Affective Computing in Anxiety Disorders: A Rapid Literature Review of Emotion Recognition Applications

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Abstract: Anxiety disorders (ADs) affect roughly one in ten people in the UK, and this number is expected to increase, intensifying the need for innovation. Digital technologies such as affective computing (AC, technology to detect human emotions) could foster a more patient-centric approach, enhancing therapy adherence and optimizing clinician-patient interactions. This paper reviews the literature relevant to the integration of affective computing in clinical pathways for ADs. A search was conducted on Google Scholar and PubMed using the keywords “affective computing” and subtypes of anxiety disorders. A total of 355 results were filtered to focus on peer-reviewed articles that specifically addressed emotion recognition in pathological anxiety as opposed to simply feeling anxious. Findings underscore prevalent studies focusing on post-traumatic stress disorder (PTSD) and the widespread use of valence and arousal for emotion quantification. Various approaches for both eliciting and detecting emotions are explored, offering technical and practical insights. Diverse applications, from monitoring treatment progression in behavioral therapies to assessing the efficiency of deep brain stimulation for intractable obsessive-compulsive disorder, highlight affective computing's versatility and promise. A significant advantage of digital technologies is their potential to capture longitudinal and contextualized data beyond clinical confines. Such assessments elucidate patients' daily challenges and triggers, enabling tailored interventions. The literature suggests that AC has the potential to support mental healthcare and improve patient outcomes. However, further evidence of its effective benefits is required, especially for ADs beyond PTSD, and further exploration of its implementation in clinical pathways is needed.

1 INTRODUCTION

In recent years, there has been a concerted effort to use digital technologies to support mental health and well-being (De Witte et al., 2021) and several self-help solutions are available on the market. However, the integration of these technologies with clinical pathways, a more complex yet potentially impactful application, has received relatively little attention.

1.1 Anxiety Disorders, a Clinical Context

According to a 2007 survey in the UK, the prevalence of any lifetime mental disorder was 45.5% (Slade et al., 2009). Additionally, a 2014 survey indicated that

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approximately one in ten people in the UK are affected by ADs (*Adult Psychiatric Morbidity Survey*, 2014). This situation has been worsened by the Covid-19 pandemic, in which the necessary restrictions and social rules introduced (e.g. lockdowns, quarantines, social distance, etc) have triggered disorders otherwise somehow controlled, and sharpened the ones already manifest (Ugbolue et al., 2020; Shevlin et al., 2020).

In psychiatry there is a continuous debate about the taxonomy of mental disorders. For a matter of simplicity, in this text we refer to 'Anxiety Disorders' (ADs) based on the definition provided by the U.S. National Institutes of Mental Health, which includes five major types (U.S. Department of Health & Human Services, 2024): Generalized Anxiety Disorder (GAD), Obsessive-Compulsive Disorder (OCD), Panic Disorder (PD), Post-Traumatic Stress Disorder (PTSD), Social Phobia (or Social Anxiety Disorder, SAD).

Anxiety disorders (ADs) remain significantly under- and misdiagnosed, partly due to challenges in distinguishing between subtypes and the prevalence of co-occurring somatic complaints and comorbidities. These challenges are particularly widespread; for instance, comorbidities affect approximately 90% of patients with obsessive-compulsive disorder (OCD) (Stein et al., 2019; Yehuda et al., 2015). Current diagnostic methods face notable limitations. Standard self-reported approaches rely paradoxically on patients' ability to assess their own emotional awareness, a capability often impaired in ADs (Berking et al., 2011; Berking & Wupperman, 2012). Structured clinical interviews, while widely used, frequently lack flexibility, specificity, and cross-cultural validity. Additionally, these interviews can fail to detect concealed or simulated symptoms. For example, only 11% of PTSD patients are correctly identified through structured interviews (Yehuda et al., 2015). Beyond these diagnostic challenges, there is a lack of objective tools capable of differentiating between stages of ADs and quantifying their impact on patients' quality of life (Stein et al., 2019; Yehuda et al., 2015). An objective tool is also desirable to provide data to assess the efficacy of pharmaceuticals, psychological and alternative treatments (Bystritsky et al., 2013; Stein et al., 2019; Yehuda et al., 2015).

Moreover, the healthcare system is under pressure worldwide due to a shortage of workforce compared to the increasing demand (Michelutti & Relić, 2022). This scenario leads to high level of stress and burnout among the clinicians and to a reduction of time per-patient. Therefore, more research is needed to investigate the use of digital technologies to support patients' self-management and involvement, as well as to enable more efficient patient-clinician interactions.

