Facial expressions in conversational AI: the hot trend that boosts empathy but flops on trust

Abstract :

Dynamic facial expressions in AI conversational agents are a rising trend, enhancing emotional engagement and user satisfaction by making interactions feel more personal and engaging. An experimental design comparing two chatbots—one with dynamic expressions and one without—showed that while expressions enhance emotional connection, they fall short in improving trust or advice quality. Absence of expressions fits contexts requiring objectivity and transparency. These findings stress the growing importance of a context-sensitive design in conversational AI, where emotional cues are carefully balanced to match user expectations.

Key words: *Conversational AI, emotional engagement, social presence, trust in AI, nonverbal cues*

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INTRODUCTION

Conversational AI tools, such as ChatGPT and other chatbots, have become central to customer service, digital marketing, and brand engagement by simulating human behavior and providing constant accessibility (Mariani et al. 2023). Most systems lack nonverbal cues, despite their proven role in emotional engagement, trust, and satisfaction (Sagliano et al. 2022).

A recent trend in conversational AI design involves integrating dynamic facial expressions into chatbots to enhance user experiences further. These expressions let chatbots react visually to conversational tone, such as showing compassion in sensitive situations (Duan et al. 2018; Dong et al. 2023). Such nonverbal cues aim to humanize digital interactions, aligning with social presence theory (Biocca et al. 2003) and social response theory (Nass & Moon 2000), which suggest users often apply human social norms to anthropomorphic technologies.

AI-driven services offer scalability and efficiency which is convenient for companies, although it remains uncertain whether they can fully replicate the emotional intelligence and adaptability of human agents over time. Studies suggest that AI's lack of genuine empathy may limit its capacity to create lasting customer satisfaction and trust in high-contact services such as healthcare and hospitality (Fakhimi et al. 2023)

Although AI systems are convenient for companies, not all users are equally comfortable or satisfied. Perceived empathy often falls short compared to human agents, especially in emotionally charged contexts (Rostami & Navabinejad 2023 ; Brunswicker et al. 2024).

However, while dynamic facial expressions may improve emotional closeness and enhance social presence, their influence on trust, transparency, and objectivity remains poorly understood. Emotional cues could foster deeper engagement but also introduce ethical risks, such as perceived emotional manipulation or reduced neutrality, particularly in contexts demanding professional detachment like healthcare or financial advising (Floridi & Cowls 2019; Balasubramaniam et al. 2023).

To our knowledge, no empirical research has yet systematically explored the impact of dynamic facial expressions on user perceptions of trust, transparency, and emotional engagement in conversational AI. This gap may stem from the recent technological advancements that now allow for more sophisticated emotional expressiveness. To address this, the present study investigates three key questions:

- How do dynamic facial expressions influence emotional engagement in AI interactions?
- What impact do they have on trust, ethical perception, and transparency?
- What balance between emotional connection and professional neutrality should brands adopt when designing conversational AI systems?

By empirically exploring these dimensions, this study contributes both theoretical insights and practical recommendations for designing emotionally expressive AI conversational agents, emphasizing the need for context-sensitive design where emotional cues are strategically deployed to balance engagement and credibility (Jin 2024).

LITERATURE REVIEW

Social presence and human-AI interactions

Social presence theory posits that human-like traits in artificial agents increase perceived intimacy and realism during interaction, thereby enhancing user engagement and satisfaction (Biocca et al. 2003). These effects are amplified when agents display anthropomorphic features—such as facial expressions, empathetic reactions, or gaze behaviors—that fulfill users' need for emotional connection (Odhiambo 2024). Recent work has refined the notion of social presence, conceptualizing it as a multidimensional construct encompassing empathy, affability, responsiveness, communication versatility, and competence. These dimensions interact to shape users' perception of human-likeness in AI and are central to trust and engagement outcomes (Liao et al. 2024). Integrating this multidimensional view provides a more nuanced framework for analyzing emotional closeness and perceived realism in human–AI interaction.

Empirical studies confirm that expressive conversational agents enhance relational closeness and improve user experiences in education and customer service (Lindgren et al. 2024; Adam et al. 2021). Complementarily, social response theory (Nass & Moon 2000) explains users' tendency to apply human social scripts to machines when they exhibit emotionally congruent behaviors, reinforcing the illusion of meaningful interaction.

Perceived "mind" attribution plays a central role in this dynamic. Lee et al. (2020) show that subtle social cues—such as emotionally synchronized verbal or visual signals—increase users' sense of co-presence, emotional closeness, and reuse intentions. Seeger et al. (2021) stress that such cues, when consistent with the interactional context, reinforce affective engagement and interaction credibility. Similarly, Van Pinxteren et al. (2020) demonstrate that tone, style, and facial expressiveness shape trust and perceived empathy.

In this framework, facial expressions function as key nonverbal signals, simulating emotional responsiveness and relational warmth. They amplify users' perception of social presence and personal connection. Virtual features like facial identity cues also impact user attitudes by triggering identity-related effects (Gerlich 2023), thereby reinforcing the emotional salience of the interaction. The perceived authenticity of these emotional signals remains a challenge. While users often respond positively to empathetic expressions, many remain aware of their artificiality, which can evoke ambivalence and weaken engagement over time (Rostami & Navabinejad 2023). This perception gap between apparent and actual empathy becomes particularly salient in sensitive domains such as health or counseling.

