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Review

Pain recognition and pain empathy from a human-centered AI perspective

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SUMMARY

Sensory and emotional experiences are essential for mental and physical well-being, especially within the realm of psychiatry. This article highlights recent advances in cognitive neuroscience, emphasizing the significance of pain recognition and empathic artificial intelligence (AI) in healthcare. We provide an overview of the recent development process in computational pain recognition and cognitive neuroscience regarding the mechanisms of pain and empathy. Through a comprehensive discussion, the article delves into critical questions such as the methodologies for AI in recognizing pain from diverse sources of information, the necessity for AI to exhibit empathic responses, and the associated advantages and obstacles linked with the development of empathic AI. Moreover, insights into the prospects and challenges are emphasized in relation to fostering artificial empathy. By delineating potential pathways for future research, the article aims to contribute to developing effective assistants equipped with empathic capabilities, thereby introducing safe and meaningful interactions between humans and AI, particularly in the context of mental health and psychiatry.

INTRODUCTION

Recent research has defined pain as an uncomfortable sensory and negative emotional experience with or without discernible tissue damage.[1] From an evolutionary perspective, pain expression significantly affects interpersonal relationships.[2] Indeed, empathy often manifests as a genuine understanding and shared emotional experience when witnessing others in pain. This emotional resonance typically motivates individuals to offer assistance in alleviating the suffering of others.[3] A broad range of research on mental illnesses characterized by social impairments considers a lack of empathy to be central to clinical diagnoses concerning DSM-5.[4] However, it is frequently observed that psychiatric patients exhibit diminished or distinct pain experiences, often displaying inappropriate expressions of pain or an inability to comprehend and appropriately respond to the emotions of others.[5] Through the lens of a 4D model proposed by Decety and Moriguchi, the decomposition of empathy is insightful to guide us to shrink the gap between pain and empathy within the field of psychiatry. Within this model, the concepts of mental flexibility, involving the adaptation of another's subjective responses (pain recognition) and regulatory processes (artificial empathy) shed light on effective treatments and pain management interventions for psychiatric patients in a quantitative way.[6] Assistive artificial technologies hold great promise in aiding individuals with disabilities by enhancing their perception of the social environment and facilitating a better comprehension of the mental states of others.

The overarching goal of this review is to shed light on empathetic responses from AI agents (artificial empathy) and training for empathy through computational pain recognition and to improve our understanding of what is needed to build a human-in-the-loop (HITL) system for pain recognition and artificial pain empathy. To begin with, the identification of the pain is reviewed regarding three major modalities: face, voice, and body (see Figure 1 left; Table 1). Then, this work discusses cross-disciplinary ideas for existing and potential pain recognition practices are presented based on research in psychology and cognitive neuroscience (see Figure 1 middle). While pain empathy plays a vital role in social functioning and implications in psychiatry, artificial pain empathy has received little attention. Therefore, We also present a growing body of knowledge concerning artificial pain empathy. We discuss the following questions in more detail: How can AI recognize pain from unimodal or multimodal inputs? Is it possible for AIs to learn empathetic responses by studying human beings? Can psychiatry benefit from a human-centered AI system with artificial empathy? Is an empathic AI necessary? Our final discussion focuses on several major challenges faced in the psychiatry application, such as ethical considerations in research and prospective applications.

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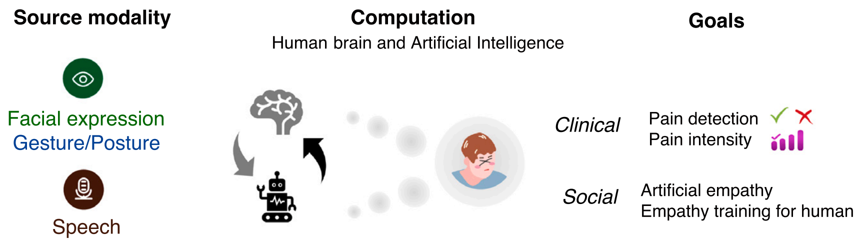

Figure 1. An overall illustration of pain detection and artificial empathy

PAIN RECOGNITION

Pain recognition has gained significant attention as a computational problem for advancing high-level functions such as artificial empathy. However, a few challenges in artificial pain analysis remain insufficiently addressed: (1) A lack of cognitive, linguistic, and social abilities can hinder the accuracy of subjective assessments, particularly for young children and patients unable to express their feelings. (2) Self-reporting of pain has long been the predominant measure in medicine but if large-scale health monitoring is required, it can be unreliable and time-consuming. Most importantly, how reliable is the medical diagnosis of pain evaluation? There has been an ongoing argument about the potential lack of rigor and efficiency in clinical diagnoses, mainly when subjectivity plays a significant role in the diagnostic process. For example, depressed patients can display happiness briefly without a genuinely happy mood, indicating that cues that are easy to overlook may mislead diagnosis. Considering that clinical decisions may not be always reliable or objective, a new field in artificial pain recognition appears to emerge. A growing body of research examines the issue from the perspectives of cognitive neuroscience, philosophy, and human-centered AI. (3) A gap in healthcare provision for elderly individuals. Aging is thought to reduce sensitivity for low-level pain and this reduction can be position- and source-sensitive, like head pain and heat pain. There is a need for more specialized and advanced research on pain and its management in elderly populations to address this inadequacy.[7–13]

