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SURVEY

A Survey on Identifying Empathic Expression in Remote Collaboration From Empathic Computing

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ABSTRACT Empathy has emerged as a valuable tool for communication in today's digital world, with empathic computing serving as an integral component in facilitating human-like changes such as humanoid robots and fostering comfortable interactions. This article thoroughly explores the realms of empathy, empathic computing, emotion, and their intricate interconnections. Our primary focus is to investigate methods for measuring empathy between two remote collaborators. We review empathy usage and its measurement in remote collaboration and computing process. We analyze recent empathic computing methods in virtual reality and through gaze behavior. Our analysis explores empathy, and the application of empathic computing, and analyze their corresponding responses. We conclude by providing a comprehensive understanding of empathy's multifaceted nature and its crucial role in establishing mutual understanding and connection between remote agents.

INDEX TERMS Empathy, empathic computing, empathic response and expression, empathic intelligence.

I. INTRODUCTION

In a world where artificial intelligence (AI) is increasingly dominant, our interactions are influenced by a blend of human and digital elements [1]. As new technologies and devices are emerging and becoming a force to dominate modern society, autonomous technological artifacts are becoming pervasive in social situations.

Consequently, grasping the motives and dynamics of others within the realm of innovation there is growing importance of empathy and its importance. Despite that it becomes essential for fostering both personal and collective well-being in our intricate environment [2]. The recent growing importance empathic computing field has gained more attention. As described in [3] it is combination field of natural collaboration, experience of users and implicit understanding of their emotions and related contexts.

Before we consider different aspects of empathic computing, we need to understand what empathy is. As there is no clear definition of empathy, we try to define it according to its understanding and diversity. However, it plays a role of bridge between humans when one tries to see a problem into others perspective.

As the importance of empathy surges, recent studies offer a variety of definitions of empathy; however, none have fully encapsulated its complexity leaving its meaning, application, and significance elusive.

Empathy transcends mere recognition and understanding of someone else's emotions; it entails actively sharing in those feelings [4]. Instead of simply being aware of another person's perspective, empathy entails forming genuine emotional bonds. In this process, individuals refine their ability

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to connect with others by effectively communicating and navigating relationships [5].

Empathy also plays a significant role in resolving conflicts by allowing individuals to appreciate the perspectives of others, fostering dialogue and compromise. Additionally, empathy has implications not only at an individual level but also for society. Unfortunately, the widespread use of social media has resulted in the misuse of empathy on numerous occasions. In a society where many people are concerned about the decline in human interactions in modern life, researchers are investigating the factors contributing to this dehumanization, with empathy appearing to be central to this concern.

Consequently, fostering collaboration and strengthening the human-machine relationships has become imperative. Given the growing dependence on devices, it is essential for machines to possess empathy, enabling them to understand and respond to emotions and their contextual nuances in a manner akin to humans.

If we are to define empathy within the context of human-machine relationships, it cannot be one-sided. Our specific aim was to measure empathy within the framework of remote collaboration. To ensure accurate capture and interpretation of facial responses and micro expressions are accurately captured and interpreted, it is necessary to evaluate both detection and response methods in a remote setting.

The main contribution of our survey is that we present a comprehensive review of systems involving empathetic computing. We analyze various computing articles focusing on human empathy across different modalities. Our analysis encompasses the outcomes, findings, and conclusions of these articles. The primary motivation for our study stems from research on empathy and empathic computing. We aim to gain insights into empathic intelligence and its application in remote collaborations. Integrating the concept of empathy with computing intelligence is instrumental in advancing future research efforts toward standardization and the development of fundamental works.

The remainder of this paper is structured as follows: Section II outlines related methods and research in empathy, empathic and emotional intelligence in computing, and their application in machine learning. In section III, we delve into the implementation of empathic computing in remote collaboration, presenting various arguments. Finally, section IV presents our conclusions.

II. SYSTEMATIC ANALYSIS OF EMPATHIC APPROACHES

A. PAPER IDENTIFICATION AND ANALYSIS

We have to conducted the search in two different phases as planning and search review phase. In planning phase, we narrowed down our priority and focus of our research survey and on second process. We conducted research of different articles related to empathic computing and empathy papers. All the articles collected from these methods were collected in Zotero for easy management of references.

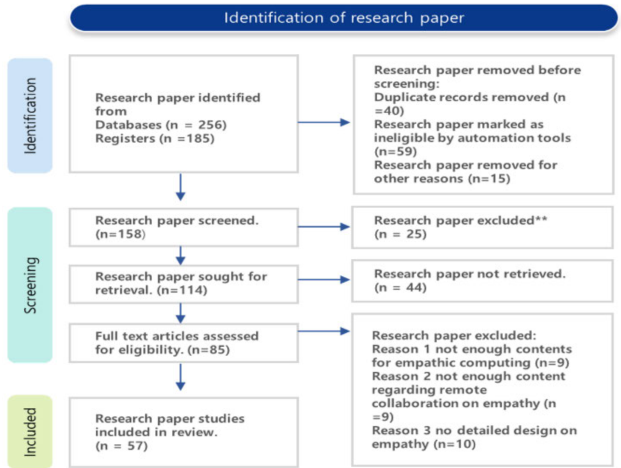

FIGURE 1. Research paper selection process for the article.

