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Original Research Article

Enhancing Human–Computer Interaction Through Emotion Detection in Chatbots

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Abstract

The ongoing use of chatbots in healthcare, education, customer service, and mental health has made more apparent the weaknesses of entirely task-focused conversational systems that are non-emotional. Emotion detection has become an essential process of improving human-computer interaction that allows the chatbots to detect the affective states of users and react in a more human-centric and situational behalf. This paper gives a synthesis of the research on emotion-aware chatbot systems and how emotion detection methods, data modalities, and architecture can be used to enhance the quality of interaction. Fifty chosen studies were systematically analyzed to study the trends of publications, prevalent emotion detecting techniques, effectiveness of modality, and system design method. The results show that there is an increasing concentration of quality research in traditional human-computer interaction and artificial intelligence outlets, and there is a growing global concern in the last few years. The use of text-based emotion detection is the most popular in that it is more scalable, whereas the speech, visual, and multimodal detection use more emotion expressiveness and resilience in real life. Multimodal architectures can capture more complex emotional cues better than other electric stimuli, but face difficulties in terms of complexity, privacy and evaluation of the system. The review also shows that most of the current chatbot frameworks are more focused on the technical measures of performance rather than long-term, human-focused evaluation outcomes. In general, the present study provides an insight into the achievements and limitations of the existing research on emotion-sensitive chatbots and emphasizes the necessity to create ethically oriented, culturally sensitive and systematically tested conversational agents in order to promote the development of emotionally intelligent human-computer interaction.

Keywords: Emotion Detection; Emotion-Aware Chatbots; Human–Computer Interaction; Affective Computing; Conversational Agents; Multimodal Emotion Recognition; Empathetic AI.

1. INTRODUCTION

The new level of artificial intelligence (AI) development, specifically the use of conversational agents and chatbots, has radically changed Human-Computer Interaction (HCI). Modern chatbots do not serve as rule-based question-answer systems anymore, but rather are implemented as intelligent assistants and can be used in fields like healthcare, education, customer support, and mental health support (Bilquise *et al.,* 2022; Hamad *et al.,* 2024). Nevertheless, despite these achievements, there is one stable drawback, namely, most chatbots are unable to detect and react to the emotional conditions of the users promptly, which makes interactions seem artificial, unemotional, and non-cognitive (Chaves and Gerosa, 2020; Haugeland *et al.,* 2022).

Emotion is important in human interaction and decision making, as well as, trust, engagement, and satisfaction. In human-to-human communication, the flow and effectiveness of the communication is determined by the use of emotional cues, which include tone, facial expression, choice of words, and other physiological cues. Failure to add or pay attention to such cues in human-computer interaction can result in user frustration, disconnection, and decreased trust in intelligent systems (Safaei and Ghafourian, 2022; Zhu *et al.,* 2022). As a result, the emotion-conscious mechanisms of improving HCI have become an important research agenda in conversational AI.

Emotion detection in chatbots is the process of computational recognition of the affective state of the users based on textual, vocal, physical or visual information provided and the process of modifying system responses to satisfy that affective state. Recently, it has been shown that, through incorporation of emotion recognition functionality, perceived empathy, social presence, and user satisfaction are enhanced (Hamad *et al.,* 2024; Kovačević *et al.,* 2024). E.g., an attention-based sentiment and emotion modeling framework have demonstrated quantitatively better results in empathetic responses generation, lexical diversity, and natural chatting (Hamad *et al.,* 2024). On the same note, multimodal emotion recognition systems that integrate text, audio, and visual signal detection have been stronger than other single-modality techniques, especially in natural uncontrolled settings (Kovačević *et al.,* 2024).

Even though the current emotion-sensitive chatbots are promising, there are still a number of challenges. To start with, most systems only use sentiment polarity (positive/negative) that is not enough to reflect the complexity of human feelings, like frustration, anxiety, or confusion (Bedi, 2024; Machová *et al.,* 2023). Second, the content validity to detect emotions tends to reduce in noisy or cross-cultural environments because of a low level of portfolio diversification and situational confusion (Alnuaim *et al.,* 2022; Dar and Delhibabu, 2024). Third, many studies introduce technical models yet less literature evaluates the direct methods of improving the general HCI outcomes, including engagement, trust, continuity of use, and perceived intelligence (Jin and Youn, 2023; Kuhail *et al.,* 2025).

The second gap is also an acute one related to the disjointed character of the current research. Current literature has been spread across different fields such as computer science, psychology, linguistics, and HCI, and has not incorporated much of the technical emotion detection systems and human-centered design principles (Bilquise *et al.,* 2022; Oktafiani *et al.,* 2024). Consequently, the disjointed consensus is created about the best emotion detection methods to enhance chatbot interaction quality and in which situations they ensure substantial HCI payback.

Also, there are new uses of chatbots like mental health assistance, education, or therapy-oriented chatbots that require greater sensitivity to emotions and ethical considerations. It has been empirically confirmed that users who engaged with affectively attentive chatbots indicate improved engagement and perceived support especially when the situation is sensitive (Andotra, 2023; Kannangara, 2025). Nevertheless, the issues surrounding the lack of depth in empathy and prejudice, as well as the lack of correct emotional reactions are clear indicators of the necessity of more systematic, transparent, and morally sound strategies (Cuadra & Wang, 2024).

To counter such challenges, the present paper seeks to offer an in-depth analysis of the role of emotion detection applications in enhancing human-computer interaction in chatbot applications. Based on a systematic review of 50 peer-reviewed articles, this study summarizes the current methods, determines common methodologies and data sets, and points to the key gaps in the current design of emotion-aware chatbots. The integration of technical, psychological, and interactional viewpoints makes the research contribution to a better understanding of emotion-driven HCI and provides the directions of the further development of an emotionally intelligent conversational agent.

Related Studies:

The studies summarized in Table 1 are all related with each other and provide a detailed picture of the latest research works that were conducted to improve human-computer interaction by detecting emotions in chatbot systems. All these works indicate a renewed understanding that emotional intelligence can be considered a key ingredient to a successful conversational agent, especially when it comes to scenarios where empathy, trust, and maintenance of user interaction are needed. The chosen works occupy the variety of methodological approaches, such as development of experimental systems, the mixed methods user studies, the systematic literature review, and conceptual analysis, which is a characteristic feature of the interdisciplinary nature of the emotion-aware HCI study.

The large percentage of the reviewed studies deal with the deep learning-based emotion recognition methods, including speech emotion recognition (SER), sentiment-emotion fusion models, and multimodal affect analysis, to enhance chatbot responsiveness and perceived empathy (Hamad *et al.,* 2024; Kannangara, 2025; Kovačević *et al.,* 2024). The strategies indicate that using emotional cues, whether they are in the form of text, speech, image, or body language, can make chatbots deliver more contextually suitable and human-like responses, which improves the user experience and quality of interaction. Empirical evidence reliably states that the user satisfaction, engagement and trust is enhanced when emotion detection mechanisms are incorporated in conversational systems.

