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Digital Voice Biomarkers For Substance Use Disorders In Older Adults: A Systematic Review With Implications For India

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Abstract
Substance Use Disorders (SUDs) in India's elderly population are growing as a public health concern but often compounded by delayed diagnosis and comorbidities. Traditional screening and treatment approaches fail to capture the subtle age-related manifestations of substance misuse, underscoring the need for innovative and effective solutions. Recent advances, particularly audio-assisted methods that analyze voice, speech and acoustic markers offer a promising non-invasive pathway for early detection and personalized management. This paper aims to synthesize evidence of the identification and use of audio-assisted AI tools in screening, monitoring and intervention for SUDs among older adults in Indian context.
Literature was sourced from databases including PubMed, PsycINFO, Scopus, and IEEE Xplore, covering studies from 2010 to 2025. Search terms included combinations of "audio biomarkers," "speech analysis," "AI in SUDs," "elderly," and "India." Inclusion criteria encompassed studies involving participants aged 60 and above, research employing AI-based or audio-assisted tools for substance use detection or intervention, and publications in English. Findings suggest emerging evidence supporting the feasibility of speech-based biomarkers in detecting relapse risk, tracking progress and enhancing individualized digital interventions though significant gaps remain in elderly-specific validation, linguistic adaptation and ethical safeguards in India. The review underscores the need for interdisciplinary research, ethical implementations, and adoption of human-centered AI solutions into sustainable clinical practice.
Keywords: *audio biomarkers. substance use disorders, voice analysis, artificial intelligence, india, personalized care.*

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I. Introduction

Substance Use Disorders (SUDs) among older adults in India are an emerging public health concern, magnified by the country's rapidly aging population. The population of elderly substance users is gradually increasing in India, driven by demographic shifts and longer life expectancies (Sarkar, Parmer & Chatterjee, 2015; Lin et al., 2023). Unlike younger populations, older adults often present with subtle or atypical symptoms of substance misuse that can be easily overlooked. Age-related physiological changes and medical comorbidities such as chronic illnesses and cognitive decline can mask or mimic SUD symptoms, leading to delayed diagnosis and missed opportunities for early intervention (Lin et al., 2023; Yarnell et al., 2020). Traditional screening questionnaires and clinician assessments may not be fully attuned to the nuances of substance misuse in a geriatric context, as most were validated in younger or middle-aged adults (Sarkar et al., 2015). This gap underscores an urgent need for innovative and non-invasive methods capable of detecting and monitoring SUDs in the elderly more effectively.

Recent advances in artificial intelligence (AI) offer promising solutions. In particular, audio-assisted AI, the analysis of voice, speech, and acoustic markers through machine learning has emerged as a novel approach to health diagnostics and monitoring. Human speech carries a wealth of information beyond words: vocal tone, pitch, jitter, cadence, and other acoustic features can reflect underlying neurophysiological states (Fagherazzi et al., 2021; Low et al., 2020). Researchers are now leveraging AI to turn the human voice into a digital biomarker for various medical conditions. For instance, AI algorithms have been developed to analyze voice recordings and successfully detect conditions like heart disease,

Alzheimer's, and depression based on vocal changes (Fagherazzi et al., 2021). The allure of voice-based analysis lies in its non-invasive and accessible nature; a short speech sample, even from a simple phone call, can be analyzed for health indicators without the need for blood tests or in-person exams (Low et al., 2020).

In the context of SUDs, especially among older adults, audio-based AI could be transformative. Substance use and its related states such as intoxication, withdrawal, craving, or relapse often manifest in voice changes such as slurred speech, altered pitch from tremors, slowed or accelerated speech rate, and emotional tone shifts (Agurto et al., 2020; Suffoletto et al., 2023). Capturing these vocal cues with AI could enable early detection of risky substance use or impending relapse, even before a clinical crisis occurs. Moreover, many older adults in India face barriers to frequent in-person care, including mobility limitations, reduced access to specialized services, and stigma, which further underscores the value of remote, voice-based monitoring tools (Lin et al., 2023; Yarnell et al., 2020). A voice-analysis system deployed via telephone or smartphone could unobtrusively monitor an older adult's status and alert caregivers when concerning patterns emerge. This systematic review aims to synthesize current evidence on audio-assisted AI tools for screening, monitoring, and intervention in SUDs among older adults in India.