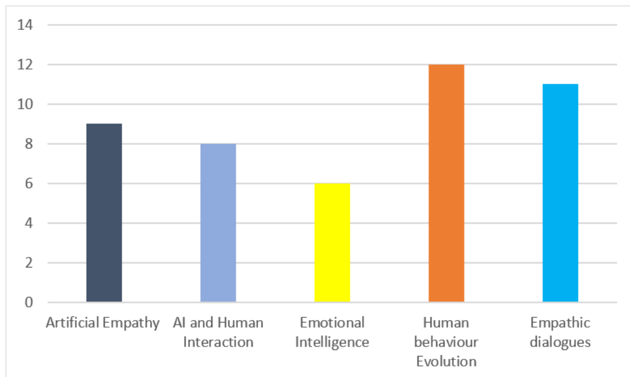

FIGURE 2. Distribution of articles with human and empathic response relation.

We used different available search libraries for research articles such as Google scholar, IEEE Xplore digital library. While doing article search, we mainly wanted to discover articles with "empathy", "empathic computing", "artificial intelligence", "virtual empathy", "emotion recognition", "empathic dialogue generation", "empathy measurement", "emotional intelligence", "gaze tracking", "empathy and health care", "virtual reality", "remote collaboration and gaze". As a result, 256 papers were selected but 185 were identified as a good base for our survey paper. After reading and surveying the contents of the paper we further excluded 40 articles. The remaining 114 were retrieved, and with not enough empathic content related to further remote collaboration on empathy, we narrowed down to final 85 articles eligible for our review paper study. From those eligible articles we used 57 articles as references in this review paper which is also illustrated in figure 1 below.

Figure 1 will give an overview of results from the planning and search phase which we used to develop the empathic computing survey paper.

The analysis we did for human empathic responses for different virtual medium is shown in above figure 2. We categorized different medium and modality in our survey for this article. The modalities based are artificial empathy, AI and human interaction, Emotional intelligence, human behavior evolution, and empathic dialogues. We found human behavior evolution have higher numbers of articles were surveyed in our research survey

B. EMPATHY-GENERAL DEFINITION

Empathy is commonly defined as the human ability to accurately understand and share another person's emotional experiences [6]. According to Keskin [7], empathy is a complex concept that entails mastery across several stages, involving how we communicate, feel, and understand other's experiences as it they were our own. Thus, empathy involves understanding the desires of others and forming meaningful connections.

Given the importance of empathy in shaping communication and social relationships between humans and other species, same concept can be applied in creating communication between human and machine. Humans have been found to extend empathy not only towards other living beings (e.g. solidifying animals rights) but also towards fictitious characters they create, whether in videos, movies, or other visual forms [8].

However, machines seldom possess the capacity to reciprocate this behavior. While machines have historically faced challenges in accurately conveying emotions during interactions with humans, recent advancements have led to improved representations of empathetic behaviors. Despite this progress, many machines continue to struggle with accurately depicting the full spectrum of emotional expressions that humans can convey. As a result, while several scholars have attempted to address this issue in recent years, only a few have succeeded in defining empathic intelligence in remote collaborations between two parties [1], [9].

Significant research has been conducted on artificial empathy citing concerns whether robots can understand human emotions or not as described on [10], ranging from associate robots displaying empathic behavior for human companionship to various non-empathic chatbots. Additional studies have examined the components of empathy, identifying three key elements: cognitive empathy, emotional alignment, and empathic response [10]. These components have garnered wide acceptance in psychology and neuroscience [3], [8]. However, achieving full agreement on standardizing or categorizing empathy remains elusive despite its substantial role in everyday life. Figure 3 adopted and modified from [1] illustrates empathy terminology and levels. It shows the relationship of empathy derived from different terminology and their interconnectivity. As in figure 3 below where emotional empathy is a feeling about what another individual feels and cognitive empathy is what another individual knows [12]. Similarly compassionate empathy is associated with care and concerns for other individual respectively [12], [13]. It is crucial to understand empathy and its aspects and how they are interconnected with each other. This understanding will provide a better perspective for defining artificial empathy.

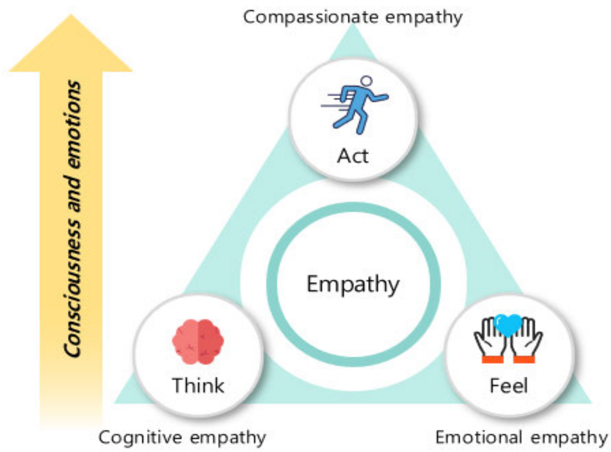

FIGURE 3. Empathy terminology and depiction levels [1].