Pain recognition can be divided into two questions: pain detection and pain intensity assessment. The pain detection problem involves a binary classification task to determine whether an individual is experiencing pain. In consideration of precision, the research focus has gradually transitioned from pain detection to the more nuanced task of estimating pain intensity. A recent review showed AI-driven pain recognition based on facial expressions shows a minor accuracy difference in detection but a significant variation in intensity estimation. It pointed out that the reported accuracy for pain detection ranged from 80.9% to 89.59%, while in pain intensity estimation, the accuracy range was between 51.7% and 96%.[14] As a starting point for pain recognition, we analyzed several published pain databases based on a variety of modalities (see Table S1) and summarized recent work and performance metrics in pain detection (see Table S2). Each database collected pain expressions in different modes, mainly categorized into three types: acted, spontaneous, and elicited (acted expressions are from actors. Spontaneous expressions are from patients with chronic or acute pain. Elicited expressions indicate expressions evoked by audiovisual media or real interpersonal interaction). The collection of data in a laboratory setting is, however, controversial. Zhang et al.[15] pointed out that people tend to change their biophysical signals to improve the extent to which their minds are being "read". Consequently, intentional noise leads to data instability and invalidity, making data collection challenging regardless of the methods used. Meanwhile, a comprehensive evaluation of the rapidly evolving field of pain recognition proved challenging. This is due to the implementation of various AI-based image processing approaches, where the model selection depends on the specific task and dataset, and different models may excel in different contexts.[16] In the future, a more systematic standard of performance comparison is expected to address the inconsistencies among various studies and enable more valid comparisons of advanced technologies.

Face

Human faces are the most reliable and informative indicators of mental states, particularly emotions.[17] Researchers established the Facial Action Coding System (FACS) to identify different facial muscles (action units, AUs) that represent all kinds of emotions.[18] Based on FACS, a well-established pain assessment standard with a 16-point scale was developed, known as Prkachin and Solomon[19] Pain Intensity (PSPI). In addition, an Active Appearance Model (AAM) is also commonly used by researchers to identify facial patterns associated with spontaneous pain.[20]

A growing concern has been raised regarding the ambiguity of pain, as some reports suggested that pain can sometimes appear as a combination of other emotions, such as disgust.[21] Identifying specific characteristics of pain is one of the most important aspects of pain recognition. Furthermore, whether methods frequently used for estimating pain intensity, such as regression, are stable has been controversial. For example, pain and eye closure have a positive correlation, while blinking and eye closure have similar facial characteristics when viewed independently. Pain intensity will be overestimated in images with closed eyes, increasing variance in continuous pain evaluations.[22] Future research should aim to distinguish between video frame sequences based on their temporal relationships, thereby contributing to a more nuanced understanding of the dynamics involved in computational pain recognition.

Voice

Despite extensive research on facial cues, few studies have examined how pain can be detected through vocal signals. For humans in the initial developmental stage, sounds are more informative to express their feelings (i.e., crying babies).[23] However, research on vocal

Table 1. Modality-specific issues

Modality	Concept/Method	Description	Reference(s)
Face	Facial Action Coding System (FACS)	Identifies facial muscles (action units, AUs) representing various emotions	Kaltwang et al.[17]; Ekman and Friesen[18]
	Prkachin and Solomon Pain Intensity (PSPI)	Pain assessment standard based on FACS with a 16-point scale	Prkachin and Solomon[19]
	Active Appearance Model (AAM)	Identifies facial patterns associated with spontaneous pain	Ashraf et al.[20]
	Ambiguity of Pain	Pain can sometimes appear as a combination of other emotions, such as disgust	Kunz et al.[21]
	Controversy[31] of Pain Intensity Estimation Methods	Debate over the stability of methods like regression for estimating pain intensity	Zhou et al.[22]
Voice	Linguistic and Non-linguistic Signals	Vocal signals can be linguistic (textual) or non-linguistic (pitch, intensity, tone)	Tuduce et al.[23]; Bell and Sejnowski[24]; Herault and Jutten[25]; Campanella and Belin[26]; Noroozi et al.[27]
	Extraction of Speech Features	OpenSMILE toolkit proposed for extracting voice features	Eyben et al.[32]
	Background Noise Reduction	Reduction of background noise to improve voice-based pain recognition	Hao et al.[34]
Body	Gestures	Gestures as indicators of pain in multimodal pain recognition	Castellano et al.,[36] 2008; Stathopoulou and Tsihrintzis,[39] 2011; Castellano et al.,[40] 2007
	Body-based Pain Recognition	Feasibility and importance of incorporating body movements into pain recognition	Werner et al.,[111] 2018; Semwal and Londhe,[38] 2021
Multi-modality	Psychophysiological Pain Indicators	Accessing additional sources of psychophysiological pain indicators such as EEG and EDA	Kächele et al.,[112] 2015; Walter et al.,[41] 2013
	Physiological Signals	Physiological signals related to underlying emotional representation dimensions (valence, arousal, dominance) can estimate pain intensity	Schlosberg,[43] 1954; Gruss et al.,[44] 2015