The relevance of framework-driven designs is also stressed in several works in the table; they propose designed architectures, including attention-based sentiment and emotion model, multimodal emotion recognizer pipeline and emotionally adaptive digital human frameworks (Hamad *et al.,* 2024; Okochi *et al.,* 2025). These frameworks are systematic instructions on how to integrate the emotion detection into chatbot pipelines as a more holistic approach to affective computing, as opposed to ad hoc sentiment analysis. Nonetheless, not every study proposes clear structures, especially review-oriented or theoretical work, which means that there is a lack of theoretical knowledge and practical system modeling.

Concerning the application, the reviewed literature shows the applicability of emotion-sensitive chatbots to domains including mental health support, education, therapy, and voice-based interaction systems (Andotra, 2023; Kuhail *et al.,* 2025; Chugh and Pondal, 2025). Emotional sensitivity is depicted to play a particularly crucial role in the continuity of interaction and meaningful user support in such settings. However, the table also shows that teaching and learning tools are not as represented and so, educational chatbots are being talked about, whereas the pedagogical integration is not as organized.

Table 1: Related Studies

Sr.	References	Paper title	Focus of Survey	Publish Year	Survey Approach	Quality Assessment	Research Framework	Teaching and Learning Tools	Content
1	Kannangara, 2025	Humanizing AI Chatbots: The Role of SER with Deep Learning for Improved UX	Uses speech emotion recognition (SER) with deep learning to make chatbots more emotionally aware and improve user experience in HCI.	2025	Experimental study (SER deep-learning models integrated conceptually into chatbots)	✓	✓ (Deep-learning SER architecture for HCI)	✗	✓
2	Okochi, Chinedum & Olebara, 2025	Design & Development of an Intelligent Web-Based Digital Human for Emotionally Aware HCI	Develops an emotionally aware digital human that detects user emotions and adapts responses to enhance human–computer interaction.	2025	Mixed-methods (surveys, expert feedback + system design & testing)	✓	✓ (Modular Digital Human Framework with emotion + memory)	✗	✓
3	Chugh & Pondal, 2025	Human-Computer Interaction with Voice-Driven AI Chatbots	Reviews voice-driven AI chatbots focusing on how sentiment/emotion handling can improve natural and effective HCI.	2025	Narrative / conceptual review	✓	✗ (No formal named framework)	✗	✓
4	Hamad, Hamdi & Shaban, 2024	ASEM: Enhancing Empathy in Chatbots through Attention-based Sentiment & Emotion Modeling	Proposes ASEM model that combines sentiment + emotion embedding to generate empathetic chatbot responses, directly targeting emotional HCI.	2024	Experimental deep-learning study (multi-expert attention model evaluated on dialog datasets)	✓	✓ (ASEM – Attention-based Sentiment & Emotion Modeling framework)	✗	✓
5	Kovačević, Holz, Gross & Wampfler, 2024	On Multimodal Emotion Recognition for Human-Chatbot Interaction in the Wild	Builds a real-world multimodal (text–audio–video) emotion recognition pipeline to improve chatbot interaction quality "in the wild".	2024	Experimental user study with multimodal dataset & transformer-based ERC model	✓	✓ (ERC personalization pipeline for HCI)	✗	✓

3. METHODOLOGY

The research methodology in this study is a Systematic Literature Review (SLR) because it is essential to thoroughly study the role of emotion detection in chatbots in improving the Human-Computer Interaction (HCI). The primary goal of the study is to critically review and summarize the available literature, which investigates the role of emotional awareness in chatbot systems, emotion detection methods, and their effects on user engagement and satisfaction, as well as the issues associated with the development of emotionally intelligent conversational agents. Another area that this review will concentrate on is the identification of important approaches, datasets, models, and best practices that are used in this field. The procedure by which the study selection, data extraction and analysis is carried out is clear, open and replicable and has a structured and well-defined review protocol as shown in Figure 1.

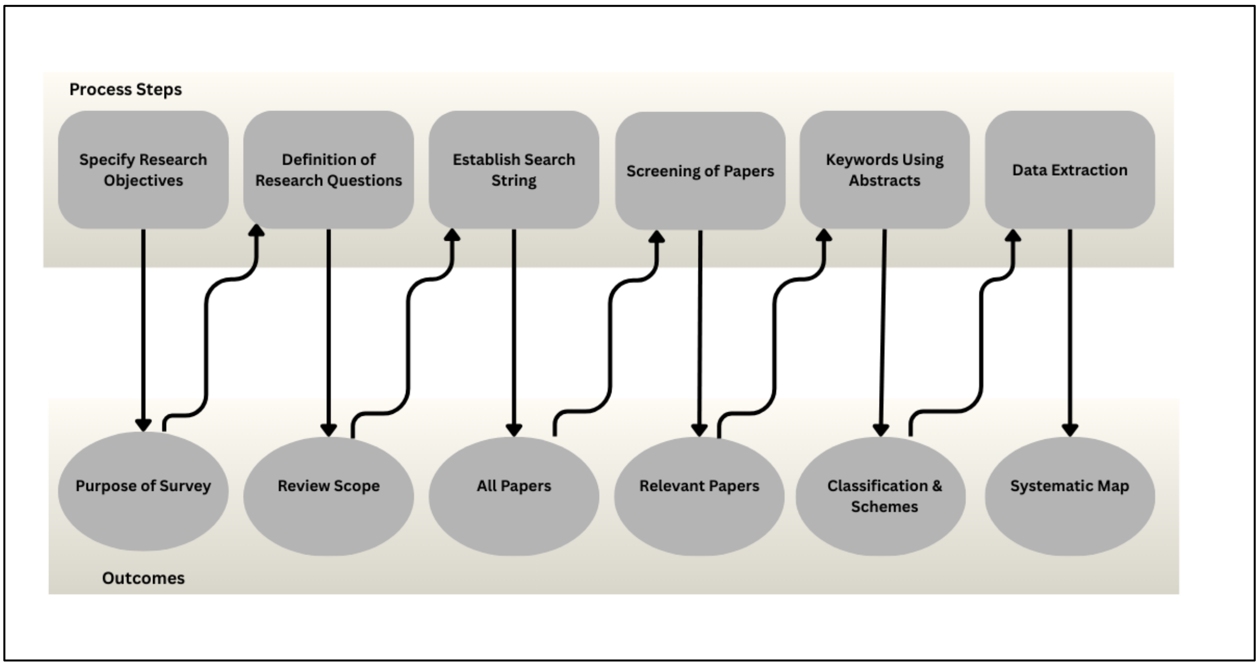

Figure 1: Systematic Literature Review (SLR) Process Steps and Outcomes

3.1 Research Questions & Objectives:

Phase 1 of the suggested Systematic Literature Review (SLR) is aimed at developing the research questions and performing a preliminary evaluation of the current body of knowledge on the topic of emotion detection in chatbots and its contribution to the improvement of Human-Computer Interaction (HCI). The purpose of this step would be to develop the scope of the study, define the key themes, challenges, and research trends in this field. The SLR focuses on the question of the implementation of emotional awareness in conversational agents, its effects on user experience, and the split of technological and methodological solutions to the problem, which are currently being pursued by addressing five well-crafted research questions. A clear motivation to each research question is presented in Table 2 just to make sure that the review is focused, systematic, and aligned with the overall objectives of the study.

