

Data Representativeness Through a Sociocultural Lens in AI Modeling for Mental Health

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Abstract

Background: Artificial Intelligence (AI) is reshaping mental health diagnosis and treatment. However, most AI models are built on Western-centric datasets, limiting their applicability in culturally diverse settings like India. Socio-cultural realities need to inform datasets, and this review seeks to understand the challenges in making data more culturally nuanced and representative. This paper aims to identify the socio-cultural aspects that affect data representativeness in AI modeling in anxiety and depression in the Indian context. A literature survey was conducted of studies from 2000–2024 focusing on AI in mental health and the socio-cultural dimensions of anxiety and depression in India based on the exclusion and inclusion criteria that were defined for the survey. PRISMA guidelines are used to report these criteria.

35 studies out of 101 studies reviewed were included in the final review. Two major themes emerged: (1) The socio-cultural context in the manifestation of anxiety and depression in India, specific anxiety and depression symptoms in India and idioms of distress with respect to anxiety and depression in India and (2) Missed opportunities in data collection due to stigma, lack of screenings in public health, and underrepresentation certain groups and absence of evidence-based treatments. The implications of these themes in terms of data representation in AI modeling are discussed. The review informs practitioners, AI developers, and end-users about the critical issue of representativeness bias within socio-cultural frameworks in mental health.

Keywords: AI, Mental Health, Data Representativeness, Sociocultural Context, Anxiety, Depressive Disorders

1. Introduction

The use of AI-based models for mental health diagnosis and prognosis comes with several challenges. Developing rigorous, reliable, and valid AI models is difficult due to reliance on self-reported data, which often lacks objective verification [1]. Additionally, generative AI models in mental health encounter significant obstacles, including issues of data privacy, limitations in data quality, interpretability, transparency, gaps between technological advancements and practical applications, lack of representativeness, and biased datasets [2,3].

One of the key limitations in AI-driven mental health models is the lack of inclusiveness in datasets. Addressing the problem

of representativeness is critical to improving the accuracy and effectiveness of AI models [2]. Bias in these models remains a pressing concern, affecting the fairness and reliability of diagnostic and therapeutic interventions. AI systems, trained on large datasets, often underrepresent certain demographic groups, leading to biased predictions and potentially harmful outcomes [3-5]. This bias can worsen existing health disparities rather than mitigate them. Nazer et al. (2023), emphasizes that bias arises at multiple stages, including data collection, algorithm design, and model deployment and advocate for greater representation in AI datasets and interdisciplinary collaboration as essential steps toward addressing these challenges [6].

It is crucial for research to identify and address potential sources of bias in datasets, as these can disproportionately skew outcomes, favoring or disadvantaging certain groups. Furthermore, addressing biases is essential to improving data accuracy and reliability of AI models in mental health.

Studies indicate that AI models trained predominantly on western-centric datasets struggle to generalize across diverse populations, thereby perpetuating systemic inequalities in mental healthcare access and treatment outcomes [7]. While the challenges of AI data modeling and potential solutions have been extensively discussed, and the need for culturally specific context have been suggested, there remains a noticeable gap in the literature concerning the use of culturally specific contexts to inform data collection and analysis.

1.1. Need for Data Representativeness in the Indian Context

Given the growing applications of AI in the field of mental health, and the increasing body of recent research in this emerging domain, this paper focuses on fostering inclusivity and representativeness in AI datasets, specifically through the lens of mental illness within the Indian cultural context. To ensure greater accuracy in AI modeling for mental health, it is vital that any data-input tools incorporate cultural nuances and influences on mental health. Such an approach would enable the development of culturally informed diagnostic tools that ask the right questions to elicit more accurate and contextually relevant diagnoses.

Currently, no comprehensive study exists that addresses the challenges of data input biases and representation within the Indian context. Therefore, as an illustration for broader applications of sociocultural considerations for AI in mental health, we considered the example of anxiety and depression within the Indian context, exploring how sociocultural factors are manifest in the illnesses themselves, and how these sociocultural factors could impact the data representativeness with respect to these disorders. This has broader implications for considerations across a spectrum of mental disorders and across various cultures globally.

In this paper, we narrowed our focus to anxiety and depressive

disorders, given their significantly higher estimated prevalence in India compared to other major mental illnesses [8]. It is hoped that similar analyses will be expanded to encompass other mental illnesses in the future within specific cultures.