information traditionally focused on fundamental problems such as blind source separation.[24,25] A preliminary study found that facial signals can sometimes be independent of voice generation, such as the fundamental frequencies of phonation and intonation.[26] The separation of voice and facial expressions raises the question of whether we can independently extract pain information from voice or consider voice a complementary source that benefits pain recognition. Literature on computational pain recognition has not yet addressed the voice-based signal.

In general, the vocal signal can be divided into two categories (linguistic and non-linguistic), each with distinct characteristics[27] that can be helpful in the medical service.[28] On the one hand, the linguistic signal is more complex and subjective than the non-linguistic signal and natural language varies in different contexts (i.e., recreation and work). Currently, text analysis is less commonly utilized in computational medical diagnostics, despite its potential to significantly enhance early and foundational online medical consultations in the long term.

On the other hand, information delivery depends on how we use non-linguistic signs—such as pitch, intensity, and tone. Non-linguistic transformations (i.e., Mel-frequency cepstral coefficients, MFCCs; filter bank energies, FBEs; linear spectral pairs, LSP) are critical to extract useful indicators for pain recognition.[29] For example, people can subtly convey opposite information, such as using words of appreciation to express sarcasm by adjusting their tone and stress.[30] A study found a correlation between bio-signal parameters related to speech prosody and self-reported pain levels.[31] Therefore, "how" we speak (non-linguistic) is sometimes even more important than "what" we say (linguistic). Thus, the extraction of speech features from speech and models for recognizing pain based on speech is crucial to study. A popular audio feature extraction toolkit called OpenSMILE has been proposed to extract voice features.[32,33] Additionally, background noise can interfere with voice-based pain recognition. To reduce background noise, researchers need to extract only meaningful audio information.[34] Generally, pain recognition through vocal coding is at a very early stage of feature mining compared to sophisticated facial coding systems. A meta-learning process like stacked ensemble learning, capable of assimilating various forms of information may provide valuable insights for speech-based pain recognition (Figure 2).

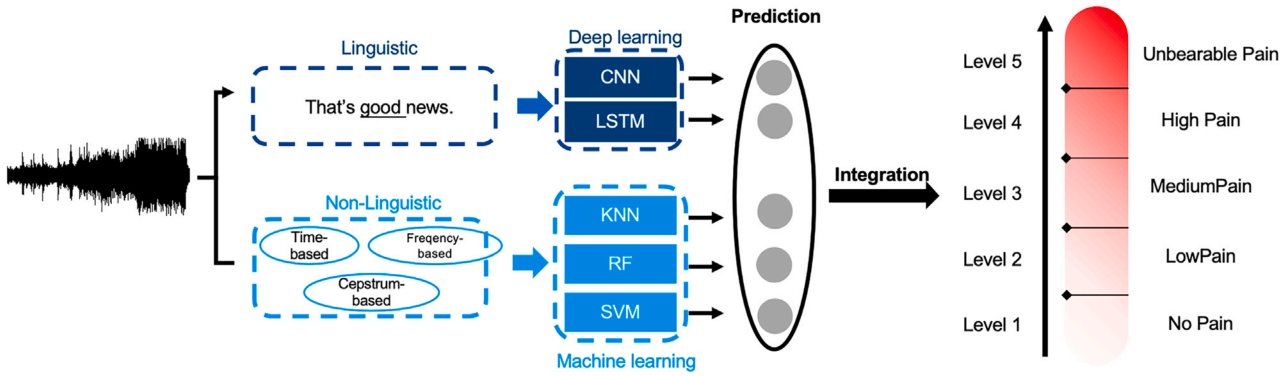

Figure 2. A meta-learning process for voice-based pain assessment

Body

Advanced algorithmic models in computer vision relating to human visual systems have driven the development of body-based data processing.[35] Symbolic movements (such as head nodding) can provide an implicit explanation. Castellano et al.[36] suggested that gestures could be the most accurate indicator of pain in a unimodal emotion recognition system, followed by speech and facial expressions. As a result, incorporating body movements into multimodal pain recognition could be beneficial in the long run.[37] In three databases, studies have examined the head movements and posture patterns of patients in pain- and non-pain states and found remarkable differences, suggesting that body-based pain recognition is feasible.[38] In contrast to a large amount of research on face-based pain recognition, few studies have considered body-based pain recognition.