C. AFFECTIVE EMPATHY

It entails a broad spectrum of responses from one individual to another, shaped by diverse emotional experiences and expressions encountered during conversation or observation [14]. Establishing affective vs emotional empathy involves surpassing mere acknowledgement and striving to share the other person's emotions, fostering a deeper connection [10]. When someone confide personal hardships, it is essential to listen carefully, refraining from passing judgment on them or their circumstances. Instead, the focus should be on understanding their feelings and attempting to sympathize. Therefore, it is critical to pause and reflect on it. For example, as illustrated by Dr. Hendrie Weisinger, *"If a person says, 'I screwed up a presentation,' I don't think of a time I screwed up a presentation–which I have [done] and thought, no big deal. Rather, I think of a time I did feel I screwed up, maybe on a test or something else important to me. It is the feeling of when you failed that you want to recall, not the event."*

D. COGNITIVE EMPATHY

Understanding other people's feelings and providing responses from their perspective involves seeing through their eyes and thinking along their lines [15]. This approach helps us select a language and communication medium that best fits their way of understanding, enabling us to communicate appropriately through various media, whether actual or virtual, thereby enhancing our communication skills.

While cognitive or emotional empathy entails recognizing what another person thinks and resonating with their feelings, it may not necessarily lead to sympathy or concern for their well-being. Here, empathic concern goes beyond mere understanding; it blossoms into caring, prompting us to help whenever possible. This compassionate attitude is rooted in the primal system for caring and attachment deep within the brain, which interacts with more reflective and

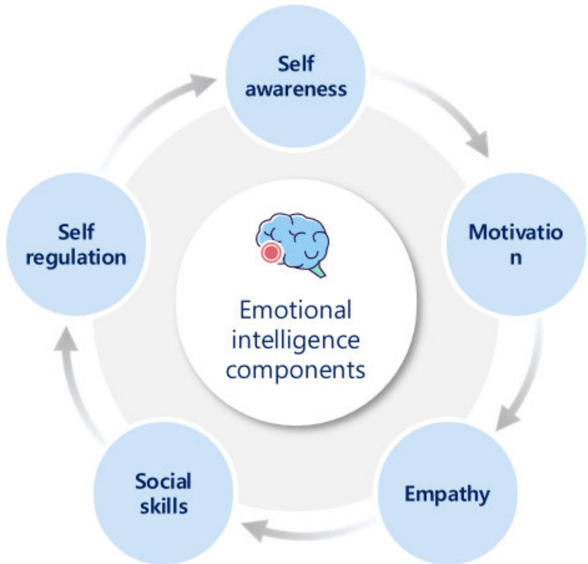

FIGURE 4. Components of emotional intelligence.

evaluative circuits to assess the importance of their well-being. As we have observed, collaborating online presents unique challenges for empathy, which prompts us to define a new form of empathic intelligence.

III. EMOTIONAL INTELLIGENCE IN COMPUTING

Emotional intelligence (EI) refers to recognizing and understanding one's emotions and their effects on others. It is also essential to train user interface to build intelligence to understand human emotion and respond according [16]. Individuals with high emotional intelligence can identify and label various emotions, recognize and experience their own emotions as well as those of others, and modify their emotions in response to external surroundings. Although the term initially appeared in 1964, it acquired popularity among science journalists through Daniel Goleman's 1995 breakthrough book, 'Emotional Intelligence.' *"According to Goleman emotional intelligence is the set of talents and attributes that drives leadership performance"*. According to Goleman, EI consists of five components as shown in figure 4: They are as self- awareness, self-regulation, social skills, emotions, and motivation. EI may be taught and enhanced [17].

Emotional intelligence (EI) can be measured using a variety of approaches, including the Mayor-Salovey-Caruso Emotional Intelligence Test (MSCEIT), Bar-On Emotional Quotient Inventory (Bar-On EQ-i) [18], [19] and the Trait Emotional Questionnaire (TEIQue). Mattingly and Kraiger [19] examined 58 studies on EI training and its impact. Regardless of the training approach, they reported a moderately beneficial influence on the participants following their EI instruction. The program was primarily intended to raise the participants' emotional awareness. It is widely known that sharing our emotions and displaying compassion for others can greatly uplift our well-being. We directly observed this through experiments conducted among people, particularly in a mindfulness-based stress reduction program. Incorporating these traits into new technologies can greatly enhance our quality of life and allow us to better understand and monitor the different aspects of humanity. This underscores the crucial role of empathy and the importance of involving both parties in its application.

