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Sensing and Interventions for Social Anxiety: A Review

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In recent years, there has been increasing interest in leveraging behavioural and physiological data to detect Social Anxiety (SA), with multimodal sensing and machine learning techniques showing significant promise. Concurrently, a growing body of research explores technology-assisted psychological interventions designed to improve treatment outcomes by addressing limitations in traditional therapies. These interventions aim to adapt to individual differences in anxiety levels, symptom severity and user preferences. This review presents a comprehensive overview of technical approaches to supporting individuals with SA, with a dual focus on advancements in sensing and intervention technologies. It synthesises emerging trends across disciplines, highlights existing research gaps and proposes directions for future work at the intersection of artificial intelligence, human-centred sensing and mental health support.

CCS Concepts: • **General and reference → Surveys and overviews**; • **Applied computing → Health informatics**; • **Computing methodologies → Artificial intelligence**.

Additional Key Words and Phrases: Social Anxiety, Social Anxiety Disorder, Sensing, Interventions, Diagnosis, Treatment

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1 Introduction

Social connectedness is among the most important predictors of a happy, healthy, fulfilling and meaningful life [168]. Rooted in our innate sociability, the capacity to cultivate and nurture meaningful and enriching connections through our interactions [91] is strongly linked to a sense of belonging and critical to our well-being [78]. The presence of discomfort in social settings, the desire to be alone and the unwillingness to keep in touch with others can be associated with **Social Anxiety (SA)**. Characterised by emotional discomfort, fear, apprehension, or worry regarding social situations and the potential of evaluation by others, SA often leads to avoidance of social situations.

In more severe cases, SA may become pervasive and debilitating, impairing daily functioning—a condition known as **Social Anxiety Disorder (SAD)** or social phobia [115]. SAD is prevalent and can significantly affect social interactions and quality of life [78]. It can be classified as specific or generalised [78]. Specific forms typically

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occur in performance situations, such as public speaking or musical performances [158], while generalised forms are triggered by nearly all social situations [78].

The experience of emotions such as fear, shame and embarrassment, as well as the capacity to regulate these emotions, are critical to SAD [77]. While the reported distress, functional impairment [123] and high rates of treatment attrition [15] underscore the need to enhance traditional clinical practices [102], it is equally important to recognise that most individuals experiencing SA do not meet diagnostic criteria due to their ability to avoid triggering social situations [57].

The very nature of SAD often hinders individuals from seeking professional help, as doing so typically involves engaging in the types of social interactions they fear most [90]. This paradox creates a significant barrier to early diagnosis and treatment. At the same time, emerging research suggests that technological innovations—such as virtual agents and **Socially Assistive Robots (SARs)**—may be well received by users in mental health contexts, particularly due to their potential to reduce the perceived threat of social evaluation [107]. These developments point to a promising role for technology in supporting individuals with SA. In particular, sensor-based systems may prove helpful in augmenting diagnosis by detecting socially anxious states and their associated bio-behaviours [149]. Furthermore, technology-enabled interventions may offer alternative and complementary pathways to treatment that may feel less intimidating than traditional face-to-face therapy [10, 83, 135, 151].

This article presents a *scoping review* [163] offering a comprehensive perspective on both sensing and intervention technologies specifically aimed at supporting individuals with *generalised SA*.

While *prior work* has provided valuable insights into technology in the broader context of mental health, most existing surveys focus either on mental health in general or on specific types of interventions. For instance, Preum et al. [131] reviewed existing cognitive assistants for healthcare based on characteristic features such as interactivity, context-awareness and adaptability. Woodward et al. [176] present a survey on emerging technologies for mental well-being from mobile applications to tangible feedback interfaces. Two meta-analyses examine the effectiveness of technology-assisted interventions for individuals across all anxiety disorders [125] and SAD [83]. More recent reviews by Shahid et al. [151] and Andersen et al. [10] emphasise the general effectiveness, safety, usability and acceptability of virtual reality interventions for treating adults with SAD and anxiety disorders, respectively. Similarly, Rasouli et al. [135] focus on the potential applications of social robots for SA. Various characteristics of anxiety disorders in adults are reviewed by Senaratne et al. [149] in addition to the application of multimodal-multisensor analytics based on these characteristics. Senaratne et al. [149] do explore multimodal sensing in the context of anxiety disorders, but do not examine the spectrum of interventions alongside it. Critically, this review bridges the gap between both the sensing and intervention aspects in the context of SA, providing an essential, end-to-end overview of how technology can be leveraged throughout the support pipeline—from detecting relevant states to delivering personalised and scalable interventions.

Structure of the Review. Section 2 presents the search and selection methodology supporting this scoping review. *Section 3* provides an introduction and overview of the theoretical foundations of SA and SAD, highlighting the significance of emotion and **Emotion Regulation (ER)** as well as the role of cultural and personality factors. *Section 4* covers conventional diagnostic criteria and treatments for SAD. *Section 5* reports the work connected to sensing for SA and SAD detection and details the research of technological interventions for SA and SAD. *Section 6* discusses the challenges, gaps, trends and future directions. Finally, *Section 7* presents the conclusions.

Figure 1 illustrates the relationship between conventional approaches for SAD, detailed in *Section 4* and sensing and interventions for SA and SAD, which are presented in *Section 5*.

2 Methodology

The preliminary stage of the process involved planning the review, which included defining the research objectives, designing the search strategy, outlining inclusion and exclusion criteria, setting quality evaluation standards and determining the data extraction methods for analysis, following the approach suggested in [164].

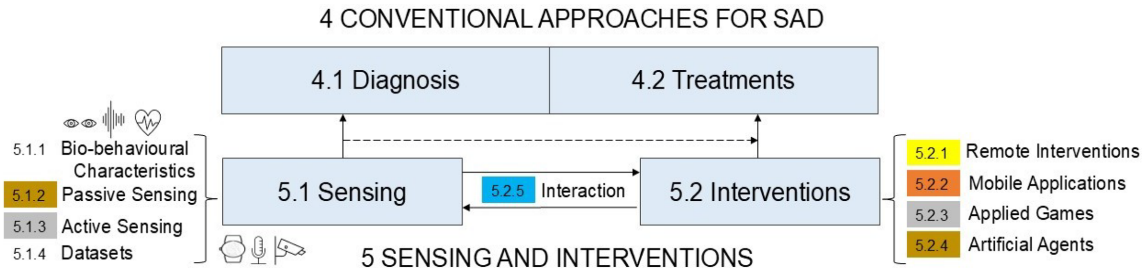

Fig. 1. Diagram mapping the relationship between clinical and technological concepts, indicating the manuscript sections in which each concept is addressed.

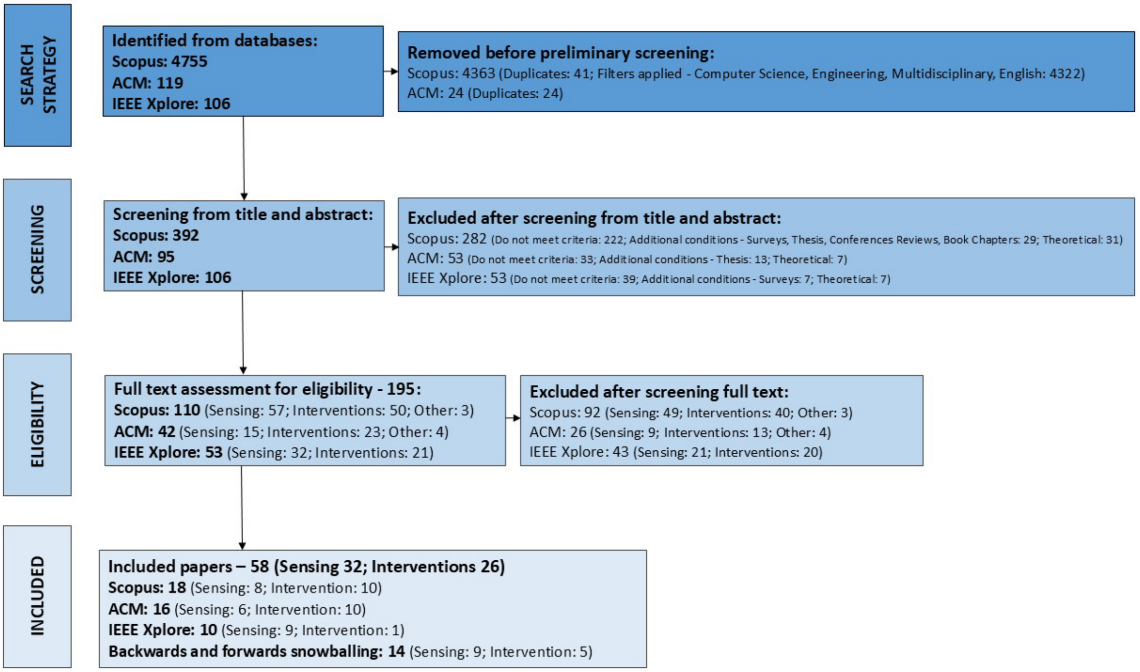

Fig. 2. Flow chart illustrating the process used to filter papers for consideration.

The *research objectives* of this review can be summarised as follows:

(1) Detailing the theoretical background of SA and SAD.
(2) Identifying the predictive characteristics for state-of-the-art automatic sensing and reviewing their application in the detection.
(3) Examining the state-of-the-art technological interventions.
(4) Revealing the current trends, critically evaluating the reviewed studies, identifying research gaps and challenges and proposing directions for future research.

Figure 2 visualises the process used to filter papers for consideration, adhering to the *PRISMA Extension for Scoping Reviews* framework guidelines [164].

Search Strategy. The search was conducted in August 2024 by aggregating the Scopus database, IEEE Xplore and ACM Digital Library to ensure the inclusion of the most pertinent literature. Papers published from 2014 to August 2024 were included. The following search string was crafted for Scopus: ((‘social anxiety’ OR ‘social phobia’ OR ‘social fear’) AND (‘intervention’ OR ‘therapy’ OR ‘support*’ OR ‘treat*’) AND (‘virtual*’ OR ‘agent*’ OR ‘*bot’ OR ‘*reality‘ OR ‘app*’ OR ‘system’)) OR ((‘social anxiety’ OR ‘social phobia’ OR ‘social fear’) AND (‘sens*’ OR ‘predict*’ OR ‘recogni*’ OR ‘detect*’)) to identify technological solutions for detection, interventions and their combination of generalised SA, which was applied for searching in abstracts and titles. The same search string returned a limited number of papers in IEEE Xplore and ACM Digital Library; consequently, the search string used for IEEE Xplore and ACM Digital Library was (‘social anxiety’ OR ‘social phobia’ OR ‘social fear’), and it was applied to titles and abstracts without additional restrictions to ensure the inclusion of all relevant technical papers.

Inclusion and Exclusion Criteria. Preliminary exclusion criteria for Scopus involved excluding papers that were not written in English or were not classified under ‘Computer Science’, ‘Engineering’, or ‘Multidisciplinary’. After *removing duplicates*, all paper titles and abstracts were screened as part of the *screening* phase. Given the diversity of technological approaches addressing generalised SA, the inclusion and exclusion criteria were defined in accordance with the methodology recommended by [126]. More specifically, the *inclusion criteria* were as follows: papers that examined the automatic detection of generalised SA, papers focused on identifying or characterising sensing modalities for detection, papers that presented interventions for generalised SA and papers that combined both sensing and intervention approaches. During the screening, additional papers meeting the following *exclusion criteria*: papers covering specific social anxieties, position papers, papers that were not in peer-reviewed journals and conference proceedings, surveys, theses, conference reviews, book chapters were excluded. Only papers that met these inclusion and exclusion criteria were deemed eligible for full-text assessment to proceed within this review. After the selected papers were obtained, they underwent a comprehensive *full-text assessment* by the first author, during which additional exclusions were applied in line with the pre-defined inclusion and exclusion criteria, following guidelines by [95]. When multiple papers reported the same research at different stages or iterations, only the most recent and comprehensive version was selected for inclusion. A full-text quality assessment was conducted through multiple iterations, involving an in-depth review of each paper, with any uncertainties regarding eligibility resolved through systematic evaluation of each paper with respect to study design, analysis and conclusions to determine *eligibility* for final inclusion. Additionally, a number of papers were added through *snowballing techniques*, including both forward citation tracking and backward citation searching, from the eligible pool of papers.

Data Extraction and Analysis. As final steps, this process involved extracting information from the selected papers and identifying relevant data that will help achieve the objectives of this review. A set of questions was formulated to facilitate the summarisation, consolidation and analysis of the presented studies:

- What are the key research questions investigated within the context of SA?
- Which kind of modalities are used and what type of sensing?
- What types of interventions are featured in the study and how are these interventions assessed?
- What findings and outcomes emerge from the study?
- How do these outcomes contribute to knowledge acquisition, offering insights, lessons, or guidelines? (Note: In some papers, this may overlap with the previous question.)
- Does the paper present challenges and outline future research directions?

Following a full-text assessment of the included papers, relevant information was identified and used to define the dimensions for data extraction for both sensing (see Table 3) and interventions (see Table 9). A separate set of dimensions was also defined to enable systematic comparisons across the types of sensing (see Table 6) and intervention types (see Table 13).

3 Background of SA and SAD

SAD is a common mental disorder that is fairly prevalent worldwide, occurring in as much as 13% of the population [78]. Although it typically manifests at a young age [1], its course can be chronic and lifelong [78]. The key feature of SAD is a persistent fear of social situations in which feelings of embarrassment or humiliation may occur [1]. This persistent fear about experiencing the scrutiny of others is so prominent that individuals with this condition either completely avoid social situations or endure them with extreme discomfort [158] despite their desire for social relationships [61]. SAD can manifest in specific forms such as performance situations [158] or as a *generalised SAD* that can be triggered by nearly all situations and is considered more chronic [78].