1.2 Affective Computing in Mental Health

Emotions are central to the human experience, and play a crucial role in our lives: they influence our learning, attention, decision making and perception (Picard, 1997). From a neurobiological perspective, emotions are bioregulatory reactions regulated by chemical and neural responses regarding 'emotionally competent stimuli' (i.e. objects, situations, or memories).

There are mainly two families of classifications for emotions (Yazdani et al., 2013): 1. Discrete Emotional Model (DEM) which is a categorical model based on standard terms used as references, and the selection of emotions used varies between studies. Furthermore, there could be cultural biases in the interpretation of the meaning of each emotion used. Some of the most common labels used are: 'anger', 'sadness', 'joy', 'disgust', 'surprise', 'fear' (Ekman et al., 1972). 2. Affective Dimensional Model (ADM) or Continuous Dimensional Model which, instead, is a system of coordinates for emotions, which is based on Valence and Arousal for the 2D models, plus Dominance (Mehrabian, 1997) for the 3D ones (VAD model). The Valence dimension expresses the degree of pleasantness, while Arousal captures intensity, ranging from calm to energized; Dominance is used to represent the level of control and freedom to act, ranging from submissive to empowered (Mehrabian & Russell, 1974). Moreover, some authors (Verma & Tiwary, 2017) proposed a 3D matrix in which VAD emotion values essentially serve as coordinates for DEM labels clustered in 5 main groups, bridging the two emotion classification approaches.

Some researchers emphasise the key role that affective assessment plays in psychotherapy: both to assist patients in their therapeutic journey and to provide the clinician with a framework for intervention (Greenberg & Safran, 1990). There are also studies supporting the role of arousal in facilitating anxiety reduction in fear-avoidance problems (Greenberg & Safran, 1989), such as PTSD (Hyer et al., 1991).

Affective Computing (AC) is a multidisciplinary field which studies emotions through technology (Calvo et al., 2015). Many studies have explored how

AC can detect common anxiety, which is the normal and expected response to everyday challenges or stress. However, fewer studies have focused on pathological anxiety, an anxiety that is too intense, lasts too long, or occurs in ways that disrupt daily life. This work aims to explore how AC techniques have been developed and evaluated specifically for ADs.

2 METHODOLOGY

A previous overview of affective computing solutions in healthcare found that 28.3% of the publications prior to 2020 were related to mental health, excluding studies that referred to the use of wearables other than eye tracking, which differentiates it from the present work (Apablaza & Cano, 2020). In a 2014 review, 34 studies on digital solutions for anxiety disorders were examined, emphasizing the Ecological Momentary Assessment (EMA) approach's ability to provide insights into the temporal variability of symptoms and associations among daily affect, behaviors, and situational cues thanks to the collection of longitudinal data. The study also noted successful combinations of EMA with ambulatory assessment of physiological variables and treatment evaluations (Walz et al., 2014). Other literature reviews focused on specific data modalities and/or techniques in come ADs sub-disorders (e.g. machine learning (ML) for speech analysis in PTSD (Anitha, 2022; Suneetha & Anitha, 2024), or fMRI in SAD (Hattingh et al., 2013)).

The research question that this paper aims to address can be summarised as follows: How effectively has affective computing proven to be for supporting clinical pathways in anxiety disorders, and what are the technological and pragmatic challenges that shape its implementation? Under this main question, sub-questions can help in addressing this aim comprehensively:

a. Technical Feasibility: What types of affective computing technologies have shown potential in detecting and assessing anxiety disorders symptoms? What evidence exists regarding their accuracy, robustness, and usability?

b. Clinical Feasibility and Integration: To what extent have these technologies been incorporated into clinical pathways, and what specific use cases have shown promise?

c. Sociological and Ethical Considerations: What cultural considerations could influence the widespread integration of AC in ADs?