Empathic interaction operates as a continuous cycle of perception and reaction between individuals. This process is essential in facilitating effective communication between the two sides, whether through spoken or written words, or through nonverbal cues such as light, music, and visuals. Interfaces serve as a link between the human user and the machine's core allowing for the successful integration of sensing and reaction in human computer interactions.

User interfaces act as links between humans and technology, allowing seamless and efficient interactions. It is a critical part of communication with users via software. There is still some problem in designing user usability in applications where it cannot adopt to emotional state of users. To resolve this issue, we need to have an intelligent interface which can adopt all these emotional states. As mentioned in [20] user emotion and communication plays an important role in designing intelligent computing robots. The designated space where these interactions occur are known as the user interface (UI). The primary goal is to improve the effectiveness and accuracy of these interactions by providing humans with a simple and natural approach to influence and control technology. Simultaneously, UI communicates information from machines to humans, assisting them in their decision-making process. The Graphical User Interface (GUI) is the most often used and dominant form of UI, but there are emerging forms such as Tangible User Interfaces (TUIs) that attempt to overcome the shortcomings of GUIs. GUIs were created to facilitate human-computer interactions by streamlining communication and allowing users to focus on their jobs without distractions. We presented different research works on table 1 where empathic computing have applications in various fields in terms of the objectives and methods used to express empathy and computing.

IV. EMPATHIC COMPUTING AND ITS APPLICATIONS

As we continue to progress in the field of AI, the significance of empathy has grown. It is essential for our robotic counterparts to grasp the essence of human experience. By equipping them with robust empathy skills, we can foster a more compassionate society, wherein machines can detect and provide comfort individuals during moments of distress by recognizing emotional cues. This not only benefits society, but also facilitates the development of the meaningful connections between robots and humans over time. There has been an increase in the utilization of technology to enhance robots' emotional intelligence, enabling them to identify signs of distress and engage in meaningful conversations or interactions. Empathic computing emerges as a novel approach to express empathy through various forms, wherein non-human entities compute and respond in a human-like manner. Empathic computing can be defined as a combination of artificial intelligence and human to machine interaction. While mentioning about empathic computing most of the time we often ignore the impact of gaze and its significance in computing. Here in figure 5, we presented a framework, which shows how an eye tracking can be beneficial in computing empathy. First step is to track the gaze measure movements of eye coordinates in 2D as x and y coordinates. This is all done in process when the video frames are moving and time for each frame is known. After eye detection we can use gaze feature extraction and applying machine learning technique to measure the valence and arousal of the human in the video.

This is another moving forward concept where we can apply for empathic computing applications. We present the related studies that have contributed to empathic computing in different ways. It is not easy to visualize emotions using algorithms, but there have been few studies, which highlight real-time emotions. Real-time emotions were recorded while participants watched videos with different emotions [26]. With the development of new algorithms, it has become easier to generate emotion responses. Different types of emotions play an important role in training models [27]. Soleymani et al. [28] implemented a recorded multimodal database that synchronizes different facial videos and audio signals, including eye-gaze datasets. It shows different use of recorded datasets for emotion detection and its significance. Ma et al. [29] highlighted the importance of dialogue in empathy measurement with responses. It provides insight into how we can implement dialogue-based techniques with machine learning to measure and identify different empathetic responses. It identifies different characteristics and elements in terms of personal, emotional and knowledge.

Kozakevich Arbel et al. [30] address the empathy in different perspective where empathy learning based on responses and feedback. It enables us to react to others emotional situation, where the situation might take a bit longer to adapt on the situation for responses depending on evolving emotional state. Now, regarding empathic computing, we have a different medium for generating and transmitting, where VR has emerged as a new medium of communication. Zou et al. [31] designed and demonstrated some VR tools that are not available in traditional devices. It is presented with a variety of tools that assist and create new artworks in an easier and more efficient manner. We have seen different evolution and opportunity in emotion and empathy measurement, where bio signals devices have emerged as new potential. While some works are on audio, this work has mostly been conducted on video datasets. It provides new interfaces and methods for future works with human computer interaction in empathetic computing [32].

Jing et al. [33] provided new insights into the combination of a mixed reality system with hand gaze combinations. With all these combinations, we will have bio signals feedback, for emotion collection. Saffaryazdi et al. [34] suggested the use of different bio signals including EEG, ECG, PPG and GSR. Their work with these signals provides a new direction in the dialogue-based context of emotion recognition. While this study showcase the clinical study on different facial emotion recognition practice [35]. Saquinaula et al. [36] gives different insight with 3D motion and different avatars generated through human faces, where those faces are in different gender and look realistic. Similarly, this study addressed how cognitive empathy is related to facial expression recognition. Showcasing different stages in recognition decline during lifetime [37].