However, anthropomorphic design introduces risks. Najafi & Mohammadi (2024) warn that poorly timed or exaggerated cues can disrupt the illusion of authenticity, decreasing user trust. Pelau et al. (2021) further argue that overexposure to emotionally intelligent systems may reduce human empathy and distort identity development.

From a cognitive perspective, recent research shows that anthropomorphized AI systems can subtly influence user behavior and decision-making, increasing emotional dependency and reducing perceived autonomy (Xu et al. 2025). This suggests that emotional closeness may come at the cost of independent reasoning, particularly when cues simulate relational intimacy.

Therefore, we propose the following:

H1a. Dynamic facial expressions in AI agents enhance emotional closeness.
H1b. Dynamic facial expressions in AI agents increase user satisfaction.
H1c. Dynamic facial expressions in AI agents reduce perceived autonomy.

Nonverbal cues, empathy, and engagement

Nonverbal signals—especially facial expressions, gaze, and subtle gestures—are fundamental in social communication. In human–AI interactions, these cues provide emotional framing and interpretive depth, transforming neutral or transactional dialogues into more meaningful exchanges (Zhang et al. 2023).

Dong et al. (2023) demonstrated that when a chatbot displayed a confused expression following a user error, participants responded with more empathy and engagement than when the same content was text-only. Similarly, Gobron et al. (2013) found that subtle facial expressions in virtual avatars enhanced emotional realism, leading to stronger perceptions of warmth and shared understanding.

However, as Seeger et al. (2021) and Derks et al. (2024) caution, the benefits of facial cues rely heavily on their consistency and subtlety. Incoherent expressions or those that fall into the "uncanny valley" can elicit discomfort and undermine the agent's credibility. To be effective, emotionally responsive AI should maintain coherence by ensuring that facial cues align with dialogue and conversational context; moderation, by avoiding overly intense or intrusive expressions; and cultural adaptability, as users' interpretations of emotional signals are shaped by cultural expectations (Yang et al. 2024).

While facial expressiveness can indeed foster affective closeness and enhance user satisfaction, it also carries the risk of diminishing perceived autonomy. Wang et al. (2024) found that emotionally expressive agents may unintentionally steer users' feelings, subtly influencing their emotional states and reducing their sense of independent decision-making.

These dynamics raise further questions about emotional perception and advice evaluation:

H3a. Dynamic facial expressions in AI agents increase trust.
H3b. Dynamic facial expressions in AI agents strengthen perceived empathy.
H3c. Dynamic facial expressions in AI agents improve the perceived quality of advice.

Neuroscientific studies reveal that, despite behavioral realism, users process interactions with AI differently at the neural level. Human presence triggers broader and deeper brain engagement than even the most advanced AI agents, suggesting a biological limitation to simulated empathy and co-presence (Harris 2023).

These mechanisms not only impact emotional connection, but may also influence broader evaluative perceptions such as empathy, trust, and perceived advice quality—dimensions explored in hypotheses H3a–H3c.

Ethics, transparency, and trustworthiness

Beyond engagement, emotional expressiveness in AI agents raises pressing ethical concerns. While emotional cues may signal empathy, they can also mislead users when the system lacks genuine understanding or intentionality (Floridi & Cowls 2019).

Lindgren et al. (2024) warn that users may misinterpret pre-programmed expressions as authentic concern, particularly in sensitive contexts such as healthcare or legal services. This can undermine trust if users feel manipulated. Transparency is therefore essential.

In parallel, scholars have raised concerns that emotionally expressive AI may commodify care and simulate relationships without genuine reciprocity, particularly in contexts of loneliness or psychological vulnerability. This “artificial companionship” can create emotional dependencies while lacking the ethical depth of human care relationships (Savic 2024). Balasubramaniam et al. (2023) stress that emotional AI systems must clearly disclose whether expressions are static, contextually generated, or adaptive.

Moreover, vulnerable populations such as younger and older users may over-attribute emotion to non-human systems (Brunswicker et al. 2024), further highlighting the importance of transparency and digital literacy.
Neutral interfaces, by contrast, are more likely to be perceived as transparent and ethically aligned, particularly in contexts where neutrality and objectivity are valued (Krauter 2024).

Thus, we propose:

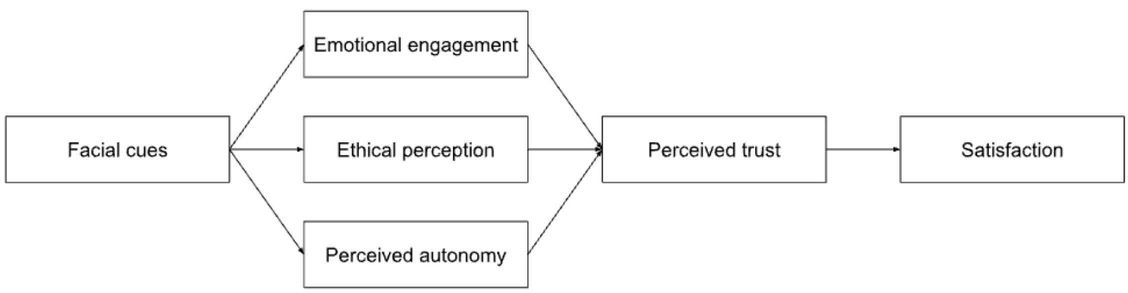
H2a. AI agents without dynamic facial expressions are perceived as more transparent.
H2b. AI agents without dynamic facial expressions are perceived as more ethical.

