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A Survey on Emotion Recognition with Human Centred Software Engineering

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Abstract

The survey explores the connection between emotion recognition technology and Human-Centered Software Engineering (HCSE) and, in particular, how the two aspects can be integrated to enhance user experiences, especially in customer services. The big picture is to research how emotional intelligence can be built into software system, and how this can lead to more empathic response with human beings. The work is grounded on the critical review of the current developments in the field of emotion identification, particularly on how deep learning models, namely Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks are being utilized. such models are evaluated in terms of their role in real-time detection of emotional states and ratio of enhanced classification. Also, the research takes into account the multimodal recognition approaches, which involve facial expression, voice, and physiological signals to perform a thorough analysis of emotions. The survey also covers such significant implementation issues as technical constraints, ethical concerns, and algorithmic biases that exist. The results of this effort have broad implications in many fields, such as customer support, healthcare, education, and entertainment, and provide clues on how to create emotionally intelligent systems that can make the human-computer interactions much more personalized and productive.

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1. Introduction

Recent software systems are incorporating emotion recognition technologies in order to enhance human-computer interactions, where the systems are able to react to human emotional states, i.e., facial expressions, voice tone, body signals. This trend towards emotionally reactive systems is especially important in customer service uses, where user emotions can also be detected and reacted to greatly increase user satisfaction and decrease frustration. These interfaces are not aimed at being merely functional, they should also be capable of providing emotional support, which is one of the main factors in creating inclusive and user-friendly systems (Ali et al., 2023).

In the paradigm of Human-Centered Software Engineering (HCSE), the software is being constructed with the primary consideration of human needs, mental patterns, and emotional states. HCSE goes past technical optimization to include design thinking and psychology that aid emotionally intelligent user interfaces. These interfaces are aimed not just to be functional but to be able to provide emotional support as well which is important to include in the design of inclusive and usable systems (Khaleel and Salih, 2024) (AL thanoon et al., 2024).

One of the most important aspects here is emotional intelligence or the ability of the system to detect, analyze, and react to human emotions in the proper way. Even though the use of deep learning models, including CNNs, RNNs, and GANs, has grown in emotional state detection (Mohamed, 2024), there is still a massive research gap in implementing emotional intelligence into HCSE approaches. The majority of the existing studies focus on technical performance and recognition accuracy without paying due attention to the overall user experience and emotional flexibility of systems (Zeng et al., 2018)

The proposed survey will contribute to bridging this research gap by systematically overviews of recent developments in emotion recognition technologies. It studies the way in which these systems can be exploited towards developing adaptive, emotionally intelligent applications. The paper suggests the possibility to turn the customer service, healthcare, education, and entertainment spheres into more personal and emotion-provoking. It mainly dwells on the benefits that emotion recognition can provide to customer service as a result of which more effective and empathic interactions can be developed. Throughout the paper, the author illustrates how the combination of these technologies can promote user satisfaction and responsiveness of the system to the emotional state of a user.

2.Literature Review

Recent research focuses on the incorporation of emotion recognition technologies into Human-Centered Software Engineering (HCSE) because these technologies aim to enhance user interfaces through emotional state detection. Multiple research projects studied how awareness of emotions enhances user experiences in various ways as described in table (1):

The researchers use advanced methods for incorporating neural and physiological signals into conversation agents that would display increased empathetic capabilities. Scientists researched ways signals would detect emotional states in users then produce human-like compassionate responses for the system. Creating better emotionally aware AI systems becomes possible because of this discovery and constitutes a necessity for enhancing customer service interactions because empathy remains essential (Saffaryazdi et al., 2025).

The researchers examined how to enhance large language model-based conversational AI systems through improved emotional sensitivity. The system achieves improved user experience through AI emotional recognition that allows it to modify its tone together with its approach based on detected user emotions. The addition of this emotional sensitivity would enhance customer satisfaction because it would create an impression of deep comprehension and professional expertise within critical customer service encounters (Brun et al., 2025).