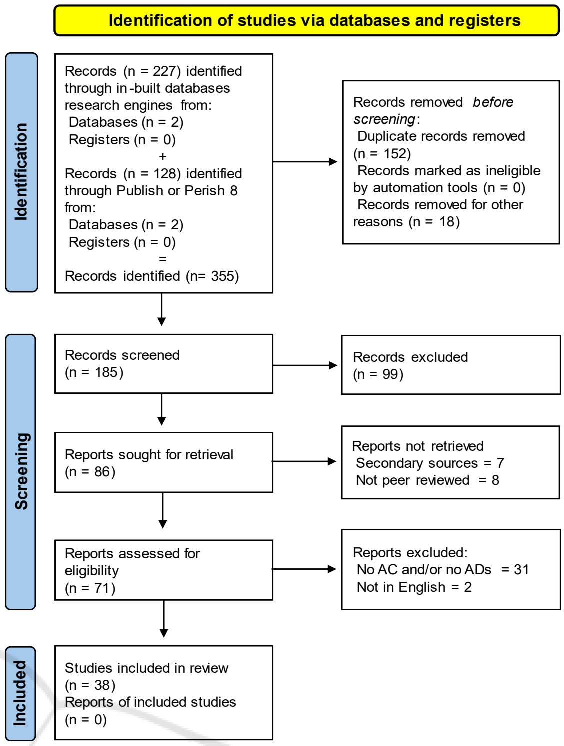

Figure 1: PRISMA 2020 flow diagram adapted for this rapid literature review.

2.1 Search Strategy and Data Sources

This literature review sets various challenges given the use of similar terminology from different fields within different meanings. An example of this semantic overlap relates to the keywords "emotion detection" or "emotion recognition": while in psychology this refers to the capability of individuals of understanding others' emotions, in technology this refers to AC solutions capable of finding emotional patterns in certain data modalities. In order to overcome these challenges, a bivalent research approach has been proposed and implemented. This approach comprises two distinct methods. The first is conducted through the databases' native interfaces, while the second exploits certain features of the free software "Publish or Perish 8" (https://harzing.com/). The latter method utilises the software's “search in the references” feature. The two approaches were carried out using two distinct databases to provide comprehensive coverage across all academic disciplines: Google Scholar and PubMed. An overview of the methodology and a quantification of the results are presented in Fig. 1.

The prompt used within the native interfaces of the aforementioned databases was adapted to their respective features and constraints.

- in PubMed: (("affective computing" OR "emotion recognition" OR "emotion detection"[Title/Abstract]) AND (*disorder*[Title/Abstract]))
- in Google Scholar: for title only: allintitle: "affective computing" OR "emotion recognition" OR "emotion detection" "*disorder*". Where *disorder* was substituted with the followings in different entries: obsessive compulsive disorder, OCD, post-traumatic disorder, PTSD, panic disorder, panic attack, social anxiety, social phobia, generalised anxiety disorder, GAD.

The parallel search strategy based on Publish or Perish focused on the term "affective computing" within the text, including references, to ensure a thorough exploration of relevant literature. The search strategy involved filtering articles with titles containing specific keywords related to anxiety disorders (i.e. the aforementioned in *disorder*).

2.2 Screening and Selection

Of the 355 reports initially found combining the two research approaches, 152 have been discarded as duplicates. For the subsequent selection process, exclusion criteria were established to ensure the relevance and quality of the chosen papers. Excluded papers included non-peer-reviewed sources such as books, theses, and magazine articles (n=8), as well as works in languages other than English (n=2). Additionally, meta-analysis or review papers (n=7), as well as papers focused on non-pathological anxiety or on aspects other than emotion recognition and detection through technology (e.g. virtual reality implementation) were omitted (n=31).

2.3 Results Overview

38 papers met the inclusion criteria. Of these two are purely theoretical without involving experimentation (Hinduja et al., 2024; Howard et al., 2014), one was a pivot study (Cohn et al., 2018) of another (Provenza et al., 2021), and another one (Kathan et al., 2024) an integration study of a previous one (Kathan et al., 2023). In Fig. 2 has been reported the distribution of papers over the years and which sub-type of anxiety disorders they focus on. The most evident insights from this stacked column chart is that PTSD is the most studied sub-disorder and that there is a consistent increasing research effort in this field in the last seven years (data updated to October 2024).

3 FINDINGS AND DISCUSSION

In this section the results of the literature review will be contextualised within the three research questions introduced in the methodology.