The perception of emotional cues as sincere or manipulative can strongly affect users’ ethical evaluation of the system—especially in sensitive or high-stakes domains.

RESEARCH DESIGN

This study uses an exploratory framework to examine the relationships between facial expressions, emotional closeness, satisfaction, and trust, aiming to validate a conceptual model for enhancing AI chatbot interactions. The model suggests facial cues strengthen emotional closeness, satisfaction, trust, and perceptions of transparency and ethics—key for effective customer experiences. It builds on foundational works from Mayer et al. (1995) on trust, Oliver (1999) on satisfaction, and Nass & Moon (2000) on human-machine interactions. Structural equation modeling (PLS-SEM) with bootstrapping (5000 resamples) was used to test the hypotheses, suitable for complex models with smaller samples. Figure 1 presents the conceptual model.

Figure 1
Conceptual Model



The preceding literature review highlights how dynamic emotional cues, particularly facial expressions, influence users' perceptions across multiple dimensions of interaction. These cues act as socio-emotional signals that modulate perceived empathy, satisfaction, and credibility in human–AI communication. Building on these theoretical insights, we now derive the hypotheses tested in the present study.

H1a, H1b, and H1c: emotional engagement and autonomy

Facial expressions—when congruent with the interactional context—enhance social presence by triggering anthropomorphic perceptions (Biocca et al. 2003; Odhiambo 2024). Prior studies demonstrate that emotionally expressive agents improve relational closeness (Lindgren et al. 2024) and user compliance in customer service contexts (Adam et al. 2021). Perceived mind attribution and emotional realism, facilitated by consistent nonverbal cues, are known to foster emotional closeness and affective involvement (Lee et al. 2020; Seeger et al. 2021). These findings support the assumption that expressive agents foster emotional proximity (H1a) and user satisfaction (H1b).

At the same time, several scholars caution that emotionally adaptive agents—especially those deploying subtle nonverbal modulation—may "steer" user reactions or create a sense of emotional influence, thereby reducing perceived autonomy (Wang et al. 2024; Pelau et al. 2021). This justifies the hypothesis that emotional expressiveness could decrease users' perception of control or autonomy (H1c).

H2a and H2b: perceived transparency and ethical alignment

While expressiveness can simulate warmth, it may also obscure the inner logic of AI systems. In contexts where neutrality and fairness are expected—such as healthcare or financial services—excessive emotion can be viewed as biasing or manipulative (Floridi & Cowls 2019). Prior research suggests that neutral interfaces, devoid of affective cues, are more readily perceived as objective and transparent (Krauter 2024).

Moreover, ethical perception is closely tied to system explainability and the authenticity of interaction (Brunswicker et al. 2024). Users who cannot distinguish genuine empathy from artificial simulation may question the moral integrity of the system. Algorithmic transparency—especially concerning emotional signals—is thus critical to avoid ethical ambiguity (Balasubramaniam et al. 2023). Based on this, we hypothesize that neutral agents will be rated as more transparent (H2a) and more ethically aligned (H2b) than expressive agents.

H3a, H3b, and H3c: trust, empathy, and advice quality

Prior work has emphasized that emotional expressiveness can serve as a trust cue, suggesting warmth, competence, and relational intent (Seeger et al. 2021; Van Pinxteren et al. 2020).

However, trust formation also depends on perceived competence, consistency, and contextual appropriateness (Lee & See 2004). While we expect emotional cues to increase empathy perception (H3b), their role in trust (H3a) and advice quality (H3c) may be more complex.

Evidence from spontaneous interaction studies (Gobron et al. 2013; Dong et al. 2023) shows that emotional cues do improve relational warmth, but not necessarily judgment-related trust or perceived informational value. Recent findings (Lindgren et al. 2024) even suggest that neutral expressions can enhance advice credibility by reducing the perception of bias. Thus, while facial expressions are likely to increase empathy, they may not translate into higher trust or perceived informational quality.

METHOD

This within-subjects experiment involved 48 voluntary participants (27 female, 21 male) from a French university, all fluent in English. Written consent was obtained, and participants were informed of their right to withdraw at any time.

Procedure

Participants interacted with two chatbots presented in a randomized order (digital ID randomizer):

KukiAI: A chatbot equipped with dynamic facial expressions. The expressions were automatically triggered in real-time based on the emotional tone of the conversation. KukiAI's visual face reacted dynamically by detecting sentiment cues from participants' messages and adjusting expressions (e.g., smiling for positive input, concerned expressions for negative contexts).

ChatGPT: A text-based chatbot without any visual representation.

Each participant completed two unscripted interactions per chatbot: one personal inquiry and one formal task, covering both emotional and objective topics. A brief classroom demonstration with an expressive agent was conducted beforehand to reduce novelty effects. Each session lasted 10-15 minutes per chatbot, with a one-hour total limit, including questionnaire completion.

The 15-minute familiarization phase was designed to reduce potential novelty effects, drawing on established protocols in human-agent interaction research (e.g., Admoni et al. 2017). However, we note that participants in this study were not complete novices in AI interaction: all were enrolled in a digital marketing program and had previously used ChatGPT in class-based assignments and exercises. This prior exposure likely reduced the risk of biased responses linked to unfamiliarity or surprise, especially regarding the chatbot's capabilities and behavior. Nonetheless, we acknowledge that emotional expressiveness may still produce more subtle novelty effects, particularly in terms of facial dynamics.

