AI-based Systems for Predicting and Intervening in Generalized Anxiety Disorder (GAD) Based on Cognitive Biases: A Structured Review

Ahmed Almathami [1,2] and Richard Stone [3,*]

[1] Department of Information Systems, King Abdulaziz University, Rabigh, Saudi Arabia
[2] Human-Computer Interaction Department, Iowa State University, Ames, USA
[3] Industrial and Manufacturing Systems Engineering Department, Iowa State University, Ames, USA
Email: ahmedmo@iastate.edu (A.A.); rstone@iastate.edu (R.S.)
*Corresponding author

***Abstract*—Generalized Anxiety Disorder (GAD) is one of the most prevalent anxiety disorders and is strongly associated with cognitive biases, particularly interpretation bias and catastrophic thinking. Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have enabled the development of systems to predict, monitor, and support interventions for anxiety-related conditions. However, many existing approaches prioritize predictive performance while relying on black-box models that provide limited interpretability and insufficient integration of cognitive mechanisms. This paper presents a structured review of AI-based approaches for GAD prediction and intervention, with a particular focus on the role of cognitive biases in computational models. The reviewed studies were analyzed with respect to data sources, modeling approaches, predictive performance, explainability, and intervention capabilities. The findings indicate that although many AI systems achieve promising predictive accuracy, most rely primarily on behavioral, physiological, or symptom-based indicators and rarely incorporate features related to cognitive bias directly into the prediction process. In addition, limited model transparency remains a significant challenge for real-world deployment and clinical decision-making. Based on the findings of the reviewed studies, this paper proposes a conceptual framework that summarizes how cognitive biases, AI-based assessment methods, prediction mechanisms, explainability, and intervention strategies can be integrated within future GAD support systems. The framework highlights the relationships between cognitive psychology and AI and provides a foundation for developing more transparent, interpretable, and personalized GAD prediction and intervention systems. The main contribution of this review is the development of this conceptual framework, along with the identification of current research gaps and future directions for cognitively informed and explainable mental health technologies.**

***Keywords*—Generalized Anxiety Disorder (GAD), Artificial Intelligence (AI), Machine Learning (ML), cognitive biases, Explainable AI (XAI), mental health, prediction systems**

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I. Introduction

Anxiety disorders are among the most prevalent mental health conditions worldwide and affect individuals across different age groups and populations [1]. Generalized Anxiety Disorder (GAD) is one of the most common forms of anxiety and is characterized by persistent and excessive worry that can significantly impair daily functioning. Due to its chronic nature and long-term consequences, GAD is associated with reduced quality of life and substantial social and economic burdens. In addition, GAD shares symptoms with other mental health conditions, particularly depression, which increases the complexity of diagnosis and management [2, 3].

Despite its prevalence, GAD remains challenging to predict and diagnose in clinical practice. The disorder is frequently associated with disability, comorbidity, and repeated healthcare utilization, while many individuals present with symptoms that lack clear physical causes [4–6]. These challenges have sparked growing interest in computational approaches that support early detection, monitoring, and intervention.

Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have enabled the development of systems to predict, monitor, and support interventions for anxiety-related conditions. Existing studies have explored a variety of data sources, including psychosocial indicators, behavioral information, physiological signals, and digital phenotyping data. Evidence suggests that integrating heterogeneous data sources can improve predictive performance and enable more personalized support [7, 8]. Furthermore, emerging research indicates that incorporating information on cognitive biases may enhance AI systems' ability to capture the psychological mechanisms underlying anxiety disorders [9–12].

However, several important challenges remain. Many existing approaches rely primarily on observable symptoms or physiological indicators and provide limited insight into the cognitive mechanisms underlying GAD [7, 13]. In addition, many high-performing models operate as black-box systems, limiting transparency

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and reducing their applicability in real-world decision-making [12]. Challenges related to generalizability, interpretability, and the translation of predictive outcomes into personalized intervention strategies also remain insufficiently addressed [8, 13, 14]. These limitations highlight the need for more explainable, cognitively informed, and human-centered AI systems for GAD prediction and intervention.

This paper presents a structured review of AI-based approaches for GAD prediction and intervention, with a particular focus on cognitive biases, including catastrophic thinking and interpretation bias. The reviewed studies were analyzed with respect to data sources, modeling approaches, predictive performance, explainability, and intervention capabilities. Furthermore, the review identifies key research gaps in the integration of cognitive biases, model interpretability, and support for personalized interventions. Based on the findings of the reviewed studies, a conceptual framework is proposed to illustrate how cognitive biases, AI-based assessment methods, prediction mechanisms, explainability components, and intervention strategies can be integrated within future GAD support systems.

The main contributions of this paper are summarized as follows:

- A structured review of AI and ML approaches for GAD prediction, monitoring, and intervention.
- A comparative analysis of existing approaches, highlighting their strengths, limitations, and levels of interpretability.
- Identification of key research gaps, particularly the limited integration of cognitive bias mechanisms, the lack of explainability, and challenges related to personalized intervention support.
- Development of a conceptual framework that integrates cognitive biases, AI-based assessment methods, prediction mechanisms, explainability components, and intervention strategies for future GAD support systems.
- A discussion of future research directions toward explainable, bias-aware, and human-centered AI systems for mental health.

II. Background

A. Anxiety Disorders

Anxiety disorders are a group of mental health conditions that affect many individuals across different countries. They are characterized by excessive fear and anxiety that can significantly impair daily functioning. These disorders differ from normal anxiety, which is a natural stress response, in terms of their duration and intensity, as they are often disproportionate to the actual threat [15–18].