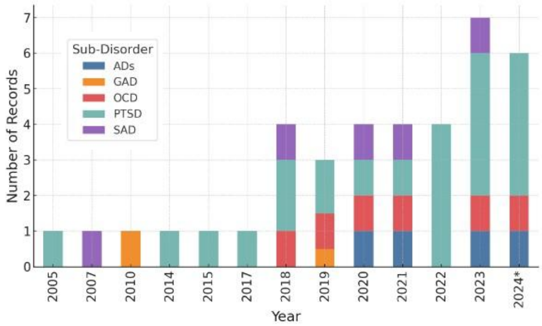

Figure 2: Annual distribution (up to October 2024*) and classification by anxiety sub-disorders of the publications included in this review.

3.1 Technical Feasibility of AC for ADs

By comparing the studies found in this review it is important to consider the diversity among anxiety sub-disorders, data modalities implemented, and dataset used. These aspects are summarised in Tab. 1, with a particular attention for the data used as this is useful not only to evaluate the reliability of the studies, but also to consider the mentioned datasets for future research. Some of the studies, for instance, utilized previous works or distinct datasets as benchmarks (Attas et al., 2022) to assess the generalization capabilities of ML algorithms (Chappidi Suneetha, 2024), or to develop multimodal approaches, which appear to outperform their unimodal counterparts (Kalanadhabhatta et al., 2023). Moreover, ML models (transformers above all) require a huge quantity of data to be trained, leading to the need of merging different datasets or taking advantage of alternative methods, such as transfer learning (Dia et al., 2024). However, not all the works reviewed relied on ML, in fact a third of the studies opted for pure statistical solutions, which, whenever applicable, offer more straightforward and explainable results.

The results declared by several studies, included in Tab. 1, are promising for future in-wild or clinical explorations. However, it is mandatory to also refer to the dimension of the datasets used for testing them as well as the nature of the data, given that real-case scenario data are often noisier and more difficult to manage. From a pragmatic perspective it's also important to consider the kind of implementation for which each technology is suggested for, as different requirements and characteristics might be prioritised.

Of the reviewed studies 43.3% referred to DEM, 56.7% to ADM emotion classifications. However, in both cases there is not an absolute consistency in the number or types of labels used. For example two studies only included dominance in their ADM emotion evaluations (Kathan et al., 2023; Serrano et al., 2019), and one study referred to positive and negative emotions (Zhu et al., 2024). This heterogeneity is a further challenge for the comparison of different ML approaches and for the implementation of different datasets in the same work.

When studying emotions and emotional responses, the first step faced is the need of triggering the target emotions. Emotional elicitation methods varied, with most studies employing clinical situations (e.g. interviews, therapy, cognitive tasks), while some altered environmental conditions (e.g. reproducing natural sounds (Ge et al., 2023; Sundaravadivel et al., 2020) or using virtual reality (VR) (Moussaoui et al., 2007)) or utilized Ecological Momentary Assessments (EMAs) in period of time ranging from 3 (Boukhechba et al., 2018) to 8 weeks (Olesen et al., 2023). The next step consists of the proper emotion detection. Emotion labelling has been performed following three main approaches: a) using standardized self-reported survey to define emotion labels (e.g. Kruskal-Wallis test (Ge et al., 2023), or "Positive and Negative Affect Schedule" (Watson et al., 1988), combined with "Somatic Arousal – Fear questionnaire" (NIH, 2024) and "10-item Perceived Stress Scale" (Cohen et al., 1983)); b) relaying on previously validated datasets (e.g. RECOLA or RAVDESS); c) expert annotations of subjects' responses to stimuli (e.g. clinical interviews); d) using already validated emotional-related proxies ML models and/filters (e.g. General Purpose Emotion Lexicon (GPEL) for text analysis (Bandhakavi et al., 2017), GeMAPS from openSMILE toolkit for speech analysis (Eyben et al., 2016)). Both for emotion eliciting and labelling, using standardized approaches not only reduces the workload required for designing a new experiment, but also brings benefits in terms of reproducibility and evaluation.

3.2 Clinical Integration and Applications in Anxiety Pathways

Ten studies proposed innovations suitable for clinical pathways (Cohn et al., 2018; Attas, 2022; Ding et al., 2021; Flechsenhar et al., 2024; Hinduja et al., 2024; Moussaoui et al., 2007; Olesen et al., 2023; Popovic et al., 2006; Provenza et al., 2021; Wörtwein & Scherer, 2017), while most of the works were more oriented towards pure scientific exploration, such as analysing alexithymia (i.e. the impairment of recognition and description of one's own emotional states) in ADs, or optimizing technological solutions such as ML models in AC for ADs, or improving our understanding of how people affected by ADs experience emotions and which are the characteristic differences that can help in detecting and monitoring them. (Bakker et al., 2014) underlined the importance of incorporating the dimension of Dominance to achieve a more comprehensive understanding of the emotional spectrum. Integrating Dominance poses a challenge due to the scarcity of datasets that label this dimension. Therefore, the development of more datasets including the three scales would be greatly valued for the research community (Verma & Tiwary, 2017). It is also been discussed that alterations in the dominance motivation, dominant and subordinate behaviour, and responsivity to perceptions of power and subordination are linked to a broad range of psychopathologies (Johnson et al., 2012).