Measurement and analysis

A 5-point Likert scale questionnaire measured emotional engagement, trust, ethicality, autonomy, and satisfaction, adapted from Davis (1983) and Deci & Ryan (2000). Data were analyzed using PLS-SEM with 5000-bootstrap resampling, CFA, and ANOVA to compare conditions.

Reliability and sample adequacy

Cronbach's alpha values exceeded 0.75, confirming strong internal consistency. Convergent and discriminant validity were established (AVE >0.50, HTMT ratios within thresholds).

The sample size (n=48) was adequate for exploratory PLS-SEM analysis, as recommended by Hair et al. (2021), considering the effect sizes (R^2 = 0.08 to 0.46) and bootstrapping with 5000 resamples to ensure statistical robustness.

Experimental modality: rationale and bias control

The expressive chatbot used in this study is not a CGI-rendered figure, but a minimalist visual avatar capable of displaying the six facial expressions (Sharma et al. 2017), triggered in real-time by message polarity. These expressions (e.g., smile, concern, neutral) provide a form of emotional feedback, yet do not constitute a high-fidelity 3D animation or realistic human simulation. This low-complexity anthropomorphic layer was chosen to reflect real-world applications where emotional cues are increasingly embedded in service interfaces.

The decision to explore facial expressiveness rather than vocal tone (e.g., prosody) stems from both technical and conceptual reasons. First, while emotional intonation—what researchers describe as emotional prosodic texture—is theoretically relevant, it is not yet supported in most commercial voice assistants like Siri or Alexa. Conversely to human interaction (André et al. 2016), these systems generally produce emotionally neutral, flat vocal output that cannot be dynamically adjusted in real time to the user's input. As such, integrating an audio-based interface would not have created the expressive contrast needed for this study. Second, facial expressions have been shown to have a stronger and more immediate impact on perceived empathy and social presence than auditory cues alone (Gobron et al. 2013; Zhang et al. 2023). This makes them an appropriate starting point for assessing emotional modulation in conversational AI.

FINDINGS

Experimental modality: rationale and bias control

Cronbach's alpha values for all variables exceeded 0.750, indicating strong internal reliability and minimal measurement errors. The values ranged from 0.756 (KAUTO) to 0.953 (KPROX) for the model with facial expressions, and from 0.758 (SAT) to 0.926 (PROX) for the model without facial expressions, which aligns with Nunnally's (1978) criteria for robust internal consistency.

Convergent validity was supported by factor loadings above the 0.600 threshold and Average Variance Extracted (AVE) values exceeding 0.500, consistent with Fornell and Larcker's (1981) recommendations. Discriminant validity was verified as the Heterotrait-Monotrait (HTMT) ratios of inter-construct correlations were within recommended thresholds, with confidence intervals falling within acceptable limits (Table 2).

To further verify discriminant validity, inter-construct correlations were compared with the square roots of the corresponding AVE values. The square roots of the AVE values consistently exceeded the inter-construct correlations (Table 1), confirming conceptual distinctiveness (Bagozzi et al. 1991).

Table 1

Convergent Validity (AVE) analysis: strong convergent validity across all measured variables

	Mean (M)	**Standard Deviation (STDEV)**	**t-statistics**	**p-value**
KAUTO	0,465	0,061	7,626	0,000
KCONF	0,681	0,042	16,116	0,000
KETHIC	0,705	0,052	13,523	0,000
KPROX	0,779	0,042	18,445	0,000
KSAT	0,575	0,053	10,937	0,000
	Mean (M)	**Standard Deviation (STDEV)**	**t-statistics**	**p-value**
AUTO	0,56	0,051	10,943	0,000
CONF	0,581	0,056	10,287	0,000
ETHI	0,647	0,05	12,849	0,000
PROX	0,71	0,04	17,558	0,000
SAT	0,434	0,094	4,629	0,000

Table 2

Heterotrait-Monotrait Ratio (HTMT): evidence of discriminant validity among variables

	2.5%	**97.5%**
CONF <-> AUTO	0,64	0,836
ETHIC <-> AUTO	0,407	0,68
ETHIC <-> CONF	0,662	0,824
PROX <-> AUTO	0,765	0,943
SAT <-> PROX	0,847	0,955
	2.5%	**97.5%**
CONF <-> AUTO	0,384	0,678
ETHI <-> AUTO	0,572	0,788
PROX <-> AUTO	0,641	0,816
SAT <-> PROX	0,388	0,661

Common method bias (CMB) was assessed using the common latent factor (CLF) analysis. The differences between the CLF and non-CLF model estimations ranged from 0.012 to 0.038, staying below the 0.050 threshold recommended by Podsakoff et al. (2003), indicating no significant method biases.

The structural model was assessed using PLS-SEM, evaluating six direct paths for the model with facial expressions and five for the model without facial expressions. The goodness-of-fit value SMR supported the model's quality (Table 3).

Table 3
Internal Consistency (Cronbach's Alpha): high reliability across both experimental conditions

	Mean (M)	**Standard Deviation (STDEV)**	**t-statistics**	**p-value**
KAUTO	0,756	0,078	9,712	0,000
KCONF	0,931	0,015	61,007	0,000
KETHIC	0,915	0,022	41,008	0,000
KPROX	0,953	0,013	76,022	0,000
KSAT	0,842	0,044	19,301	0,000
	Mean (M)	**Standard Deviation (STDEV)**	**t-statistics**	**p-value**
AUTO	0,862	0,03	28,808	0,000
CONF	0,891	0,028	31,576	0,000
ETHI	0,885	0,028	31,163	0,000
PROX	0,926	0,016	56,61	0,000
SAT	0,758	0,075	10,078	0,000

Key findings from structural relationships and ANOVA

The ANOVA results reveal significant patterns in how dynamic facial expressions influence user perceptions across multiple dimensions (Table 4).