A research analysis studied how emotion detection methods could enhance user interactions with live systems. Functionality in content presentation adapts automatically to match the user's emotional state thus providing individualized interaction experiences. Real-time emotional adaptation makes these systems feel emotionally supportive and engaging because this feature benefits operations that require emotional tone recognition for guiding customer service interactions (Yurtay et al., 2024).

Researchers conducted a review paper which explored current developments in generative technology applied to emotion recognition. Various studies analyze ways to enhance artificial intelligence models for detecting and interacting with human emotions in different operational environments. The review gives important information about emotion technology development to support applications especially in customer service because emotional intelligence directly advances service success rates (Zhou et al., 2024).

A system uses video analysis for real-time emotion recognition in human beings. Researchers demonstrated that this system technology could be used for individualized educational programs as well as customized customer interaction processes. A user experiences a more interactive and responsive interface when these systems respond to detected emotional cues through visual signals. System recognition of user emotions enables better customer service because it modifies the interaction according to the detected emotional state (Yuan et al., 2024).

In 2024 researchers reviewed the wider significance of emotion recognition solutions to enhance human-machine interaction functions. Research showed emotional sensitivity toward user interactions enables machines to perform more likeable and operating in real-time. The implementation of these systems demonstrates advanced emotional capabilities in customer service applications because they enable stronger relationships between customers and machines (Govindaraju and Thangam, 2024).

The authors established an ongoing framework for detecting emotions during real-time customer service telephone interactions. Through their work they created a vast emotional recognition database while developing technology capable of detecting emotions as customers speak. The technological system enables representatives to modify their support approach instantly through customer emotional indications that results in better tailored service. The research verifies that emotion recognition boosts service system flexibility and responsiveness while serving customers (Feng, 2023).

The Researcher examined emotion recognition within customer service call centers as reported in 2022. A newly designed system tracks customer-agent communication to detect the emotional state displayed by the caller. Agents can modify their responses while speaking to align with what the customer needs in real-time leading to more appropriate and empathetic communications.

Service quality improvement became the central focus as the strategist aimed to provide agents with emotional understanding skills through which they could better support customers during their sessions (Plaza et al.,2022).
Researchers examined the analysis of emotional content in voice communication between customers and agents in 2022. Through analysis of voice tonality and speech patterns the researchers explained how vital emotional expressions become in detecting customer frustration and satisfaction profiles. The system enables better customer service through real-time emotional feedback which helps agents to address their needs more effectively (Albahri et al., 2022).
The authors investigated the potential of few-shot learning in emotion recognition system development with limited labeling data through their 2021 study. The researchers developed Sequential Prototypical Networks as a method which enables systems to detect emotions from limited data collections. The approach becomes efficient for customer service applications because emotion recognition remains effective when only limited emotionally labeled data exists (Albahri et al., 2022).

Table (1): Studies on Emotion Recognition in Human-Centered Software Engineering

Researchers	Year	Technologies Used	Strengths	Weaknesses	Accuracy
Saffaryazdi et al.	2025	Neural and physiological signals for emotion detection	High accuracy in emotional response generation	Requires specific hardware, limited to certain environments	Very High
Brun et al.	2025	Large language models (LLMs) with emotion recognition	Emotion-sensitive AI, enhances customer satisfaction	Under development, scalability issues for broader use cases	Moderate
Yurtay et al.	2024	Emotion recognition algorithms, content adaptation	Dynamic real-time content adjustment, improves engagement	Limited to real-time environments	High
Zhou et al.	2024	Generative AI models for emotion detection	Highly adaptable, responsive to various emotional cues	Relies on model complexity, requires diverse datasets	High
Yuan et al.	2024	Video-based emotion recognition system	Real-time emotion detection through visual cues	Limited by lighting, facial expression variability	High
Thangam et al.	2024	Emotion detection in human-machine interaction	Creates meaningful, emotionally aware interactions	Performance drops with non-verbal emotional cues	Moderate-High
Feng et al.	2023	End-to-end emotion recognition framework	Real-time adaptation during live calls	Complex framework, deployment challenges	High