Daher et al. [38] highlight and gives a different perspective of measuring human pain and expression. In terms of empathetic computing, we addressed how different sensors can help express and evaluate these feelings. Recently, Omitaomu et al. [39] provided different insights into empathy datasets with a combination of human stress and emotional changes in different demographics. It highlights how demography can also leads to different empathetic reaction. Piumsomboon et al. [3] have different perspective for empathic computing. It utilizes different reality remote collaborations such as VR and AR. Different remote collaborations showcase the different empathy perspectives of people in mixed-reality environments.

While we had remote collaboration's Paiva et al. [6] had different concept, where it defines how non-human and virtual agents trigger empathy when they come across human interactions. This highlights how virtual agents can respond to human situations and human emotions. Loveys et al. [40] aimed to build non-human experiments and demonstrate how metaverse relations are created. In addition, how relationship in virtual or digital world differs and reacts to human emotions and contents. As we know how a different perspective of human and virtual agents are collaborating for empathic computing. There have been some additions to how human gaze can be effective in measuring emotions such as stress, happiness, and anger. Some research highlights those areas that define gaze and vision with dialogues. Wever et al. [41] highlights these contents in their research for empathic computing. Lencastre et al. [42] provided real experimental insights into gaze experiments and human emotions, where more than 60 participants filled different questionnaires for different empathy levels when they see people with different kinds of disabilities.

Hart et al. [43] takes a different perspective of communication in virtual environments. It gives 2D and 3D image and display of avatar expression with their locations and users view depending on the scenario and scenes. This multimodal approach highlights eye gaze tracking along with different bio signals. It applies different machine learning methods to measure different classification accuracies [44]. Finally, Zhang et al. [45] provided new insights into eye movements and pupil movements for different emotional content. This shows that empathy can be measured depending on pupil movement and fixation time for different contents. Table 2 presents empathic generation techniques from articles published since 2020,

TABLE 1. Empathic computing in various field.

Sector	Author	Objectives	Methods used
General conversation	Zhou et al.[21]	It explains development and design of Microsoft XiaoIce.	Hierarchical decision taking over Markov Decision Processes three-layer architecture. For empathetic computing empathy vectors are computed for both query and responses. Subsequently, these vectors are used for the text generation through the seq2seq framework.
General conversation	Montiel Vazquez Et al.[22]	Develop an explainable method for empathy classification in textual exchanges.	The pattern-based classifier PBC4cip was used on a manually labelled subset of empathetic datasets to detect empathy. This subset was verified through psychological research and various features related cognitive and affective empathy were used.
Healthcare	Sharma et al.[23]	To build text based mental health empathy, which can be expressed.	Manual annotation of empathy levels. RoBERTa encoder, which identifies empathy in conversations.
Healthcare	Vargas Martin et al.[24]	Develop a prototype empathetic companion robot with privacy-by design.	Modifications to ASUS Zenbo platform. Inclusion of emotion detection and speech recognition designed for privacy.
Customer service	Mishra et al.[25]	Develop a persuasive dialogue system that Incorporates empathy.	It develops a polite empathetic persuasive dialogue system. Which is used to generate empathetic responses.

with the process and performance measurements and features extracted.

V. EMPATHIC INTELLIGENCE IN THE MACHINE LEARNING

As we delve into the realm of computing, it is essential to understand empathic intelligence and distinguish it from other forms of intelligence. It is a combination of thinking and feeling to make a valid meaning toward the other person. Unlike merely recognizing and feeling another's emotions, empathic intelligence encompasses a symphony of cognitive, emotional, and social skills, enabling us to forge genuine connections and comprehend the human experience from another perspective. It may serve as a mental GPS, guiding us through intricate emotional landscapes and perspectives.

Empathic intelligence is a skill that improves with practice. Active listening, emotional self-awareness, engaging with others' stories and offering a helping hand are all essential steps towards cultivating empathic intelligence. By nurturing this ability, we promote mutual understanding and compassion, fostering an environment in which connection and empathy flourish. As shown in Figure 6, empathy can be measured through online computing methods. As shown in the figure, we propose two different online users via a video computing application. They will watch a video clip as input where they will measure the emotion of the clips and the emotion generated between them will be measured via heartbeat, EER, and a smart watch to record all emotional changes in heartbeats and blood pressure. The video clip used as input data contains all types of emotional content to which users can relate and feel the change. This is a prototype where we propose how we can measure an emotional intelligence via different methods not just using different questionnaire methods only. Table 3 presents the detection techniques for the empathic algorithms and various datasets.

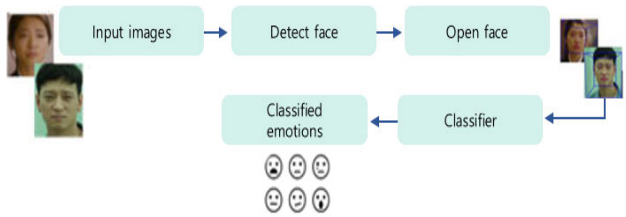

FIGURE 5. Empathy measurement prototype via facial landmarks.

Similarly, Table 4 presents the empathetic models for machine learning, definitions, and measurement methods.