Emotional closeness increased significantly with facial expressions (H1A: $F = 8.016$, $p = 0.006$, $R^2 = 0.08$), indicating a moderate but meaningful enhancement of emotional connection when dynamic cues were present. Satisfaction showed a highly significant rise under the same conditions (H1B: $F = 78.347$, $p < 0.0001$, $R^2 = 0.46$), emphasizing a substantial effect size and the capacity of dynamic cues to amplify emotional engagement and interaction quality.

Perceived autonomy, however, showed no significant differences between conditions (H1C: p = 0.829), suggesting that while emotional engagement was influenced, users' sense of control remained unaffected. Transparency perceptions were stronger in the absence of facial expressions (H2A: F = 55.46, p < 0.0001, R^2 = 0.369), suggesting interactions without facial cues were seen as more neutral and objective, possibly due to reduced emotional modulation. Ethical perception, however, showed no significant impact (H2B: p = 0.175), indicating emotional expressiveness plays a minor role in ethical judgments, which may relate more to reliability and transparency than non-verbal behaviors.

Empathy increased significantly in the presence of facial expressions (H3B: F = 8.559, p = 0.004; M = 3.234 vs. 2.447), highlighting the positive contribution of dynamic cues in fostering emotional warmth and perceived emotional intelligence during interactions. Trust, however, was not significantly influenced (H3A: p = 0.171), suggesting other factors like communication clarity and predictability may play a stronger role in trust formation.

Perceived advice quality was rated higher without facial expressions (H3C: F = 5.196, p = 0.025; M = 3.44 vs. 2.901), suggesting a preference for objectivity and more credible feedback when emotional modulation was minimized (Table 4). The detailed SEM model parameters for each hypothesis are provided in Table 5.

Table 4

ANOVA by hypothesis: positive impact of facial expressions on emotional closeness and satisfaction, no effect on trust

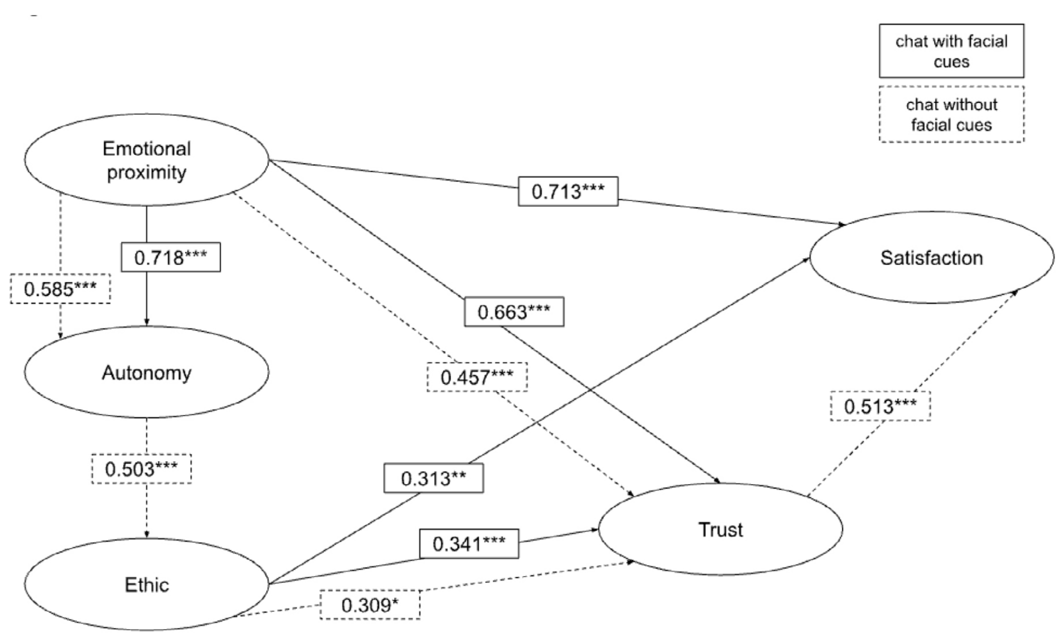
Hypothesis	Source	F	p-value	Significance
H1A	Modèle	8,016	0,006	**
H1B	Modèle	78,347	<0,0001	***
H1C	Modèle	0,047	0,829	-
H2A	Modèle	55,46	<0,0001	***
H2B	Modèle	1,872	0,175	-
H3A	Modèle	1,905	0,171	-
H3B	Modèle	8,559	0,004	**
H3C	Modèle	5,196	0,025	*

Table 5
SEM model parameters: facial expressions significantly influence satisfaction and emotional closeness but have no effect on trust perception

Hypothesis	Constant	Coefficient Q1-1	p-value	Significance
H1A	3,091 (p < 0,0001)	-0,647	0,006	**
H1B	2,663 (p < 0,0001)	1,298	< 0,0001	***
H1C	3,407 (p < 0,0001)	0,033	0,829	-
H2A	2,809 (p < 0,0001)	1,245	< 0,0001	***
H2B	2,894 (p < 0,0001)	0,241	0,175	-
H3A	2,907 (p < 0,0001)	0,269	0,171	-
H3B	3,234 (p < 0,0001)	-0,787	0,004	**
H3C	2,901 (p < 0,0001)	0,539	0,025	*

Figure 2 summarizes these relationships across both experimental conditions.