Table 2: Research Objectives and Motivations for Faculty Training and Professional Development in AI Adoption

RQ Statement	Objective	Motivation
RQ1. What are the high-quality publication channels for "Enhancing Human–Computer Interaction Through Emotion Detection in Chatbots" and how are the selected research papers distributed by publication year and geographical areas targeting this research over the years?	To identify and analyze reputable journals and conferences publishing research on emotion-aware chatbots and to examine temporal (year-wise) and geographical (country/continent-wise) research trends.	Understanding publication channels and research distribution helps assess the maturity, global interest, and evolution of the field, guiding researchers toward suitable venues and highlighting underrepresented regions and emerging research trends.
RQ2. What emotion detection techniques are currently used in chatbot systems to enhance human–computer interaction?	To systematically categorize and analyze the emotion detection techniques employed in chatbot systems, including machine learning, deep learning, sentiment–emotion fusion, and affective computing approaches.	Identifying existing techniques provides insights into dominant and emerging methods, helps compare their effectiveness, and supports the selection of appropriate models for improving emotionally intelligent chatbot interactions.
RQ3. Which data modalities (textual, vocal, visual, or multimodal) are most	To evaluate and compare different data modalities used for emotion	Emotion expression varies across modalities; understanding which

RQ Statement	Objective	Motivation
effective for emotion detection in chatbot-based interactions?	detection in chatbots and assess their effectiveness in enhancing interaction quality.	modalities or combinations yield better performance is essential for designing robust, real-world emotion-aware chatbot systems.
RQ4. What research frameworks and architectural approaches have been proposed to embed emotion detection within chatbot systems, and how systematically are they evaluated?	To examine existing research frameworks and system architectures that integrate emotion detection into chatbots and analyze the rigor of their evaluation methods.	A structured understanding of frameworks and evaluation practices helps bridge the gap between theoretical models and practical deployment, enabling the development of reliable, scalable, and well-evaluated emotion-aware conversational agents.

3.1 Search String:

Several academic databases were searched with well-developed search strings in order to perform a systematic and wide search. Within the frames of this work, the key academic sources like Google Scholar, IEEE Xplore, ScienceDirect, MDPI, and SpringerLink were used, as illustrated in Table 3. The search terms were designed in such a manner that they could include research done on emotion detection, sentiment analysis, affective computing, and chatbot-based Human-Computer Interaction. These keywords were chosen in a systematic and interrelated way so that only high-relevant studies of the emotionally sensitive conversational agent would be obtained. Where necessary, the search results were narrowed with the help of the use of Boolean operators, truncation, and proximity operators to select only high-quality and topic-specific publications. The wide and restricted search strategy allowed gathering a variety of academic viewpoints and methods of technical implementation of emotion-sensitive chatbots. Through the use of various databases, the review was in a position to get a holistic picture of the existing research in emotion-driven Human-Computer Interaction systems.

Table 3: Search Strings Used Across Selected Databases for Identifying Relevant Studies

Sources	Search String
Google Scholar, ACM Digital Library, WoS, IEEE Xplore, Science Direct, MDPI, Springer Link	(Emotion Detection OR Sentiment Analysis OR Affective Computing OR Emotion Recognition) AND (Chatbots OR Conversational Agents OR Virtual Assistants OR Dialogue Systems) AND (Human–Computer Interaction OR User Experience OR User Engagement OR HCI)

3.3. Selection based on Inclusion/Exclusion criteria:

At the first stage of identification, the specified search protocol was run on the Web of Science (WoS) Core Collection database where 17,700 records concerning emotion detection, chatbots, and Human-Computer Interaction were identified. According to the preset exclusion criteria, 9,671 records were excluded since they were out of scope and 8,029 studies were additionally screened.

In the screening phase, the rest 8,029 records were filtered using their titles and 6700 studies were eliminated on the basis of irrelevancy in the research scope. This led to the retention of 1,329 articles to have its eligibility evaluated.

During the eligibility stage, 1,329 papers have been reviewed based on their introductions and conclusions, and 1,279 data was filtered out due to the lack of focus on emotion detection in chatbots and its positive impact on Human-Computer Interaction. As a result, 50 articles that satisfied all the inclusion criteria were found to be synthesized as shown in Figure 2.

To find the reliability of screening, repeated and redundant records were cautiously taken away, and the inter-rater agreement of two independent reviewers was determined using Cohen Kappa coefficient, which gave a value of 0.91 revealing excellent inter-rater reliability. Through this stringent and orderly process of filtering, only quality and highly relevant works were qualified to give a strong basis of analyzing the role of emotion detection in chatbots in improving Human-Computer Interaction.

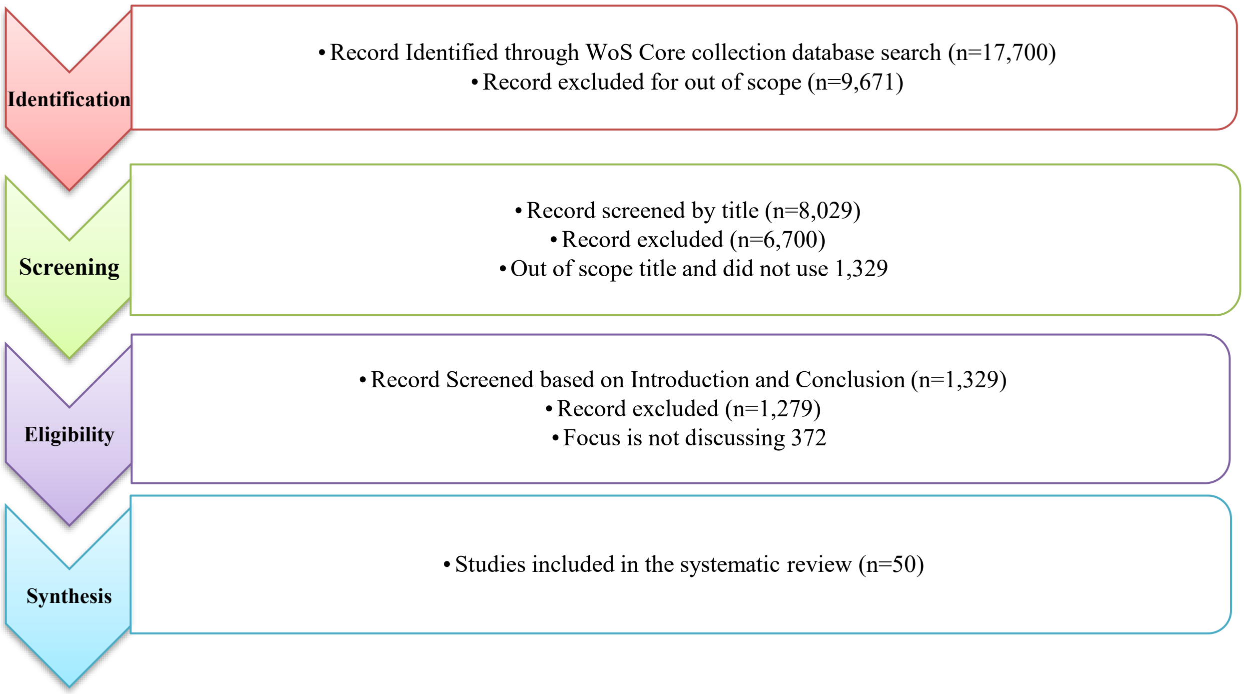

Figure 2: (Inclusion/Exclusion)