Individuals with SAD often exhibit shyness [127], quietness in groups and withdrawal in unfamiliar social settings [158], leading to their SA symptoms being mistaken for shyness by others [127]. When they interact with others, they usually show evidence of discomfort, such as blushing and not making eye contact, invariably experiencing intense emotional and/or physical symptoms [158]. Exposure to such situations often leads to physical symptoms such as sweating, shaking, heart racing, garbled speech, dizziness, nausea, muscle tension, gastrointestinal distress, respiratory distress and difficulty concentrating [158].

Subthreshold or Subclinical SA refers to symptoms of SA that do not meet the criteria for a diagnosis of SAD. SA is widespread, with recent studies indicating an increase in the frequency of these symptoms after the COVID-19 pandemic [94]. Most individuals who experience SA do not meet the diagnostic criteria for SAD due to their ability to avoid triggering social situations [57]. Despite arising in different situations [1], SA can vary between individuals and contexts, with certain situations, such as interacting with unfamiliar people, eliciting more SA than others [37]. A distinction can also be made between trait and state SA, with *trait SA* representing relatively stable individual differences and *state SA* indicating an emotional condition of tension and apprehension that refers to the moment-to-moment experience of those feelings, thus being more fluctuant and context dependent [88].

The Influence of Emotions and ER. Individuals with SAD experience a persistent and intense emotion of fear [158] often triggered in anticipation of or during social interactions. These emotional experiences can be difficult to regulate, which can make navigating social situations challenging.

A review of emotional constructs in SAD by Rozen and Aderka [138] suggests that individuals with SAD may have a reduced ability to perceive, label, express and understand their own emotions (i.e., both compared to individuals without the disorder as well as compared to individuals with other anxiety disorders). Although SAD has been historically associated with shame and embarrassment, the literature suggests that it may also be related to several additional emotions, such as anger, loneliness, envy and pride [138].

ER is a common intrapersonal process that, along with self-referential processes (i.e., central to the generation of negative self-beliefs and images) and cognitive processes (e.g., attention, interpretation and memory), involves an interplay of content and processes regarding self and others [56]. These processes are informed by the motivations and goals surrounding social interactions and are essential determinants of how individuals respond to social stress [56]. ER refers to the ability to manage, modify and evaluate one's emotional expression and responses [64]. There are two broad kinds of ER strategies: antecedent-focused strategies used before the emotional response has fully begun and response-focused strategies used once the emotional response is ongoing [63, 65].

ER for SAD represents how individuals might try to mitigate negative emotions during a social situation [77], using avoidance and approach-oriented strategies [31], suppression of emotions [138], cognitive reappraisal (i.e., reinterpreting negative beliefs) [35, 138], or acceptance (i.e., experiencing thoughts and emotions without judgement) [35]. In the context of SAD, individuals employ both maladaptive ER strategies, such as rumination [139] and adaptive ER strategies to prevent emotions associated with phobic stimuli from forming [183].

The Role of Cultural and Personality Factors. Research shows that an individual's culture and personality can affect the development, expression and experience of SAD. Hofmann et al. [69] suggest that SAD symptoms and

their experience might be influenced by multiple culture-connected factors. They illustrate that certain factors, such as individualism/collectivism, social norms, self-construals, gender role and gender role identification, vary by culture and hence lead to a different trajectory of SAD [69]. Xu et al. [177] examine gender differences and show that SAD tends to be slightly more prevalent among women than men. However, these differences are relatively small and include variations in symptom presentations and rates of treatment seeking. Kaplan et al. [86] assess the relationship between SA and personality. Their results show that neuroticism is positively associated with SA symptoms [86]. In addition, they find extraversion, agreeableness and openness to experience to be negatively associated with SA symptoms, suggesting that high levels of openness may prevent SA as individuals who are curious and open to novel experiences may be less likely to avoid situations they fear [86]. Both Kaplan et al. [86] and Norton et al. [122] suggest that specific personality traits such as high neuroticism and low extraversion increase the likelihood of individuals developing SA symptoms. Similarly, Rukmini et al. [139] highlight the role of perfectionism as a maintaining factor in SA.

Impact. The potential impact of this condition on quality of life includes limited job and leisure opportunities due to reduced social contact, self-isolating at home and an increased risk of self-medication through substance abuse [1]. Additionally, a wider range of co-morbid conditions is recognised to include Depression, Autism Spectrum Conditions and **Attention Deficit Hyperactivity Disorder (ADHD)**, for which SA is relevant and a concern [158].

4 Conventional Approaches for SAD

Conventional approaches for SAD consist of conventional diagnostic criteria and treatments. Diagnosis typically includes standardised questionnaires to evaluate symptoms, while treatments often consist of therapy combined with pharmacotherapy for alleviation.

4.1 SAD Diagnosis

An individual can be diagnosed with SAD if they meet the diagnostic criteria for SAD defined according to the fifth edition of the **Diagnostic and Statistical Manual of Mental Disorders (DSM-V)** [1].

Techniques available to clinicians include structured and semi-structured clinical interviews, self-report or clinician-administered rating scales and observations. These clinical interviews rely on individuals' subjective inputs for diagnosing the presence of SAD [66]. The following rating scales [109] are noteworthy: the **Liebowitz Social Anxiety Scale (LSAS)** [49], the **Social Phobia Scale (SPS)** [109], the **Social Phobia Inventory (SPIN)** [28], the **Social Interaction Anxiety Scale (SIAS)** [109], as well as the **Positive and Negative Affect Schedule (PANAS)**, which is frequently used to measure state affect. Many standard questionnaires are available online and can be used for receiving preliminary assessments [66]. Behavioural assessment methods, including behavioural interviews and behavioural observations, are also used with socially anxious individuals [58]. These current standards rely on clinicians' subjective judgements that depend on their expertise and clinical background [66].

One approach that provides insights into the context and variability of SA symptoms is **Ecological Momentary Assessment (EMA)** [153]. EMA involves frequent, brief assessments delivered via smartphones, wearables, or other digital devices at random or pre-specified times during the day. It may be used to track SA states and to identify triggering situations and hence to provide insights into the context and variability of SA symptoms for different individuals.

Ongoing Challenges in clinical practice relate to the differential diagnosis and prognosis of SAD. These are further complicated due to the frequent co-occurrence of SAD with one or more mood disorders, other anxiety disorders and substance abuse disorders [78]. Additionally, many individuals with SA rely on avoidance strategies [57] that reduce visibility in clinical settings and hinder formal identification.

4.2 Treatments for SAD

Conventional treatments for SAD address behaviours, cognitions and beliefs related to SAD and are frequently employed in conjunction with pharmacotherapy.

Cognitive Behavioural Therapy (CBT), delivered individually or in groups by a qualified therapist, is the most widely used psychotherapeutic treatment for SAD [78]. Grounded in cognitive and behavioural psychology, CBT combines cognitive methods (e.g., cognitive restructuring) and behavioural techniques (e.g., exposure) [162] to help individuals understand the relationship between thoughts, feelings and behaviours and to reframe maladaptive reactions [103]. **Exposure Therapy (ET)**, a key component of CBT [14], utilises the principles of emotional processing and fear structure to guide exposure-based CBT [46]. By collaboratively creating a hierarchy of feared situations, therapists and individuals with SAD work to challenge maladaptive beliefs and promote habituation and symptom reduction [46]. Strategies such as maximising the discrepancy between feared and actual outcomes and reducing safety signals or behaviours, further enhance the efficacy of exposure-based interventions [29, 30].

Cognitive Bias Modification (CBM) for SAD is shown to provide benefits [106]. According to the cognitive models of SAD, SA is associated with cognitive biases (i.e., attention bias and interpretation bias) in the processing of emotional information [106]. Individuals with SA automatically and selectively attend to socially threatening information and use ambiguous phrases or paragraphs to interpret emotionally ambiguous events as threatening [106]. CBM can reduce SAD by modifying attention and interpretation biases that involve repeated practice on cognitive tasks [13].

Social Skills Training is often implemented as a treatment for SAD that includes therapist corrective feedback, social reinforcement and behavioural rehearsal for individuals with SAD [68]. It may be easily combined with exposure and may provide benefits due to the training aspects and the exposure aspects (e.g., confrontation of feared situations) [68].

Biofeedback is a self-regulation training technique that enables individuals to gain voluntary control over their psychophysiological state by monitoring biological responses [48]. It helps with awareness of the thoughts, feelings and behaviours and supports learning to self-regulate [48]. Sessions typically take place in a therapist's office with the necessary equipment, and given the strong physiological aspects of SA, biofeedback is particularly relevant as a treatment [48].

Mindfulness as a treatment for SAD is relatively new. It focuses on encouraging individuals to be present at the moment, observing their feelings and thoughts without judgement, increasing the awareness of their feelings and thoughts, learning to distance from self-critical cognitions and helping to reduce distressing physiological symptoms [16, 97].

Treatment Barriers for individuals with SAD include treatment avoidance due to the belief that they can manage their symptoms, a characteristic fear of both negative and positive evaluation by others and financial barriers [123]. Additionally, qualified therapists are often hard to find [78], which further complicates access to necessary care. Despite the reported distress, functional impairment and feelings of social isolation [123], there exists a notable trend of treatment avoidance and attrition in SAD [15]. Only half of all individuals seek treatment, often pursuing it after years of experiencing the symptoms [78, 158]. This care avoidance indicates the potential benefit of using technology.

5 Sensing and Interventions

While conventional approaches provide a foundation for diagnosing and treating SAD, the increasing prevalence of the condition and the shortage of qualified therapists underscore the need for innovative solutions. Moreover, as many individuals with SA do not meet the diagnostic criteria for SAD due to their ability to avoid triggering

Table 1. List of All Papers Identified Using PRISMA Organised by Sensing and Interventions

Sensing/ interventions	Paper category	Paper subcategory	List of references
Sensing			
	Characteristics	Physiological	[5, 6, 9, 73, 147]
		Behavioural	[2, 47, 59, 62, 70, 74, 98, 110]
	Passive sensing	Smartphone-based	[21, 60, 75, 76, 79, 134]
		Wearable sensing	[152]
		EEG-based	[8, 111, 112]
	Active sensing		[33, 40, 140, 142, 150, 169]
	Datasets		[19, 39, 148]
Interventions			
	Remote interventions		[36, 121, 165]
	Mobile applications		[124, 137]
	Applied games		[17, 22, 50, 53, 104]
	Artificial agents	VRET	[18, 67, 82, 93, 178]
		Virtual audiences	[32, 81, 85, 100, 132, 159]
		SARs	[119, 182]
	Interventions with sensing		[20, 26, 181]

EEG, electroencephalography; VRET, virtual reality exposure therapy; SARs, socially assistive robots.
Papers [21, 60, 76, 79, 140, 150, 152] are listed and counted under their respective passive and active sensing paper categories/subcategories, although they are also discussed in the corresponding SA characteristics parts. Paper [142] is counted under active sensing, while it is also discussed under the datasets.
Total number of papers = 58.
Total number of papers for sensing = 32.
Total number of papers for interventions = 26.

social situations, alternative forms of support are needed. Technological advancements have the potential to enhance the understanding, design, implementation and evaluation of solutions to detect SA.

This section reviews automatic sensing for SAD detection as a potential complement to conventional diagnostic methods, as well as its use in detecting subclinical SA as an alternative approach. It also outlines the diverse technological interventions for SA and SAD, while noting that the combination of both sensing and intervention remains promising yet limited. The methodological issues identified across the studies reviewed are connected to small and medium sample sizes, various forms of bias, study designs and limited replicability, with some studies focusing on subclinical SA. The references of all papers included in this section, as identified using PRISMA, are reported in Table 1, organised by sensing and interventions.

5.1 Automatic Sensing in the Context of SA

Conventional methods (e.g., semi-structured diagnostic interviews, self-reported measures and behavioural measures) offer distinct insights and provide different types of information that may be relevant for diagnosis. However, they rely on individuals' subjective inputs as well as clinicians' subjective judgments [66]. Automatic sensing can contribute to diminishing this subjectivity by providing objective measurements.

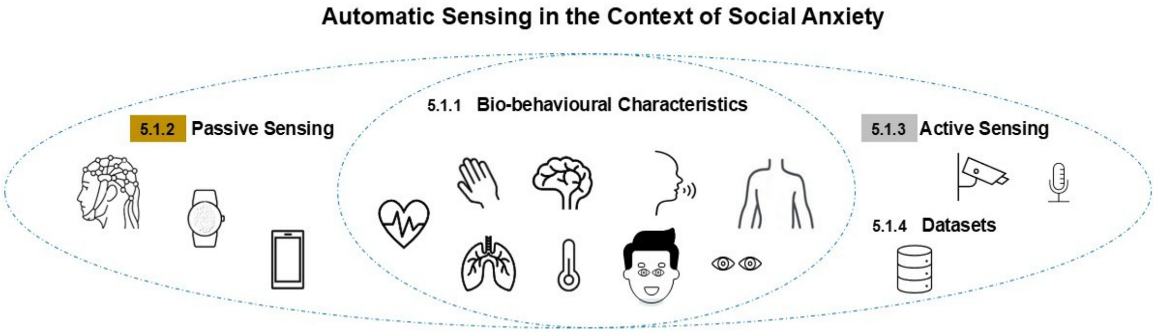

Fig. 3. Visual overview of the sensing types and bio-behavioural characteristics associated with SA.