The gap in body-based pain recognition could be partly due to the need for a valid interpretation model for body movements. An analysis of previous research on emotion recognition provides insight into the model of body movement. In particular, two aspects of gestures are examined: propositional (marker-based) and non-propositional (non-selected marker-based) movements. Video sequences capture a variety of body movements, and positional markers are selected from those movements.[39] For non-positional movement qualities, Castellano et al.[40] used amplitude, speed, and fluidity of movement to classify eight emotions instead of gestures. Mapping specific body action units to pain using specific body models is a top-down approach to studying the robust link between the body and pain. Meanwhile, a bottom-up approach focuses on raw data for feature selection, supplementary to a thorough understanding of body-based pain analysis.

Toward multi-modality

Notably, the advancements in pain recognition have stemmed from a generalization of the methodologies derived from essential emotion recognition, underscoring the interdisciplinary nature of this progress. With the advent of wearable and portable technologies and dry electrode technology, researchers have been able to access additional sources of psychophysiological pain indicators, including electroencephalography (EEG) and electrodermal activity (EDA) (i.e., monitoring ICU patients).[41,42] One of the most significant aspects of bio-signaling is that physiological parameters may not be correlated with specific emotional states but are related to the underlying emotional representation dimensions (valence, arousal, and dominance).[43] Hence, physiological signals can provide useful information in estimating pain intensity.[44] A general understanding of the unimodal development of pain recognition presented in this article can assist researchers in developing an optimal multimodal framework or system in the future (Figure 3).

CROSS-DISCIPLINARY PERSPECTIVES ON PAIN RECOGNITION

In addition to serving as a spontaneous and bottom-up response to pain stimuli, pain expression is also produced for social purposes and can be shaped by high-level cognition. Physical signals acquired by AI may be confused with social signals related to pain. So, instead of focusing on furthering method-oriented issues, present research should lean toward a problem-focused perspective by understanding human cognitive, behavioral, and neurological processes.

So far, there has been little attention to how people can accurately recognize another person's pain states based on multimodal information. Part of the answers have already been provided in studies of human cognition, with which insights from human studies enable an interesting practice called HITL. Through the framework of HITL, this section highlights technical developments based on human cognitive systems, such as multimodal information integration and memory systems, which we regard as a form of indirect learning from humans (Figure 4 bottom). Furthermore, we propose that computational pain recognition can be improved by learning directly from human studies by focusing on how individuals perceive and respond to the pain of others (Figure 4 top).

Indirect learning from human neural mechanisms

Integration and processing of multimodal signals

Mental processes are believed to be derived from interconnected subsystems in the human brain, and each subsystem contributes to several mental processes.[45] The brain is able to exchange and match cross-modal information (face and voice) in order to identify others.[46,47] Humans

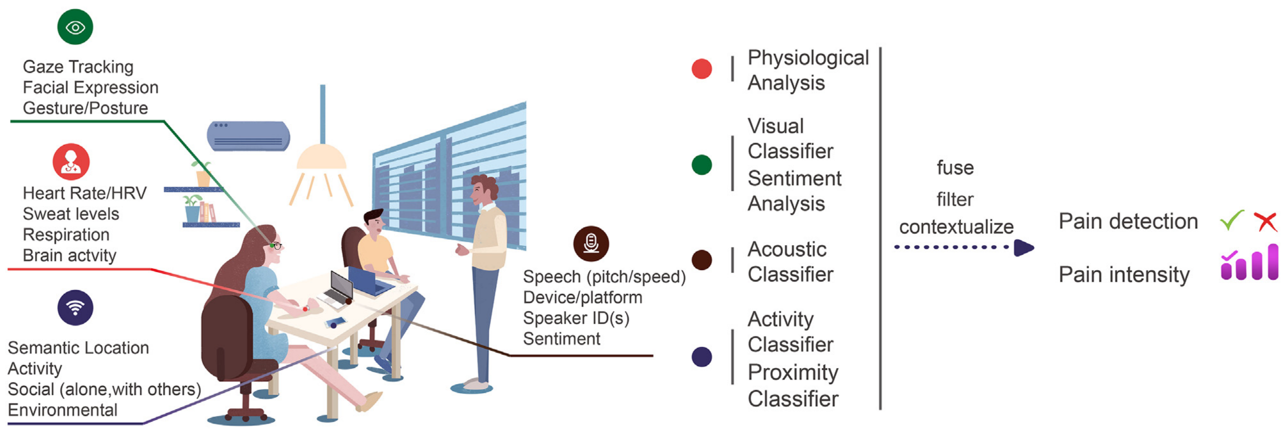

Figure 3. A sketch of a real-time multimodal pain recognition application

are capable of integrating multimodal information by selectively prioritizing pertinent inputs that are associated with their objectives or tasks at hand.[48] Beyond unimodality, multimodal feature integration methods have come into being and have been examined successfully.[49–51] Kächele et al.[42] showed that multimodal information was more advantageous than unimodal in identifying pain from facial expressions, head posture, and physiological signals in videos. Unlike unimodal systems, multimodal data fusion has substantially improved recognition accuracy.[52]

Memory and learning

Prior knowledge improves our understanding of a new situation, and previous experience accelerates an initial response to handle new situations.[53] For example, personal medical history is a precious source of clinical information. Patients with different types of pain (i.e., acute pain and chronic pain) show a distinct way of processing and expressing pain. For example, researchers have found distinct information processing when patients experience acute pain compared to chronic pain.[54] Within the medical domain, the identification and recognition of pain can be significantly enhanced by leveraging the AI's ability to process detailed patient information.