Assessment and Discussion of Research Questions:

RQ1. What are the good quality publication sources of Enhancing Human-Computer Interaction through Emotion Detection in Chatbots and how are the sampled research articles dispersed across the years and geographical locations targeting the research?

Answer: The active development of the study of emotion-aware chatbots has brought a growing range of literature that is being published in various journals and conferences in the sub-disciplines of human-computer interaction, artificial intelligence, and affective computing. When assessing the maturity of scholarly quality of research publications, their credibility and dissemination patterns, it is important to identify the high-quality channels of publication that is aimed at improving human-computer interaction with the help of emotion detection in chatbots. The study of the publication location of the study will give the insight into the disciplinary inclination of the area and mention the sites that are more focused on rigorous methodological and human-oriented reviews. Besides, considering the temporal distribution of publications, the growth of academic interest in emotion-conscious conversational agents has changed with time as a measure of technological progress and new application requirements. Simultaneously, the evaluation of the geographical distribution of research work will enable determining the strengths of research in particular regions, trends in collaboration, and gaps. The combination of these analyses creates a background knowledge of the research area as summarized in Table 4 and reasons why it is necessary to conduct a systematic study of the channels of publication and yearly increase and worldwide involvement in the development of emotion-based chatbot interaction studies.

Table 4: Distribution of Selected Studies by Journal and Conference Venue

Sr No	Journal / Conference Name	No of Publication
1	International Journal of Human–Computer Interaction	6
2	Frontiers in Psychology	2
3	Association for Computational Linguistics / LAW-2020	1
4	International Journal of Human–Computer Studies (Elsevier)	1
5	Shodh Sagar – Journal of Artificial Intelligence & Machine Learning	1
6	Вестник КазНПУ (Psychology Series)	1
7	arXiv Preprint (Survey Research)	1
8	ACM Multimedia 2018	1
9	LREC-COLING 2024	1
10	AAAI AIIDE 2023	1
11	ACM Conversational User Interfaces (CUI 2022)	1
12	Journal of Management and Research (JMR)	1
13	CHI Conference on Human Factors in Computing Systems	1

Sr No	Journal / Conference Name	No of Publication
14	International Conference on Software Development & Technologies for Enhancing Accessibility & Fighting Info-exclusion (DSAI 2024)	1
15	Journal of Physics: Conference Series	1
16	International Journal of Advanced Human–Computer Interaction	1
17	Computational Intelligence & Neuroscience (Hindawi)	1
18	Applications of Digital Signal Processing (IntechOpen Book Chapter)	1
19	AIS Transactions on Human–Computer Interaction	1
20	Undergraduate Research Study (Bournemouth University)	1
21	Electronics & Communication Engineering Research	1
22	International Journal of Advanced Computer Science & Applications	1
23	APSIPA ASC	1
24	Frontiers in Public Health	1
25	Frontiers in Artificial Intelligence	1
26	Human Behavior and Emerging Technologies	1
27	IJSREM – International Journal of Scientific Research in Engineering & Management	1
28	– (Preprint / Research Study)	1
29	International Journal of Research in Computer	1
30	Future Generation Computer Systems	1
31	Sign Systems Studies	1
32	Journal of Artificial Intelligence and Technology	1
33	Journal of Business Research	1
34	Jurnal ADAT (Cultural Arts & Design)	1
35	ACM International Conference on Multimodal Interaction (ICMI ’24)	1
36	Master Thesis — Unitec Te Pūkenga	1
37	Social media + Society	1
38	Journal of Natural & Artificial Scientific Systems	1
39	Personal and Ubiquitous Computing	1
40	International Journal of Educational Technology in Higher Education	1
41	IEEE Access	1
42	Journal of Computer Science & Software Applications	1
43	Smart Computing Conference (SC40)	1
44	International Journal of Interactive Mobile Technologies (Education Technology)	1
Total		50

Geographical Area:

Table 5: Geographical Distribution of Publications by Continent and Country

Sr No	Continent	Country	No of Publication	Total
1	Asia	Bangladesh	1	21
		China	2	
		India	5	
		Indonesia	1	
		Iran	1	
		Kazakhstan	1	
		Pakistan	1	
		Qatar	2	
		Saudi Arabia	4	
		Singapore	1	
		Sri Lanka	1	
		UAE	1	
2	Europe	Denmark	1	20
		France	1	
		Germany	1	
		Italy	4	
		Netherlands	1	
		Norway	1	
		Poland	1	
		Portugal	1	

Sr No	Continent	Country	No of Publication	Total
		Slovakia Spain Switzerland UK	1 2 2 4	
3	North America	Canada USA	1 4	5
4	Oceania	Australia New Zealand	1 2	3
5	Africa	Nigeria	1	1
Total				**50**

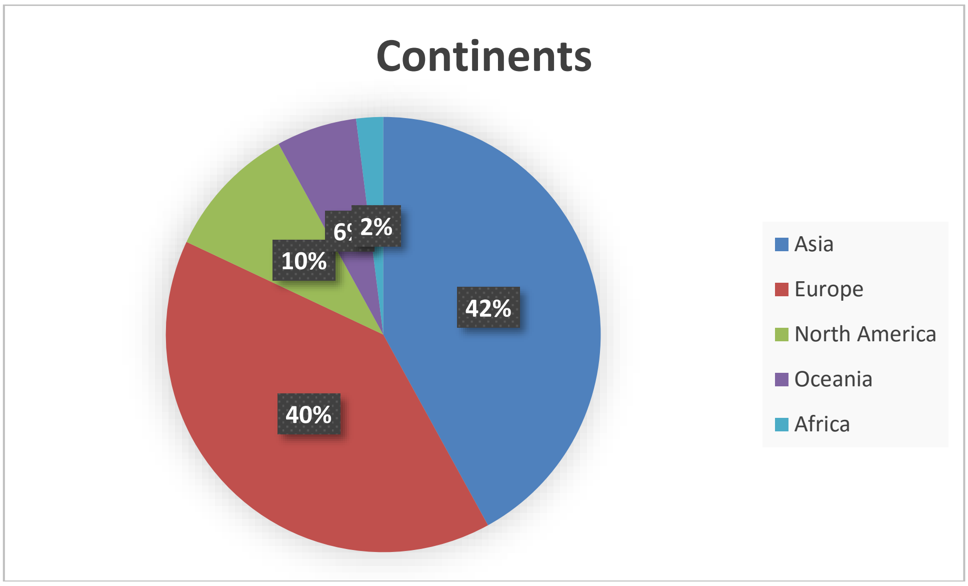

Figure 3: Continental Distribution of Selected Studies on Emotion-Aware Chatbots for Human–Computer Interaction