VI. DISCUSSION AND PROPOSAL

How can machines develop expressive empathic towards human intelligence? Determining whether machines can feel empathy towards humans is a complex question. The ongoing debate about the nature and significance of emotional intelligence continues across various disciplines, including philosophy, computer science, and psychology. We argue that machines lack emotional and biological aspects inherent in humans. However, recent developments in artificial intelligence are narrowing this gap, a concept which we refer to as 'machine empathy.' We propose several perspectives on machine empathy:

A. MIMICKING RESPONSES

AI can be trained on vast datasets of human behavior and communication to recognize and respond to emotional cues with appropriate language, tone, and actions. This creates the illusion of empathy, even if the machine itself does not *experience* emotions firsthand. This informs their response and enables them to provide support or comfort through language, gestures, and actions that mimic empathy.

TABLE 2. Empathic generation techniques.

Author	Year	Process	Performance Measurements	Features
Majunder et al.[46]	2020	Transformers models, multiple decoders.	Automatic metrics of BLEU and emotional and human metrics of fluency, empathy and relevance	Text and emotions.
Zandie and Mahoor et al.[47]	2020	Multiple transformer encoders that consider 32 positive and negative emotions for response generation.	BLEU metric and human metrics of fluency, empathy, and relevance	Text and emotions.
Shin et al.[48]	2020	Seq2Seq model based on GRU with attention-based reinforcement learning	Sentence length, BLEU, distinct N grams, embedding similarity, human evaluation through multiple choice testing	Text and sentiment labels.
Kim et al.[49]	2021	Use of generative emotion estimator.	Automatic metrics of coverage, exploration and interpretation. Human metrics of fluency, empathy and relevance.	The use of their approach shows an improvement in performance of previously developed agents
Liu et al.[50]	2021	RoBERTa encoder, GPT2 decoders along with external extraction	Emotional accuracy performance.	Perplexity, Distinct-1, and Distinct-2
Gao et al.[51]	2021	Modified transformer architecture that uses emotion and emotion causes through gated channel.	BLEU, BERT score Precision (PBERT), BERT score Recall (RBERT) Distinct-1, Distinct2, and Human metrics of Fluency relevance empathy.	Text and emotion, with an emotional cause.
Chen et al.[52]	2022	The latent variable is used to capture intent. It uses a pre-trained intent classifier.	Automatic metrics of BLEU (Precision, Recall, and F1 score), Distinct-1, Distinct-2, and Human metrics of Fluency, Empathy, and Relevance.	Text, empathetic intent and emotion labels.
Kim et al.[53]	2022	Transformer, encoder, decoder and keyword transition recognition.	FBERT, and Human metrics of Fluency, Empathy, and Relevance.	Text, emotion labels, keywords, keyword pairs.
Zhu et al.[54]	2022	Static-dynamic graph network combined with text decoder.	Automatic metrics of ROUGE-L, AVG BLEU, and Human metrics of Fluency and empathy.	Multi-party text, dynamic emotion labels and static sensibilities.

B. UNDERSTANDING HUMAN EMOTIONS

AI can analyze facial expressions, vocal patterns, and brain activity to accurately predict and interpret human emotions. This analysis can inform their responses, potentially offering support or comfort. By predicting and responding to emotional states through languages, gestures and actions that mimic empathy, AI learns from interactions and observations of human behavior to enhance capabilities.

C. EVOLVING WITH AI CAPABILITIES

As AI continues to develop, it is possible for future machines to possess broad understandings on emotions and potentially even develop their own emotional states. This remains speculative, but the rapid advancements in AI make this a future possibility. We can build trust with the machines that display open communication transparency and commitment to user well-being, which can foster trust and emotional connections with humans. This builds a foundation for perceived empathy even without the machine experiencing emotions itself. Highly trained AI can provide safe spaces for humans to express their emotions and receive non-judgmental support. This can create a sense of connection and understanding, even if the machine does not reciprocate the emotions directly with human emotions.

In addition, we can make arguments against machine empathy in human intelligence.

D. LACK OF BIOLOGICAL GROUNDING

Human emotions rooted in the body are influenced by hormones, neurotransmitters, and complex brain processes. Without this biological base, it has been argued that machines