Human top-down cognitive systems can modulate pain perception, but significant inter-individual differences exist.[55] Individual differences in pain expression make prior experience with similar stimuli crucial for specific pain analysis. One of the challenges in recognizing pain is that individuals exhibit varying expressions for the same stimuli.[56] A personalization of pain intensity estimation systems[57] with multimodal analysis can make the most of high-dimensional pain-related features to process past information about pain. Humans primarily rely on a central hub called hippocampus for memory storage. The hippocampus is activated when an episodic experience replays during resting and sleeping, which has been considered a process that integrates short- and long-term memory.[58] Specifically, researchers proposed an example-based manner by which memory "replays" itself offline to learn the successes or failure cases that occurred in the past.[59] The replay process emphasizes the recirculation of learning. Over time, data can be trained offline to improve algorithms in specific environments (i.e., hospitals, homes, and public places), similar to human episodic memory, replaying during sleep to realize a conceptual life-long learning system. However, advanced applications require translating an individual's past experience, pain threshold, or pain display characteristics to a person-specific feature space before training.

Direct learning from human studies

Modulation of pain expression through social contexts

From recognition to cognition, cognitive patterns (i.e., pain sensitivity) are essential individual differences that are also context-dependent. For example, our discomfort toward aversive stimuli is lower when we are in the company of others than when we are alone, referring to the social buffering effect.[60,61] Meanwhile, high social threats, such as high electrocutaneous stimuli administered by others, increase pain intensity and unpleasant feelings.[62] It has been shown that explicit expressions are influenced by whether people are surrounded by whom they trust (workplace, hospital, or home).[63] Therefore, target separation and context analysis are fundamental issues to address for improvement in real-life applications of pain estimation.

Pain recognition and response to others' pain in human studies

In clinical settings, adaptable empathy is expected to give better patient experiences. Two ways can lead to breakthroughs in general practice. Understanding and catering to the specific emotional and psychological needs of patients allows healthcare providers to improve patient satisfaction, adherence to treatment plans, and health outcomes. This framework of feedback adaptation was initially proposed in in-person counseling based on real-time cues from the recipient, allowing for more effective and supportive interactions.[64,65] However, this

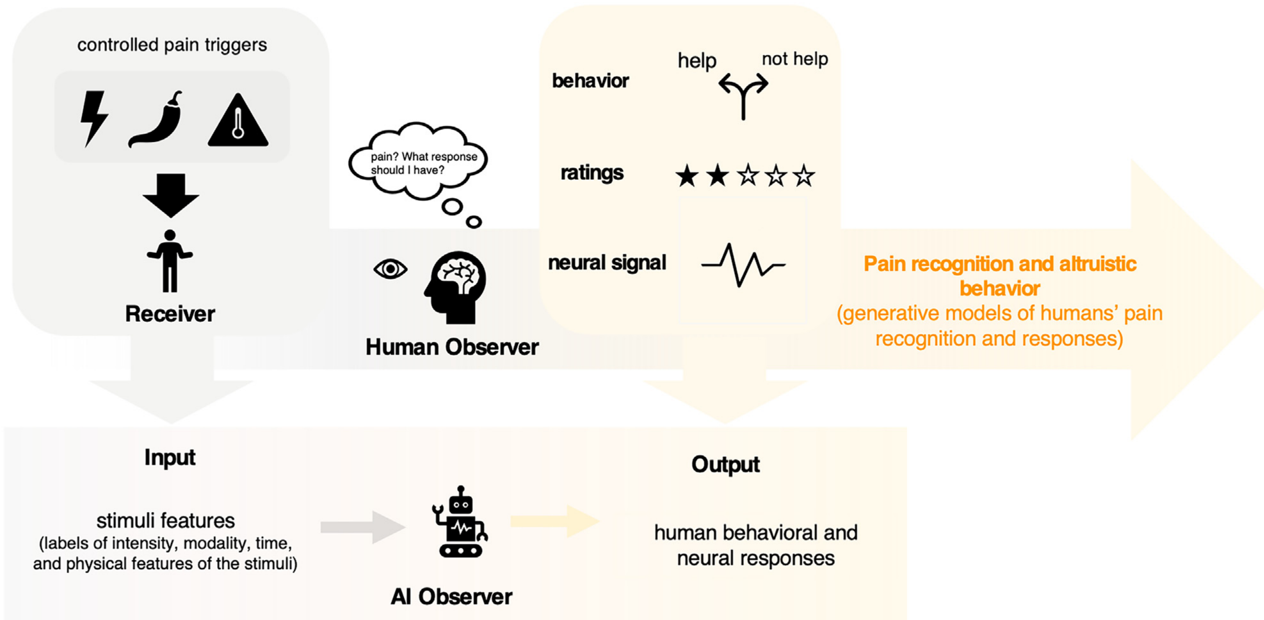

Figure 4. Pain recognition under the Human-In-The-Loop framework

definition reveals that adaptability is understood in an individual-specific way as it changes in every person. Thus, a challenging work is to customize a quantitative benchmark for users in need under the framework of some general empathic practices such as emotional validation, context-sensitive responses, active listening, and constructive guidance. This top-down approach ensures empathy feedback is constrained in the validated framework that has been verified for years, and reserves to be fine-tuned.