Table 5 displays the distribution of the chosen literature on the continents and countries, which indicates the worldwide research activity on how to improve human-computer interaction by using emotion detection in chatbots. The findings suggest that Asia is the most contributing constituent with 21 of 50 publications being contributed by it, which signifies a high level of research in such nations like India (5 studies), Saudi Arabia (4 studies), China (2 studies), and Qatar (2 studies). This superiority implies that people show a rising interest in emotion-conscious chatbot systems in Asian countries, mostly predetermined by the progress in the field of artificial intelligence, speech processing, and person-oriented computing applications.

Europe is in close pursuit with 20 publications indicating a similar degree of research activities. Interestingly, Italy and the United Kingdom are the countries that contribute four studies each, and Spain and Switzerland contribute two studies respectively, which means that there is a strong and diversified research presence of Europeans. Its spread across the various European countries indicates that there is a prevalent interdisciplinary cooperation and continued academic interest on the emotional intelligence and human-computer interaction research.

Conversely, North America is adding five articles, most of them, in the United States, which means that the research activity is moderate but narrow. There are three publications by Oceania, and Australia and New Zealand make their contributions, and Africa has one study per Nigeria, which underscores a high level of underrepresentation of African continent research.

On the whole, geographical distribution shows that the studies on emotion detection in the chatbot-based human–computer interaction are mostly concentrated in the countries of Asia and Europe with other territories being under-represented. Such an imbalance highlights the necessity of the global engagement and cross-cultural research to make emotion-sensitive systems of chatbots accommodating and culturally sensitive and universal to be used by different groups of users.

RQ2. Which are currently used emotion detection techniques in chatbot systems to improve human-computer interaction?
Answer: One of the fundamental features of the so-called emotion-aware or empathetic chatbots is emotion detection since it enables the system to estimate the way an individual feels (e.g., frustrated, sad, joyful, anxious) and adjust its dialogue policy to meet its needs this way.

This is relevant in the context of HCI since users do not evaluate a chatbot based on its success in a task but also on how well it is perceived to understand and support them. Research in customer service, education, mental health support, and digital humans indicate that the more a chatbot is in line with the mood and the information of the user, the more satisfied customers will be, the more engaged they perceive it, and the more they will feel empathy (Hamad *et al.,* 2024; Haugeland *et al.,* 2022; Kovačević *et al.,* 2024). On the other hand, chatbots which are emotionally blind can be destructive, cause mistrust, and raise dropout rates of a conversation, particularly in sensitive settings, such as therapy or mental health assistance (Andotra, 2023; Kuhail *et al.,* 2025; Safaei and Ghafourian, 2022).

Throughout the literature reviewed, emotion detection methods can be perceived as a pipe with three standard processes: (1) signal capture, (2) emotion inference, and (3) response adaptation. It is the first step that is based on the modality (text, voice, face, physiological signals). The second stage applies classifiers or deep models to signal to category of emotions (basic emotions, sentiment, or dimensional emotion). In the third step, it is determined how the chatbot reacts to the identified emotion, whether it is choosing an empathetic template, modifying the response style, or changing the policy of conversation. According to the table 6 summary, a large number of studies are robust in steps (1)-(2) (high accuracy classification) but weak in step (3) (limited/short-term assessment of whether emotion detection actually increases the HCI outcomes in terms of trust, continuance intention or perceived empathy) (Jin & Youn, 2023; Cuadra and Wang, 2024).

Deeper synthesis of techniques

1) Text-based emotion detection

- The text-based methods get the emotions based on user messages, using:
- Classical ML: SVM, Naive bayes, TFIDF features Logistic regression.
- Deep learning: LSTM/BiLSTM and transformer-based (BERT-style) models: Contextual meaning.

Purpose of use in chatbots: one can always have text in chat.

HCI advantage: improved contextual sensitivity will lead to a higher number of emotion-appropriate responses and decrease the number of tone-deaf responses (Hamad *et al.,* 2024; Machová *et al.,* 2023).

Weaknesses: sarcasm, ambivalent feelings and culture-specific expression are hard to do; sentiment polarity is too simplistic (Bedi, 2024).

2) Speech Emotion Recognition (SER) of voice-based chatbots

SER identifies voice-based emotion based on:

- Acoustic characteristics: MFCCs, pitch, energy, spectral characteristics.
- Models: CNN, RNN, CRNN, BiLSTM.

Why used: voice has high affective cues even in cases of text that is neutral.

HCI advantage: the assistants become more natural to talk to; they appear more human-like and can be easily interacted with (Alnuaim *et al.,* 2022; Kannangara, 2025).

Limitations There is an adverse influence of noise, accents, cross-language transfer, and dataset bias on accuracy (Dar & Delhibabu, 2024).

3) Embodied agent visual / face emotion recognition.

Facial expression is used to identify emotion using computer vision:

- Faces CNN based face classifiers, face landmarks and (in others) multimodal fusion of audio.

Reasons why it is used: facial expressions are significant non-verbal communication.

HCI advantage: enhances the level of social presence of avatars/digital humans; makes the process more alive (Hendry *et al.,* 2023; Ciechanowski *et al.,* 2018).

Constraints: privacy and camera access, real-life lighting/angle.

4) Multimodal emotion detection

The multi-source fusion approaches involve signals of several sources:

- Early fusion or late fusion.

Multimodal transformers and personalization pipes.

Why necessary: human beings are emotional and they communicate through different channels, and single-modality may overlook significant information.

HCI advantage: enhanced strength in the field and superior emotion understanding of adaptive reactions (Kovačević *et al.,* 2024).

Constraints: increased complexity, synchronization and increased demanding data collection.

5) Attention-based sentiment emotion fusion (empathy-focused)

Others have explicit combinations of sentiment + emotion and attention processes (e.g., multi-expert attention).

HCI benefit: produces more understanding, inclusive reactions and less generalized behavior of I am sorry to hear that (Hamad *et al.,* 2024).

6) According to physiological and neural signals: emotion detection (emerging)
These are based on the EEG/ECG/GSR and other biosignals to make inferences about affect.
HCI advantage: it might be significantly more stable than facial cues in masked/noisy conditions and high-stakes conditions (e.g., mental health) (Saffaryazdi and Gunasekaran *et al.,* 2025).
Limitations: expensive, user burdened, ethics and privacy of data, low scalability.