Plaza et al.	2022	Voice-based emotion recognition	Real-time feedback for agents, enhances empathy	Limited to voice data, doesn't include other emotional cues	Moderate
Albahri et al.	2022	Speech emotion detection algorithms	Improves customer-agent interactions, real-time application	Susceptible to noise, may miss subtle emotional cues	High
wang et al.	2021	Sequential Prototypical Networks (Few-shot)	Effective with small datasets, scalable emotion detection	Limited scalability with larger datasets	Moderate-High

2. Human-Centered Software Engineering (HCSE)

The Human-Centered Software Engineering (HCSE) methodology enables software designers to create programs for users' benefits first. User needs together with emotions and experiences rank above technical aspects and performance in the Human-Centered Software Engineering framework. Three components including psychology and design thinking and user experience (UX) research unite to produce systems that combine effective operation with intuitive user-friendly and responsive capabilities (Edan and Hadeed, 2022).
HCSE establishes as its central principle the development of software which considers users' experience needs together with emotional states during every stage of development. HCSE emphasizes developing systems which detect user emotions and modify their behavior accordingly. A system with HCSE capabilities should identify user frustration and confusion so it can deliver supportive features which enhance the user experience. The implementation of emotional intelligence in software design produces superior user satisfaction results and fosters deep user engagement and builds highest levels of software trust (Ali, 2023).

3. Emotion Recognition

Emotion recognition is an actively developing branch of affective computing, the task of which is to identify and analyze the human emotional state based on computational techniques. It has a significant part in making human-computer interaction more effective, natural and understanding by making systems react more human-like and empathetic. Different input modalities on which emotion recognition is usually applied include facial expression analysis, voice tone, body posture, physiological signals, to distinguish happiness, anger, sadness, or surprise (Poria et al., 2017). The methods in this area consist of conventional machine learning, i.e., Support Vector Machines and Random Forests, to the more recent deep learning models i.e., Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, which are more precise in complicated and real-time situations (Yin et al., 2017). Emotion recognition incorporated into software programs has brought vital changes in fields like customer service, education, healthcare, and entertainment by way of enabling more responsive and user-sensitive systems.

3.1. Methods of emotion Recognition

1. Facial expression recognition (FER):

The detection of emotions happens most naturally through FER. The system analyzes facial muscle movement patterns to identify gladness or distress and anger along with astonishment as well as other emotional expressions. FER maintains high operational strength from its ability to use cultural universal visible cues which computers can easily interpret and respond to (Li et al., 2017). FER utilizes Convolutional Neural Network (CNNs) and the Facial Action Coding System (FACS) to analyze facial movements through muscle contractions for emotion detection purposes (Mohamed et al., 2023) (Ekman and Friesen, 2011).
Real-life image pattern recognition performances excel within CNNs while FACS analyzes facial expressions through specific facial muscle activities (Li et al., 2017).

The application of FER techniques exists primarily in customer service through service systems that adapt their communication to detect and address customer emotions. The system operates in two application areas of market research alongside interactive gaming.
The detection accuracy suffers from variables that affect facial expressions such as lighting conditions and cultural expressions and personal mannerisms (Li et al., 2017).

2. Speech Emotion Recognition (SER):

Vocal cues such as tone, pitch and speed of speech serve as inputs for SER to determine emotional states. We recognize emotional states in people through their voice just as computers analyze specific vocal cues to identify emotions based on (Mohammad and Al-Khateeb, 2019).
The process of detecting emotions in speech through Speech Emotion Recognition (SER) depends on analyzing pitch along with speech rate and energy parameters by using Mel-frequency cepstral coefficients (MFCCs) to extract these features. Time-based speech patterns are detected through Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks which help identify emotional cues according to (Wang et al, 2019).
Call centers utilize SER as a tool to modify their responses depending on detected customer emotions for better service delivery. The technology operates in virtual assistants including Siri and Alexa to develop emotional responsiveness in user interactions (Ramana and Srinivasan ,2017).
SER encounters obstacles causing inaccuracies in its performance including background noise as well as accents and the nuanced expressions of emotions (Ramana and Srinivasan ,2017).