While being guided by a mature empathy structure that gets the whole work under control, the structure seems uninterpretable for AI systems because of the lack of samples to generate variable and flexible responses. An adaptive form of AI empathy can be developed by comprehensively studying human empathy. This bottom-up method gives rise to the collaboration of psychological studies and computational modeling, in which computation of human responses to empathy-triggered events builds models for a more human-like AI empathy. A systematic review concluded that there is substantial evidence supporting the positive effects of empathy in general practice. Empathetic communication by General Practitioners is beneficial for patient satisfaction, clinical outcomes, adherence to treatment, and psychological well-being. However, the authors note the need for more standardized methods of measuring empathy and outcomes to strengthen the evidence base.[66] Human studies provide a strong foundation for AI pain recognition as they have established precise pain models (i.e., heat, cold pressure, or video).[67,68] Also, rich data about observers' responses were recorded, such as ratings, neural signals (EEG, fMRI) of processing these stimuli, and observers' choices.[69,70] Those are crucial elements to mapping natural pain sources to their elicited reactions. In addition, two insights can be gained from some studies concerning human reactions to others in pain. McQuiggan and Lester[71] explored the integration of empathy in AI to enhance accountability and interaction quality. They proposed a data-driven framework that allows AI agents to learn empathetic behaviors by observing human interactions. This early research sheds light on the aims to make AI systems more responsive to human emotions, thus improving their effectiveness in various applications, such as tutoring systems and companion robots. For one thing, stimuli used for eliciting human responses to others' pain have inherent features (standardized labels of others' pain state, and physical features of the stimuli), both of which can serve as potential inputs for various algorithms. For another thing, the experiments captured human responses across multiple dimensions, including behavioral ratings and decisions to aid individuals experiencing pain, serving as feasible endpoints for AI learning. Ultimately, this line of studies can illuminate the "black box" systems within the human cognitive framework, bridging the gap between input stimuli from individuals in pain and the corresponding responses from observers.

BEYOND PAIN RECOGNITION

In retrospect, pain is often but not necessarily associated with empathy and altruism.[72–74] Empathic people can recognize and comprehend others' emotions by experiencing and sharing the emotional states of others.[75] An AI agent with human-like empathic responses is considered more caring, likable, and trustworthy.[76] However, AI research has not addressed the gap between pain and empathy. A fundamental component of artificial pain empathy is the recognition of pain.[77] Artificial empathy refers to the capacity of computer systems to recognize and respond to people's behaviors, expressions, and emotions.[78–80] In this section, we propose a relatively novel field associated with an affective AI – artificial pain empathy.

Artificial pain empathy

Mimicry

Pain empathy is the capacity associated with feeling and evaluating others' pain states and understanding others, often prompting prosocial actions,[81–83] which is critical for pain recognition therapy. Studies from animals and humans suggested that mimicry of body movement is the underlying mechanism for empathy, which derives from a mirror system in the human brain.[84] Emotional mimicry is crucial in social interactions since it reflects a desire to connect with another person.[85] Thus, the initial step to model pain empathy is to recognize and imitate human facial expressions or gestures in real-time. To some extent, mimicry generates similarity and, in turn, facilitates people's empathy toward a human-designed machine.[86] Miura et al.[87] found that human-like body movements make it easier for people to empathize, and the embodiment of an interactive partner influences human mimicry behaviors. A physical presence and human-like artificial entity tend to generate more mimicry than virtual non-human counterparts.[88] In addition, emotional mimicry by robots may show its empathic "trait", improving the human-robot interaction experience.[89]

Modulation by top-down cognitive processes

Can AI agents show empathy even though they cannot feel pain? Some clues can be gained from studies on people born with the congenital absence of pain. Danziger et al.[9] found that pain-related brain regions of congenitally pain-free patients are activated when seeing others experiencing pain, indicating a shared synchrony pain aversion with others. Krishnan et al.[10] found that the experience of vicarious pain (observing others in pain) is neurologically separate from experiencing actual pain on our own, suggesting that empathy is more cognitive than sensational. Thus, empathy not only has the intrinsic characteristics of sensibility but also comprises the process of top-down cognitive regulation. Heyes[90] proposed a dual-system model of empathy, which includes both early views in which empathy largely depends on a bottom-up process, a spontaneous response activated by stimuli (system I). Meanwhile, it also covers the control mechanism of empathy that belongs to a top-down process, indicating that high-level cognitive systems contribute to the regulation of empathy (system II). The two-system model of empathy lays the foundation for the investigations on artificial empathy from a cognitive perspective.