Over the past decade, there has been a growing interest in investigating *machine and deep learning algorithms* to distinguish affect-related states and associated behaviours. Unimodal and multimodal sensing have been used to gather data from one or multiple types of sensors or modalities, respectively. *Unimodal sensing* focuses on one specific kind of input, such as visual or auditory information. In contrast, *multimodal sensing* integrates data from multiple sensors or modalities, allowing for a richer, more comprehensive understanding by combining diverse types of inputs together. If the data are collected in the background with minimal input from the individual, it is considered *passive sensing*, whereas *active sensing* refers to the form of sensing in which individuals interact in some specific way to allow data collection. Figure 3 provides a visual overview of the sensing types and characteristics associated with SA, summarising the main aspects discussed in this subsection.

5.1.1 Bio-Behavioural Characteristics. Individuals with SA may experience a wide range of behaviours and changes in physiology when the SA occurs. Scherer et al. [144] have noted that observable behaviour is a complex interplay between push factors that are physiologically driven and pull factors, which are governed by how emotional expressions are regulated to follow social norms and the desired perception of self. This section outlines a set of physiological and behavioural characteristics of SAD that can potentially be used for automatic sensing. To illustrate, recent research has identified blushing [118], avoidance of social situations where one might perform poorly and attempts to distract others from signs of one's SA [45] often occur in SAD. Physiological responses, including cardiovascular changes and **Electrodermal Activity (EDA)**, provide valuable insights into the understanding of SA. In addition to this, behavioural indicators such as vocalisations, speech patterns and posture further contribute to the overall picture. The combination of these characteristics, when analysed through sophisticated machine or deep learning algorithms, offers the potential for the development of more accurate models for detecting SA. However, improving detection requires careful consideration of additional factors, such as social context and individual differences [87].

Figure 4 synthesises the physiological and behavioural characteristics of SA, with arrows indicating the direction of observed trends.

Physiological Characteristics. Physiological characteristics and measures are one potential way to objectively detect SA. The presence of a possible threat triggers affect different bodily systems, including the cardiovascular, electrodermal, respiratory and nervous systems.

Cardiovascular Measures, which are linked to cardiovascular activity, can provide valuable insights into how the body reacts during socially anxious situations.

— **Heart Rate (HR)**, which refers to the heart beats per time interval, is often studied in relation to SA, with research discovering significantly higher HRs in response to social triggers [73, 146].

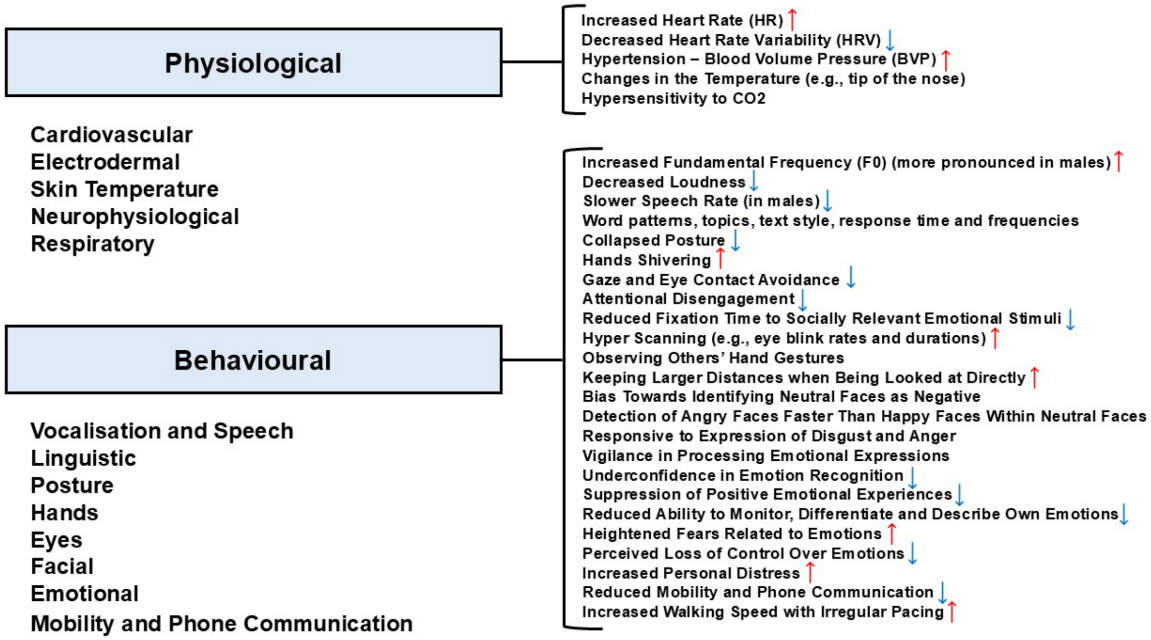

Fig. 4. Bio-behavioural characteristics of SA.

- **Heart Rate Variability (HRV)** is the difference in time intervals between successive heart beats; studies have demonstrated decreased HRV during socially anxious states in response to social triggers [160, 184]. However, while HRV appears reduced for SA, it is also reduced across anxiety disorders and several other conditions [160].
- *Blood Volume Pressure* is the pressure that blood flow exerts against the walls of blood vessels. SAD has been associated with hypertension [157]; however, recent findings indicate a lack of support for the association between blood pressure and SA in younger individuals.

Electrodermal Measures are connected to the changes in the electrical properties of the skin, indicating how well the skin conducts electricity in relation to sweat secretion. EDA has been identified as an effective singular modality when differentiating between baseline and SA states [152].

Skin Temperature Measures are also associated with SA. It has been identified as an effective modality in individuals with SA of differing severity [152]. Another study that emphasises the importance of thermography [42] has studied thermal changes in different body regions, especially facial regions, and has shown a tip-of-the-nose thermal change as a physiological index associated with SA.

Neurophysiological Measures refer to brain functions captured through various modalities, such as the frequently used magnetic resonance imaging and **Electroencephalography (EEG)**. EEG, in particular, offers a less invasive and cost-effective method to study the electrophysiological and cognitive states of the human brain [7]. These measures are encouraging in illustrating the neural correlations of SAD [7]. One study indicates the regional Fuzzy Entropy measures as putative in detecting the symptoms of SAD when analysing the EEG complexity of SAD individuals [5]. Similarly, the involvement of the phase slope index algorithm in alpha oscillations to estimate **Effective Connectivity (EC)** network might provide higher recognition of SAD level due to its sensitivity to characterise it [9]. Frontal Theta-Beta Ratio and **Frontal Midline Theta (FMT)** are also suggested as possible

neurophysiological markers for SAD [6]. This concept of slow wave/fast wave and FMT may provide a useful tool in studying affect and the neural mechanism of ER [6].

Respiratory Measures can be assessed in different ways, with a positive association between CO_2 hypersensitivity and SA symptoms being reported [147].

Behavioural Characteristics. Several behavioural characteristics and measures are related to SA.

Vocalisation and Speech Measures refer to vocal activity, a primary mode of human communication used to express emotions, and to linguistic speech content, which is connected to the cognitive symptoms of SA.

- *Fundamental Frequency (F0)*, which refers to the rate of vibrations of vocal cords, is a measure of vocal pitch. The relationship between vocal pitch and SA indicates that an increased F0 serves as a marker, with more pronounced changes observed in males [105, 170, 173].
- *Chroma 9* (the ninth feature within the 12 chroma features category) shows a notable correlation with SA severity [140]. Chroma features are typically associated with music and tone, and limited literature assesses their relationship with SA [140].
- *Loudness* reflects the energy and intensity of vocalisations. SA has been correlated to decreases or lesser increases in loudness [105, 154].
- *Speech Rate* has also been studied in relation to SA. In men, SA has been associated with a slower speech rate, whereas this association has not been observed in women [105, 154].
- *Speech Disfluencies*, such as increased pauses and other impairments, have also been linked to SA [105, 154].

Linguistic Measures that refer to writing patterns are used for the prediction of therapeutic outcomes by analysing patterns of the words, sentiments, topics and the style of text [59, 70]. A correlation is identified between SA and several text features, such as response times and frequencies [70].

Posture Measures provide insights into affective states through observation. Collapsed posture has been associated with SA [170].

Hand Measures such as hand shivering have a positive relation with SA [79].

Eye Measures, such as gaze avoidance, have been identified as a marker of SAD in response to both positive and negative social feedback [27, 171, 172]. Additionally, individuals diagnosed with SAD exhibit attentional disengagement, reduced total fixation time to socially relevant emotional stimuli [25], alongside hyperscanning, eye blink rates and durations [62]. However, findings suggest that individuals with SAD despite avoiding eye contact [150], still monitor others' emotions by closely observing their hand gestures [99]. Supplementary findings show that individuals with SA keep larger distances when being looked at directly, indicating a nuanced interplay of gaze, proxemics and SA [110].

Facial Measures are related to the way how individuals with SA exhibit a bias towards identifying briefly presented negative and neutral faces as negative [175] and detect angry faces faster than happy faces within a group of neutral faces [55]. In SA, perceptual biases are directed towards others' faces, opposite to the focus of general emotion detection research, which examines the signals expressed by the individuals themselves.

Emotional Measures are closely linked to the conveyance of information about feelings and intentions from one person to another [89]. Research demonstrates that individuals with SA have vigilance in processing emotional expression [98], underconfidence in emotion recognition [47, 74] and tend to strongly suppress their emotional experiences [155], particularly positive emotions [166]. They also have a reduced ability to monitor, differentiate and describe their own emotions and experience heightened fears related to emotions and a perceived loss of control over them [155]. Moreover, they are particularly responsive to expressions of disgust or anger [2]. While highly socially anxious individuals report experiencing more personal distress, they do not differ in empathic concern [74].

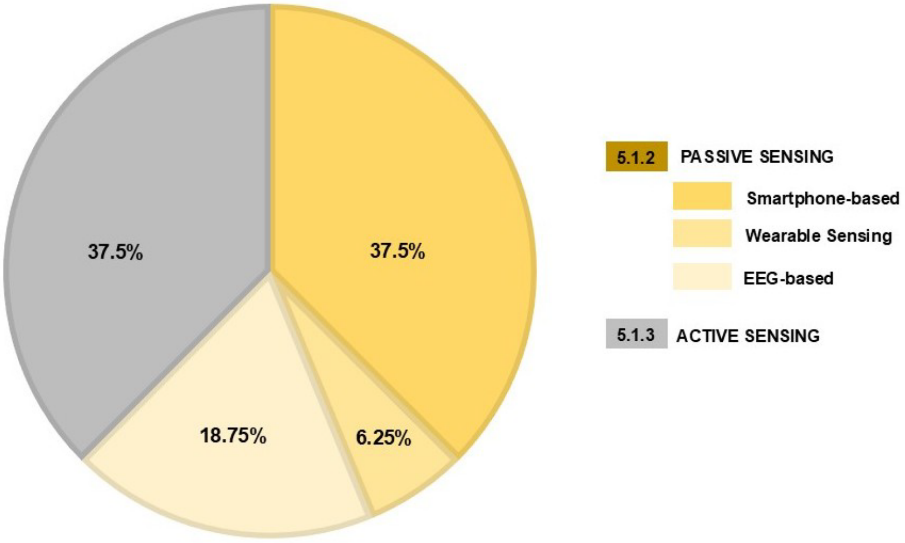

Fig. 5. Distribution of included papers categorised on sensing types.

Table 2. Sensing Papers Identified and Selected Following PRISMA, Categorised on Sensing Types

Paper category	Paper subcategory	List of references
Passive Sensing (Section 5.1.2)	Smartphone-based	[21, 60, 75, 76, 79, 134]
	Wearable sensing	[152]
	EEG-based	[8, 111, 112]
Active Sensing (Section 5.1.3)		[33, 40, 140, 142, 150, 169]

Mobility and Phone Communication Measures represent behavioural characteristics associated with SA, characterised by increased walking speed with irregular pacing [76] as well as reduced mobility and phone communication [21], especially in unfamiliar locations [60].

Distribution of Papers by Sensing Types. Figure 5 shows the percentage distribution of included papers by sensing type, and Table 2 provides lists of selected papers by sensing type. A larger proportion of papers focus on passive sensing compared with active sensing. Within passive sensing, smartphone-based solutions account for 37.5% of papers, which is the same proportion as in active sensing. Wearable sensing accounts for 18.75% of the sensing papers, while EEG-based sensing represents 6.25%. A detailed analysis of the selected papers within each sensing type was conducted to support a synthesis aimed at identifying key trends and gaps in existing research.

Table 3 provides an overview of the dimensions used for data extraction from the selected papers, while detailed study characteristics for passive and active sensing papers are summarised in Tables 4 and 5, respectively. Cross-sensing comparisons are presented in Table 6.

5.1.2 Passive Sensing. Passive sensing that collects physiological, behavioural and brain activity data has been implemented for the detection of SA. This includes a range of studies that have investigated smartphone-based sensing, wearable devices such as wristbands, or EEG-based sensing through brain monitoring.