Mental health conditions, including anxiety and depression, contribute substantially to the global disease burden. For example, these conditions contribute substantially to disability and premature mortality worldwide [19]. In terms of economic impact, the United States spends more than $42 billion annually on mental health conditions such as anxiety, stress, and depression, while Europe spends over 74.4 billion euros each year [20]. According to the World Health Organization (WHO), mental health disorders cost the global economy approximately one trillion dollars annually in lost productivity. Additionally, suicide rates remain a major concern, with around 800,000 deaths each year linked to mental health conditions [21].

The classification of anxiety disorders: Anxiety disorders represent a diverse group of psychiatric conditions characterized by excessive fear, anxiety, and related behavioral disturbances. According to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), major anxiety disorders include panic disorder, social anxiety disorder, specific phobias, agoraphobia, and GAD [22]. Although these disorders share common features related to heightened anxiety and emotional distress, they differ in their triggers, symptom presentation, and clinical manifestations. Among these conditions, GAD is particularly important because it is characterized by persistent and excessive worry across multiple domains of daily life and is frequently associated with significant functional impairment [23, 24].

B. Generalized Anxiety Disorder (GAD)

GAD is characterized by excessive and persistent worry about various aspects of daily life, including health, work, and relationships. Individuals with GAD often experience additional symptoms such as sleep disturbances, fatigue, muscle tension, and irritability. The chronic nature of GAD can lead to significant emotional distress and impaired functioning [24].

1) Prevalence of Generalized Anxiety Disorder (GAD)

Anxiety disorders affect more than 300 million people worldwide, with GAD representing one of the most common forms [25]. Its prevalence varies across age groups, regions, and sociocultural contexts. Studies consistently show that GAD is more prevalent among women than men [26].

Among younger populations, GAD is often associated with factors such as academic pressure, family expectations, and physical health concerns [27]. For example, the lifetime prevalence of GAD among children and adolescents in Iran is reported to be 2.6% [28], while studies in China estimate a prevalence of approximately 1.3% among school-aged individuals [29]. Although these prevalence rates are lower than those reported in adults, they highlight the importance of early detection and intervention.

In adult populations, prevalence rates vary by region and gender. A community-based study in Italy reported a lifetime prevalence of 2.3%, with higher rates among women (3.6%) compared to men (0.9%) [26]. In Japan, the GAD-7 screening tool estimates a prevalence of 7.6%, which may reflect cultural and methodological differences in reporting [30].

In the United States, GAD is also highly prevalent, with approximately 2.7% of adults experiencing the disorder within 12 months, and a lifetime prevalence of 5.7% [31]. Recent data from the National Health

Interview Survey (NHIS) indicate an increase in anxiety symptoms, rising from 15.6% in 2019 to 18.2% in 2022 [32]. Additionally, the COVID-19 pandemic has contributed to a significant increase in GAD prevalence in Europe [33], as illustrated in Fig. 1.

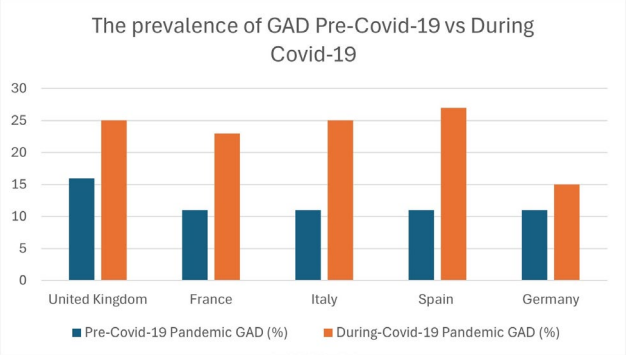

Fig. 1. Generalized Anxiety Disorder (GAD) prevalence before and during the COVID-19 pandemic across selected European countries, adapted from Ref. [34].

The observed increase highlights the growing burden of anxiety disorders and emphasizes the need for scalable approaches that can support early detection, continuous monitoring, and timely intervention.

2) Impact of Generalized Anxiety Disorder (GAD)

GAD is associated with excessive worry and a range of physical, cognitive, and emotional symptoms that significantly affect daily life and may increase the risk of suicidal thoughts [35, 36]. These symptoms can be categorized into multiple dimensions, as illustrated in Fig. 2, highlighting the disorder's complexity.

Fig. 2 highlights the multidimensional nature of GAD by illustrating its cognitive, emotional, behavioral, and physiological symptoms. The diversity of these symptoms underscores the complexity of accurately identifying and monitoring GAD, which has motivated the use of AI and ML techniques capable of integrating heterogeneous data sources. Such complexity also supports the need for explainable and cognitively informed models that can capture different aspects of anxiety-related behavior.