Despite the consistent number of papers, there is a lack of prior work on detecting PTSD in daily activities, especially in non-military populations (Kalanadhabhatta et al., 2023). It is reasonable to assume that military organizations offer financial support for PTSD research given its correlation with combat experiences and provide easy environments for participant recruitment, mitigating two major research challenges. Hyperarousal is considered symptomatic in PTSD during re-experiencing traumatic memories (Fontana, 2022), and an altered disgust perception is considered a relevant feature in OCD (Serrano et al., 2019), hence they have been explored for detection and monitoring using affective computing solutions.

Moreover, not all the sub-disorders are equally represented: PTSD accounted for 21 out of the 38 selected papers (55.26%), while other sub-types such as OCD (n=6), SAD (n=5), generic ADs (n=4), and GAD (n=2) were underrepresented. This underlines a notable gap in the literature that might be filled by transposing to different sub-disorders approaches included in this review. 18 studies were based on data collected ex-novo, instead of pre-built dataset (n=11). This presented the researchers with the need to assess the presence and eventually the gravity of the ADs in their participants. The Hamilton Anxiety Rating Scale (HAM-A) was used for evaluating broad ADs (Ge et al., 2023), while specific tests were applied for the sub-types, including versions for adult or paediatric populations (on which 4 studies only where focused (Heyn et al., 2022; Kleberg et al., 2021; Olesen et al., 2023; Zeghari et al., 2023)), but also to verify the

Table 1: Data modalities used for emotion detection (the study marked with an * focuses on both PTSD and GAD).

Paper	Dataset	Speech	Facial expression	Accelerometer	Eye-tracking	Heart rate	Electroencephalogram (EEG)	Electrocardiogram (ECG)	Electrodermal activity (EDA)	Respiration	Text	Self-reported surveys	Body temperature	fMRI	Results
Studies focused on PTSD															
Suneetha, 2024	RAVDESS (Livingstone & Russo, 2018); EmoDB (Burkhardt et al., 2005)	✓													accuracy 98.11%, precision 98.53%, F1-score 98.68%
Dia et al., 2024	DAIC: 253 clinical interviews (Gratch et al., 2014)	✓	✓								✓				RMSE of 1.98
Hu et al., 2024	139 participants: 76 with and 63 without PTSD	✓													95% accuracy
Juliana et al., 2022	RAVDESS (Livingstone & Russo, 2018)	✓													98.68% accuracy
Kathan et al., 2023	15 female participants with (n=7) and without (n=8) PTSD	✓													32% accuracy for session-based prediction
Popovic et al., 2006		✓													
Wiegersma et al., 2020	BEPP (Gersons et al., 2000)	✓									✓				0.52 mean F1-score
Zeghari et al., 2023	60 children (7-15y) with PTSD	✓													
Stratou et al., 2015	53 semi-structured interviews for PTSD	✓	✓												
Kathan et al., 2024	ITW, 634 participants of which 317 with PTSD (Sawadogo et al., 2022); LMU: 7 participants with and 13 without PTSD (Kathan et al., 2023)	✓													AUC of 70.1 % cross-linguistically
Wörtwein & Scherer, 2017	114 (18-65y): 38 PTSD participants, 43 traumatized, 33 controls		✓												
Passardi et al., 2019			✓												
Flechsenhar et al., 2024	103 participants (24 with PTSD; 48 with other disorders; 31 controls)				✓										
Heyn et al., 2022	96 youth (7-17y) (PTSD, n = 48)				✓									✓	
Kalanadhabhatta et al., 2023	31 female adults with PTSD						✓	✓	✓	✓					0.91 F1-score
Chakravarthi et al., 2022	SEED-V (Lu and Zheng, 2023)							✓							
Mallol-Ragolta et al., 2018	EASE: 110 participants over 3 sessions (Dhamija & Boult, 2017)								✓			✓			
Sawalha et al., 2022	188 individuals without PTSD, and 87 with PTSD										✓				80.4% accuracy
*Gavrilescu & Vizireanu, 2020	128 participants (18-35y; 64 males and 64 females)		✓												93% accuracy for PTSD
Studies focused on OCD															
Hinduja et al., 2024	6 participants receiving DBS for refractory OCD	✓	✓		✓										
Cohn et al., 2018	BP4D (Zhang et al., 2014); 2 participants receiving DBS for refractory OCD		✓												
Ding et al., 2021	1 male participant completing a two-year long trial		✓												
Provenza et al., 2021			✓												
Olesen et al., 2023	18 children and adolescents with OCD (8-16y)			✓		✓			✓				✓		
Serrano et al., 2019	27 nonclinical (control) and OCD subclinical participants					✓									
Studies focused on SAD															
Madison et al., 2021	124 female undergraduate students	✓				✓									
Folz et al., 2023	57 participants (50 females and 7 males, age M=22.75, SD=3.27)		✓												
Boukhechba et al., 2018	20 participants with SAD			✓		✓									
Kleberg et al., 2021	100 (n=61 with SAD, and n=39 healthy controls, 10–17y);				✓										80% accuracy
Studies focused on ADs															
Attas, et al, 2022	54 participants (39% female, 16-74y)	✓													
Sundaravadivel et al., 2020					✓	✓									
Zhu et al., 2024	6082 social media posts containing the keyword "anxiety disorder"								✓						0.8742 accuracy and 0.8747 F1-score
Ge et al., 2023	46 adults scoring at least 14 in the HAMA											✓			
Studies focused on GAD															
Palm et al., 2011	31 participants (15 female GAD patients and 16 female controls)													✓	
*Gavrilescu & Vizireanu, 2020	128 participants (18-35y; 64 males and 64 females)		✓												85% accuracy for GAD