Table 3. Overview of Dimensions Used for Data Extraction and Comparison of Sensing Types in Selected Papers

Data extraction	
Dimension	**Description**
Ref.	Citation reference number of the included study
Study	Description of the study design/objective
SA/SAD	Condition examined in the study (SA or SAD)
Data size	Type and length of data (e.g., video samples 5 minutes)
Sample size	Total number of participants in the study
Age (mean)	Mean age of the participants (e.g., adults (32.51); WHO age categories)
Ground truth	Reference data
Data types	Nature of the data used
Method and principle	Algorithms used and validation
Performance/results	Reported metrics (e.g., accuracy, F1 score) and results

Smartphone-Based Sensing. A study that uses a sample of 59 adult participants from a public dataset [19] combines behavioural metrics for detecting SA by collecting passive data from smartphones (e.g., movement patterns and social contact such as incoming and outgoing calls and texts) captured over 2 weeks [76]. They derive features and then combine them using a late fusion technique and an XGBoost model (i.e., Extreme Gradient Boosting Machine). One of the conclusions of this study is that individuals with high SA may exhibit walking patterns characterised by increased speed, reduced confidence, or irregular pacing; however, further research is needed to evaluate the relevance of these metrics. Their results indicate that SA symptom severity can be accurately predicted using passive sensor data (i.e., $r = 0.702$ between predicted and observed symptom severity) and demonstrate discriminant validity between depression, negative affect and positive affect. A study of 50 adult participants based on GPS location, text messages and call data collected over a 2-week period, reports that high SA levels are associated with a narrower range of activities (i.e., accuracy of SA level prediction with mobility and communication data of 85%) [21]. Another similar study of 52 adult participants using behavioural markers extracted from smartphone data over a 2-week period and an accelerometer reveals a significant difference in behaviours for individuals based on SA levels and locations when comparing individuals with high and low SA around the time of phone calls, especially in an unfamiliar location [60]. A study of 80 socially anxious adult participants combines behavioural metrics over a 5-week period for detecting SA from smartphones using a Mixed-Effects RF model (i.e., an extension of the **Random Forest (RF)** model), RF model and Catboost (i.e., Boosting ensemble-based machine learning method) [134]. This study explores the predictability of seven different self-reported dimensions of SA (i.e., related to perceived social effectiveness, social enjoyment, perceived social acceptance, social avoidance, concern about evaluation, negative affect and anxiety) and four imputation methods to handle missing data. It evaluates the effectiveness of predicting subjective measures from passive data and shows that the imputation of missing data reduces prediction error. A study of 32 adult participants uses smartphone sensing (e.g., HR, HRV and GPS location) and a personalised LSTM (i.e., Long short-term memory) to predict future symptoms as well as hour-to-hour changes in symptoms, among individuals with scores in the clinical range of well-validated self-report measures for SA predicting the majority of total variation in anxiety symptoms [75]. Another study proposes an architecture for detecting SA, using smartphone image data to obtain hand shivering and negative thinking patterns using Simplified-Fast-AlexNet and **Decision Trees (DT)** with respective accuracies (96.56% and 98.54%) [79]. Smartphone-based studies suggest certain behavioural characteristics associated with SA, particularly including a positive relation of SA with hand shivering [79],

Table 4. Details of the Included Sensing Studies—Passive Sensing

Ref.	Study	SA/ SAD	Data size	Sample size	Age (mean)	Ground truth	Data type	Method and principle	Performance/ results
Passive Sensing (Section 5.1.2)—Smartphone-Based; Wearable Sensing; EEG-Based									
[76]	Lab visit (SA screening) + App. + Lab visit 2 weeks later	SA	2 weeks	59	Adults (19.8)	SIAS DASS PANAS	Calls Texts Accelerometer	XGboost	SA prediction accuracy (r = 0.702) Discriminant validity between depression, negative and positive affect
[21]	Lab visit (SA screening) + App. + Lab visit 2 weeks later	SA	2 weeks	50	Adults (NR)	SIAS	Calls Texts GPS	Predictive model with Pearson correlation (cross-validation)	SA level predict.–mobility (Acc 67%) SA level predict.–mobility+ communicat. (Acc 85%) High SA connected to narrower range of activities
[60]	Lab visit (SA screening) + App. + Lab visit 2 weeks later	SA	2 weeks	52 (20.5)	Adults	SIAS	Calls, Textx, GPS, Accelerometer	Prediction with Linear Dynamic Model	SA level (high and low) significant behaviour diff. (phone calls and unfamiliar locations)
[134]	SA screening + App.	SA	5 weeks	80	Adults (20.51)	SIAS 7 SR dim.	Calls, Texts, GPS, Activity, Accelerometer, Pedometer	RF Catboost MERF (5-fold cross-validation)	High correlation of predicted values with respective observed values (r = 6.2, all p-values < 0.01) Imputation of missing data reduces prediction error
[75]	Lab visit (SA screening) + App. + Lab visit 8 days later	SA	1 week (hourly)	32	Adults (19.56)	SPDQ PANAS	HR, HRV, GPS	LSTM	Prediction of variation in SA symptoms ($R^2 = 0.748$) Prediction of within-person variation ($R^2 = 0.385$)
[79]	SA insight from image data from smartphone	SA	NR	NR	NR	NR	Hand shivering Negative TP	Simplified-Fast-Alexnet DT	SFA (Accuracy 96.56%; F Score 95.76%) DT (Accuracy 98.53%)
[152]	Speech task three contexts: (1) Baseline and SA (2) Baseline, anticipation, reactive (3) SA among ind. with different severity	SA	NR	12	Adults (NR)	LSAS-SR	HR EDA ST	SVM DT RF kNN (10-fold cross-validation)	Combined modalities SVM (Acc: 99.48%; 98.10%; 99.52%) Singular modality HR—kNN (Acc: 68.18%; 53.91%; 72.00%) EDA—kNN (Acc: 80.46%; 70.02%); RF (Acc: 75.96%) ST—kNN (Acc: 76.30%; 68.32%; 89.47%)
[8]	Resting-state condition for SAD detection	SAD	6 minutes	88	NR	SIAS	EC	CNN LSTM CNN+LSTM	SAD (severe, moderate and mild) and HC CNN + LSTM outperforms the other models Accuracy 92.86%; 92.86%; 96.43% and 89.29% Sensitivities 85.71%, 85.71%, 87.50% and 83.33% Specificities 95.24%, 95.24%, 100% and 90.91%
[111]	Two models of EEG spatial configuration	SAD	2-7 minutes session	64	NR	NR	34 EEG data channels	SVM kNN CNN (8-fold cross-validation)	Model I CNN (Accuracy 80%; Sensitivity 81%; Specificity 78%) Model II CNN (Accuracy 87%; Sensitivity 90%; Specificity 84%)
[112]	Two tasks: (1) SAD classification (2) emotion analysis	SAD	4 minutes 40 minutes sessions	64 32	NR	NR	32 EEG data channels	SVM, kNN, CNN, (7-fold cross-validation, LOOCV, LOSOCV)	SAD dataset CNN (Accuracy 92.19%; F1 Score 92.31%) DEAP dataset Energy and entropy CNN outperforms in all cases

DT, decision trees. See Appendix A, Table A1 for abbreviations.

increased walking speed with irregular pacing [76] and reduced mobility and communication (i.e., phone calls) [21], especially in unfamiliar locations [60] (see Table 4 for details). Overall, these methods are non-invasive, practical, assess SA and have been applied to medium-sized adult samples, demonstrating moderate efficacy and potential for ecological validity (see Table 6).

Wearable Sensing. A study of 12 participants (i.e., mean age not reported; described by the authors as young) with self-reported subclinical SA (i.e., measured using the LSAS) and physiological data (e.g., HR, skin temperature and EDA obtained from Empatica E4 wristband uses a supervised machine learning approach and various

Table 5. Details of the Included Sensing Studies—Active Sensing

Ref.	Study	SA/ SAD	Data size	Sample size	Age (mean)	Ground truth	Data type	Method and principle	Performance/ results
Active Sensing (Section 5.1.3)									
[40]	Text for SAD detection	SAD	NR	214	Adults (30.96)	SPIN LSAS	Emotional char. Physical char.	ANFIS (NN + fuzzy logic) (5-fold cross-validation)	NN (Accuracy 98.67%)
[169]	Dyadic conversations for State SA detection	SA	Audio samples	35	Adults (19.45)	SIAS DASS BFNES DERS	Acoustic Syntactic Lexical	kNN SVM XGboost MLP, RF	Personalised detection outperformed baseline models (Accuracy 75.55%, Precision 74.64%, F Score 74.69%)
[140]	Speech for SAD detection	SAD	Audio samples 2.5 minutes	105	Adults (21.05)	SPIN	Acoustic Linguistic	CNN, RF, SVM, kNN, LR, NN	Only acoustic (LR; Accuracy 85.71%, Precision 92.86%) Only linguistic (RF; Accuracy 85, 71%, Precision 82.35%) (CNN; audio—Accuracy 76.19%, Precision 70.00%)
[150]	Using gaze for SAD detection	SAD	Video samples 5 minutes	50	Adults (NR)	LSAS	Gaze	DT Haar Cascade	SAD detection (four classes) with accuracy above 70% Higher SA connected to gaze avoidance
[33]	Differential detection SAD ASD and EP	SAD	NR	83	Adults (22.34)	SIAS	Cognition Memory Mood	RF BART (10-fold cross-validation)	SAD and ASD shared feature empathy SAD and EP shared feature attention SAD has a high level of co-morbid depression
[142]	Spontaneous speech for SA detection	SA	Audio samples 3 minutes	101	Adults (19.24)	SIAS SPS	Audio	BLSTM-MIL (weakly supervised)	SA (F1 score 90.1%, Accuracy 90%) State SA (F1 score of 93.49%, Accuracy 90.2%)

See Appendix A, Table A1 for abbreviations.

Table 6. Cross-Sensing Comparisons

Sensing type	Sensing subtype	SA/SAD	Sample size	Population	Practicality	Invasiveness	Efficacy	Ecological validity
Passive Sensing (Section 5.1.2)	Smartphone-based Wearable sensing EEG-based	SA SA SAD	Medium Small Medium	Adults Adults N/A	Yes Yes No	Non-invasive Minimally Invasive	Moderate High Moderate	Potential Potential Low
Active Sensing (Section 5.1.3)		Both	Large	Adults	No	Non-invasive	Moderate	Low

SA/SAD = Mean Category; SA, subclinical; SAD, diagnosed disorder; both, SA/SAD.
Sample Size = Mean Category; Small (<25), Medium (25–50) and Large (>50).
Population = Mean Category; Children (0–12), Adolescents (13–17), Adults (18–64) and Elderly (65+) (WHO age categories).
Practicality = Category; No and Yes.
Invasiveness = Category; Non-invasive, Minimally, Invasive.
Efficacy = Mean Category; Low, Moderate, High (dependent on accuracy).
Ecological Validity = Category; Low, Potential and High.
N/A indicates that the information was not available in the original studies.

classification algorithms such as **Support Vector Machine (SVM)**, DT, RF and **k-Nearest Neighbours (kNN)** [152]. This study identifies EDA as the most effective singular modality when differentiating between baseline and SA states (i.e., kNN; accuracy of 80.46%), whereas skin temperature is identified as the most effective modality when differentiating anxiety among individuals with SA of differing severity (i.e., kNN; 89.47%). They yield

higher accuracies when combining all modalities, with SVM outperforming other algorithms (see Table 4 for details). Wearables, minimally invasive sensors, such as the Empatica E4, offer a practical approach with potential ecological validity and high efficacy; however, the study is limited by a small sample of adult participants with SA (see Table 6).

EEG-Based Sensing. Mokarten et al. [111] detect SAD based on EEG signals by utilising the spatial configuration of the EEG electrodes in a classification task, applying various sensing algorithms such as SVM, kNN and **Convolutional Neural Networks (CNN)**. They achieve the best performance accuracy with CNN, and when taking advantage of the channel positions, the CNN shows a 7% improvement in accuracy compared with the same CNN configuration that ignores channel positions. In their later study [112], they assess the effectiveness using two EEG datasets: SAD for patient/control classification and DEAP for emotion recognition [96] and achieve the best results with CNN among the investigated algorithms (see Table 4 for details). A study of 88 participants evaluates deep learning models (i.e., CNN, LSTM and CNN+LSTM) for the classification of SAD severity level based on EC from EEG signals [8], and CNN + LSTM outperfoms the others across severe, moderate, mild SAD and healthy controls, achieving high accuracy (see Table 4 for details). They demonstrate that using EC features holds promising potential for the emerging field of deep learning in understanding neuroimaging biomarkers. EEG-based approaches are relatively invasive, not practical and exhibit moderate efficacy and low ecological validity because of laboratory-based acquisition, and they have been investigated using medium-sized samples of adult participants with SAD (see Table 6).

Using passive sensing, such as smartphone-based or wrist-worn wearables, might help to ensure that participants remain comfortable and free from distractions, nervousness, or additional anxiety. In addition to accuracy, comfort is particularly important for vulnerable populations [167]. Other than to wrist-worn wearable devices, smart socks or earables might offer additional benefits for individuals with SA. The proximity of earables to the brain enables them to detect complex modalities such as EEG [12], which might make them applicable in this context. Moreover, Noori et al. [120] approach demonstrates the potential for non-invasive physiological monitoring in virtual environments, particularly in applications like SA analysing head movement data captured through a virtual reality to predict HR.

5.1.3 Active Sensing. Active sensing, from audio, video and text, is also used to detect SA. Studies mentioned in this section focus on active sensing for SA detection as well as for differential detection, allowing for the distinction between SA and other mental health conditions.