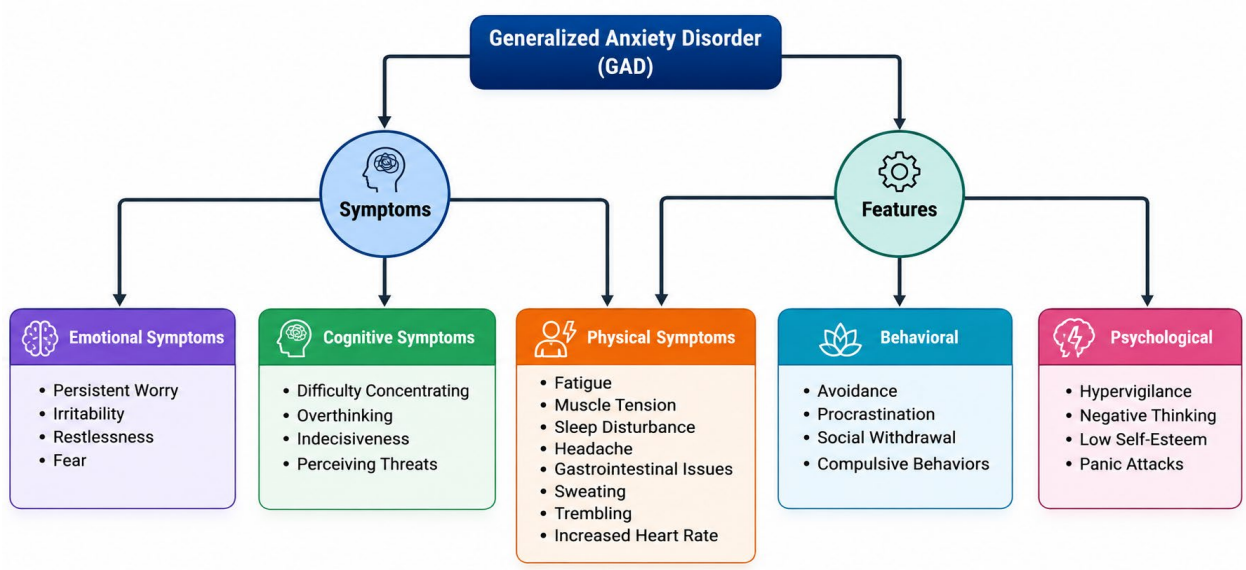

Fig. 2. Symptom classification of GAD. Developed by the authors based on information synthesized from Refs. [37–43].

GAD has a broad impact on individuals' mental, physical, and social well-being. It is commonly associated with reduced work performance, academic difficulties, and impaired interpersonal relationships [4, 44]. Additionally, individuals with GAD are at higher risk of developing comorbid conditions, such as major depressive disorder and substance use disorders, which further complicate diagnosis and treatment [45–47].

From a physiological perspective, chronic anxiety is linked to prolonged activation of the stress response system, which may contribute to cardiovascular, neurological, and gastrointestinal conditions, as well as sleep disturbances [48, 49]. At the societal level, GAD imposes a significant economic burden by increasing healthcare utilization and reducing productivity. If left untreated, it can lead to long-term functional impairment, emphasizing the importance of early detection and intervention [50, 51].

C. Cognitive Biases

Cognitive biases are systematic errors in thinking that lead to deviations from logical, rational reasoning. These distortions affect the way people perceive, process, and interpret certain situations. The human mind develops efficient mental shortcuts, known as heuristics, that facilitate rapid decision-making in complex or uncertain situations but can sometimes lead to inaccurate judgments [52–55]. Evolutionary processes have shaped these heuristics to support efficient information processing. However, they may also compromise the accuracy of judgment and influence perception, decision-making, and problem-solving [56]. Consequently, heuristics can provide adaptive advantages

in certain situations but may also produce systematic errors that reinforce inaccurate perceptions and pre-existing beliefs [57].

Psychological and neuroscience studies have identified a broad range of cognitive biases that influence human reasoning. One widely reported trend is confirmation bias, in which individuals seek out or focus on information that supports their beliefs about certain subjects. Another general tendency is the anchoring effect, in which individuals tend to give undue weight to the initial information they receive, even when later information contradicts it [58]. Collectively, these biases not only influence individual decision-making but also organizational and policy decision-making, with broader implications for financial systems, medical practice, and government processes.

1) Cognitive biases as core mechanisms

Cognitive biases, systematic distortions in the processing of information, are increasingly recognized as core processes in the pathogenesis and maintenance of mental illness. These biases influence the ways people focus on, interpret, and remember information and tend to propagate negative thought and feeling patterns. Such biases in clinical psychology and psychiatry are valuable for understanding the emergence and persistence of certain symptoms over time and across contexts [59].

2) Impact and types of cognitive biases

Different types of cognitive biases have distinct effects on psychopathology. The most widely studied biases are attention, interpretation, and memory. Interpretation and memory biases are strong predictors of anxiety and depressive symptoms at all stages of life, whereas attention bias is less consistent as a predictor. It is important to note that biases manifest in children, adolescents, and adults, and their intensity and nature may vary by diagnosis. As an example, interpretation bias tends to be especially prominent in obsessive-compulsive disorder, and attention bias tends to be common in panic disorder. These patterns, specific to each disorder, emphasize the critical importance of studying how specific biases relate to specific symptom clusters [60, 61]. Table I shows the different types of cognitive biases and their association with each mental illness disorder.

TABLE I. TYPES OF COGNITIVE BIASES AND THEIR ASSOCIATED MENTAL HEALTH DISORDERS

Cognitive Bias Type	Description	Associated Disorders	References
Attention Bias	Focus on life-threatening stimuli	GAD, Depression, Psychosis, OCD	[61, 62]
Interpretation Bias	Interpreting ambiguous situations as a threat	GAD, Depression, Psychosis, OCD	[59, 62]
Memory Bias	Tendency to remember negative information related to GAD	GAD, Depression, Psychosis	[61, 63]
Attributional Bias	A logical fallacy in the explanation of the reasons for behavior or events	Depression, Psychosis, Schizophrenia	[60, 64]
Reasoning Bias	Inferring or drawing distorted or inaccurate information	Psychosis	[60, 65]
Catastrophizing	Exaggerated anticipation of negative events	GAD, Depression	[64, 66]
Belief Inflexibility	Problem changing beliefs in the face of conflicting evidence	Psychosis, Schizophrenia	[64, 67]
Personalizing Bias	Believing that oneself is the cause of negative events	Psychosis, Schizophrenia	[60, 64]
Emotional Reasoning	Concluding based on the emotional condition and not on objective facts	Depression, Psychosis	[64]
Confirmation Bias	Seeking out negative information that confirms beliefs	Psychosis, depression, schizophrenia, GAD	[60, 64, 68]
Judgment Bias	Pessimism and catastrophizing based on mood	Depression, GAD, psychosis	[68, 69]
Self-Referential Bias	Focusing on negative information or evaluations related to the self	Depression, GAD	[63, 70]