1.2. Objective and Search Strategy

The objective of the review was to identify the socio-cultural aspects that can affect data representativeness in AI modeling for anxiety and depression in India.

This paper is based on a survey of research papers related to anxiety and depression in the Indian context, and AI in Mental Health in general and in India in particular, from the years 2000-2024.

To identify relevant resources, we conducted searches using Google Scholar and Litmaps software, refining the results to include relevant papers from the past 24 years. To access studies on the AI in mental health and cultural aspects of mental illness, and particularly anxiety and depression in India, we employed the following targeted search terms : “AI in mental health” “AI in mental health in India” “cultural aspects of mental illness in India,” “cultural factors in anxiety disorders in India,” “cultural factors in depressive disorders in India,” “evidence-based practice in mental health in India,” and “stigma associated with mental health in India.”

A total of 101 papers were accessed through 2 databases- Litmaps Software and Google Scholar and manual search of relevant papers. 16 papers were found to be duplicates. In the final review, 35 papers were included based on the following inclusion and exclusion criteria: We included peer-reviewed papers, including primary studies and systematic reviews, and papers that reported cultural aspects of anxiety and depression in India. Papers excluded from the review were technical papers and review papers that described the technology in machine learning, efficacy, challenges, use of AI; use of chatbots, ethics of AI, papers that were not focused on the Indian context of anxiety and depression, or general health conditions, those that focused on etiology of anxiety or depression and those that were not peer reviewed or were grey literature. Details of the exclusion criteria are given in the PRISMA diagram.

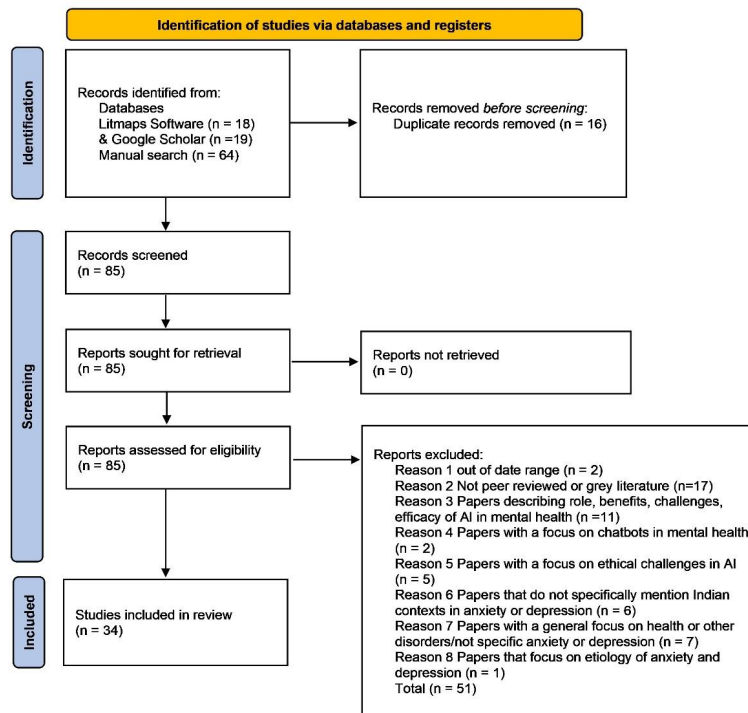


Figure 1: PRISMA Flow Diagram for Identification of Studies for The Review with Eligibility Criteria

Note: PRISMA Preferred Reporting Item for Systematic Reviews and Meta Analyses, Page, et al. (2021) (www.prisma-statement.org) [9].

2. Themes

Two broad themes emerged from the review of literature that have significant implications for data representativeness in mental health in India. 3 subthemes emerged from Theme 1, and 4 subthemes emerged from Theme 2.

2.1. Theme 1: Socio-Cultural Context of Anxiety and Depression

The papers we explored could be broadly classified into sub-themes as manifestation of anxiety and depression symptoms in India, examples of culturally specific anxiety syndromes and idioms of distress. The three sub-themes are:

2.1.1. Manifestation of Anxiety and Depression Symptoms

Cultural nuances can heavily influence how anxiety disorders manifest. When these cultural subtleties are overlooked by mental health practitioners, misdiagnosis or failure to diagnose may occur. For example, broader cultural factors such as the emphasis on collective identity or culturally distinct notions of shame have been linked to anxiety disorders, particularly Social Anxiety Disorder [10].