Fathi et al. [40] present a design of a system for detecting SAD from text using a public dataset of 214 adult participants collected from an online-based repository [39], reporting accuracy of 98.67%. They employ an adaptive neuro-fuzzy method for classification, which is a combination of fuzzy logic to solve uncertainties and ambiguities, and a **Neural Network (NN)** to manage noisy data. The ability of personalised machine learning to detect state SA from linguistic biomarkers is tested by Wang et al. [169]. They propose a personalised machine learning pipeline that progressively trains the model according to different domain knowledge (i.e., contextual and subgroup), outperforming (i.e., accuracy of 74.55%) baseline models (i.e., kNN, SVM and RF). Sahu et al. [140] use speech for SAD detection, identifying correlations between extracted features and SAD severity and comparing classical machine learning (i.e., kNN, SVM, RF and NN) and deep learning algorithms (i.e., CNN). Their results demonstrate that both acoustic and linguistic machine learning individually outperform when combined and deep learning (i.e., they attribute CNN accuracy to the limited sample size) (see Table 5 for details). This study also indicates a notable correlation between the Chroma 9 acoustic feature and SA severity. A weakly supervised learning framework Bidirectional Long Short-Term Memory—Multiple Instance Learning for detecting SA and depression from long audio clips that includes a novel feature modelling technique is developed by Salekin et al. [142]. They propose a weakly supervised learning framework achieving higher scores than those of the best available baselines showing SA detection from audio data with an F1 score of 90.1% and an accuracy of 90%.

Table 7. Overview of Publicly Available Datasets on SA

Dataset	Sample size	Modalities	Labels	Dataset size	Publicly available
DemonicSalmon (Boukhechba al. [19])	59	GPS, accelerometer, calls and texts	Positive mood or negative mood, high SA, or low SA	2-week sensing period	Yes
(Salekin et al. [142])	101	Audio (spontaneous speech)	Presence or absence of symptoms	3-minute samples per person	Yes
(Fathi et al. [39])	214	Text	SAD/no SAD	Text repository (size not reported) of demographic, emotional and physical symptoms	Yes
Anxiety phases dataset (Senaratne al. [148])	95	Physiological, audio and video	High anxiety or low anxiety	3-minute samples per person	Partial access

Shafique et al. [150] propose an automatic technique to detect SAD using gaze interaction/avoidance that uses the Haar Cascade classifier with 50 adult participants and show that higher levels of SA are associated with increased gaze avoidance. Another study uses machine learning RF and Bayesian Additive Regression Trees for differential detection between Autism (**Autism Spectrum Disorder (ASD)**), **Early Psychosis (EP)** and SAD with 83 adult participants [33]. They detect shared profile features, which might provide a framework for identifying transdiagnostic dimensions, including empathy that SAD shares with ASD, attention that SAD shares with EP, and the high level of co-morbid depression observed in SAD.

Active sensing shows promising results, and its potential of presonalisation might allow more tailored solutions. However, better use of affective signals, such as facial cues that provide deeper insights into emotional states, together with the integration of multiple modalities, might enhance detection. Taken together, active sensing studies address both SA and SAD, are non-invasive and typically conducted on large adult samples, yet remain impractical due to their controlled nature and reliance on audio and video recordings, exhibiting moderate efficacy and low ecological validity (see Table 6).

Cross-Sensing Comparisons. Table 6 summarises comparisons across different types and subtypes of sensing.

As summarised in Table 6, passive sensing approaches, including smartphone-based and wearables, are non-invasive and minimally invasive, respectively, generally practical and applied to small-to-medium adult samples, demonstrating moderate-to-high efficacy with potential for ecological validity. EEG-based passive sensing performed on medium-sized adult samples, in contrast, relies on invasive equipment, is laboratory based and shows moderate efficacy with low ecological validity. Active sensing approaches, although non-invasive, are typically less practical, applied to large adult samples and exhibit moderate efficacy with low ecological validity. Reported performances are influenced by differences in experimental conditions, sample sizes, labelling and evaluation criteria, highlighting the need for standardised benchmarking. Overall, passive sensing tends to balance practicality, invasiveness and ecological validity better than active sensing, whereas active sensing may require more controlled settings and resources despite being non-invasive. Findings from sensing studies on subthreshold SA are regarded as relevant for SAD, given their shared behavioural markers and assessment objectives.

5.1.4 Datasets. Sensing research is not possible without high-quality datasets. Currently, only a limited number of datasets are available as open datasets for SA; some of them restrict open access due to ethical concerns. Table 7 provides an overview of existing publicly available datasets, indicating whether each dataset is fully public or partially accessible. These datasets are described in greater detail herein.

Boukhechba et al. [19] collected the DemonicSalmon dataset that consists of data collected from 59 participants over a 2-week period. They incorporated both self-reported measures, including SIAS and PANAS, as well as an impromptu speech task. They monitored college students day-to-day using a passive sensing mobile app Sensus to collect GPS location data every 150 seconds, accelerometer data (1 Hz) and call and text logs over the course of the study. Limitations of this dataset: important events, particularly in the late evening or early morning, may not have been captured.

Salekin et al. [142] collected data from students of different ethnicities, selected based on a screening survey at the start of the semester that included the SIAS and an item from the SPS. Task: Participants were instructed to give an approximately 3-minute speech on things they liked and disliked about college or their hometown. Spontaneous speech samples consisted of 3-minute segments that were weakly labelled. Right after the speech, participants were asked to report their peak level of SA during the speech.

Fathi et al. [39, 40] collected a text repository on the attributes of SAD based on DSM-V criteria, categorising data into demographic, emotional and physical symptoms from 214 participants through a web site. Subsequently, two standard tests, the SPIN and the LSAS, were used to assess participants for SAD. Taking the LSAS test was optional and served to validate the results of the SPIN test as a part of the triangulation method. Some participants were excluded from the study due to inconsistencies in their test results. Their target variable for the study was the outcome of these tests.

Senaratne et al. [148] collected data from 95 young adults recruited through advertising at a university, psychology clinics and local social media groups, including mental health support groups. All participants were free of other clinically diagnosed mental health disorders, though co-morbid depression was common among those who had received support. To minimise potential effects on physiological and behavioural measures, participants were excluded based on several criteria, including medication use, non-English speaking and a diagnosis of panic disorders. The study included two counterbalanced tasks designed to induce two common presentations of anxiety: a bug phobia task and a speech anxiety task, which involved giving a 3-minute speech on the most challenging of three provided topics. Aside from the differences in triggers, both tasks shared similar components. The participants were asked to describe their feelings and actions during each task and to complete a post-study questionnaire. During the study, various sensors captured physiological data (e.g., electrocardiogram and skin resistance) and behavioural data of participants through audio and video recordings.

Datasets integrating recordings from multiple sources, such as physiological signals, behavioural observations and ground truth in the form of self-reports or external observations, are key in furthering research on SA sensing and interventions. However, their collection comes with challenges, such as participant recruitment, ecological validity, recording quality in various environments, data loss and ethical and privacy concerns.

5.2 Technological Interventions for SA

Technological interventions have been developed to enhance support for users with SA and SAD by increasing treatment efficacy and addressing shortcomings of existing treatments regarding access, acceptance and implementation. Among these innovations, **Internet-Delivered Cognitive Behavioural Therapy (iCBT)** is one of the earliest methods used to provide structured therapy remotely. Mobile applications further enhance accessibility, offering users real-time support. Applied games introduce an interactive element, allowing users to engage in simulated scenarios. Additionally, artificial agents, such as SARs, emerge as a particularly promising avenue for delivering support.

Figure 6 provides a visual overview of the intervention types for SA that are covered in this subsection.

Distribution of Papers by Intervention Types. Figure 7 shows the percentage distribution of included papers by intervention type, and Table 8 provides lists of selected papers by intervention type. Overall, the distribution of studies across intervention types is fairly even. The broader category of artificial agent-based interventions

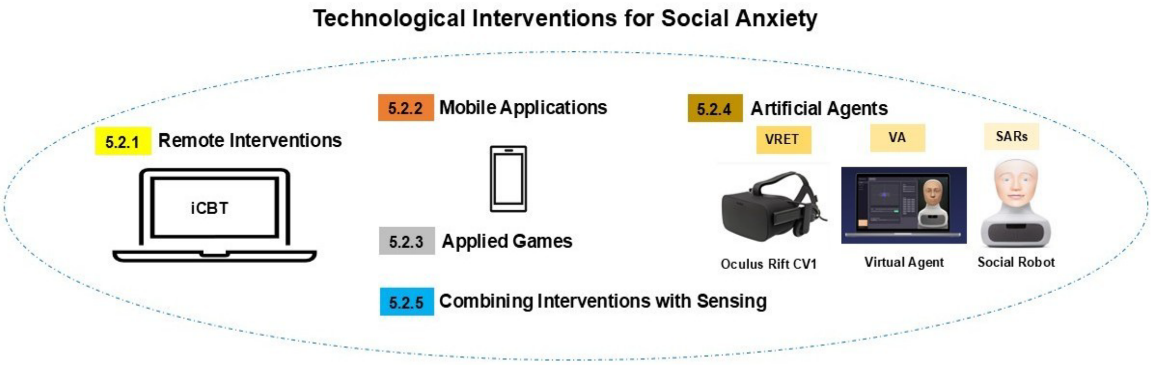

Fig. 6. Visual overview of the intervention types for SA.

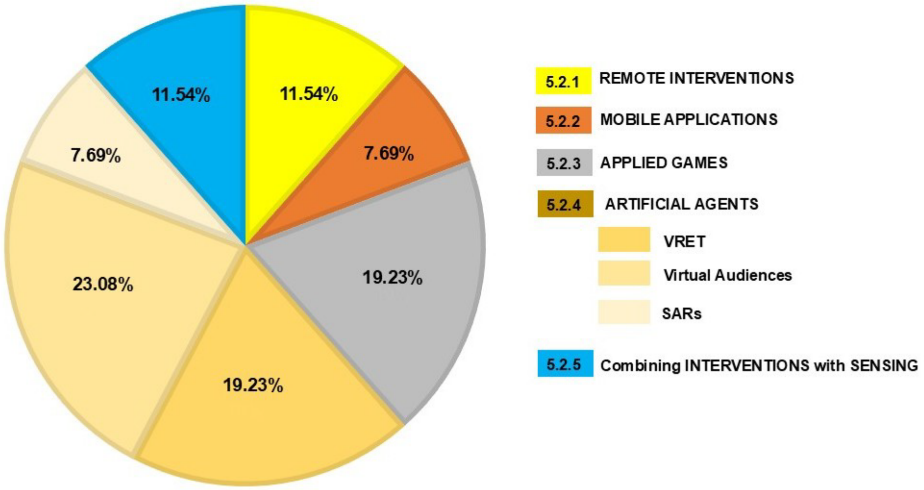

Fig. 7. Distribution of included papers categorised on intervention types.

accounts for the largest proportion of papers, with virtual audiences the most common type, accounting for 23.08% of the papers. Both **Virtual Reality Exposure Therapy (VRET)** and applied games each represent 19.23% of interventions, while remote interventions and interventions incorporating sensing each account for the same percentage of 11.54%. Mobile applications and SARs are less frequently represented, each comprising 7.69% of the papers. For each intervention type, the selected papers are analysed in detail, forming the basis for a synthesis that highlights key trends and research gaps.

Table 9 provides an overview of the dimensions used for data extraction from the selected papers, while detailed study characteristics are summarised in Tables 10–12. Cross-intervention comparisons are presented in Table 13.

5.2.1 Remote Interventions. Remote interventions, such as iCBT for SAD, offer a potential to enhance access to treatment by overcoming economic, geographic and psychological barriers [174]. iCBT uses technology to provide structured, guided or unguided CBT lessons or modules online. To date, iCBT is the most used format for delivering remote CBT treatment [174].

Table 8. Intervention Papers Identified and Selected Following PRISMA, Categorised on Intervention Types

Paper category	Paper subcategory	List of references
Remote Interventions (Section 5.2.1)		[36, 121, 165]
Mobile Applications (Section 5.2.2)		[124, 137]
Applied Games (Section 5.2.3)		[17, 22, 50, 53, 104]
Artificial Agents (Section 5.2.4)	VRET	[18, 67, 82, 93, 178]
	Virtual audiences	[32, 81, 85, 100, 132, 159]
	SARs	[119, 182]
Combining Interventions with Sensing (Section 5.2.5)		[20, 26, 181]

Table 9. Overview of Dimensions Used for Data Extraction and Comparison of Intervention Types in Selected Papers

Data extraction	
Dimension	**Description**
Ref.	Citation reference number of the included study
Study goal	Study objective(s) as stated by the authors
Study type	Type of study (e.g., Randomised Control Trial—RCT)
Study design	Specific study design
SA/SAD	Condition examined in the study (SA and/or SAD)
Guided	Guidance by a therapist (No or Yes)
Study duration	Length of the study period (e.g., weeks)
Sample Size	Total number of participants in the study
Age (mean)	Mean age of the participants (e.g., adults (32.51); WHO age categories)
Screening	Screening method used to identify SA/SAD (e.g., specific SA questionnaire)
Outcome measures	Methods used to assess outcomes
Results	Key results/main findings of the study
Recommendations	Key recommendations reported by the authors

The iCBT studies that are included in this review (see Table 10), each employ therapist-supported (i.e., guided) iCBT for SAD. The study conducted on a large sample of 764 adults over a 4-year period [36] indicates that co-morbid ADHD and male gender are associated with poorer treatment outcomes. Satisfaction and recovery rates near or below 50% [36, 121] suggest moderate user acceptance, highlighting the potential value of personalisation [36, 165], addressing the co-morbid condition of ADHD [36] and including motivational strategies to support adherence and engagement [165]. Overall, these studies on guided iCBT for SAD with adult participants indicate moderate efficacy, potential for scalable delivery, moderate cost and moderate ecological validity (see Table 13).

5.2.2 Mobile Applications. Mobile applications are beneficial due to their accessibility and affordability compared to traditional psychotherapy. They primarily incorporate the principles of CBT, which is recognised as an effective therapeutic approach for treating SA [78].