3) Predictive and transdiagnostic roles of cognitive biases

There is longitudinal and meta-analytic evidence that cognitive biases not only co-occur with symptoms but are also capable of predicting the onset and progression of mental health issues. The self-referential memory bias, for example, is a reliable predictor of the development and exacerbation of depressive symptoms, while interpretive bias has a parallel effect on the course of anxiety. In particular, these predictive effects hold even when one considers stable personality characteristics such as neuroticism. These results provide strong evidence for cognitive models that view biases not only as correlates but also as causal and maintenance factors in psychopathology [61, 71, 72]. Cognitive biases are not associated with a single diagnosis. Rather, they show a transdiagnostic profile, which cuts across depression, anxiety, psychosis, and obsessive-compulsive disorder. This cross-cutting characteristic implies that biases can be typical underlying mechanisms of mental illness. In addition, recent network analysis studies suggest that interactions among several biases can be particularly significant. These biases in network strength and structure appear to correlate with general mental health conditions, suggesting that interventions may need to focus not only on individual biases but also on their interactions [59, 73].

Regarding the neurobiological underpinnings, neural circuits underlying maladaptive cognitive biases are increasingly being elucidated by advances in neuroscience. A frontal-limbic network (including the amygdala, hippocampus, and prefrontal cortex) is identified as the basis of biased information processing. In depression, increased reactivity of the amygdala and failure of the prefrontal system to regulate negative interpretations and memories may enhance the intensity of negative interpretations and memories, which further strengthen the maladaptive cognitive patterns. These results connect cognitive theories to neurobiological models and provide multilevel explanations of mental health disorders [74].

D. The Relationship between GAD and Cognitive Biases

GAD is strongly associated with several cognitive biases, as explained in Table I. These include interpretation bias and catastrophic thinking, which are considered critical determinants of GAD development and persistence. People with GAD tend to perceive neutral or ambiguous stimuli as threatening, contributing to a vicious cycle in which persistent worry and anxiety reinforce one another over time [75]. These cognitive biases reinforce anxious thought patterns and represent important targets for evidence-based psychological interventions aimed at reducing GAD symptoms.

Interpretation bias is one of the most common cognitive distortions observed in individuals with GAD. It reflects a tendency to interpret uncertain or ambiguous situations negatively, thereby reinforcing chronic anxiety. Empirical evidence has demonstrated that GAD patients are characterized by much greater interpretation bias than non-anxious individuals, and that interpretation bias is highly correlated with anxiety symptom severity [10, 61]. In addition, it predicts the future development of anxiety and depressive disorders. Theoretical and clinical data suggest that worry can be mitigated by therapeutic interventions or pharmacological therapy to break the cycle of reinforcement of anxiety perceptions and reduce their interpretation bias [76, 77].

Catastrophic thinking is another salient bias in GAD. It involves anticipating the worst that may happen in a situation, even when no evidence supports it. A recent study of individuals with GAD found catastrophizing among the cognitive distortions observed in this population [78]. Dugas *et al.* [79] also highlighted the important role of intolerance of uncertainty and catastrophic beliefs about uncertainty in GAD. In a case study of GAD comorbid with Parkinson's disease, CBT targeting catastrophic thinking and worry was associated with a reduction in anxiety symptoms, highlighting the clinical relevance of these cognitive processes in GAD [80].

Collectively, these biases contribute to distorted patterns of evaluation, anticipation, and recall that perpetuate anxiety. These tendencies reinforce one another, forming a vicious cycle of thinking that increases susceptibility and prolongs symptom persistence. These findings highlight the importance of addressing cognitive biases as interconnected processes rather than in isolation during clinical practice [40, 81, 82].

The important role of cognitive biases in GAD has motivated growing interest in computational approaches for identifying these maladaptive cognitive patterns. Consequently, recent advances in AI have created new opportunities to develop intelligent systems that support mental health assessment, prediction, and intervention.

E. Artificial Intelligence in Mental Health

Recent years have witnessed rapid growth in the use of AI in mental health research and clinical practice, driven by the increasing prevalence of psychological disorders across populations and the need for data-driven, scalable interventions. Patients face numerous barriers to accessing traditional mental health care, including financial constraints, limited service availability, and shortages of qualified mental health professionals worldwide. Research suggests that AI can improve the accuracy of mental health diagnosis and support personalized intervention strategies, enabling earlier detection of psychiatric disorders [83]. AI is transforming mental health services by introducing new approaches to screening and therapeutic interactions, and by mitigating cognitive bias [56].

AI-driven mental health support has advanced considerably through the development of personalized, real-time psychological interventions. Two AI-based mental health applications, namely Woebot and Wysa, leverage Natural Language Processing (NLP) to enable virtual mental health assistant functions that mimic human communication patterns and deliver Cognitive-Behavioral Therapy (CBT)-based support [84]. AI-based mental health support systems guide users through structured mental exercises that help them identify and challenge maladaptive beliefs, monitor emotional responses, and develop effective coping strategies [85]. These applications can also dynamically adapt their responses and tailor mental health interventions to each individual's needs using AI-powered sentiment analysis tools [86].

