)	Significance (p)
Accuracy and Trust	0.58	$p < 0.01$
Empathy and Trust	0.71	$p < 0.01$
Accuracy and Empathy	0.44	$p < 0.01$

Table 4 presents correlation results between the three core variables. Accuracy and trust showed a moderate positive correlation. Empathy and trust showed a stronger positive correlation than accuracy and trust. This finding suggested that empathy, more than accuracy, drove participants' trust in AI systems. Accuracy and empathy showed a weaker, though still significant, correlation. This indicated that accurate detection did not automatically produce a perception of empathy. The researchers read this as evidence that users judge emotional intelligence along more than one dimension.

QUALITATIVE ANALYSIS

Theme 1: Mechanical Competence without Warmth

Many participants described AI responses as competent but emotionally cold. Participants noted that the systems produced grammatically correct and situationally appropriate replies. However, participants felt these replies lacked genuine warmth. Several participants compared the experience to speaking with a well-trained customer service script. This theme captured a recurring perception that technical competence did not equate to emotional presence.

Theme 2: Inconsistent Recognition of Complex Emotion

Participants frequently reported that AI systems misread emotions during moments of ambivalence. Several participants described feeling both frustrated and amused during a single interaction. The AI systems typically responded to only one of these emotions. Participants found this selective recognition frustrating. This theme highlighted a gap between the complexity of lived emotional experience and the simplified categories used by AI systems.

Theme 3: Trust Built Through Consistency, Not Accuracy Alone

Participants explained that trust grew primarily through repeated, consistent interactions over time. A single accurate response did not establish trust on its own. Several participants noted that consistent, predictable behavior mattered more than occasional impressive accuracy. A few participants described losing trust after just one clumsy response, even following several accurate ones. This theme suggested that trust in emotional AI develops cumulatively, rather than instantly, through sustained interaction.

Theme 4: Cultural Misalignment in Emotional Expression

Several participants, particularly those communicating in a non-native language, reported frequent misinterpretation of their emotional expressions. Participants attributed this misinterpretation to cultural differences in emotional display. Some participants described feeling as though the system expected a distinctly Western style of emotional expression. Others felt their restrained expressions of distress went entirely unrecognized. This theme underscored a persistent cultural bias built into current emotion-recognition systems.

Theme 5: Awareness of the Simulation

Most participants expressed clear awareness that AI empathy was simulated rather than genuinely felt. Participants nonetheless found simulated empathy useful in low-stakes situations, such as casual conversation. Several participants expressed

discomfort with simulated empathy in emotionally sensitive situations, such as grief or personal crisis. This theme revealed the situational boundaries within which users found artificial empathy acceptable rather than inappropriate.

Theme 6: Desire for Transparency

Many participants expressed a wish for clearer disclosure about the limitations of AI emotional understanding. Participants felt that developers should clearly communicate that AI empathy is simulated. Several participants suggested that such transparency would improve, rather than undermine, their trust in these systems. This theme reflected a broader participant preference for honesty over the impression of seamless emotional understanding.

DISCUSSION

This study examined whether AI systems truly understand human affect. The findings suggested a clear distinction between detection and understanding. AI systems detected basic emotions with reasonable accuracy. These same systems struggled with nuanced or mixed emotional states. Participants rated empathy lower than accuracy, revealing a persistent gap. Trust depended more on perceived empathy than on technical accuracy alone. Interview data reinforced this pattern. Participants described AI responses as competent but emotionally shallow. Participants also valued transparency about the simulated nature of AI empathy, particularly in emotionally sensitive contexts such as grief or crisis. These findings support a functionalist rather than an experiential view of machine understanding. Current AI systems simulate emotional responsiveness effectively. They do not achieve genuine affective comprehension. Cultural bias further limited system performance for participants outside dominant training populations. This distinction carries significant implications for the future design of emotionally intelligent machines.

CONCLUSION

This study examined the extent to which AI systems understand human emotion. The

researchers combined quantitative measurement with qualitative exploration. Results showed that AI systems detect basic emotions reasonably well. These systems struggle with nuanced, mixed, and culturally varied emotional expression. Participants valued empathy and transparency over raw technical accuracy. Trust proved fragile and cumulative, built gradually through consistent interaction rather than isolated accurate responses. The study concludes that current AI systems simulate, rather than genuinely understand, human affect. This conclusion carries important implications for developers, users, and policymakers seeking to build responsible, emotionally aware technology.

RECOMMENDATIONS

Developers should prioritize clear transparency about the simulated nature of AI empathy. Developers should also diversify training datasets to reduce cultural bias in emotion recognition. Mental health and crisis-related applications should apply stricter accuracy standards than low-stakes applications. System designers should prioritize consistency over occasional high accuracy, since consistency builds user trust more reliably. Future researchers should further explore emotion recognition across diverse cultural, linguistic, and age-based populations.

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