3. Physiological Signal Analysis:

Monitoring heart rate and skin conductance and brain activity enables researchers to explore the emotional states of people effectively. Wearable technology consists of heart rate monitors and EEG headsets to measure bodily response changes (Alahi,2021).
The detection of emotional states relies on Heart Rate Variability (HRV) and Electrodermal Activity (EDA) combined with EEG (Electroencephalography) systems as components of Physiological Signal Analysis. The pace and fluctuations of heartbeats known as HRV serve as signs for measuring both stress and neurological activation. Motion of skin conductance and brainwaves are two types of physiological signals monitored using EDA and EEG devices to monitor emotional arousal and cognitive and emotional processing.
The technology serves three functions: it monitors medical patients' emotional stress and serves stress management applications and helps marketing organizations to gauge consumer responses. This system demonstrates the ability to adjust service contacts automatically through stress and comfort metrics (Alahi,2021).
The interpretation of physiological signals becomes more complex due to factors that include physical activity together with environmental conditions because proper context and calibration are needed (Alahi,2021).

3.2. Emotion Recognition Methodology

The methodology of emotion recognition is a multi-step approach, currently combining data acquisition, feature extraction, classification and evaluation to recognize human emotional state based on different kinds of inputs (Moufaq et al., 2011). Most frequently, the process starts with gathering information, which can be facial expression, speech signal, physiological (e.g., heart rate, galvanic skin response) indicators or a multimodal combination of them (Calvo & D'Mello, 2010). Techniques of feature extraction are then used to convert raw data into something meaningful- such as extracting Mel-frequency cepstral coefficients (MFCCs) of an audio signal or facial landmarks of an image. Once we have gathered and processed the features, we inputted it to various models capable of utilizing either machine learning or deep learning. Support Vector Machines (SVM), eXtreme Gradient Boosting (XGBoost), Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). It is through these models that we can analyze the data and having the various emotions that we are trying to understand put in the right categories. The current methods demonstrate a rising tendency to use deep learning frameworks due to the capability to extract complex features and temporal patterns automatically, especially in real-time emotion recognition systems (Zhao et al., 2021). Lastly, the system performance is determined through accuracy, F1-score, and confusion matrix. Such a systematic approach to emotion recognition is a reliable mechanism and is crucial in creating adaptive systems that are user-conscious in areas like customer care, health, and education (Altalabani et al., 2024). See figure 1:

Figure1: Emotion Recognition Structure

3.3. Deep Learning for Emotion Recognition

The application of deep learning models particularly Convolutional Neural Networks (CNNs) Recurrent Neural Networks (RNNs) and Generative Adversarial Networks (GANs) has transformed our ability to recognize emotions through various sources of data. These models function as mental components in emotion recognition systems that can spot and analyze emotional expressions from facial movements as well as speech patterns together with bodily indicators (Alom et al., 2018).

3.3.1. Convolutional Neural Networks (CNNs)

CNNs exceed at processing visual information therefore they are a great solution for Facial Expression Recognition (FER) applications. These networks possess an advanced ability to detect patterns in images that leads to emotion recognition from facial movements without receiving specific programming instructions (Abdulmajeed and Saleem ,2021). It's used for:

• Facial expression features of individuals activate automatically through CNNs to recognize emotional states such as surprise or happiness (Mohammad and Al-Khateeb ,2019) (Shukur et al.,2023)

• CNNs automatically extract significant facial expression features such as eyebrow movements or facial smiles which helps identify emotions of surprise or happiness (Mohammad and Al-Khateeb ,2019)