Presence of social partners

A social buffering effect indicates that the presence of social partners effectively modulates human reactions toward aversive stimuli.[61] A recent study on rodents found a closely related neural circuit underlying this buffering effect. Their results showed that brief social interaction with a peer mouse experiencing pain or morphine analgesia resulted in the transfer of these experiences to its social partner.[13] Theoretically, painless robots may serve as analgesic companions, thereby reducing people's perception of pain. Some effort has been made to develop human-centered and user-friendly services using AI technologies. For example, the Institute for Creative Technologies at the University of Southern California created an empathic AI system that functions as a virtual counselor and mainly serves veterans with post-traumatic stress disorder.[91] The emergence of the Language and Learning Model (LLM) empathy chatbox in psychiatry provides the potential use of AI-powered chatbots to provide empathetic support and assistance to individuals seeking mental health treatment. These chatbots are designed to understand and respond to human emotions, providing a more personalized and compassionate interaction, as a partner or therapist[92] without compassion fatigue.[93]

Furthermore, when people suffer together, they are more likely to form ties.[70] In this sense, a demonstration of artificial agents sharing pain increases the possibility of building trust.[94] A more advanced practice in human studies is neuromodulation, a surgical electrical therapy with mostly non-invasive stimuli conducive to pain relief.[95] By performing neurofeedback training, people can self-adjust their responses to a specific range of stimuli by giving them positive feedback when making desired responses. The self-adjustment technique is also supported by evidence that indicates that pain-associated EEG signals can be deliberately trained. Nevertheless, future research is required to examine the effectiveness of individualized neurofeedback for pain regulation due to varying training efficacy.[55]

Empathy training for humans

AI research can also contribute to the human-in-the-loop systems in the context of a generative model. The generative models that generate human images and speech have come close to equivalents in the real-world. On the one hand, synthetic data can be endlessly used to train the recognition models. On the other hand, the data can be applied to the training process for medical caregivers to improve people's estimation of pain intensity. A recent study indicated the feasibility of such training pain. People underwent a 3.5- to 5-h online training program called the Index of Facial Pain Expression (IFPE). After the short training, observers improved their identification of others' psychiatric pain expressions.[96] Hence, an essential task for future artificial agents is to help people with emotional deficiency establish the ability to perceive, interpret, express, and regulate emotions.[97] Artificial assistants for pain modulation have become much more available to people in need of medical services. Their presence and simple pain-sharing displays from them can have a significant effect in reducing pain perception. Sharma et al.[98] explored the use of AI to enhance empathy in online mental health support. The researchers designed a study with 300 participants on the TalkLife using Hailey, an AI tool that provides real-time feedback to peer supporters to help them respond more empathically. They found a 19.6% increase in empathic responses when using Hailey. This approach was particularly beneficial for training people in relevant professions who struggled with expressing empathy, leading to an increase in the quality of service and conversation. More sophisticated neuromodulation is also feasible in the future application of artificial medical assistants. To jointly contribute to the field, it is required to integrate psychology, ethics, and cognitive neuroscience.

Future potential

Empathy, primarily driven by mimicry of body movements, is crucial for recognizing and interpreting others' pain, reflecting a desire for connection. This mimicry, rooted in the mirror neuron system, can enhance the human perception of empathy in robots. Cognitive processes also play a significant role, as empathy involves both bottom-up sensory responses and top-down cognitive regulation. AI can simulate empathy through these mechanisms, potentially reducing pain perception in humans. For instance, empathetic AI systems have been developed to assist individuals with mental health issues, like virtual counselors for veterans with PTSD. Additionally, the presence of social partners, including robots, can modulate human reactions to pain. AI can also enhance empathy training for humans, as demonstrated by AI tools like Hailey, which improve empathic responses in online mental health support.

With the emerging development of advanced LLMs, research has shown that NLP technologies, including LLMs, can effectively analyze patient narratives to identify and respond to expressions of pain and distress. This capability enhances the ability of AI systems to provide empathetic support. Studies on the use of chatbots for mental health support have demonstrated that these tools can provide empathetic responses and emotional support to users.[99] For example, Woebot, a mental health chatbot, uses NLP to offer cognitive-behavioral therapy (CBT) techniques and empathetic conversations, which have been shown to reduce symptoms of anxiety and depression.[100] Melo et al.[101] investigated that AI chatbots like ChatGPT can enhance the patient-reported quality of life in a psychiatric setting. Dawoodbhoy et al.[102] showed that AI systems can be beneficial for three aspects: optimization of resource allocation, clinician decision-making support, and preventative, personalized management. A pilot study using several advanced models to predict trends of occurrence of mental disorders based on lifestyle, environmental, and addiction-based factors, showcased the power of rapidly developed algorithms and their implications on mental healthcare.[103]