7) Logic of emotion-aware responses that is rule based (lightweight integration)
With even ML-based detection, most systems apply rule-based response adaptation (e.g. empathetic templates, change policy in dialogue policy).
HCI advantage: realistic and implementable; assists in the upholding of conversational safety and consistency.
Weaknesses: inflexibility; conflict in subtle emotional movements.

- The majority of emotion-conscious chatbots begin with text emotion recognition since it is inexpensive and can be accessed at any time, yet advanced systems are adding voice and vision to provide a richer HCI.
- Methods are moving out of sentiment polarity methods to multi-class emotion and context conscious methods to minimize confusion and aggravation.

Multimodal models tend to be stronger in the real world, although they require more resources and have privacy issues.

- Another significant distinction among the literature is the presence or absence of detecting emotions to achieve classification accuracy or HCI outcome (e.g., satisfaction, trust, engagement, continuance).

Empathy is maximized with the combination of emotion detection and response adaptation strategies (dialogue policy, style/tone shifting, or empathetic generation models).

Emerging work in the field of using physiological signals is promising, though their practical use and ethics are still not addressed.

Table 6: Emotion Detection Techniques Used in Chatbots and their Impact on Human–Computer Interaction

Emotion Detection Technique	Typical Inputs	Typical Models / Methods	How It's Used in Chatbots	HCI Impact (What Improves)	Common Limitations
Text-based emotion detection	User messages	TF–IDF+SVM/NB; LSTM/BiLSTM; transformers	Detect emotion/sentiment → adjust tone, content, or escalation	Relevance, empathy, engagement	Sarcasm, mixed emotions, cultural language variation
Speech emotion recognition (SER)	Voice/audio	MFCC + CNN/RNN/CRNN/BiLSTM	Voice assistant detects affect → adapts prosody/wording	Naturalness, human-likeness, reduced frustration	Noise, accent, cross-language bias, dataset limitations
Facial emotion recognition	Face video/images	CNN, landmarks, vision models	Digital humans/avatars read expressions → adapt responses	Social presence, non-verbal alignment	Privacy, camera availability, lighting/angle sensitivity
Multimodal fusion	Text + voice + face	Fusion models; multimodal transformers	Combine channels for stronger emotion inference	Robustness, accuracy, realism	Complexity, synchronization, data collection burden
Attention-based sentiment–emotion fusion	Mostly text (sometimes multi)	Attention + multi-expert models	Emotion-conditioned empathetic response generation	Empathy, response diversity, conversational quality	Requires careful training data and evaluation
Physiological/neural emotion detection	EEG/ECG/GSR etc.	Signal processing + neural models	High-stakes empathetic interaction support	Reliability, deeper affect inference	Cost, intrusiveness, ethical/privacy constraints
Rule-based emotional adaptation	Detected emotion label	Templates/rules/dialogue policy	Choose supportive wording, safety responses, escalation	Consistency, safety, deployability	Rigidity; limited nuance and personalization

RQ3. What data modalities (textual, vocal, visual, or multimodal) can best be used in emotion detection on chatbots?

Answer: Human communication is multimodal in the expression of emotions and this multimodality includes verbal, vocal and facial expressions and physiological reactions. This means that the ability of chatbots to detect emotion in human-computer interaction (HCI) is highly reliant on the data modality employed to identify the affective states of the users. Although early chatbot apps used text as the primary input method because of the simplicity of input and low processing power, recent developments in affective computing have made it possible to use the voice, visual, and multimodal signals to better understand and interpret the emotions of individuals. The response to RQ3, this section analyzed the role of alternative data modalities in improving the accuracy of emotion detection and their effectiveness in improving the quality of chatbot interactions in different application settings.

According to the reviewed articles, there is no single modality that is universally the best; instead, the effectiveness of each modality varies depending on factors like interaction contexts, system constraints, and user environment and evaluation purposes. Scalability and deployability Textual data provide scalability and the ability to deploy, paralinguistic emotional responses Vocal data to capture paralinguistic emotional responses, non-verbal affect recognition with visual data, and multimodal methods to integrate complementary signals to provide overcoming limitations inherent in single channels. To conclude, as Table 7 summarizes, to build chatbot systems that are both emotionally intelligent and also deployable in practice, it is necessary to comprehend the strengths and weaknesses of each modality.

1) Textual Modality

Text based emotion detection involves the processing of the written message of users through emotion classification or sentiment analysis. It is the most popular modality of chatbots systems because it is available in almost every conversational interface.

Effectiveness:

- Very efficient in elicitation of explicit expressions of emotions (e.g. I feel frustrated).

Scaleable in areas like customer service, education and information systems.

HCI impact: Emotion recognition based on texts will improve the contextual relevance, decrease the response of emotional inappropriateness and increase the perception of empathy when paired with adaptive dialogue methods (Hamad *et al.,* 2024; Machová *et al.,* 2023).

Limitations:

- Difficulties in sarcasm, implicit emotion and cultural language gap.
- Reduced frequently to a sentiment polarity, instead of an ambivalent emotional state.

2) Speech emotion recognition (Vocal Modality)

Speech emotion recognition (SER) is an acoustic feature recognition method that uses voice inputs to determine emotion through the use of pitch, intensity, and spectral characteristics.

Effectiveness:

- More emotional intensity sensitive and stress sensitive than text.
- Especially successful when used in voice-based assistants as well as conversational agents.

HCI impact:

SER increases the level of naturalness and human-like voice-based chatbots, making them more likely to engage users and minimise frustration during the interaction (Alnuaim *et al.,* 2022; Kannangara, 2025).

Limitations:

- Bad performance in disturbed environments.
- The variability of cross-language and accent influences generalization.

3) Visual Modality

Visual emotion recognition is a computer vision method that is used to analyze faces and gestures.

Effectiveness:

- Records the emotional cues, which are non-verbal and can also be missing in verbal expression.
- Applicable in embodied agents, avatars and virtual humans.

HCI impact:

Visual emotion recognition enhances the social presence and emotional congruence, which raises the level of immersion and realism of human-chatbot interactions (Ciechanowski *et al.,* 2018; Hendry *et al.,* 2023).

Limitations:

- Needs access to the camera and the consent of the user.
- Light-sensitive, with respect to occlusion and variation of point of view.

4) Multimodal Modality

Multimodal emotion detection combines two or more modalities (e.g. text + voice, text + face or text + voice + face).

Effectiveness:

- Always performs better in real world scenarios as compared to single modality.

- Less sensitive to ambiguity, noise and partial signal loss.

HCI impact:

Based on multimodal systems, more accurate emotion inference is possible, which results in adaptive, context-informed chatbot reactions and more realistically simulated interaction (Kovačević *et al.,* 2024).

Limitations:

- The complexity of computation and implementation increases.
- Higher issues on privacy, synchronization of data and system cost.

Key Points:

Textual modality is the most common to use because it can be scaled and is easy to implement.