One of the most promising applications of AI in mental health is mitigating cognitive bias. Cognitive biases such as negativity bias, confirmation bias, and catastrophizing contribute to psychological distress by reinforcing dysfunctional thinking patterns. The presence of these distortions increases psychological distress and keeps maladaptive cognitive patterns in place [57]. Sentiment analysis, coupled with ML algorithms, can help AI-driven cognitive restructuring platforms detect biased thoughts in real time, enabling timely cognitive restructuring and more adaptive thinking. AI-based journaling systems analyze users' language using linguistic pattern recognition to identify cognitive biases that lead to alternative explanations, thereby fostering more balanced cognitive activity [86]. These interventions are based on existing cognitive-behavioral models, making them applicable to large-scale implementation [56].

However, AI-based mental health systems require extensive data collection, which raises concerns about user confidentiality, data security, and informed consent [83]. Algorithmic biases arising from unbalanced or non-representative training data may lead to inaccurate predictions and unequal outcomes across demographic groups, underscoring the importance of fairness and transparency in AI-based mental health systems [87]. Overreliance on AI in providing psychological support may undermine human professionalism and emotional involvement in mental health treatment [86, 88]. Close collaboration among AI researchers, psychologists, and ethicists is essential to ensure that AI-based mental health technologies remain effective while adhering to ethical standards. These advancements highlight the growing role of AI-driven

systems in understanding and predicting mental health conditions.

III. Review Methodology

This study follows a structured literature review methodology to examine the current state of AI and ML applications for GAD, with a particular focus on cognitive biases, predictive modeling, monitoring systems, intervention technologies, and Explainable AI (XAI) approaches. The objective of the review is to identify current research trends, evaluate existing approaches, highlight their limitations, and identify future research opportunities to develop more transparent and cognitively informed AI systems.

A. Search Strategy

A comprehensive literature search was conducted using several major scientific databases, including Scopus, IEEE Xplore, PubMed, Web of Science, and Google Scholar. These databases were selected because they collectively cover research in computer science, AI, psychology, psychiatry, and digital health.

The search process used keyword combinations related to GAD, AI, ML, cognitive biases, and digital mental health technologies. Examples of search terms included:

- "Generalized Anxiety Disorder" OR "GAD".
- "Machine Learning" OR "Artificial Intelligence".
- "Digital Phenotyping".
- "Wearable Sensors".
- "Cognitive Bias".
- "Interpretation Bias".
- "Catastrophic Thinking".
- "Explainable AI".
- "Mental Health Intervention".

The search focused on studies published between 2015 and 2025 to capture recent advances in AI-based mental health systems while retaining sufficient historical context for comparison.

B. Study Selection

The study selection process was performed in multiple stages. First, records were retrieved from the selected databases, and duplicate entries were removed. Second, titles and abstracts were screened for relevance to GAD, anxiety prediction, AI-based assessment, cognitive bias modeling, or digital intervention systems. Third, full-text articles were evaluated against predefined inclusion and exclusion criteria.

A total of 285 records were initially identified through database searches. After removing 55 duplicate records, 230 articles remained for title and abstract screening. During this stage, 140 records were excluded based on relevance, leaving 90 full-text articles for eligibility assessment. Following full-text evaluation, 38 articles were excluded according to the predefined inclusion and exclusion criteria, resulting in 52 studies that were included in the final qualitative synthesis.

Additional references were incorporated throughout the manuscript to provide background on GAD prevalence and symptomatology, cognitive bias theories, explainable AI, methodological guidance, and broader mental health research relevant to the study.

The study selection process followed PRISMA-inspired reporting principles. Fig. 3 illustrates the identification, screening, eligibility assessment, and inclusion stages used in this review.

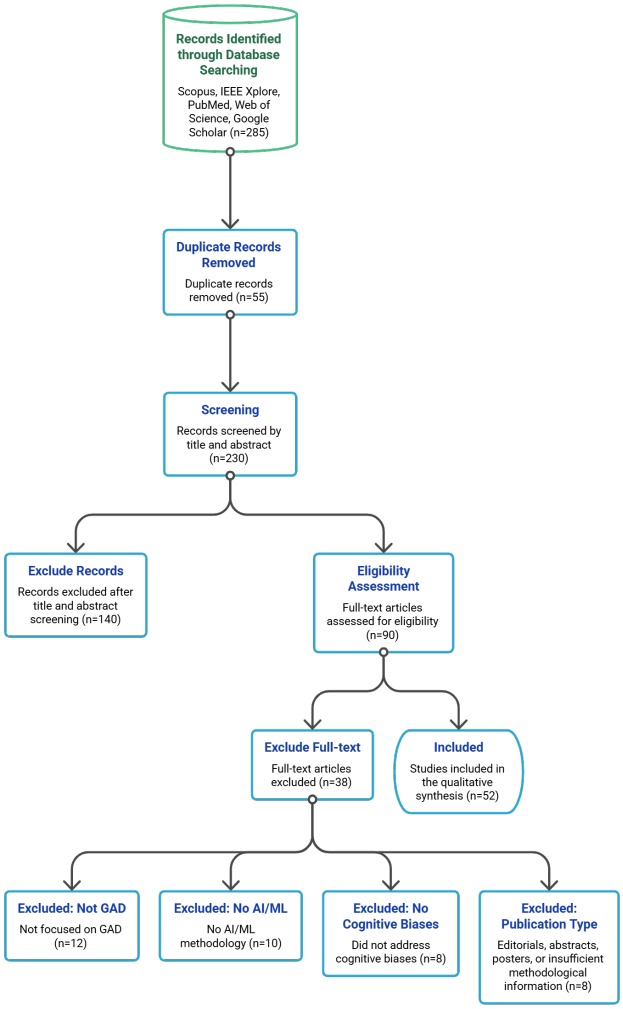

Fig. 3. PRISMA-inspired study selection process.