Figure 2
Experimental results: increased emotional closeness and satisfaction, no impact on trust



*Solid lines indicate effects with facial expressions; dashed lines indicate effects without.
Note: ***p < 0.001, **p < 0.01, p < 0.05.

DISCUSSION

This study examined how dynamic facial expressions affect user perceptions across multiple dimensions of human–AI interaction. The results provide empirical confirmation and theoretical nuance to several of the hypotheses tested and reveal new tensions between emotional engagement and ethical evaluation.

Regarding emotional engagement and satisfaction, dynamic facial expressions significantly enhanced both emotional closeness and user satisfaction (H1a, H1b). These findings confirm predictions from social presence theory (Biocca et al. 2003) and echo recent evidence showing that calibrated emotional cues heighten perceived warmth and human-likeness in AI agents, even in low-stakes contexts (Chen et al. 2024; Lindgren et al. 2024). They also align with Admoni et al. (2016) and Vicci (2024), who emphasize that moderate anthropomorphism can foster connection without triggering discomfort.

Regarding perceived autonomy, the hypothesis (H1c) was not supported: dynamic expressions did not reduce users' sense of control. Contrary to prior concerns that anthropomorphic cues may steer behavior or diminish agency (Song & Luximon 2021; Deci & Ryan 2000), our results suggest that subtle emotional modulation, when well-calibrated, does not compromise perceived autonomy. This implies that emotional expressiveness can be integrated without threatening user independence, offering reassurance to designers aiming to balance affective engagement with user agency.

Regarding transparency, agents without facial expressions were perceived as significantly more transparent (H2a). This supports ethical design frameworks that prioritize neutrality and clarity, particularly in high-stakes or advisory settings (Floridi & Cowls 2019; Krauter 2024). It also reinforces concerns that emotional cues—even when well-intended—may obscure system logic or suggest artificial emotional understanding.

Regarding perceived ethicality, dynamic expressions had no significant effect (H2b). Users did not equate emotional expressiveness with higher ethical risk, unless manipulation or insincerity was perceived. This highlights the importance of transparency mechanisms, such as disclosures about how facial expressions are generated, as emphasized by (Balasubramaniam et al. 2023). Emotional modulation alone may not compromise ethical judgments unless contextual cues imply deception.

Regarding trust (H3a), no significant improvement was detected with facial expressions—despite increases in empathy (H3b), as predicted. This supports the idea that while emotional signals may evoke relational warmth, they do not necessarily foster deeper or lasting trust. Indeed, one possible explanation lies in the nature of perceived empathy itself: users may feel momentarily understood, but this perception does not always translate into durable trust. As Pelau et al. (2021) caution, repeated interactions with emotionally engaging AI could even erode essential human soft skills and distort identity regulation. In addition, Cheng et al. (2024) highlight that trust-building is especially fragile during first encounters, where perceived authenticity plays a pivotal role. If the AI agent's emotional signals are not trusted, users may disengage entirely—limiting the long-term effectiveness of even the most expressive designs.

Regarding empathy, dynamic expressions did significantly improve perceived empathy, consistent with expectations (H3b). Users interpreted expressive agents as more emotionally attuned, which aligns with prior studies emphasizing the relational benefits of nonverbal cues (Dong et al. 2023; Gobron et al. 2013). However, this relational gain did not extend to perceptions of trust or ethicality, suggesting a disconnect between momentary emotional resonance and broader evaluative judgments.

Regarding advice quality, agents without facial expressions were rated more positively (H3c), suggesting that emotional cues may undermine perceptions of objectivity. In informational or analytical contexts—such as finance or healthcare—users may prefer emotionally neutral agents who appear more competent and unbiased. This supports dual-process models of interaction in which affective engagement and cognitive credibility are evaluated independently.

Regarding user attachment and brand loyalty, enhanced satisfaction and empathy from expressive agents may foster stronger emotional bonds. Yet, overreliance on emotional cues may reduce long-term credibility if not matched with clarity and competence. Emotional resonance should be seen as a complement—not a substitute—for transparent and reliable system behavior.

Regarding the "uncanny valley" hypothesis, our findings challenge assumptions that facial expressiveness increases discomfort. Moderate, well-timed expressions improved perceptions without evoking unease (Krauter 2024). This suggests that minimal but emotionally congruent cues may provide an optimal balance between affective warmth and user comfort.

This study ultimately positions emotional expressiveness not as a universal enhancer, but as a context-bound lever that must be aligned with ethical design, task expectations, and user trust requirements.

THEORETICAL CONTRIBUTIONS

This research contributes to the theoretical understanding of emotional design in conversational AI by clarifying how dynamic facial expressions impact relational, ethical, and cognitive user outcomes. It addresses a gap in prior work by integrating emotional cues with broader user perceptions such as transparency, autonomy, and trust—key factors in the sustainable adoption of AI.

First, the study deepens social presence theory (Biocca et al. 2003) by confirming that moderate facial expressions—rather than fully human-like simulation—can sufficiently stimulate affective closeness and satisfaction. This shows that users respond positively to subtle relational cues, expanding current models of anthropomorphic engagement in everyday contexts.