- Vocal modality is more emotionally expressive, in particular to stress and arousal, but is also vulnerable to noise and language change.
- Visual modality enhances emotional intelligence in embodied chatbots with practical and ethical limitations.
- Multimodal emotion detection is generally the most efficient that is, more accurate and resistant to real world chatbot conversation.

Selection of modality must be in accordance with application context and resource availability and HCI evaluation objectives.

Table 7: Comparison of Data Modalities for Emotion Detection and Their Effectiveness in Human–Computer Interaction

Data Modality	Typical Inputs	Strengths	Limitations	Effectiveness for HCI Enhancement	Common Application Contexts
Textual	Chat messages	Scalable, low cost, easy integration	Limited nuance, sarcasm handling	Moderate	Customer service, educational chatbots
Vocal	Speech/audio	Captures emotional intensity, natural interaction	Noise sensitivity, language bias	High	Voice assistants, virtual agents
Visual	Facial expressions, gestures	Non-verbal emotion capture, high social presence	Privacy concerns, hardware dependency	High (context-dependent)	Digital humans, embodied agents
Multimodal	Text + voice + visual	High accuracy, robust emotion inference	Complexity, privacy and cost	Very High	Mental health, therapy, advanced HCI systems

RQ4. What are the research frameworks and architectural approaches that have been suggested to implement emotion detection in chatbot systems and to what extent are they systematically evaluated?

Answer: Adding emotion recognition to chatbot systems is not solely a modeling challenge (detecting affect), but also an architectural issue: the system needs to determine how emotion is identified, how this affects the dialogue management, and how the responses of the chatbot can be modified safely, predictably and in a user-friendly manner. This is why numerous works suggest frameworks and architectures that design emotion-aware functionality in the pipeline form which typically consists of (1) input capture, (2) emotion inference, (3) context and user-state modeling, (4) response planning, and (5) response generation (Hamad *et al.,* 2024; Kovačević *et al.,* 2024). Nevertheless, some of the works, despite being user studies, also report the results of interaction and others are mostly classification-based or present conceptual models that cannot be systematically validated (Cuadra & Wang, 2024; Jin and Youn, 2023). To answer RQ4, this part is a synthesis of the key types of frameworks suggested to be used in emotion-aware chatbots and the evaluation of their systematization in the areas of technical performance and the impact on HCI as summarized in Table 8.

1) Chatbot architectures based on emotions (most typical) that are based on pipelines

It is an architectural pattern widely used to incorporate emotion detection as a specialized component, with the unfolding of conversational logic being fed by it:

Typical modules

- Text/audio/video input processing.
- Inference of emotions (classifier/model)
- State/context manager (user profile + history of conversation)
- Dialogue manager (policy/strategy selection)

Why it matters for HCI

The structure enables straightforward integration and enables teams to upgrade components without modifying dialogue manager (e.g. replace an emotion model without modifying the dialogue manager). Such pipelines usually enhance the rightness of the response and lower levels of frustration since state of emotion becomes a first-class cue in the processing of response planning (Sanguinetti *et al.,* 2020; Hamad *et al.,* 2024).

Main limitation

Most pipeline systems end with the step of detect emotion, select empathetic response, without justifying the system enhances actual HCI performance (long-term engagement, trust, continuance).

2) Interpersonal close relation sentiment Attention-based sentiment-emotion fusion frameworks (empathy-centric)

Other work suggests explicit emotion sentimental fusion architectures, in which attention systems are trained on the importance of which emotion cues to pay attention to in order to generate responses. These models are aimed at making generic empathy less, and emotional specificity more.

Contribution

They enhance empathetic generation and richness of conversation and are frequently reported to be better than baselines with benchmark data (Hamad *et al.,* 2024).

Evaluation pattern

Such studies are generally comparing:

- Performance in predicting emotion/sentiment accuracy/F1
- Automatic measures of the quality of response and occasionally, human rating.

Gap

The assessments based on HCI (e.g., user trust, perceived support, sustained interaction) are not reported so much.

3) Multimodal framework and personalization and multimodal in the wild

One of the architectural improvements is customized emotion recognition pipelines which are responsive to real user variability. In the actual environment, individuals are not as emotional as models that are trained using laboratory datasets, fail. The performance and strength of frameworks that have built personalization (user calibration or adaptation layers) can be demonstrated to have measurable improvements (Kovačević *et al.,* 2024).

Evaluation strength

These methods are generally more methodologically powerful as they:

Sources of information: Gather real world interaction data, establish on naturalistic environments, compensate against impersonalized baselines.

4) Digital human / embodied conversational agent models

There are other studies that implement emotion detection in embedded agents or digital humans, in which emotional perception is not only relevant to words but also tone, facial expression, and interactive behaviour.

Architectural features

- Behavior controller and emotion detector.
- Avatar expression defining / talking head.
- Relational modules / social presence.

HCI benefit

This leads to more social presence and realism, as well as poses threats of uncanny valley effects and misalignment of human-likeness and trust (Ciechanowski *et al.,* 2018; Hendry *et al.,* 2023).

Evaluation pattern

The psychophysiological measures or user perception surveys are often included which is more powerful than the evaluation based on technical aspects.

5) Mental health / therapy chatbot models that are emotion aware

Emotion-sensitive architectures are especially essential in mental health settings where empathy, safety, and trust are the key considerations. There are those works that deal with emotion-conscious support logic (Andotra, 2023), and there are those that deal with comparing the perceived quality of AI vs human therapy transcripts (Kuhail *et al.,* 2025).

Evaluation need

There should be better validation of these systems, preferably longitudinal, clinically based, ethical reviewed yet most studies continue to be based on the short-term assessment or on personal measures.

6) Integrated empathy frameworks (developing) Physiological/neural signals

Other architectures are also built by adding biosignals (EEG/ECG/GSR) to the conversational empathy pipelines to address voice/face cues. These systems suggest greater affect inference and increased reliability under restricted conditions (e.g. masked faces, noisy audio) (Saffaryazdi and Gunasekaran *et al.,* 2025).

Evaluation status

This research is usually associated with controlled experiments but is scalable, and can be deployed to the real world with low cost and privacy issues.

To what extent are such structures assessed in a systematic manner?

In the examined literature, the assessment is more likely to be based on four scales (weakest to strongest):

1. Conceptual/Theoretical validation

- Theorizes a framework and does not test it empirically.
- Good positioning evidence but poor evidence.

2. Technical evaluation only

- A good reports classification/F1 but does not have user-centered results.
- Usually found in SER and text emotion detectors.

3. Short-term evaluation (user-perception).

- Surveys, manipulated experiments, laboratory experiments to gauge satisfaction/empathy.
- Greater but occasionally confined sample sizes and length.

4. In-the-wild/ longitudinal + multimodal (strongest) evaluation

- Real usage settings, customization, history of interaction, long-term.
- The majority of the robust to HCI conclusions (Kovačević *et al.,* 2024)

The vast majority of emotion-sensitive chatbots utilize modular pipeline designs in which emotion recognition is used in dialogue strategy and response generation.