presence of comorbidities (e.g. depression). Some studies encountered challenges in recruiting male participants, resulting in either female-only studies (Kalanadhabhatta et al., 2023; Kathan et al., 2023) or deliberate focus on females only (Madison et al., 2021; Serrano et al., 2019).

3.3 Practical and Pragmatic Challenges

Gender and culture significantly influence our perception and emotional responses, affecting how mental health disorders are experienced and manifested (Maner et al., 2008; Stratou et al., 2015). In according to this assumption, gender-dependent models outperformed gender-agnostic approaches in PTSD, underscoring the importance of considering gender in AC machine learning models for ADs (Cohn et al., 2018). Some models trained on a language (e.g. Zhu et al., 2024) might not generalize that well when applied on other ones, as demonstrated by (Kathan et al., 2024).

As we navigate the realm of emotions, one of the most intimate aspects of human nature, it is imperative to prioritize the privacy and security of the frameworks proposed. However, apart from one exception (i.e. Dia et al., 2024), none of the selected papers gives substantial attention to the ethical implications of detecting emotions from individuals or the potential ramifications in future clinical integrations. However, it is crucial to consider the ethical dimensions surrounding emotion recognition technologies, particularly in mental health contexts.

Cameras and microphones, commonly used for emotion recognition, as confirmed by this review, are perceived as non-invasive sensors. Yet, their ease of data collection raises significant privacy concerns, potentially infringing on individuals' privacy rights without their consent or awareness. In contrast, physiological approaches offer users greater control over data acquisition and minimize the risk of manipulation compared to facial expression analysis. However, the deeper privacy implications of understanding individuals' emotions highlight the need for a cautious and ethical approach to prevent misuse and protect individual freedoms (Bunn, 2012).

The sensitive nature of emotion understanding underscores the importance of ethical considerations to prevent potential misuse and safeguard privacy rights. The EU AI Act, the first of its kind, recognizing ethical emotion detection as a critical task for AI, emphasizes the need for responsible practices in this area (European Parliament, 2023).

Additionally, recognizing gender and cultural differences in emotional expression and experience (Butler et al., 2007), it is imperative to collect diverse datasets to train and test AI models before deployment, ensuring inclusivity and avoiding biases.

Moreover, studies involving individuals with mental health conditions raise concerns about the potential triggering of anxiety-related crises during emotion elicitation tasks. While ethical approval is obtained from institutional review boards, and methodologies are often justified by their resemblance to clinical practices such as exposure therapy, further caution and attention to this matter are warranted. Consulting with patients and clinicians, ideally through a co-production approach, would not only aid in developing more relevant solutions but also ensure the design of more comfortable experimental settings.