Second, it advances trust formation models in AI by demonstrating that emotional signals alone do not guarantee increased trust (H3a). Instead, trust appears to rely more heavily on transparency, clarity, and system explainability (Lee & See 2004). This nuance challenges the assumption that emotional warmth automatically enhances credibility, particularly in sectors like healthcare, where perceived impartiality is critical.

Third, the findings refine the Automatic Cognitive Empathy Model (ACEM) (Cacioppo et al. 2000), which posits that empathy triggers engagement. While we confirmed that facial expressions increase perceived empathy (H3b), this did not translate into higher trust, nor did it compromise autonomy—contrary to prior assumptions (Song & Luximon 2021). This suggests a more situated model of emotional AI, where emotional design must be adapted to context and task.

Fourth, this research complements ethical AI literature (Floridi & Cowls 2019) by showing that emotional cues are ethically sensitive—but not inherently manipulative. When disclosed transparently and used in moderation, emotional expressiveness may enhance user experience without violating ethical boundaries. However, the lack of perceived ethicality change (H2b) indicates that transparency—not expressiveness—is the main driver of ethical judgment.

Fifth, this study provides theoretical nuance on the relationship between emotional expressiveness and advice quality, a lesser-explored dimension in conversational AI literature. While empathy was strengthened (H3b), perceived advice quality improved in the absence of expressions (H3c), suggesting that objectivity may be interpreted as a proxy for competence in certain contexts. This challenges the assumption that emotional personalization always improves perceived value and points toward a dual-process model of human-AI evaluation, where warmth and credibility are assessed separately. This insight is particularly relevant for understanding brand trust and loyalty, as it highlights the importance of managing both affective and cognitive perceptions in long-term AI-mediated customer relationships.

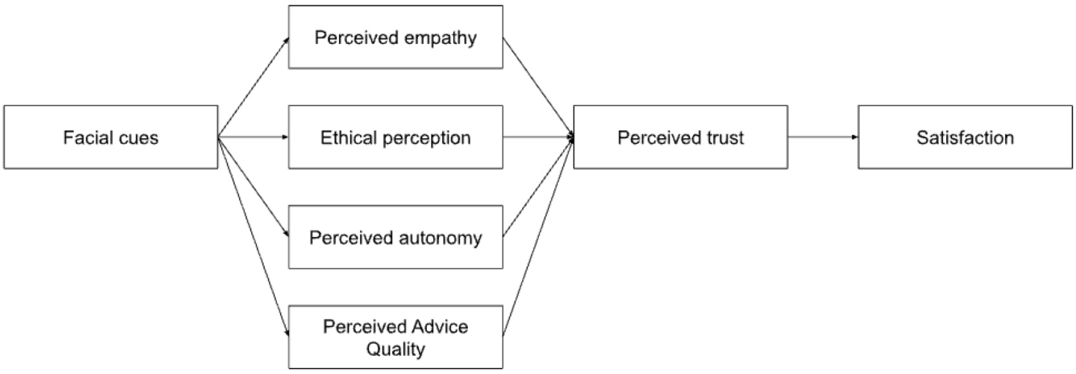
Sixth, our findings build on prior work such as Gobron et al. (2013), who demonstrated that subtle facial cues in virtual agents enhance emotional intensity and perceived presence during spontaneous chatting. While their work validated the emotional salience of micro-expressions, it did not explore how these cues shape broader user judgments such as transparency, trust, or advice quality. Our study extends this foundational research by systematically comparing expressive versus neutral agents and showing that emotional cues—while enhancing empathy—can reduce perceptions of neutrality, particularly in informational contexts. This positions facial expressiveness not only as a relational tool but also as a variable affecting cognitive and ethical appraisals in AI-mediated decision-making.

As a synthesis, the research contributes to inform cross-domain models of AI design. While emotional expressiveness may benefit customer-facing services, its use in expert or advisory contexts must be carefully balanced to avoid undermining trust. This insight supports context-aware models that adapt AI expressiveness based on task sensitivity and user expectations.

Together, these contributions argue for a more integrated framework for AI design—one that aligns emotional expressiveness with transparency, autonomy, and sector-specific norms, rather than treating them as separate design goals.

The effective relationships between facial cues, AI perception, and user engagement are summarized in figure 3.

Figure 3
Revised conceptual model of the study



MANAGERIAL CONTRIBUTIONS

This study provides valuable insights for digital marketers, AI managers, and chatbot developers seeking to improve emotional engagement and user satisfaction. Dynamic facial expressions in AI systems are not merely aesthetic; they are crucial tools for fostering emotional connections, enriching user experiences, and enhancing relational bonds. When strategically integrated, these expressions play a critical role in shaping customer experience design.

To effectively personalize AI interactions, it is recommended to use tailored facial expressions that align with users' emotional needs. Emotionally expressive interfaces significantly amplify perceptions of competence and empathy, which are essential for building strong, long-term customer relationships. Consistently incorporating dynamic facial cues throughout the customer journey—from the first interaction to post-purchase follow-ups—creates deeper emotional resonance, leaves lasting impressions, and strengthens customer retention and brand loyalty.

The study also highlights the importance of implementing sector-specific emotional AI strategies. In industries where emotional connection is key, such as healthcare, counseling, and hospitality, emotionally intelligent agents can improve user comfort and trust, making interactions feel more supportive and human. In contrast, in industries where neutrality and factual accuracy are paramount, such as legal services and financial consulting, minimizing emotional expressiveness is advisable. Focusing on clarity and impartiality helps reduce perceived biases and builds credibility and trust.