3.3.2. Recurrent Neural Networks (RNNs)

Algorithms like Long Short-Term Memory (LSTM) networks perfectly process series-based data which includes Speech Emotion Recognition (SER) along with continuous physiological information analysis. The networks excel at discovering emotional change patterns through speech and body signals. It's used for:

- RNNs effectively process sequences in time because these networks maintain outstanding capabilities in analyzing data through speech patterns which show emotional states (Wang et al., 2019).
- The LSTM variant of RNN networks demonstrates time-based understanding through the maintenance of significant chronological information which enables systems to identify escalating frustration during discussions (Sultan and Ibrahim, 2024).

3.3.3. Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) have been introduced as a practical deep learning architecture in the area of emotion recognition because of the ability to generate lifelike artificial information in addition to enhancing the robustness of models. A Generative Adversarial Network (GAN) consists of two components the generator and the discriminator, which compete in a way of friendly competition. The role of the generator is to produce outputs that are as realistic as possible, such as realistic facial expressions. In the meantime, the discriminator is to question these outputs and decide whether they are real by contrasting them with real samples. The dialogue between the two networks is useful to refine both of them, and in the end, the results will be more and more realistic (Goodfellow et al., 2014).

Generative Adversarial Networks (GANs) have also been applied in emotion recognition to augment the available datasets with various face expressions or audio signals. This is useful especially in emotion classes which tend to be underrepresented. In such a way, GANs may enhance the accuracy of classifiers and contribute to avoiding overfitting that frequently occurs during training models with a small amount of data (Song et al., 2020). Moreover, the introduction of conditional GANs (cGANs) has made it possible to synthesize emotions given a certain emotional label, which has been useful in data augmentation as well as in providing interpretation to the model (Zhang et al., 2022). Generative Adversarial Networks (GANs) are not only the methods of generating new data but also might be used in order to comprehend and model complicated emotions. This capability makes the systems that detect emotions more flexible and general, and thus more applicable in practice.

4. Challenges and Limitations

4.1. Technical Constraints

Technical shortcomings are several, which are linked to emotion recognition systems regarding accurateness and solidness. The first one is that the input data is now variable, e.g., because of the variability of lighting, occlusion (e.g., glasses or masks), head poses, and background noise, facial or vocal emotion recognition can be substantially degraded (Zhao et al., 2021). Besides, real-time processing is computationally demanding and might not be feasible to realize in low-power or embedded platforms (Kollias et al., 2020). Moreover, the performance of models is not typically dataset-generalizable, i.e., a model trained on one dataset does not necessarily have good performance on another one due to the differences in demographic distributions, data-collection conditions, or the manner of emotion representations (Barros et al., 2019).

4.2. Ethical Concerns

Technologies of emotion recognition present severe ethical issues, especially those related to privacy, consent, and autonomy. As they frequently contain sensitive data on face expression, voice, or physiological signs, they might breach the privacy of users unintentionally, provided that the adequate consent is not gathered or the data is obtained without their notice (Mitchell et al., 2019). Furthermore, it can be emotionally manipulated, particularly in commercial or surveillance applications. Emotional information can be processed by companies to shape behavior or decision-making (George et al., 2021). Ethical issues further have been identified in the naming and interpretation of emotions, as the expression of emotion can have vast cross-cultural differences, and it is thus problematic to apply a universal construction of emotion without consideration of the sociocultural diversity (Khan, 2023).

4.3. Algorithmic Biases

Bias in algorithms is a severe concern in emotion recognition and it is usually caused by unequal training data or incorrect model assumptions. As an example, training datasets often are biased, e.g., in terms of age groups, gender, or ethnicity, resulting in models that achieve low accuracy on underrepresented groups (Buolamwini & Gebru, 2018). Otherwise, this may result in systematic discrimination and strengthening of inequalities in the society. Also, the universal aspect of certain facial expressions corresponding to certain emotions (following the model of Ekman) has been largely refuted, resulting in mislabeling and cultural ignorance in practice (Ferguson, 2019).