Designed by a multidisciplinary team, the SPICA mobile app [124] provides cognitive behavioural interventions for students undergoing therapy for SAD, with evaluations demonstrating usability scores above average. Another

Table 10. Details of the Included Intervention Studies—Remote Interventions, Mobile Applications and Applied Games

Ref.	Study goal	Study type	Study design	SA/ SAD	Guided	Study duration	Sample size	Age (mean)	Screening	Outcome measures	Results	Recommendations
Remote Interventions (Section 5.2.1)												
[36]	Adherence predictors	Observational	Sequential online modules Homework	SAD	Yes	4 years	764	Adults (32.51)	MINI	Weekly LSAS-SR Treatment adherence	Higher adherence (SAD history) Lower adherence (ADHD, males)	iCBT for severe SAD Personalisation (ADHD screen)
[121]	Effect of psychoeducation	RCT	Two conditions: (1) psychoeducation + iCBT (2) iCBT	SAD	Yes	NR	37	Adults (25.6)	MINI SPS BDI	Post-treatment: SPS, SIAS 6 months follow-up	Psychoeducation (no effect) Recovery rate nearly 50%	NR
[165]	Efficacy of iCBT	RCT	Two conditions: (1) iCBT (SAD) (2) wait-list control (SA)	SA/ SAD	Yes	9 weeks	76	Adults (30.57)	LSAS-SR SPIN	Same questionnaires Telephone interview with therapist	Recovery rate 34.2% Satisfaction 40% and 46%	Personalisation Adherence with motivational interviews
Mobile Applications (Section 5.2.2)												
[124]	Usability evaluation	App Co-Design	CBT intervention	NR	Yes	NR	10	Adults (24.6)	NR	SUS	Usability scores above average	NR
[137]	Support reflection with lifelogging	App Design with lifelogging and recording	Mobile CBT Tasks	SA/ SAD	No	NR	NR	NR	NR	Daily multimodal data (GPS, HR, video, audio)	NR	NR
Applied Games (Section 5.2.3)												
[17]	Gamified app benefits evaluation	RCT	Three conditions: (1) App and SH (6 weeks parallel) (2) SH then app (6 weeks seq.) (3) wait-list group	SAD	No	12 weeks	209	Adults (35.40)	LSAS-SR PHQ-9 GAD-7 QUOLI	LSAS-SR PHQ-9 GAD-7 QUOLI	Less SA (active users) 6 weeks treatment (d = 0.3)	Further investigation to improve engagement
[53]	Gamified app benefits evaluation	SSMB	CBT intervention (stages and levels)	SA	No	4 weeks	10	Adults (19)	LSAS-SR BFNES	LSAS-SR BFNES	Decrease in SA scores Completion rate (75.71%)	Further investigation to increase motivation
[22]	Serious game evaluation	SeqMM	CBT skills serious game	NR	No	NR	71	Adults (NR)	NR	Interviews UES-SF (HR, galvanic skin resp.)	Narrative understanding Focused attention Perceived usability	Personalisation for emotional engagement
[50]	Game streaming potential evaluation	WSD BSD	Two studies: (1) Game effectiveness (2) Effects in ET	SA	No	NR	50 331	Adults (36.8) (39.12)	LSAS	Familiarity Comfort Fear	Expected fear positively associated with SA scores (above 30)	Personalisation (for engagement) Co-design
[104]	Increase engagement Complement therapy	PGT	Two elements: CR CBT and ET CBT (role playing with voice control)	SAD	No	NR	10	NR	LSAS	SUS UES	Usability score (80.75%) Engagement score (3.73) Improved CBT knowledge	NR

See Appendix A, Table A1 for abbreviations.

mobile application is FaceIt [137], which combines several facets of guided lifelogging to assist in meeting the challenges of completing CBT tasks. Although one application was co-designed with therapist input without empirical evaluation and the other was evaluated in healthy participants, both demonstrate notable methodological aspects, including therapist-informed co-design and the consideration of multimodal data for SA assessment (see Table 10). The mobile application interventions for SA and SAD with adult participants show mixed therapist involvement, partial evidence on efficacy, limited scalability, low cost and low ecological validity (see Table 13).

5.2.3 Applied Games. Applied games, including gamification (i.e., gaming elements used outside of games) and serious games (i.e., computerised games for serious purposes), have the potential to increase the impact of mental health interventions by improving engagement and motivating change due to their appealing potential [44]. Existing applied games for SA are predominantly based on CBT techniques.

Gamification. A high rate of completion of 75.71% and a decrease of SA scores is shown with a gamification-based mobile application [53]. They nonetheless suggest further investigations into gamification as a potential mechanism for increasing adherence and motivation. Challenger [17] suggests exposure exercises by incorporating

Table 11. Details of the Included Intervention Studies—Artificial Agents

Ref.	Study goal	Study type	Study design	SA/ SAD	Guided	Study duration	Sample size	Age (mean)	Screening	Outcome measures	Results	Recommendations
Artificial Agents (Section 5.2.4)—VRET; Virtual Audiences; SARs												
[18]	Effectiveness of VR exposure in CBT for SAD	RCT	Three conditions: (1) CBT in VRET (2) CBT *in vivo* exposure (3) Waiting list	SAD	Yes	14 weekly 60 minutes Sessions	59	Adults (34.5)	LSAS-SR SPS, SIAS FNE, BDI	LSAS-SR SPS, SIAS FNE, BDI	CBT in VRET more effective than *in vivo* (6 months) Therapist preference CBT in VRET	Conducting RCT with matched stimuli between conditions
[67]	Explore stimuli during virtual exposure	WSD	Two studies: (1) Three scenarios (2) Two scenarios	SA	No	Several Sessions	16 24	Adults (22.4)	SIAS	SUD, IPQ, DEQ (HR)	Effective manipulation of social dialogues for therapeutic purposes	NR
[82]	Effectiveness of VR exposure in CBT for SAD	RCT	Three conditions: (1) Individual VRET (2) Individual *in vivo* exposure (3) waiting list	SAD	Yes	2 x weeks 90 minutes Sessions	60	Adults (36.9)	SIAS	LSAS-SR FNE, DASS, PDBQ	VRET is effective *In vivo* exposure superior	Flexible and extensive dialogues to enhance VRET Personalisation
[93]	Effectiveness of VR (interact. and partic.)	NR	VR intervention (three stages and two difficult levels)	SAD	No	Six Sessions	66	Adults (23)	SIAS SPS	List of 10 questionnaires	Significant effect, but users still exhibit symptoms after session	NR
[178]	Efficacy of self-guided VRET	RCT	Two conditions: (1) self-guided VRET (2) waiting list	SAD	No	Four Sessions	44	Adults (NR)	MINI	SIAS SPDQ PHQ	VRET efficacy for SAD and comorbidities	Complementary VRET program to therapy
[32]	Affect of the customisation of avatar	BSD	Two conditions: (1) predefined character (2) customised character	SA	No	Online Session	200	Adults (36.6)	LSAS	Fear PIS	Effect on SA on fear stronger with customised avatars	Customisation of the avatar for more committed users to the intervention
[81]	SA and agents' anthropomorphism	BSD	Two studies: (1) anthropomorphism and SA (2) personality and SA	SA	No	Online Sessions	279 607	Adults (39) (41)	SPIN	Anthropomorphism BFPT	High SA prefer anthropomorphic agents and greater tolerance for mismatch personality	NR
[85]	SA and contingency of agents' non verbal feedback	NR	Four conditions: different agent contingency and real human	NR	No	Several Sessions	131	Adults (37.5)	NR	SA Questions Shyness Self-Consciousness	Users with more SA less trust to real humans	NR
[100]	Explore level of realism of avatar	RBD	Different levels of avatars: (1) realistic 3D human avatar (2) cartoon-like 3D avatar (3) human photographs	NR	No	NR	60	Adults (25.95)	NR	Eyes avoidance behaviour Blinking percent rate	More SA in accordance with attitude of avatars than avatar's realism	NR
[132]	SA and agents synthetic emotions and human response	WSD	Six conditions with listening and speaking phase with emotional agent	SA	No	1 Session	24	Adults (26.4)	PRCS	DEQ SAM	Less speaking confidence, more negative emotions and less satisfaction	NR
[159]	Exploring the effect of social skills training system	BSD	Two conditions: (1) with training (2) without training	SA	No	4 weeks	26	Adults (27)	STAI LSAS	STAI, LSAS, GSES, SRS	Improved self-efficacy ($p = 0.02$) Reduced SA ($p = 0.04$)	NR
[119]	Explore SA when interacting with a robot	MSD	Two conditions: (1) role-play with human (2) role-play with robot	SA	No	One Session	19	Adults (21.3)	SADS	STAI-S POMS	Robot interaction causes less tension than human regardless the SA level	NR
[182]	Explore adoption of robotic training partner	NR	Two studies: (1) chose; (2) adopt robotic training partner	SA	No	NR	100 127	Adults (22)	SAS	Sense of relaxation Adoption intention	High willingness to choose and adopt to robotic training partner	NR

See Appendix A, Table A1 for abbreviations.

the principles of CBT and gamification. Their studies show that more active users benefit from using this application; however, future studies are needed to investigate how to motivate users to use the application more frequently [17].

Serious Games. SoulSkipper is a voice-controlled emotionally adaptive game based on using CBT to complement therapy for SAD [104]. Through their initial evaluation, they find that combining game elements with voice interactions helps players enhance their awareness of therapeutic skills related to SAD and approach social interactions in real-life scenarios more positively. Frommel et al. [50] propose game streaming as an ET paradigm for SA, provide evidence of elevated fear as an essential component of effective ET and recommend personalisation

Table 12. Details of the Included Intervention Studies—Combining Interventions with Sensing

Ref.	Study goal	Study type	Study design	SA/ SAD	Guided	Study duration	Sample size	Age (mean)	Screening	Outcome measures	Results	Recommendations
Combining Interventions with Sensing (Section 5.2.5)												
[20]	Explore Computerised CBM	NR	Smartphone-based CBM intervention using physiological sensor data	SAD	No	3 weeks 2 Sessions	20	Adults (NR)	SIAS	BSIQ, RRQ, EMA, (GPS, HR, accelerometer, skin conduct.)	Relationship between accelerometer and HR for CBM intervention	NR
[26]	SA severity VR sickness using ML in RT	NR	*In situ* PS (physio. signals) during VR treatment	SAD	No	6 Sessions	26	Adults (NR)	MINI	ML: LR, RF and naïve Bayes ISS, PERS, SSQ (HR, GSR)	Performance F1 score: LR (0.8421), RF (0.7059), naïve Bayes (0.7619)	NR
[181]	Alleviate SA with CBT system	SE	CBT system based on DL	SAD	No	NR	100	Adolesc. (16)	NR	Correlation prediction model based on multiobjective evolutionary algorithm	CBT system has good effect on social ability improvement	NR

See Appendix A, Table A1 for abbreviations.

Table 13. Cross-Intervention Comparisons

Intervention type	Intervention subtype	SA/SAD	Population	Therapist involvement	Efficacy	Scalability	Cost	Ecological validity
Remote Interventions (Section 5.2.1)		SAD	Adults	Yes	Moderate	Potential	Moderate	Moderate
Mobile Applications (Section 5.2.2)		Both	Adults	Mixed	N/A	Limited	Low	Low
Applied Games (Section 5.2.3)		Both	Adults	No	Moderate	Potential	Low	Moderate
Artificial Agents (Section 5.2.4)	VRET Virtual Audiences SARs	Both SA SA	Adults Adults Adults	Mixed No No	Moderate N/A Moderate	Potential Potential Potential	Moderate Moderate Moderate	Moderate Moderate Moderate
Combining Interventions with Sensing (Section 5.2.5)		SAD	Adolescents	No	N/A	Limited	Moderate	Low

SA/SAD = Mean Category; SA—subclinical, SAD—diagnosed disorder, Both—SA/SAD.
Population = Mean Category; Children (0–12), Adolescents (13-17), Adults (18-64), Elderly (65+) (WHO age categories).
Therapist Involvement = Category; No—non, Mixed—some studies, Yes—all studies.
Efficacy = Mean Category; Low, Moderate, High (dependent on accuracy).
Scalability = Category; Limited, Potential, Scalable.
Cost = Category; Low—minimal, Moderate—some, High—extensive.
Ecological Validity = Category; Low, Moderate, High.
N/A indicates that the information was not available in the original.

and co-design with experts to enhance engagement. A serious game that implements CBT within different scenarios targeting university students with SAD [22] shows positive results in terms of focused attention, perceived usability, aesthetic appeal, being worthwhile and narrative understanding. However, they suggest emotional engagement improvement by allowing more in-game personalisation with the inclusion of the users' own life experiences.

Despite gamification elements showing promise, all studies highlight the need for further investigation into personalisation strategies to enhance motivation and engagement (see Table 10). Evaluation indicates that applied games interventions target SA and SAD among adult participants with no therapist involvement, moderate efficacy, potential for scalability, low cost and moderate ecological validity (see Table 13).

5.2.4 Artificial Agents. The advancements of artificial intelligence, computing and manufacturing enable the creation of interactive artificial agents (e.g., virtual reality, on-screen virtual agents and physically embodied robots) [34]. Artificial agents hold the potential to further enhance the engaging experience, particularly given research findings that suggest that the decline in engagement may be a consequence of applications' limited social presence [34, 43]. Kang and Gratch [84] investigate the disclosure patterns of users with SA in interactions with virtual agents compared to real humans through video calls. Their findings indicate that users with SA are more likely to disclose themselves to embodied virtual agents than to real human video interactions. Similarly, Nomura et al. [119] investigate whether people with SA have less actual and anticipatory anxiety when interacting with a robot compared to when interacting with a human. They find that interacting with a robot causes less tension than interacting with a human, regardless of the individual's level of SA. This emphasises the promising role of artificial agents in supporting users with SA.