ETHICAL CONSIDERATIONS

Concerning the overarching topic, it is imperative to approach ethical concerns with attention and a sense of accountability in future developments regarding affective assistants. The ethical consideration of AI-powered tools introduces a discussion on biases adopted from human experiences. This issue has raised tremendous attention, and a recent review covered it in great detail.[104] A systematic review also found group differences in which average scores in the measures of pain beliefs and appraisals, coping responses, and catastrophizing were significantly different between people from different countries.[105] Algorithms-generated contents are largely reflected by and aligned with values, perceptions, and cognition patterns from various sources, of which pain-related content inevitably suffers from invalid human evaluation. Despite the absence of a remedy, optimism is rising around the potential of artificial systems to provide empathy-like behaviors by emulating human responses, but this direction is not the only line of work on the agenda.[106–108] Several pivotal considerations arise, including an examination of the potential advantages and benefits those artificial systems offer to human life. Equally important is the clear boundaries that these service functions must not transgress, thereby ensuring the preservation of ethical standards and safeguarding against potential harm to delicate patients.[109]

For users, they might become overly reliant on AI systems for emotional support, leading to reduced human interaction and potential detachment from meaningful relationships. In the meantime, in the event of a malfunction or error, AI responses with empathic features could inadvertently cause emotional harm to users, especially in sensitive or vulnerable situations. More importantly, AI systems may encounter complex ethical dilemmas when making decisions based on empathic responses, raising questions about the appropriate course of action in morally ambiguous situations. Assigning blame and responsibility in the context of erroneous AI systems can be a complex and nuanced issue, particularly when considering whether AI systems should be subject to punishments. It is crucial to recognize that responsibility for actions taken by AI systems typically extends beyond the technology alone, involving various sectors in their creation, implementation, and regulation.

For developers, users might worry about the effectiveness regarding how likely AI systems may misinterpret human emotions or intentions. An inappropriate or ineffective response potentially exacerbates the negative emotional state of the individual. Thus, constant feedback capture from users to facilitate iterations of AI systems in service is one of the major technique issues to improve products' quality. However, privacy and security of personal data seem to be inevitably exploited for some excuses like precision, flexibility, and convenience of advanced services. Should producers or companies b required to introduce rules to improve accountability and transparency through legal support and government supervision? To what extent the operational processes of the business can be disclosed to the government and the public? Unless people understand AI systems' limitations and have assurance from reliable sources about how the algorithms work, it is understandable for them to be skeptical about surrounding "monitoring machines" at home. Moreover, how to prevent producers from manipulating vulnerable people with psychiatric disorders for marketing, political influence, or other purposes. Technological challenges have been overcome at an astonishing speed in recent years, for instance context understanding, real-time adaptation to new emotional contexts, more tones, and informal speech are included in language models. However, exponential growth in databases with unfiltered data leads to inappropriate empathic responses. Several recent studies had a specific aim of AI technologies comparison. It is crucial to understand that the selection of a model should be based on the particular task and dataset, as different models may excel in different applications.[16,110] We hope that future tech-focused articles will establish a more systematic standard for comparison, addressing the incompatibility across various studies. This will enable more valid accuracy comparisons and provide clearer insights into advanced technologies.

For society, inequity might be exacerbated by a significant access delay or a complete inaccessibility to advanced AI technologies. Should the technology be introduced sequentially rather than entirely open? New technological updates could change interpersonal interactions and create potential risks of social stratification in the AI era. An upside in the field is to provide companionship while it might also be a risk for isolation.

Standard practices and approaches to mitigate these risks and concerns should be accompanied if artificial systems were to be released. For example, developers should prioritize the development of robust ethical frameworks, comprehensive data privacy protocols, and stringent testing procedures to ensure that AI systems with empathic responses are deployed responsibly and ethically. A default setup considered is to allow users to opt-out at any point they are dissatisfied with AI's services, which ensures that users retain control and autonomy over their interactions with AI systems. It is important to note that while AI empathy has the potential to provide valuable support, it should not be seen as a substitute for human interaction.

CONCLUSION

This article explores the potential of AI for pain recognition and discusses an artificial assistive system. By leveraging AI technology, such as AI-based pain recognition, and empathy responses, it can provide immediate and personalized support, helping individuals or doctors understand their health challenges and respond to many different cases. Our article offers an assessment of existing databases to develop algorithms capable of generating empathic expressions. We present an HILP framework, suggesting that an AI system can learn to replicate "empathic" feedback based on human-human interaction and emphasize the role and importance of human clinicians in providing comprehensive mental healthcare. Regularly monitoring pain by such assistive AI systems can ensure complementary diagnosis assitance and timely treatment for psychiatric patients and enable empathic responses in the future. Nevertheless, there are inherent limitations and challenges concerning the semantic understanding of intention and trust while processing affective information. Ongoing research and collaboration between experts in the fields of AI, psychology, and ethics are crucial for understanding and addressing the potential risks and challenges associated with the integration of empathic responses into AI technologies.

SUPPLEMENTAL INFORMATION

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AUTHOR CONTRIBUTIONS

H.W. conceived the topic. S.C. led the manuscript writing. D. F. proposed the writing structure. D. F and S.W. refine the writing. X.Y provided suggestions on writing. X.L. and H.W. supervised the writing process. All the authors contributedto the final manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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