5. Conclusion

The process of integrating emotion recognition technologies with Human-Centered Software Engineering (HCSE) aim at improving the quality of user interaction with the software systems, particularly in the customer service context. Its main issue of concern was that there are no emotionally aware systems capable of real-time recognition and response to the emotional state of users, which frequently result in impersonal or frustrating user experiences.

As a result of the extensive study of the recent advances in the field, namely, the adoption of deep learning models (CNNs, RNNs, and GANs), multimodal recognition of emotions based on facial, vocal, and physiological signals, this survey revealed major methodical and application avenues that introduce the concept of emotional intelligence to the contemporary software design. It also outlined the significant shortcoming and problems like technical limitations, ethical issues, and algorithm biases that need to be tackle to get fair and trustworthy systems.

There are already quite prominent examples of the positive effect of emotion-aware systems. AI-based chatbots have already been used in customer service and it has been shown that the user satisfaction rate is higher in chatbots with the ability to detect emotions and change their responses according to it. In education, emotionally adaptive tutoring systems have been employed to recognize signs of frustration or confusion in the student and provide them with encouragement feedback. The developments present a way for promising future in which software might evolve emotional intelligence, so that it can relate to us in a more human and sensitive manner, just as humans relate to each other.

To achieve this potential fully, future efforts must be directed towards the creation of ethically and demographically balanced datasets, better cross-cultural understanding of emotion interpretation and better real-time processing suitable to embedded applications. Such combination of emotion recognition and HCSE does not only change the way interactive systems are designed but also leads to more human-centered digital future.

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Conflict of interest

The author has no conflict of interest.

Ethical Approval

Ethical approval was not required for this study as it did not involve human participants, personal data.

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دراسة حول التعرف على المشاعر باستخدام هندسة البرمجيات المرتكزة على الإنسان

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الخلاصة: يستكشف هذا البحث العلاقة بين تقنية التعرف على المشاعر وهندسة البرمجيات المتمحورة حول الإنسان (HCSE)، وتحديدًا كيفية دمج هذين الجانبين لتحسين تجارب المستخدم، لا سيما في خدمات العملاء. ويهدف البحث بشكل عام إلى دراسة كيفية دمج الذكاء العاطفي في أنظمة البرمجيات، وكيف يمكن أن يؤدي ذلك إلى استجابة أكثر تعاطفًا مع البشر. ويستند هذا العمل إلى مراجعة نقدية للتطورات الحالية في مجال التعرف على المشاعر، وخاصةً كيفية استخدام نماذج التعلم العميق، وتحديدًا الشبكات العصبية التلافيفية (CNNs)، والشبكات العصبية المتكررة (RNNs)، والشبكات التوليدية التنافسية (GANs). ويتم تقييم هذه النماذج من حيث دورها في الكشف الفوري عن الحالات العاطفية ونسبة التصنيف المحسّن. كما يأخذ البحث في الاعتبار أساليب التعرف متعدد الوسائط، التي تتضمن تعبيرات الوجه والصوت والإشارات الفسيولوجية لإجراء تحليل شامل للمشاعر. ويغطي البحث أيضًا قضايا تطبيقية مهمة، مثل القيود التقنية، والمخاوف الأخلاقية، والتحيزات الخوارزمية الموجودة. وتتمتع نتائج هذا الجهد بتأثيرات واسعة النطاق في العديد من المجالات، مثل دعم العملاء، والرعاية الصحية، والتعليم، والترفيه، كما تقدم أدلة حول كيفية إنشاء أنظمة ذكية عاطفياً يمكنها جعل التفاعلات بين الإنسان والحاسوب أكثر تخصيصاً وإنتاجية.

الكلمات المفتاحية: HCSE (هندسة البرمجيات الموجهة نحو الإنسان)، التعرف على المشاعر، واجهات المستخدم، هندسة البرمجيات، التعلم العميق.