C. Inclusion and Exclusion Criteria

Studies were included if they satisfied the following criteria:

- Focused on GAD or anxiety-related conditions.
- Proposed, evaluated, or discussed AI or ML approaches for prediction, monitoring, diagnosis, or intervention.
- Examined behavioral, physiological, psychological, or cognitive indicators associated with anxiety.
- Investigated cognitive biases relevant to anxiety disorders.
- Were published in peer-reviewed journals or conference proceedings.
- Were written in English.

Studies were excluded if they:

- Focused exclusively on non-computational clinical treatments.
- Did not provide sufficient methodological information.
- Were editorials, abstracts, posters, or non-peer-reviewed reports.
- Were unrelated to anxiety disorders or AI-based approaches.

D. Data Extraction and Quality Assessment

Relevant information was extracted from each selected study, including study objectives, data sources, AI or ML techniques, performance metrics, cognitive bias measures, intervention strategies, interpretability mechanisms, and reported limitations. To improve the rigor of the review, studies were also assessed according to four criteria:

- Relevance to GAD or anxiety-related research.
- Methodological clarity and reproducibility.
- Contribution to AI or ML-based mental health systems.
- Discussion of limitations, interpretability, generalizability, or ethical considerations.

Studies demonstrating stronger methodological quality and clearer reporting were given greater emphasis during the comparative analysis and synthesis.

E. Synthesis Approach

A qualitative synthesis approach was used to organize the reviewed literature into four major categories:

- Predictive AI and ML Models
- Monitoring and Digital Phenotyping Systems
- AI-Based Intervention Technologies
- Cognitive-Bias-Aware AI Approaches

This categorization provides a structured framework for AI-based approaches to GAD and facilitates the identification of research gaps in interpretability, integration of cognitive biases, personalization, and real-world deployment.

IV. Related Work

Recent research shows growing interest in leveraging AI and ML techniques to predict, monitor, and support interventions for GAD. These approaches utilize diverse data sources and computational models to capture the complexity of anxiety-related conditions.

Several studies have focused on predictive modeling using combined psychological, biological, and social features. For example, Basterfield and Newman [7] developed models that integrate psychosocial and biological data to predict long-term outcomes for individuals with GAD. Their approach, which utilized Elastic Net Regression and Gradient Boosted Trees, demonstrated strong predictive performance, highlighting the value of combining heterogeneous data sources. However, these models primarily focus on prediction and provide limited insight into underlying cognitive mechanisms.

In parallel, digital phenotyping has emerged as a promising approach for continuous monitoring of anxiety symptoms. Jacobson and Feng [13] proposed a system that estimates GAD severity in real time using passive data collected from wearable devices. Their model demonstrated strong predictive capability, supporting the feasibility of real-time monitoring in naturalistic settings. Despite these advantages, such systems often face challenges related to generalizability and long-term reliability across different populations.

Computer vision-based approaches have also been explored to detect behavioral patterns associated with anxiety. Manocha and Singh [89] developed a framework for analyzing posture trajectories in video data to identify anxiety-related behaviors. Their results demonstrated strong classification performance, particularly in controlled environments such as workplaces. However, these approaches remain context-dependent and may not generalize well to less structured environments.

More general ML frameworks have been proposed to predict anxiety severity scores, such as the GAD-7 scale, to support clinical decision-making. These systems aim to support mental health screening by predicting anxiety severity scores, such as the GAD-7, thereby facilitating more efficient clinical assessment [90]. Although these approaches offer practical value, many lack transparency in their model structures and decision-making processes.

In addition to predictive models, AI-driven intervention systems have gained increasing attention. For instance, conversational agents such as Therabot have shown potential to provide scalable support and reduce anxiety symptoms while maintaining user engagement [14]. Similarly, mobile applications incorporating self-monitoring and mindfulness techniques leverage ML to personalize interventions based on user behavior [8]. These tools demonstrate the growing role of AI in bridging prediction and intervention.

Recent work has also explored advanced ensemble learning techniques for GAD classification. Lu *et al.* [12] proposed a weighted ensemble approach using biological signals, achieving high classification performance. While promising, such models are often considered black-box systems, limiting their interpretability and practical adoption.

A particularly important direction in recent research is the integration of cognitive bias measures into ML models. Studies suggest that incorporating cognitive biases, such as interpretation and attentional biases, can improve predictions and provide more personalized insights. For example, Richter *et al.* [9] and Richter *et al.* [10] used Random Forest models trained on cognitive task data to differentiate anxiety and depression and to predict symptom severity, respectively. Their results demonstrate that combining multiple cognitive bias indicators can enhance predictive performance. However, these models still face challenges related to interpretability and clinical integration.

Further studies have explored the use of ML-based behavioral assessments to detect cognitive-emotional biases. These approaches show potential for automated

screening and early intervention, reinforcing the importance of cognitive factors in GAD prediction [11].

Overall, these findings highlight the growing recognition of cognitive bias as a key component of AI-based mental health systems.