VRET is the most extensively explored for SAD, with a substantial focus on its evaluation and effectiveness. It targets social fear and allows confrontation of the fears in a highly controllable virtual environment, in which SA-relevant stimuli and social dialogues can be effectively manipulated for therapeutic purposes [67]. Bouchard et al. [18] present a randomised controlled study that compares VRET with *in vivo* therapy for SAD in the context of CBT. Fifty-nine adult users are randomly assigned to three different conditions: CBT in VRET, *in vivo* CBT and a control group on the waiting list. From the analysis of their data, CBT with VRET proves to be slightly more effective than CBT *in vivo*, and all benefits are maintained at the 6-month follow-up. In addition, therapists experienced CBT with VRET as more practical. Similarly, Kampnamm et al. [82] investigate the efficacy of a stand-alone VRET intervention comprising verbal interaction with virtual humans to target social fears in users with SAD. Sixty adult users diagnosed with SAD are randomly assigned to individual VRET, individual *in vivo* ET, or a waiting list. They show that VRET is effective in reducing SA and stress in users with generalised SAD. However, their findings are that *in vivo* ET is superior to VRET, and they recommend more flexible and extensive dialogues to enhance VRET usability with personalised responses for realistic and unpredictable social interaction. Although the two studies report different comparative outcomes for VRET, these differences can be explained by variations in how VRET was implemented. Bouchard et al. [18] evaluated VRET as an integrated, therapist-supported component of CBT, whereas Kampmann et al. [82] examined a stand-alone VRET intervention without therapist involvement, cognitive components, or adaptation to personally relevant social situations and with limited dialogue flexibility. Taken together, these findings suggest that VRET is more effective when embedded within a structured CBT framework with therapist guidance and adaptive, personalised social interactions, while stand-alone VRET with limited interaction flexibility may be less effective than *in vivo* exposure. Zainal et al. [178] also show self-guided VRET promising efficacy for SAD and related comorbidities, with the use of a virtual therapist. They recommend that therapists incorporate a VRET programme as a complementary intervention to allow repeatable social exposure. Kim et al. [93] analyse the effectiveness of a participatory and interactive virtual reality intervention on SAD. Their results shows that the virtual reality intervention has a significant effect in the SAD group, but that the users with SAD still exhibit symptoms after the sessions. This suggests that the effect alone might not be sufficient to elicit a response to the intervention or achieve remission, which is consistent with findings from other studies indicating that VRET is most effective when used as a complementary tool alongside a therapist [18, 82].

Overall, these studies emphasise the importance of integrating VRET with cognitive components as a complement to therapist-guided interventions, employing experimental designs that match stimuli across conditions

and allowing for flexible dialogues and personalisation (see Table 11). Evaluations indicate that studies applying VRET to SA and SAD have been conducted in adult samples with mixed therapist involvement, moderate efficacy, potential for scalability, moderate cost and moderate ecological validity (see Table 13).

Virtual Audiences are recognised in the treatment of SAD and can consist of *virtual avatars* (i.e., virtual representation of a human) and *virtual agents* (i.e., autonomous virtual human). Anxiety levels tend to be lowest for avatars exhibiting high levels of human likeness [156], which is in contrast with the uncanny valley effect theory [113]. Users typically perceive virtual agents as social actors even with minimal interaction, experiencing a stronger sense of personal connection when agents are visually responsive, though this effect is diminished among experienced computer users [51]. Additionally, Cerekovic et al. [24] show that human personality plays a significant role in perceiving interaction with agents.

Kwon et al. [100] investigate the level of realism required in virtual environments to ensure effectiveness in helping users (i.e., 60 adults) deal with their SA. They show that the attitude of virtual avatars affects SA more than the avatar's level of realism. Customisation of the avatar, explored by Dechant et al. [32], suggests that users (i.e., 200 adults) may feel more committed to the intervention, not only increasing their motivation and persistence but also performance and overall satisfaction. Kang et al. [85] demonstrate that agents with feedback can reduce perceived self-performance in users (i.e., 131 adults) with higher levels of SA, specifically shyness. This provides additional support to the claim that the contingency of agents' non-verbal feedback matters. Qu et al. [132] suggest that regulating the expressed synthetic emotions could be important in managing SA-provoking stimuli, as negative compared to positive synthetic emotions expressed by an agent elicit a more negative emotional state in humans, emotions expressed during the speaking phase have a stronger impact on a human than those expressed during the listening phase and humans with lower speaking confidence experience interactions with agents as less positive. Similarly, Jin and Youn [81] show that users (i.e., 279 adults) with high SA prefer anthropomorphic embodied conversational agents, and SA users (i.e., 607 adults) exhibit greater tolerance towards agents with mismatched personality. A conversational agent-based social skills training system is proposed by Tanaka et al. [159]. They reveal its usefulness after a 4-week training period and demonstrate improved self-efficacy and reduced SA.

Overall, these studies on virtual audiences (i.e., avatars and virtual agents) focus on SA, target adult populations without therapist involvement and not all evaluate efficacy, while demonstrating potential for scalability, moderate cost and moderate ecological validity (see Tables 11 and 13).

SARs that provide assistance through social interaction [41] present potential for innovative treatment of users with SA, given their successful application with vulnerable populations such as the elderly with dementia [38, 54, 72] and children with autism (ASD) [143]. Empirical evidence further indicates that the advantages of self-disclosure to social robots extend beyond providing relief, presenting opportunities for emotional interventions [101]. By simulating understanding and offering feedback, social robots can create a sense of being heard and understood, which are crucial elements of emotional support and ER [101].

Only two studies specifically address generalised SA using robots [119, 182], whereas other research with SARs has focused on specific forms of SA, such as public speaking [136], general anxiety [108], or CBT interventions with **Large Language Model (LLMs)** to reduce anxiety [92]. This highlights a promising yet unexplored research direction. The first study employs a mixed-methods design with two conditions: role-play interactions with a human confederate and with a robot [119]. Findings from a sample of 19 adults indicate that participants with higher levels of SA experience less tension when anticipating interaction with a robot rather than a human. Moreover, interaction with the robot elicits lower levels of tension than interaction with a human, regardless of their level of SA. The association between SA and the adoption of a robotic training partner is explored by Zhu and Deng [182]. They show that students with higher SA have a tendency to choose a robotic trainer partner over a human partner. Their mediation analysis reveals that the sense of relaxation provided by a robotic training partner mediates the positive effect of SA on the adoption of a robotic training partner. The results for SARs,

limited to adults with SA, indicate no therapist involvement, moderate efficacy, potential for scalability, moderate cost and moderate ecological validity (see Tables 11 and 13).

5.2.5 Combining Interventions with Sensing. Combining sensing for the detection of specific symptoms of SA with interventions represents an approach that can ensure interventions are tailored to meet users' needs. However, evidence for this approach remains limited, with only three studies addressing it.

Zheng and Ye [181] conduct a study on the detection and CBT intervention in 100 adolescents, showing improvement in their social ability. Chun et al. [26] aim to predict the severity of specific anxiety symptoms and VR sickness in patients with SAD, using machine learning (i.e., RF, **Logistic Regression (LR)** and naïve Bayes) based on physiological signals (i.e., HR and galvanic skin response) *in situ* during VR intervention sessions. Their best result is achieved using LR on a sample of 26 adult users. Boukhechba et al. [20] investigate if physiological data (i.e., HR and skin conductance) can be used to track changes over a smartphone-based CBM intervention for SAD. Their study, which involves 20 highly socially anxious adult users, focuses on the relationship between an accelerometer and HR to track change following the intervention using a smartphone and smartwatch. They provide preliminary evidence for the viability of using physiological data, specifically HR in relation to accelerometer data, to identify the change in mental state influenced by CBM interventions.

The reviewed studies explore the use of sensing to support or monitor interventions for SAD, combining physiological signals such as HR and skin conductance with accelerometer data (see Table 12 for details). These signals are collected during CBT interventions, VR-based exposure and smartphone-based CBM to detect symptom severity or track changes in mental state. The majority of the studied populations consists of adolescents, with no therapist involvement, no evidence of efficacy, limited scalability, moderate cost and low ecological validity, as the studies are conducted in controlled settings (see Table 13).

Cross-Intervention Comparisons. Table 13 summarises comparisons across different types and subtypes of interventions.

As summarised in Table 13, across intervention types, including remote interventions, mobile applications, applied games, artificial agents and interventions combined with sensing, studies involve adult populations and address a spectrum ranging from subthreshold SA to clinically defined SAD. Where explicitly stated, interventions targeting subthreshold SA are considered informative for SAD, given the shared symptomatology and overlapping therapeutic goals. Overall, therapist involvement varies substantially across intervention types/subtypes, with applied games, virtual audiences and SARs typically requiring no involvement, while mobile applications and VRET often incorporate guided or hybrid approaches. Reported efficacy remains moderate across intervention types, with limited evidence for long-term outcomes. The cost is generally favourable for mobile applications and applied games, whereas ecological validity shows little variation across intervention types.

In terms of strengths, applied games and robotic interventions do not require continuous therapist involvement, supporting autonomous use. Mobile applications, applied games and, to some extent, remote interventions are characterised by low cost, which represents an additional advantage. In contrast, several weaknesses are evident. Technologies such as social robots and virtual reality entail higher costs, and virtual reality interventions are frequently recommended to be implemented with therapeutic guidance. Moreover, virtual audiences and robotic interventions have been evaluated primarily in SA populations, and all intervention types have been assessed short-term, in adult samples, with only limited evidence for adolescents and no evidence for children or the elderly. With respect to efficacy, which is mainly moderate, no intervention type demonstrates clear advantages over the others.

The reviewed studies highlight that designing interventions with therapist input, enhanced personalisation and user engagement over time are critical factors for improving efficacy. Moreover, socially anxious users prefer artificial agents that are anthropomorphic, responsive, capable of expressing emotions and exhibit mismatched personalities.

6 Discussion

In the previous section, an overview of sensing and interventions for addressing SA is provided, highlighting both the advantages and challenges. Based on these studies, several *research gaps* are identified in both sensing and interventions:

(1) *Sensing Performance*. Research has explored the automatic detection of SA states; however, recognition remains challenging due to the considerable heterogeneity in behaviours that induce SA across individuals. While studies report results based on specific datasets, the actual performance of such recognition systems in the wild is largely unexplored. Furthermore, identifying what performance is sufficient in a clinical setting, what are the most critical points of improvement from a technology standpoint, as well as the interdependencies between current performance levels and how potentially adaptive systems might react needs further attention.
(2) *Data Collection*. The restricted access and limited scope of existing available datasets for SA hinder the ability to conduct robust analyses and build more effective sensing using existing data, highlighting the need for data collection.
(3) *Design*. Designing interventions that are effective in successfully supporting socially anxious users in managing symptoms and that their use is acceptable to both users and therapists remains an ongoing challenge.
(4) *Adaptivity*. Designing more adaptive interventions is a gap in SA research, particularly given the influence of affective states and behaviours on this condition.
(5) *Adoption and Long-Term Engagement*. As reviewed studies have noted a decline in engagement over time, SA interventions aimed at supporting adoption and long-term engagement require additional exploration.

The remainder of this section discusses in-depth the research gaps that this review has identified related to sensing, interventions, as well as ethical considerations.

6.1 Advancing Automatic Sensing: From Accurate Detection to Tailored Interventions

Datasets. The development of effective SA sensing algorithms is heavily dependent on the availability and quality of relevant datasets. As identified in research gap 2, there are currently limitations in both the quantity and scope of datasets, which are often small, limited to specific SA provoking scenarios, or constrained in demographic diversity. To build robust and generalisable sensing models, larger, more diverse multimodal datasets that encompass various SA provoking scenarios are needed. Depending on the type and granularity of data, collecting rich meta-information and ensuring high-quality ground truth is key. As SARs are a promising component of SA interventions, the collection of datasets with both human–robot aside from human–human interactions is encouraged. Collecting these datasets, however, presents significant privacy challenges. SA-related data are inherently sensitive, as it captures not only physiological responses but also behavioural and affective states in social settings. To ethically manage these concerns, protocols for data collection should include transparent consent processes [130], secure storage methods and, when possible, anonymisation techniques to protect participant privacy.

Despite efforts to ensure data availability and quality, issues can still arise, leading to cases where the data are missing or noisy. Nguyen et al. [117] suggest co-learning as a suitable future direction due to limited resources, which is a common trait of mental health datasets with small sample sizes and can enrich all modalities by transferring knowledge from one domain to another. Similarly, the approach suggested by Zantvoort et al. [179] support the possibility of pooling the data of different treatments into one dataset. Another potential alternative for addressing data scarcity while mitigating privacy and confidentiality concerns is synthetic data generation [133].

Multimodal Fusion and Context. People suffering from SA may show various manifestations of their anxiety. Some may be blushing [118], while others may be avoiding eye contact [171]. These heterogeneous manifestations pose a challenge to SA detection, especially as there is no one-on-one mapping between observable bio-behavioural patterns and a diagnosis. This challenge, which constitutes research gap 1, is further increased by how individuals show, respond to and regulate their affective states and expressions thereof in an attempt to modulate how they are perceived by others. Integrating multiple signals such as facial expression, gaze, vocal patterns and body posture is a promising avenue. Combining observable behaviours with physiological signals may account for some of the effects of ER. Novel approaches to multimodal fusion, as well as researching methods to integrate contextual information to support meaningful interpretation are critical.