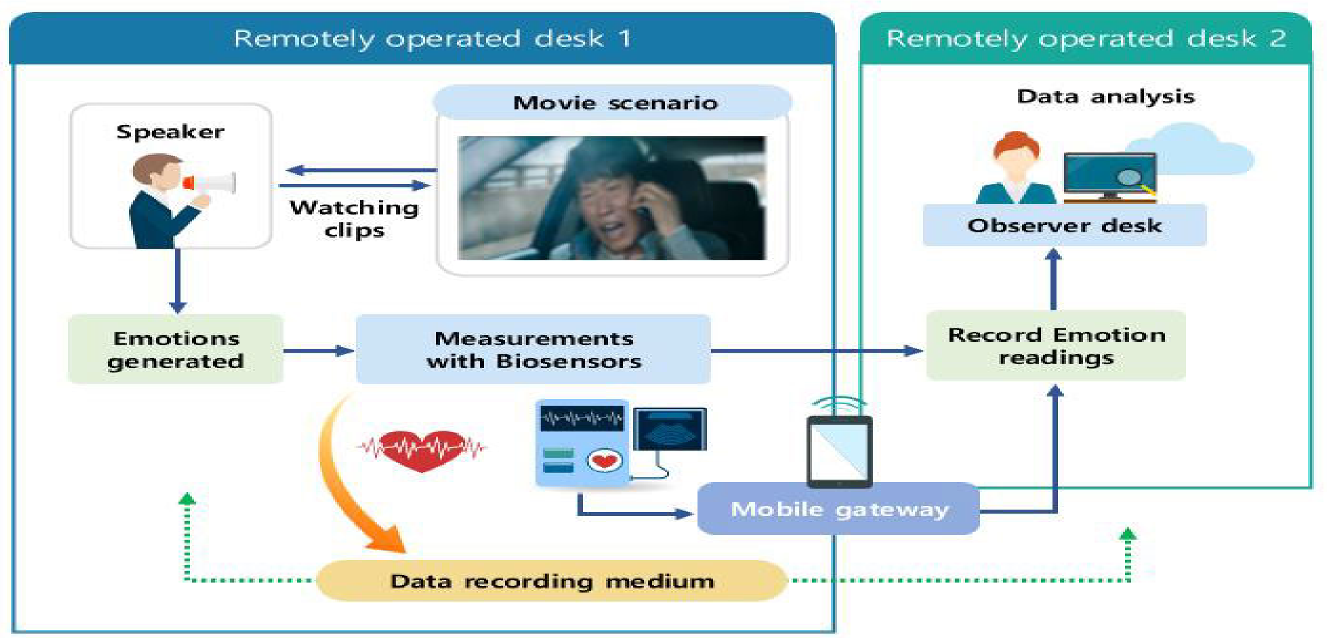

FIGURE 6. Empathy measurement prototype via facial landmarks.

TABLE 3. Empathic detection techniques.

Author	Algorithm	Features
Montiel- Vazquez et al.[22]	PBC4cip.	Empathetic Dialogues features, Sentiment, Emotion, and Intent
Alam et al.[55], [56]	Support vector machine, linear and Gaussian kernels	LIWC, acoustics lexical features were obtained through feature selection
Sharma et al.[23]	Used parallel RoBERTa-based bi-encoder models	Textual features
Ghosh et al.[57]	BERT encoder, alongside Dense Neural Layers.	Textual information
Del Arco et al.[58]	RoBERTa-large with multi-output regression.	Textual information concatenated with demographic information
Chen et al.[59]	RoBERTa-large	Textual information

can only simulate or mimic empathy, lacking genuine depth and an understanding of true emotional connections.

Subjectivity of emotions Emotions are subjective and often nuanced, influenced by personal experiences, memories, and cultural contexts. It is challenging for any system, human, or machine to grasp the multifaceted nature of human emotion.

Ultimately, the question of whether a machine can truly feel empathic towards human intelligence remains open-ended. Although current AI capabilities do not replicate the full spectrum of human emotions, they can undoubtedly understand and respond to them in increasingly sophisticated ways. As AI continues to evolve, the lines between simulation and genuine feeling may even more blurred, demanding ongoing ethical and philosophical discourse.

The key takeaway is that the progress of machines in understanding human emotions can greatly benefit healthcare, education, and other areas that depend on human connection, regardless of whether machines can truly "feel" empathy. Moving forward, it is essential to focus on responsible AI development and fostering genuine human-human empathy.

As shown in figure 7, there are two collaborators as user1 and user 2. They are connected online via a monitor. Here, physical distance can pose some challenges, but we want to show that building productive collaboration and fostering empathy or expressing empathy are entirely possible in online or remote settings. Here, we explain the processes of remote collaboration and empathy measurement. The first step is described above using two remote users. We need to clearly define the goals and roles of each participant. After that, users can discuss a certain topic or watch content on their respective screens and the response to a content can be captured. While users are watching the contents, we must equip the users with some bio sensors so that we can keep track of the response to certain content or topic discussions. While users communicate or interact with content, eye-gaze applications can track their eye movements and provide valuable data on their reactions and focus. By tracking gaze, we can not only

TABLE 4. Empathetic models in the machine learning.