It is possible that attention-based fusion frameworks can enhance the quality of the empathetic responses in comparison to the mere sentiment polarity.

Multimodal + personalization pipelines are more robust in the real world, particularly in the wild.

The embodied/digital human architectures are beneficial to social presence, but they must be well designed lest they can cause discomfort and loss of trust.

- The rigor of evaluation is skewed: numerous articles assess the accuracy of models, and others assess HCI (trust, engagement, continuance, perceived empathy).
- The best evidence is provided by research based on the real-world deployment, personalization and multi-metric assessment (technical and user results).
- The need to conduct an ethical and safety assessment is open, in particular, sensitive programs (Cuadra & Wang, 2024; Kuhail *et al.,* 2025).

Table 8: Frameworks/Architectures and Evaluation Systematicity

Framework / Architecture Type	Key Components	Typical Output	Systematic Evaluation Commonly Used	Evaluation Strength (Overall)	Main Gaps
Modular pipeline emotion-aware chatbot	Emotion detector → state/context → dialogue manager → NLG	Emotion-adapted responses	Accuracy/F1 + limited user tests	Medium	HCI outcomes not consistently measured
Attention-based sentiment–emotion fusion	Multi-expert/attention fusion + emotion-conditioned generation	More empathetic, diverse replies	Benchmark evaluation + human ratings	Medium–High	Real-world/longitudinal validation limited
Multimodal + personalization pipeline	Text/audio/video fusion + personalization layer	Robust emotion inference in real settings	Real-world data + comparative baselines	High	Privacy, cost, data collection burden
Digital human / embodied agent framework	Emotion detection + behavior/animation + expressive avatar	Social presence + nonverbal affect	User perception + psychophysiology	High (context-dependent)	Uncanny valley risks; ethical consent issues
Mental health emotion-aware support framework	Emotion inference + supportive response policy + safety logic	Therapeutic/empathetic interaction	Surveys, pilots, transcript analysis	Medium	Clinical validation and safety evaluation needed
Physiology-integrated empathy framework	EEG/ECG/GSR + affect modeling + empathetic response policy	Deeper, potentially more reliable affect inference	Controlled experiments	Medium–High	Scalability, intrusiveness, privacy/ethics

CONCLUSION

The increasing adoption of conversational agents into the realm of daily digital systems has increased the demand of more natural, empathetic, and human interactions. This paper has analyzed the possibility of emotion detection to improve human-computer interaction in chatbot systems through a systematic synthesis of evidence pertaining to fifty research studies. The discussion shows that emotion-sensitive features can no longer be considered peripheral and are essential elements of the enhancement of the quality of interactions, user satisfaction, and perceived intelligence of chatbot systems.

The data shows that the studies on emotion-sensitive chatbots are also published in the reputable journals and conferences in the sphere of human-computer interaction, artificial intelligence, and affective computing. The gradual increase in the number of publications since the last few years signifies the increasing awareness of the significance of emotional intelligence in the conversation systems. Nevertheless, the geographical representation of research indicates that contribution of Asia and Europe is heavy and that the rest of the world is not very represented. Such an imbalance indicates that further cross-cultural and more global research is required to make sure that emotion-sensitive chatbot designs are non-discriminatory and universal.

Technically, the literature indicates a broad application of emotion detection methods including traditional machine learning methods, to sophisticated deep learning and affective computing frameworks. Emotion detection based on textual content is the most widely used because of its ability to scale and be easily integrated, and speech- and vision-based detection provides more depth of emotion that promotes more naturalness and a social experience. Multimodal approaches involving amalgamation of more than two sources of data are always more robust and accurate especially in the context of real-world interaction. However, they tend to be accompanied with a rise in the complexity of the system, privacy and issues in implementation.

Regarding the system design, current chatbot architectures have come out to be more than basic emotion classification units and instead, they have been designed to be more organized with the emotion detection aspect integrating within the dialogue management, providing customization, and response generation procedures. Despite being developed through such architectural innovations that allow more responsive and compassionate relationships, the practices in evaluation are unequal. There is a high concentration on model performance measures and little evaluation of the quality of interaction in the long run, trust, ethical, or real-world deployment results in most of the studies. This underscores a gaping discipline between the technical and human-focused implementation.

Altogether, the given study seems to offer a unified overview of the existing situation in the field of emotion recognition in chatbot-mediated human-computer interaction, both in terms of advancement and the ongoing issues. The results indicate the significance of abandoning accuracy-based designs in favor of holistic, ethically-based and user-centric chatbots. Systematic assessment, cross-cultural validation, and responsible deployment should be the priorities of future research to help to fully pursue the potential of emotion-conscious chatbots in establishing meaningful and trustful human-AI interaction.

Future Work

Despite the substantial advances in the creation of emotion-conscious chatbot systems, there are still some important research directions that can be open and can be explored. The creation of more culturally adaptive and robust models of emotion detection is one of the avenues that the future work may take. Most of the existing systems are trained on small or not very diverse datasets, and this may diminish their applicability to different linguistic, cultural and social settings. The future research needs to focus on the cross-cultural data and multilingual emotion modeling that will guarantee the legitimacy of the chatbot interactions with the global users and allow them to be emotionally suitable and inclusive.

The other valuable area of direction is the longitudinal and real-world testing of emotion-sensitive chatbots. Most of the existing studies are based on short-term experiments, laboratory control or simulation-based tests. The future direction lies in implementation of emotion attentive chatbots into real-life setting over longer durations to gauge user immersion, formation of trust, dependency on emotions as well as continuity of interaction. These longitudinal studies would bring more information on how emotional intelligence affects human computer interaction beyond the novelty effects.

Ethical, privacy and transparency issues of emotion detection in conversational systems are also to be investigated in the future. The gathering and analysis of emotional information, especially when voice, visual, or physiological indicators are utilized, brings up issues to do with consent, data privacy, emotional control, and agency. To achieve responsible deployment, in particular in such sensitive domains as mental health, education, and social support, the creation of explainable emotion-aware models and rules of ethical design will be crucial.

Moreover, more integrated and standardized frameworks of evaluation are required, which are not based on technical metrics of accuracy. Combining the measures of computational performance with human-based criteria of evaluation such as perceived empathy, emotional suitability, user satisfaction, and social presence should also be considered in future work. It would help to have shared benchmarks and evaluation procedures that would enhance comparability among studies and allow to assess emotion-aware chatbot effectiveness more rigorously.

Lastly, there are emerging technologies, including adaptive personalization, multimodal fusion and generative conversational models, which have good potential of improving emotion-aware chatbots. It might be possible to have more dynamically changing emotional strategies in future systems depending on user history, the situation of interaction, and the transforming emotional patterns. The combination of these functions and ethical protection and user-friendly design considerations will play the key role in further developing the future of emotionally intelligent conversational agents.

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