Ethical concerns related to emotional manipulation are an important aspect of this study. To mitigate these risks, it is recommended to: (1) provide transparency about the emotional cues used in AI systems and how they function, (2) offer users control over the intensity and presence of these emotional cues, and (3) validate these features with diverse user panels to ensure emotional calibration is contextually appropriate.

While emotional cues can enhance engagement, they must be carefully calibrated to avoid unintended emotional influence. In contexts where factual accuracy is critical, such as medical or financial advice, neutral expressions are essential for ensuring transparency and objectivity. However, emotional expressiveness, when modulated properly, can still enhance the user experience by making interactions more relatable and engaging.

Furthermore, the study stresses the need for a contextual and culturally sensitive approach to emotional design. User expectations for emotional expressiveness vary significantly across cultures. Companies should therefore adopt flexible design strategies that account for these differences and empower users by giving them control over the emotional cues they encounter. Allowing users to adjust the intensity and presence of emotional expressions enhances their sense of autonomy, trust, and satisfaction.

By adopting a context-aware strategy—where emotional expressiveness is finely tuned to the specific goals and nature of each interaction—companies can significantly improve user satisfaction, create stronger emotional bonds, and foster long-term customer loyalty. These findings offer a practical framework for AI-driven marketing strategies, emphasizing that emotional cues should not be applied universally, but instead be thoughtfully designed to support both user engagement and transparency in human-AI interactions.

CONCLUSION, LIMITATIONS AND FUTURE RESEARCH

This study highlights the significant impact of dynamic facial expressions on emotional engagement, trust, transparency, ethics, and perceived autonomy in AI interactions. By comparing a chatbot with dynamic facial expressions to a neutral, expressionless version, we demonstrate that nonverbal cues can enhance emotional closeness and empathy but do not consistently improve trust or perceived advice quality. Context plays a critical role: while emotional signals may be beneficial in personal contexts, neutrality is often preferred for analytical tasks requiring objectivity.

As conversational systems like ChatGPT increasingly incorporate elements such as emojis, smileys, and dynamic facial features to "humanize" interactions, these findings remain highly relevant. They suggest that a flexible design strategy—alternating between emotional expressiveness and neutrality based on context—can optimize user experience. However, this study has limitations, including a small sample size and brief interaction periods. Furthermore, the study did not examine potential moderating variables such as participants' prior experience with chatbots, technological affinity, or baseline attitudes toward AI. As highlighted by Song and Luximon (2021), these individual differences can significantly shape how users interpret emotional cues and perceive agency. Future studies should incorporate such psychological or behavioral variables to assess differential effects across user profiles.

Future research could explore multimodal communication (e.g., voice and gestures), cultural differences, or the long-term effects of chatbot "humanization." Beyond the limited sample size and homogeneity (students), this study does not account for the diversity of sectoral applications of conversational AI. The role of emotional cues may vary widely across industries—from education to public services and e-commerce—requiring further contextual exploration (Yang et al. 2024). Additionally, cultural factors play a key role in how facial expressions and empathy are interpreted, and future studies should include cross-cultural samples to assess generalizability.

Given the heterogeneity of user expectations across industries, future studies should explore how dynamic emotional cues are perceived in specific contexts such as education, tourism, or healthcare, where emotional sensitivity and credibility are unequally valued.

While AI agents can simulate empathy and enhance user engagement, they still fall short of replicating genuine human connection. Perceived empathy does not always translate into actual trust or satisfaction, as users often remain skeptical of the authenticity behind AI's emotional cues (Rostami & Navabinejad 2023) and may perceive such empathy as performative rather than genuine (Pusztahelyi 2020. Human agents remain preferred in contexts requiring emotional intelligence and adaptability, due to perceptions of benevolence and authenticity that AI systems struggle to replicate (Li & Bitterly 2024), particularly when service interactions involve preferential treatment or sensitive decisions (Choi et al. 2024; Rieger et al. 2021).

Ultimately, while conversational AI provides scalable and accessible solutions, its ability to generate lasting trust and satisfaction remains limited. As shown by Gerlich (2023), emotionally engaging interfaces may prompt behavioral responses similar to those provoked by humans, but they lack the spontaneity and complexity of real social bonds. This comparison highlights a key trade-off: efficiency and availability on the one hand, versus depth of connection and adaptability on the other.

Future research should continue comparing AI-mediated and human interactions, especially in emotionally complex services like counseling, healthcare, or education, where real human contact remains irreplaceable for many users.

Although this study was conducted on participant that were not complete novices in AI interaction such as ChatGPT, we acknowledge that the way emotional cues are perceived may depend not only on task context but also on user familiarity with AI. For example, first-time users may interpret expressions differently from frequent chatbot users, whose expectations and tolerance for anthropomorphism may be more developed (Xu et al. 2025). Such moderating effects warrant further exploration.

Another avenue for future research involves the use of emotionally adaptive voice cues. While current vocal agents lack prosodic variation based on emotional context, advances in affective speech synthesis could enable more nuanced and human-like interactions. Future studies may compare facial, vocal, and multimodal emotional cues to understand their distinct and combined effects on user trust, empathy, and satisfaction.

Addressing these limitations will help develop more personalized and context-aware AI systems, grounded in user diversity and designed to evolve with familiarity and emotional expectations.

Ultimately, the findings emphasize the need to calibrate and adapt facial expressions to enrich AI-user interactions effectively. They offer valuable insights for designing more empathetic and credible conversational agents, better aligned with marketing demands and diverse consumer preferences.

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