Taken together, the reviewed studies can be grouped into four major categories: predictive ML models, digital phenotyping and monitoring systems, AI-assisted intervention technologies, and cognitive-bias-aware approaches. While predictive and monitoring systems have demonstrated strong performance in identifying anxiety-related patterns, they often prioritize accuracy over interpretability. Intervention-oriented systems improve accessibility and scalability but frequently lack long-term clinical validation. Cognitive-bias-aware approaches represent a promising direction because they incorporate psychological mechanisms directly into computational models; however, their adoption remains limited compared with symptom-based and physiological approaches.

Despite these advancements, several limitations remain across existing studies. Many approaches prioritize predictive accuracy over interpretability, rely on specific data modalities, and lack generalizability across diverse populations. These gaps highlight the need for more explainable, bias-aware, and human-centered AI systems for GAD prediction and intervention. The main characteristics of the reviewed studies are summarized in Table II.

TABLE II. COMPARATIVE SUMMARY OF AI-BASED APPROACHES FOR GAD PREDICTION AND INTERVENTION

Study	Model	Data Source	Key Findings	Limitation
Basterfield and Newman [7]	ElasticNet, Gradient Boosting	Clinical + Psychological Data	Good predictive performance (AUC ≈ 0.81)	Limited integration of cognitive biases
Jacobson and Feng 13]	Machine Learning	Wearable Sensor Data	Digital phenotyping prediction (AUC ≈ 0.89)	Limited generalizability
Manocha and Singh [89]	Computer Vision	Behavioral Video Data	Detects anxiety-related behaviors	Context dependent
Richter *et al.* [9]	Random Forest	Cognitive Tasks	Differentiates anxiety and depression using cognitive-bias measures	Limited interpretability
Richter *et al.* [10]	Random Forest	Cognitive Tasks	Predicts GAD symptom severity using cognitive-bias indicators	Limited interpretability
Lu *et al.* [12]	Ensemble ML	Biological Signals	High classification performance	Black-box nature

V. CONCEPTUAL FRAMEWORK FOR INTEGRATING COGNITIVE BIASES INTO AI-BASED GAD PREDICTION AND INTERVENTION SYSTEMS

Based on the findings of this review, a conceptual framework is proposed to illustrate how cognitive biases can be integrated into AI-based systems for the prediction and intervention of GAD (See Fig. 4). The framework synthesizes the relationships among cognitive biases, AI-based assessment methods, prediction and detection mechanisms, explainability components, intervention strategies, and expected outcomes identified throughout the reviewed literature. The framework addresses several limitations highlighted in existing studies, including limited incorporation of cognitive mechanisms, insufficient model interpretability, and challenges in delivering personalized interventions. By integrating insights from cognitive psychology and AI, the framework provides a conceptual foundation for developing more transparent, personalized, and clinically relevant GAD support systems.

The proposed framework positions cognitive biases, particularly interpretation bias and catastrophic thinking, as central elements in AI-based GAD systems [9–11]. These cognitive factors can be assessed using AI-based assessment methods, including cognitive tasks, self-report measures, and digital phenotyping data, to support risk prediction, severity assessment, and early detection of anxiety-related conditions [7, 10, 13, 89]. The framework further embeds explainability mechanisms, including model interpretation and decision transparency, to clarify how cognitive factors contribute to prediction outcomes and enhance the interpretability of AI-generated predictions for clinicians and users [12, 91]. These insights subsequently inform personalized interventions through adaptive support and continuous monitoring, creating an iterative process in which updated patient information is incorporated into subsequent AI-based assessments [8, 14]. Collectively, the framework illustrates how cognitive psychology and AI can be integrated to improve prediction capabilities, enhance interpretability, strengthen clinical decision-making, and support more effective intervention strategies for individuals with GAD.

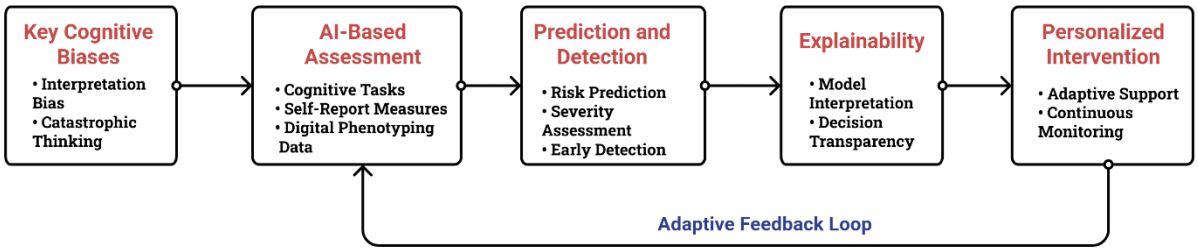

Fig. 4. Conceptual framework for integrating cognitive biases into AI-based GAD prediction and intervention systems with an adaptive feedback loop.

The reviewed literature suggests several ways to incorporate cognitive biases into AI-based GAD systems. For example, interpretation bias may be assessed using cognitive tasks involving ambiguous scenarios, language analysis, or self-report measures that capture negative interpretations of uncertain situations [9, 11]. Similarly, catastrophic thinking may be assessed using self-report measures, behavioral responses to cognitive tasks, or language-based features that reflect exaggerated expectations of negative outcomes [78, 92]. In addition, digital phenotyping data can complement these assessment methods by providing continuous behavioral and contextual information relevant to anxiety-related conditions. Collectively, these bias-related indicators can complement traditional physiological, behavioral, and clinical features, enabling AI models to incorporate cognitive mechanisms that are closely associated with GAD development and maintenance [7, 10].