At a more specific level, some cultural patterns emerge distinctly. Social Anxiety Disorder in India, for instance, often manifests in teenagers as a pronounced avoidance of public speaking [11]. In the case of panic disorder, research has shown that Indian patients may exhibit fewer cognitive symptoms compared to their counterparts

in Western societies [12]. Studies aimed at developing culturally sensitive anxiety scales for panic disorder further illustrate how anxiety symptoms are often expressed through colloquial terms, highlighting the need for physicians to understand these culturally specific expressions [13].

In the context of affective disorders, patients in India often present physical symptoms such as pain and sleep disturbances, which can mask underlying symptoms of depression [14-16] Studies have revealed that while patients readily discuss these physical symptoms, further probing often links them to psychological distress stemming from their lives. Despite acknowledging this connection, many do not consider themselves as needing primary mental health care in India [17].

2.1.2. Examples of Culturally Specific Anxiety Syndromes in India

India provides notable examples of culturally specific syndromes recognized by the ICD-10, such as *Dhat* Syndrome and *Koro* Syndrome, which present as general anxiety symptoms. *Dhat* Syndrome involves anxiety related to the perceived loss of semen, while *Koro* Syndrome is characterized by acute panic attacks triggered by the belief that one's genitals are retracting. Despite their prevalence and reports of *Koro* Syndrome reaching epidemic levels, both conditions are stigmatized as psychosexual disorders, which often prevents individuals from seeking help in psychiatric clinics or mental health facilities [18].

2.1.3. Language & Idioms of Distress

AI is trained on large language models mostly in the English language. As it is known generally, English is spoken differently in different countries and regions with local contexts where it is influenced by the region's history, culture, its own vernacular language syntax, etc. In India we have what is popularly known as "Indian English." The Western-centric models may not correctly interpret this locally used English language within the broader cultural context and therefore may not provide culturally suitable suggestions or actions. The idioms of distress is a specific example of this concept in the context of mental health.

Culture shapes the perception, expression, and treatment of anxiety and depression and different cultures often employ unique terms to articulate distress, known as "idioms of distress," [19,20]. These culturally specific expressions play a crucial role in conveying psychological distress, including anxiety and depression.

Straw & Callison-Burch (2020) found a number of biases in AI modeling for mental health that were related to linguistic labeling for distress or disorders [21]. In a study of women in rural India, Desai & Chaturvedi, (2017) found specific idioms of distress for anxiety and depression. Recognizing and understanding such idioms would enable clinicians to better interpret culturally influenced manifestations of mental distress [22].

Moreover, in the context of assessments, integrating these culturally informed terms into psychometric tools significantly enhances the validity and reliability of these tools [23]. Apart from idioms of distress, in a linguistically diverse country like India, the local vernacular languages may not inform the AI models at all.

2.1.4. Implications for Data Representativeness

Accurate diagnosis of anxiety and depression disorders requires enhancement of the input tools utilized in AI modeling. These tools should include specific questions that can reliably confirm or rule out the diagnosis, while considering the ways in which the disorder typically manifests within different cultural contexts. This will ensure the construct validity and internal validity of the AI models related to anxiety and depression within a specific culture and representativeness and reliability of the data used for modeling.

2.2. Theme 2: Missed Opportunities to Gather Mental Health Data

One major hurdle in mental health care is the frequent missed opportunities to gather essential data on mental illnesses. While it is well-recognized that certain segments of the population are disproportionately impacted by common mental health disorders, the data available is often insufficient or under-representative. As Nazer et al. (2023) suggest that biases arise at multiple stages including data collection [6]. In India, this gap stems again primarily from socio-cultural factors such as the low priority given to mental health in India, widespread lack of awareness, persistent stigma surrounding mental illnesses, and limited emphasis on evidence-based practices. The scarcity of data can be primarily

attributed to four key reasons that are captured in the following four sub-themes:

2.2.1. Lack of Emphasis on Mental Health Screening in Public Health Settings

Mental health screening often receives insufficient attention in public health systems, leading to critical data gaps. For example, maternal mental health during pregnancy and postpartum is frequently overlooked, as highlighted by Kalra et al. (2024), despite the high prevalence of perinatal common mental disorders in low-income countries [24]. In the case of the geriatric population, there is a similar situation. Despite the high prevalence of anxiety and depression among older adults, systematic screening remains absent [25,26]. Studies cite inadequate infrastructure, limited medical training, and low awareness of geriatric mental health [27,28] among the many challenges to improved geriatric care. Primary care for geriatric mental health is nearly nonexistent, and policy recommendations emphasize workforce training to enable effective early screening and intervention [27-29].