4 CHALLENGES AND FUTURE DIRECTIONS

ML, and the Transformer architecture over all, has demonstrated promising results in emotion detection (Dia et al., 2024; Wagner et al., 2023), yet it demands a substantial quantity of data, a notable limitation in the affective computing field (Mustaqeem & Brahem, Haddou, 2023). One potential solution, already explored by some authors, is to apply transfer learning, leveraging large datasets for a specific data modality and fine-tuning the model for emotional recognition tasks using smaller, specific datasets (e.g. for ECG (Dentamaro et al., 2023)). Another avenue to expand available datasets is the utilization of synthetic data, which can train ML models before being tested on natural data (Ive, 2022). This approach also offers reduction of privacy concerns related to potentially sensitive data, and the potential to lessen bias by including rare cases that represent realistic possibilities but may be challenging to source from authentic data (Gonzales et al., 2023).

Most of the considered studies focus on one subtype of ADs exclusively: PTSD. Although this approach effectively narrows the scope and ensures adequate representation of subjects within the same subtype, it may compromise differential diagnosis. Specifically, it risks attributing certain patterns to a subtype simply because they differ from non-pathological cases, such as those in a control group or data collected at different time points from the same subject Chappidi (Kathan et al., 2023). While specific emotion-eliciting conditions may contextualize collected data, structuring studies to embrace a trans-diagnostic approach could benefit pragmatic solution development for clinical implementation. In this regard, a review work comparing ECG-based evaluations for different ADs sub-types, is particularly relevant (Elgendi & Menon, 2019).

More explorative research is welcomed and needed to fill the aforementioned gaps. However, it is hoped that, works justifying their limited number of recruited subjects as pilot studies, will be followed up with extended research, as exemplified by various works (Cohn et al., 2018; Provenza et al., 2021). Failure to do so poses the risk of accumulating hypothetical considerations that remain distant from concrete integration in clinical practice.

Digital solutions in mental health are affected by a significant usage drop-off rate (Nwosu et al., 2022). There is a risk of developing solutions for longitudinal data collection (e.g. in EMA) that fail due to user non-adherence. One solution to this issue would be to involve the public early on to incorporate their perspectives, as well as clinicians, to understand how to integrate patient preferences into scientifically useful applications. Co-design, also known as co-production, offers a valuable approach to mitigate these issues (Esmail et al., 2015), and there are already valuable examples of this approach for developing mental health digital solutions (Thieme et al., 2023).

5 LIMITATIONS OF THIS STUDY

This rapid literature review relies solely on two datasets. Expanding the research to other datasets (e.g. IEEE Xplore Digital Library, Prospero, Scopus, etc.) may uncover papers not included in this analysis. Moreover, a more systematic approach could be adopted by following specific guidelines for literature reviews, such as the Cochrane methods guidance (Garritty et al., 2024; Klerings et al., 2023).

Another intriguing aspect worth considering is the comparison between studies focused on an AC approach (i.e. involving emotion recognition) versus other feature extraction approaches. Is detecting emotions genuinely valuable? Is it appreciated by patients and clinicians as an understandable way to report and interpret collected data, particularly in longitudinal approaches?

From a technical standpoint, conducting a more in-depth analysis and comparison regarding the pre-processing techniques utilized in the reviewed studies to prepare the data for emotional feature extraction would be beneficial. This analysis could offer valuable insights into optimizing the data preparation process for future research endeavours in different data modalities for affective computing.

6 CONCLUSIONS

The latest findings indicate that affective computing (AC) holds significant potential to enhance current clinical pathways in anxiety disorders (ADs). While existing studies yield promising results, further research is essential.

The main insights underlined by this review could be summarised as follows:

- Some aspects are understudied, including gender differences, paediatric populations, some sub-disorders, and their differences.
- The most used data modalities are voice and facial expressions, while multimodal approaches seem to outperform unimodal ones.
- There is a lack of large, multimodal, and standardised AC datasets for ADs to enable direct comparisons between technical approaches and account for the diversity of approaches in this field.
- Promising results have been demonstrated in research and digital environments, but more in-the-wild data collection and clinical validations are needed.

By addressing these gaps through interdisciplinary collaboration, AC can transition from a promising research avenue to a valuable tool in clinical practice for anxiety disorders.

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