VI. Discussion

The reviewed studies demonstrate a clear evolution from traditional symptom-based prediction toward more comprehensive AI-driven approaches that incorporate behavioral, physiological, and cognitive information. While substantial improvements in predictive performance have been achieved, the literature reveals an imbalance between accuracy and explainability. Most studies focus on identifying anxiety-related patterns and risk levels, whereas relatively few investigate the cognitive mechanisms underlying GAD. Furthermore, approaches that explicitly incorporate cognitive biases remain limited despite strong psychological evidence supporting their role in anxiety disorders.

These observations suggest that future research should place greater emphasis on explainable, cognitively informed AI systems rather than solely on predictive performance.

Several critical limitations remain across the existing literature. First, most existing models prioritize predictive performance over interpretability. Black-box models, such as ensemble and deep learning techniques, achieve high accuracy but provide limited insight into the underlying cognitive mechanisms driving anxiety. This lack of transparency reduces their applicability in real-world decision-making systems.

Second, despite strong theoretical evidence supporting the role of cognitive biases in anxiety disorders, their integration into computational models remains limited. Most systems rely on observable symptoms or physiological indicators, overlooking the cognitive processes that contribute to the development and persistence of GAD.

Third, generalizability remains a major concern. Many models are trained on homogeneous datasets and lack external validation across diverse populations. This restricts their scalability and real-world deployment.

Additionally, translating predictive outcomes into adaptive interventions remains underexplored. While models can identify risk levels, few systems provide actionable or personalized feedback based on profiles of cognitive biases.

From a computational perspective, there is a clear need to develop explainable, bias-aware AI systems. Integrating cognitive bias modeling into ML frameworks can enhance both predictive performance and interpretability. Such systems can support real-time monitoring and personalized interventions while maintaining transparency.

The proposed framework consolidates the evidence synthesized throughout this review by illustrating how cognitive biases, AI-based assessment methods, prediction mechanisms, explainability, and intervention strategies can be integrated into future AI-based systems for GAD. As a conceptual framework derived from the reviewed literature, it highlights key relationships among these components and provides a structured basis for developing more cognitively informed XAI systems.

Overall, future research should focus on bridging the gap between predictive accuracy and interpretability by incorporating cognitive theories into AI-driven systems, thereby enabling more robust, human-centered solutions.

VII. Conclusion and Future Work

Anxiety disorders are among the most prevalent mental health conditions worldwide, with GAD representing one of the most persistent and disabling forms due to its chronic nature and substantial impact on daily functioning. Cognitive distortions, particularly catastrophic thinking and interpretation bias, play a central role in the development and maintenance of GAD. Consequently, understanding and modeling these cognitive mechanisms is essential for developing more effective prediction and intervention strategies.

This paper presented a structured review of recent AI and ML approaches for GAD prediction, monitoring, and intervention. The review demonstrated that AI-based systems have achieved promising predictive performance using behavioral, physiological, clinical, and digital phenotyping data. However, several important limitations remain. Most existing approaches rely primarily on observable symptoms and physiological indicators, while the integration of cognitive bias mechanisms remains limited. Furthermore, many high-performing models operate as black-box systems, reducing transparency and limiting their applicability in real-world clinical decision-making. In addition, personalization remains underexplored, as many current systems do not adapt dynamically to changes in an individual's cognitive profile.

The findings of this review suggest that future GAD support systems should move beyond symptom-based predictions toward cognitively informed and interpretable AI approaches. Rather than viewing GAD solely as a collection of observable symptoms, the disorder can be understood as a dynamic cognitive process involving perception, interpretation, and behavioral response. Incorporating cognitive mechanisms into AI models may improve both predictive capability and clinical relevance

while supporting more targeted and adaptive intervention strategies.

Based on the findings of the reviewed studies, we developed a conceptual framework that summarizes how cognitive biases, AI-based assessment methods, prediction mechanisms, explainability, and intervention strategies can be integrated within future GAD support systems. The framework highlights the relationships among cognitive bias indicators, AI-driven assessment techniques, prediction models, explainability methods, and personalized intervention strategies. By linking cognitive psychology with AI, the framework provides a conceptual foundation for developing more transparent, interpretable, and personalized GAD support systems.

For AI-based GAD systems to achieve meaningful clinical impact, future research should extend beyond algorithm development to include rigorous clinical validation in collaboration with psychologists, psychiatrists, and other mental health practitioners. Such interdisciplinary collaboration is essential to ensure that cognitive bias measures, prediction models, explainability mechanisms, and intervention strategies are clinically relevant and aligned with established assessment and treatment practices for GAD. Furthermore, prospective clinical studies conducted in real-world settings will be essential for evaluating the clinical utility and practical applicability of XAI systems.

Further research should focus on developing explainable, bias-aware, and human-centered AI systems that explicitly incorporate cognitive bias indicators into computational models. This includes investigating methods for integrating cognitive bias indicators into ML frameworks, improving model transparency through XAI techniques, and enabling adaptive interventions that respond dynamically to changes in an individual's cognitive profile. Furthermore, longitudinal validation studies across diverse populations and real-world settings are needed to evaluate the robustness, generalizability, and clinical utility of these systems.

Overall, this review's findings suggest that cognitive biases are an important yet underutilized component of AI-based GAD prediction and intervention systems. Integrating cognitive mechanisms with XAI approaches may help develop more effective, interpretable, and clinically relevant mental health support technologies.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

A. Almathami and R. Stone contributed to the conceptualization of the study and reviewed and edited the manuscript; A. Almathami developed the methodology, conducted the investigation and literature review, performed the formal analysis and visualization, and prepared the original draft; R. Stone supervised the research; both authors had read and approved the final manuscript.

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