2.2.2. Stigma Associated with Mental Illness

A significant barrier complicating self-reports is the persistent stigma associated with seeking mental health care in many cultures, including India. Studies, such as those by Sidhaye & Kermode (2013), and Gururaj et al., (2016) reveal societal stigma surrounding the disclosure of mental illnesses, including conditions like anxiety and depression [29,30]. Research further delves into the nature and dynamics of this stigma within the Indian cultural context, highlighting that it often deters individuals from sharing details about their distress. This reluctance stems from concerns such as potential impacts on marriage prospects and fears of lowering the family's social standing [31].

2.2.3. Absence of Evidence-Based Treatments

A third reason for missing data in mental health treatment is the limited availability of evidence-based interventions. A systematic review of evidence-based treatments used in India since 2000 indicates that while cognitive behavioral therapy remains the preferred approach, its implementation faces significant challenges. Many mental health practitioners lack supervised training in evidence-based techniques, making it difficult to collect reliable data on client progress [32]. Recent efforts to train community health workers in effective interventions have improved access to care to some extent [33]. However, large-scale, systematic replication across different regions of India is necessary to ensure broader data representation. This has implications for AI modeling that depends on systematic data gathering to train the models to deliver effective solutions.

2.2.4. Under-Representation of Epidemiological Data in Certain Sectors

Epidemiological data on the prevalence of mental illnesses across Indian states is limited. While trends in illness prevalence are observed, this data often suffers from biases due to its insufficient scope [28]. In the National Mental Health Survey, the gaps in epidemiological data were addressed [30]. They found that

common mental health disorders remain ignored and undetected. They also find that lack of data collection and mental health treatment at primary health care centers further compounds the issue of underrepresentation and inadequate mental health services. Bhandary et al. (2023), highlight some of the challenges or limitations of the National Mental Health Survey such as the exclusion of data from the private healthcare sector and concerns regarding the inclusiveness of tools like the MINI, and the sample selection process across states [34]. Pal et al. (2022) highlighted another limitation in the National Mental Health Survey in reference to the representation of data on adolescents [35]. Further surveys need to be done that address these limitations.

2.2.5. Implications for Data Representativeness

Missing data has important consequences for building AI models in that it limits the generalizability of the data sets to those specific populations. This can have implications for representativeness, reliability and external validity of the AI models that are informed by the data. Thus, identifying the underrepresented populations will be the first step to a more accurate application of models that are developed. This would mean more groundwork by researchers, practitioners and communities to identify and report mental illness, get diagnosed, and treated for mental health conditions so that AI can be used to create accurate models for a highly culturally and economically diverse country like India.

3. Limitations of the Study

This review was an exploratory study that focused only on Anxiety and Depression in the Indian context. Expanding the review to encompass a broader range of mental illnesses is crucial for uncovering the distinct challenges of representativeness within different cultural contexts. This effort should also involve tapping into additional databases, which may provide access to a wider array of studies and insights on the subject.

4. Conclusion

The application of AI in mental health brings both challenges and opportunities, like any technological advancement. AI requires accurate data to create accurate models. However, in the context of mental health, there is lack of representativeness of data in the Indian context when viewed through a socio-cultural lens. This paper has detailed some of the challenges of making data more representative for AI modeling. The overarching goal of this review is to inform practitioners, model developers, and AI users, researchers about the significance of representativeness bias within a socio-cultural framework to make the AI models more valid, reliable and applicable in the Indian context.

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Conflict of Interest

The authors declare no conflict of interest.

Ethical Approval (If Applicable):

Not Applicable

Author Contributions

Both authors have contributed equally to the conceptualization, methodology analysis and writing the paper

Data Availability Statement

Not Applicable

State Data Availability Details

Example: Data available upon reasonable request.

AI Usage Statement

No generative AI tools used for language editing.

State whether generative AI tools were used for language editing only or not used at all.

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