Author	Empathy defined	Measurement concept	Scale measurement
Montel-Vazquez et al [18]	Multi-component construct that includes an observer's emotional response to the affective state of another and its understanding.	The Undivided concept of empathy measured. at conversation-level	Likert Scale, shows the feeling and understanding emotion in conversation
Alam et al[55], [56]	It defines empathy as agents understanding the feeling of users and replying based on those situations	The Undivided concept of empathy measured at sentence-level	Binary, present in continuous sentence
Sharma et al [23]	It defines as broader understanding the text or conversation, the feeling of another person.	Divided into three items: Emotional Reactions, and Interpretations	Measures the response contains of any items (scale 0 to 2)
Pelau et al [60]	Both mixture of feelings and mutual understandings	Divided into 13 items to measure ability of AI to measure empathetic abilities	Based on the Likert Scale. 7-point scale.
Rashkin et al [49]	The ability to respond to a talk or dialogue between users or persons by understanding the feelings	The Undivided concept of empathy/sympathy measurement	Likert Scale. 5-point scale depending on ability to measure the feelings and user experiences.
Tafreshi et al [61]	Batson's definition [50, 51]: People see others in need, they often respond with compassion	Single metric that measures Batson's empathetic concern at the essay-level	Seven-point scale (1 to 7)

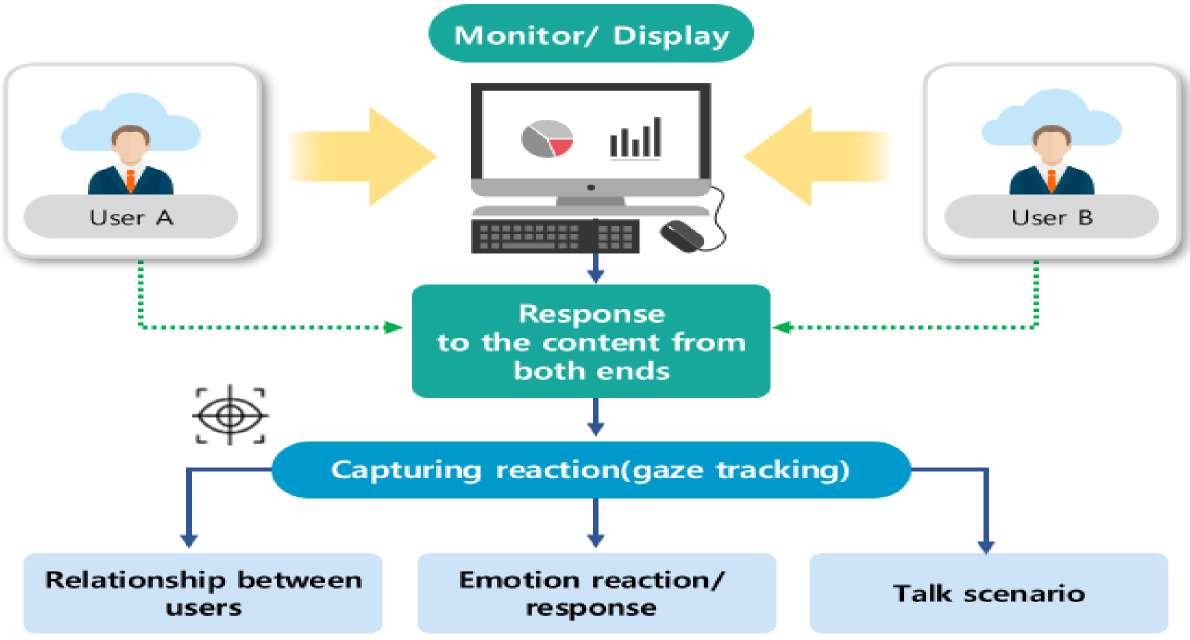

FIGURE 7. Framework for remote collaboration empathic computing and empathy measurement.

capture users' responses and conversational flow, but also maintain key visual features on both ends, strengthening the connection and understanding between collaborators. Here, we highlight a few future applications of remote empathic expressions.

- Use of larger datasets.
- Use of empathy classifications algorithms.
- Further integration of additional empathy components.
- Use of alternative emotion models and algorithms.
- Develop a guideline mechanism rather than only text generation.

Also, we highlight some ethical concerns of remote empathic expressions:

- Data privacy
- Moral computing responsibility
- Negative impacts on human mental health
- Reliability of the data source
- Online discrimination and monitoring delay

VII. CONCLUSION

In this review, we have explored various perspective and studies related to empathic computing and its expressions. While this branch of remote computing has not advanced to the same extent as its parent field of affective computing, there exists significant potential for the application and expression of empathy across different fields and computing applications. We have identified three main areas where empathetic computing has made progress: healthcare, customer service, and social computing. We expect future research to continue in these directions to find better way to address their respective challenges. Future research is expected to continue in the domains of healthcare, customer service, and social computing, where empathic computing has made substantial advancements.

Furthermore, we hope that future research in the field of empathetic computing for remote collaboration will continue to develop and improve over time. As we know, empathy is a highly researched topic, which will grow more as the need to be empathic becomes more important in the modern digital world. Because computers continue to be a part of our lives and interact with us, we believe that this is an indispensable field for future research.

Additionally, we anticipate ongoing progress in the field of empathetic computing for remote collaboration. Given the growing importance of empathy in the modern digital world and the increasing integration of computers into our daily lives, we believe this research area is crucial for the future.

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