Personalisation. The aforementioned differences across individuals, as outlined in research gap 1, emphasise the need for personalised models that can adapt to an individual's unique SA signals, behaviours and physiological patterns. Personalisation typically involves adapting model parameters based on real-time data collected from the user over time. For instance, a model trained on a general dataset might be recalibrated to account for specific SA responses such as changes in HRV or specific facial expressions that a person exhibits in social settings. Methods such as incremental learning, active learning, fine-tuning and transfer learning may be explored in the context of model adaption to specific individuals.

Active–Passive Integration. Both passive and active sensing offer promising avenues to automatically recognise SA and SA-related behaviours to aid diagnosis. Given the heterogeneous nature of SA provoked behaviours across individuals, highlighted in research gap 1, a flexible sensing system that can dynamically interpret both stable traits and situational responses would be highly valuable. Integrating passive sensing (such as wearable sensors or ambient monitoring) with active self-reporting methods, such as EMA [153], could provide a more comprehensive view of an individual's SA profile. This combination could offer a richer, more nuanced assessment of SA symptoms, although it also introduces complexities in data interpretation and integration. Considering the sensitivity and vulnerability of individuals with SAD, alternative wearables such as earables capable of detecting EEG signals [12], may provide distinct advantages over commonly used wrist-worn wearables.

Performance for Diagnosis. Significant progress has been made in automatic sensing for the detection of SAD. However, translating these advancements to clinical practice remains challenging. As addressed in research gap 1, a primary goal is determining the performance threshold required for such tools to be clinically meaningful and beneficial for clinicians. Although high accuracy in detecting SA related behaviours and physiological signals is often reported, this performance is typically assessed on specific datasets and not in real-life in-the-wild situations. Determining whether currently achieved accuracy levels are sufficient for real-world applications and align with clinicians' expectations requires further collaboration between researchers, clinicians and technology developers. Similarly, understanding if and in which cases the deployment in clinical practice requires a focus on overall trait SA or on recognising specific objective bio-behavioural patterns that reflect an individual's SA state is another call for interdisciplinary collaboration.

Performance for Tailored Treatment. Accurate sensing has the potential to enable the dynamic, real-time tailoring of interventions based on an individual's real-time emotional state and SA level. Such personalisation could be particularly impactful in contexts involving SAR interactions, where sensing could monitor SA responses and adapt the intensity of exposure in real time to prevent overwhelming the user while gradually building their tolerance to social scenarios. As indicated in research gap 1, research combining real-time sensing with interventions remains scarce, despite these promising possibilities. One obstacle is the challenge of achieving interpretability and transparency in sensing algorithms so that therapists and users can understand and trust the system's decisions. Potential biases in sensing models, such as those arising from training on limited or non-diverse data, need careful management to ensure fair treatment across different demographic groups. Improving the explainability of why certain SA signals are detected or why specific interventions are suggested would facilitate their acceptance and effectiveness in clinical settings.

6.2 Advancing Technological Interventions: Co-Designing for Adaptive and Long-Term Assistance

Co-Design. Designing effective and acceptable interventions, highlighted as research gap 3, requires the identification of features and functionalities that are viewed as engaging, desirable and effective [52, 128]. There is a growing recognition of the need for input from both therapists and potential users, as their involvement might benefit the development of more human-centered, inclusive and user-friendly interventions. Co-designing with both therapists and potential users is one approach to achieving this, as it can help identify features and functionalities while ensuring that interventions are tailored to their values, needs and preferences. **Value Sensitive Design (VSD)** emphasises the incorporation of human values and ethical considerations throughout the design process, fostering a more user-centered approach [116]. Using VSD to integrate values such as reliability, trustworthiness and privacy can facilitate greater user acceptance of technology, thus empowering users to manage their SA more effectively.

Adaptive Assistance. The ability to adapt to users and their changing states is important for enabling more natural interactions, highlighting the need for adaptive interventions, identified as research gap 4. Emotions are fundamental to social interaction [11], and understanding users' affective states and the affective affordances that emerge during interaction can provide a basis for adapting system behaviour and support. Automatic sensing of affective states and behaviours related to SA may contribute to this process by providing information about users and their responses during interaction. However, given the highly context-dependent nature of SA, sensing should extend beyond detection accuracy towards actionable and context-aware sensing that can inform when and how interventions should adapt to users' social contexts [4]. Integrating affective and contextual information may therefore support the development of more robust, real-time and personalised adaptive interventions.

Interventions that are built in a *personalised* manner for each specific user with SA may take many forms to increase adaptivity. For instance, users with SA may have unique preferences for communication style, interaction frequency and intensity in therapeutic tools. Additionally, they may have specific affinities regarding features relating to the form of an intervention, such as the appearance or voice of an artificial agent, especially when it is acting as a coach rather than in an exposure scenario. Personalisation can also be achieved by considering personal factors such as age, gender, culture and personality in the design of interventions. Besides these factors, the intervention itself can be personalised to a user by endowing the artificial agent with a distinct personality and the ability to express emotions. Additionally, a personalised hierarchy of fears can be created for each user, allowing practice according to increasing feared situations, which will differ from one user to the other.

Empathy adds an additional dimension to adaptation, particularly in the context of guidance or training therapeutic scenarios, ensuring that the interventions are emotionally resonant and potentially enhance the experience [114]. Such interventions could be perceived as providing emotional support with greater psychological safety, offering comfort and encouragement. This may simultaneously make the user experience more meaningful and engaging.

LLMs, which are growing in their capabilities [180], might offer possibilities for greater adaptivity in designing interventions. However, LLMs are typically trained on textual data, while multimodal interactions introduce additional complexities. The use of LLMs in the mental health context remains relatively unexplored, presenting both opportunities and risks that need careful consideration. By carefully identifying potential risks alongside opportunities for enhancing adaptation, the power of LLMs can be used to make a positive contribution. Risks associated with LLMs include the generation of misinformation and disinformation [80], as they may generate inaccurate or biased information, often without transparency [71]. In these contexts, misleading outputs from LLMs can unintentionally influence behaviour, potentially amplifying unfairness and human bias [3] and creating ethical, psychological and safety concerns. Therefore, to ensure that LLM-powered interventions enhance the well-being of vulnerable populations, such as individuals with SA, it is essential to verify their outputs for accuracy and safety. Ensuring interpretability and explainability of LLM decision-making processes is crucial to promote

safe interventions through the identification of errors and troubleshooting. Consequently, the trustworthiness of LLM-powered interventions should be rigorously evaluated prior to deployment with vulnerable populations.

Long-Term Assistance. Ensuring adoption and long-term engagement for SA is necessary for sustained support, yet as identified in research gap 5, existing solutions often face a decline in user engagement over extended periods, and adoption remains a challenge. Engagement is critical for success [141], and several technological approaches reviewed illustrated the potential for enhanced engagement, such as the introduction of gaming elements as well as the use of virtual agents and SARs. Furthermore, providing assistance and support on a regular long-term basis is closely connected to user satisfaction, as well as to meeting users' needs and preferences while aligning with their values [129]. As previously mentioned, VSD can encourage acceptance and continued use over time and potentially support long-term assistance for users in managing their SA.

6.3 Ethical Considerations

A move towards a more ethical design of solutions that genuinely improve our lives requires that these solutions respect our psychological needs [23]. Scheutz [145] argues that the use of appropriate emotional expressions can actually make solutions more ethical. It is essential to consider and address potential risks and ethical concerns when designing solutions for SA support, given the vulnerability of this population. VSD, as noted earlier, can ensure that ethical aspects are examined to guarantee that these solutions not only consider individuals' emotional well-being but also respect their privacy. As an important ethical consideration, sensing models should be designed and evaluated to avoid biases related to gender, age and cultural background by using diverse and balanced datasets, particularly given evidence that vocal markers of SA, such as speech rate, differ between men and women. Moreover, these models should ensure transparency in their design and decision-making processes, particularly if used by clinicians in practice, and their effectiveness should be evaluated in clinical trials, as high user interest in mental health applications does not necessarily translate into sustained usage [161]. By understanding and addressing the ethical implications, trust in technology can be enhanced, which in turn can positively affect its overall efficacy.

Future work may address overcoming the interdisciplinary challenges across fields if the solutions surveyed are to be introduced on a larger scale. An approach that *integrates diagnosis and treatment* within these technological solutions could ensure the identification and management of symptoms to lead to more customised, timely, sustained and high-quality care.

6.4 Limitations

While this review has included a large body of literature in relation to SA, several limitations need to be acknowledged. The studies reviewed use a wide range of sensing modalities, machine learning techniques, datasets on which performance was evaluated and outcome measures for interventions, which makes direct comparison challenging and hinders the ability to draw strong generalisable conclusions about best practices. Another limitation of this review that needs to be acknowledged is the exclusion of specific forms of SAD, such as public speaking. The broad scope of this review limited the consideration of these solutions, which can be addressed in future work.

7 Conclusion

This review has provided an overview of the past decade's advancements in using technology to support the diagnosis and treatment of SA, addressing both clinically diagnosed generalised forms of SA and broader applications related to SA. It reveals the close link between SA and emotions, underscoring the potential of automatic sensing to enable real-time detection of SA and the interpretation of its important characteristics.

Additionally, it provides an examination of intervention strategies for SA, emphasising considerations of behaviour and embodiment.

However, several significant challenges remain in advancing these solutions. For instance, issues such as sensing performance and enhancing long-term engagement require further research and innovation. Despite the potential of design approaches to enhance engagement, their limited adoption remains a substantial challenge that needs to be addressed. Given that ethical considerations are essential for the responsible development of these solutions, they require careful attention to ensure that solutions are implemented in ways that prioritise user well-being and privacy.

Looking forward, addressing these challenges will necessitate interdisciplinary collaborations to advance the technical, clinical and ethical aspects of technology designed to support individuals with SA.

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A Appendix

Table A1. Alphabetised List of Abbreviations in Tables 4, 5, 10, 11, and 12

Abbreviation	Description
ADHD	Attention-Deficit/Hyperactivity Disorder
ANFIS	Adaptive Neuro-Fuzzy Inference System
ASD	Autism Spectrum Disorder
BART	Bayesian Additive Regression Trees
BDI	Beck Depression Inventory
BFNES	Brief Fear of Negative Evaluation Scale
BFPT	The Big Five Personality Test
BLSTM-MIL	Bidirectional Long Short-Term Memory-Multiple Instance Learning
BSD	Between Subject Design
BSIQ	Bodily Sensations Interpretations Questionnaire
Catboost	Boosting Ensemble-Based Machine Learning Method
CBM	Cognitive Bias Modification
Char.	Characteristics
CNN	Convolutional Neural Networks
CR	Cognitive Reconstruction
DASS	Depression Anxiety Stress Scale
DEQ	Dialogue Experience Questionnaire
DERS	Difficulty with Emotion Regulation
DL	Deep Learning
EC	Effective Connectivity
EDA	Electrodermal Activity
EMA	Ecological Momentary Assessment
EP	Early Psychosis
ET	Exposure Therapy
FNE	Fear of Negative Evaluation
GAD-7	Generalised Anxiety Disorder
GPS	Global Positioning System
GSES	General Self-Efficacy Scale
GSR	Galvanic Skin Response
HC	Healthy Controls
HR	Heart Rate
HRV	Heart Rate Variability
IPQ	Igroup Presence Questionnaire
ISS	Internalised Shame Scale
kNN	k-Nearest Neighbours
LOOCV	Leave One-Out-Cross-validation
LOSOCV	Leave-One-Subject Out-Cross-Validation

(Continued)

Table A1. Continued

Abbreviation	Description
LSAS	Liebowitz Social Anxiety Scale
LSAS-SR	Liebowitz Social Anxiety Scale—Self-Report Version
LSTM	Long Short-Term Memory
LR	Logistic Regression
MERF	Mixed Effects Random Forests
MINI	Mini international neuropsychiatric interview
ML	Machine Learning
MLP	Multilayer Perceptron
MSD	Mixed Study Design
NN	Neural Network
NR	Not Reported
PANAS	Positive Affect Negative Affect Schedule
PDBQ	Personality Disorder Belief Questionnaire
PERS	Post-Event Rumination Scale
PGT	Player/Game/Therapy Model
PHQ	Patient Health Questionnaire
PIS	Player Identification Scale
POMS	Profile of Mood States
PRCS	Personal Report of Confidence as a Speaker
PS	Physiological Signals
QUOLI	Quality of Life Inventory
RBD	Randomised Block Design
RCT	Randomised Control Trial
RF	Random Forest
RRQ	Recognition Ratings Questionnaire
RT	Real Time
SADS	Social Avoidance and Distress Scale
SAM	Self-Assessment Manikin Questionnaire
SAS	Social Anxiousness Scale
SeqMM	Sequential Mixed Method
SE	Simulation Experiment
SIAS	Social Interaction Anxiety Scale
SH	Self Help Programme
SPDQ	Social Phobia Diagnostic Questionnaire
SPIN	Social Phobia Inventory
SPS	Social Phobia Scale
SRS	Social Responsiveness Scale
SR	Self-Reported
SSFB	Small-Scale Feasibility Study
SSMB	Single Subject Multiple Baseline
SSQ	Simulator Sickness Questionnaire

(Continued)

Table A1. Continued

Abbreviation	Description
ST	Skin Temperature
STAIS-S	State–Trait Anxiety Inventory-State Version
SUD	Subjective Units of Discomfort
SUS	System Usability Scale
SVM	Support Vector Machine
TP	Thinking Patterns
UES	User Engagement Scale
UES-SF	User Engagement Scale—Short Form
VR	Virtual Reality
WSD	Within Subject Design
XGboost	Extreme gradient boosting machines

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