Preliminary observations indicate that research on speech biomarkers in addiction is still nascent but growing. Early studies suggest that speech patterns can distinguish individuals with SUD from healthy individuals with high accuracy. Acoustic measures may correlate with craving or stress levels, offering a window into relapse risk (Agurto et al., 2023; Ayadi et al., 2024). Furthermore, pilot interventions have explored AI-driven voice assistants for mental health therapy, hinting at their potential to support those in recovery. However, significant challenges still persist, for instance, the current AI models often lack validation in older populations, and linguistic diversity in India thereby complicating the direct adoption of existing voice tools (Ayadi et al., 2024; Fagherazzi et al., 2021). Ethical safeguards are paramount as well. Using personal voice data for health monitoring raises privacy and consent issues, especially for a potentially vulnerable group like the elderly (Fagherazzi et al., 2021). This review therefore not only compiles the evidence to date but also discusses the interdisciplinary and ethical considerations for translating audio-based AI into clinical practice for India's seniors struggling with SUDs.

Research objectives

1. To identify and summarize audio- or speech-based biomarkers associated with substance use, intoxication, withdrawal, craving, or relapse in older adults.
2. To evaluate AI-driven speech and acoustic analysis tools used for screening, predicting relapse risk, or monitoring treatment progress in SUD populations.
3. To assess the applicability and limitations of audio-assisted AI for elderly individuals, including considerations of linguistic diversity, age-related vocal changes, and accessibility in India.
4. To identify ethical, practical, and methodological gaps that must be addressed to integrate voice-based AI systems into geriatric addiction care.

II. Methodology

This review followed the PRISMA 2020 guidelines for transparent and structured reporting of systematic reviews. A comprehensive literature search was conducted across medical and psychological databases to capture the full scope of research on AI-based speech analytics for SUD detection and monitoring. The review included studies published between 2010 and 2025, representing the most recent 15 years of advancements in digital voice biomarkers and machine learning applications in behavioral health. A narrative synthesis approach was used due to methodological heterogeneity across studies, particularly in audio features analyzed, machine learning techniques applied, and outcome measures reported.

Search strategy

The search was conducted across four major interdisciplinary databases, PubMed, PsycINFO, Scopus, and IEEE Xplore to ensure broad coverage of biomedical, psychological, and computational research. The search spanned publications from January 2010 to October 2025 to capture the rapid expansion of work in digital health technologies over the past decade.

The search strategy was structured around three core concept areas, firstly the audio biomarkers and speech analysis, secondly, artificial intelligence or machine learning, and lastly, substance use disorders in older adults within the Indian context. Because the field of digital voice biomarkers is relatively new and often interdisciplinary, reference lists of key papers were manually screened using backward-citation and forward-citation tracking, consistent with PRISMA recommendations for identifying additional eligible studies that might not appear in database searches due to varied indexing or emerging terminology.

Selection criteria

Studies were eligible for inclusion if they examined adults aged 60 years or older, or if they involved mixed-age samples in which findings were applicable to or reported for older adult subgroups. To be included, studies were required to employ an AI-based or audio-assisted tool that analyzed voice, speech, or acoustic

features for purposes related to screening, early detection, monitoring, or intervention in substance use disorders. Eligible studies could examine a range of outcomes, including the accuracy of detecting substance use or intoxication, prediction of relapse risk, treatment engagement, or the efficacy of voice-based digital interventions. Only peer-reviewed journal articles and conference proceedings published in English were considered, ensuring that included studies reflected validated and publicly accessible scientific work.

Studies were excluded if they involved non-English publications, dissertations, book chapters, commentaries, editorials, and grey literature to maintain consistency and quality in the evidence base. After duplicates were removed, titles and abstracts were screened for relevance, followed by full-text evaluation using the predefined criteria. In addition, studies were excluded if they did not report primary empirical data, lacked real-world audio samples, or did not utilize speech, voice, or acoustic-based AI techniques relevant to substance use detection. Research that focused solely on non-elderly populations, using only text-based or physiological markers without an audio component was also excluded, as these limitations prevented meaningful evaluation and comparability.

III. Results

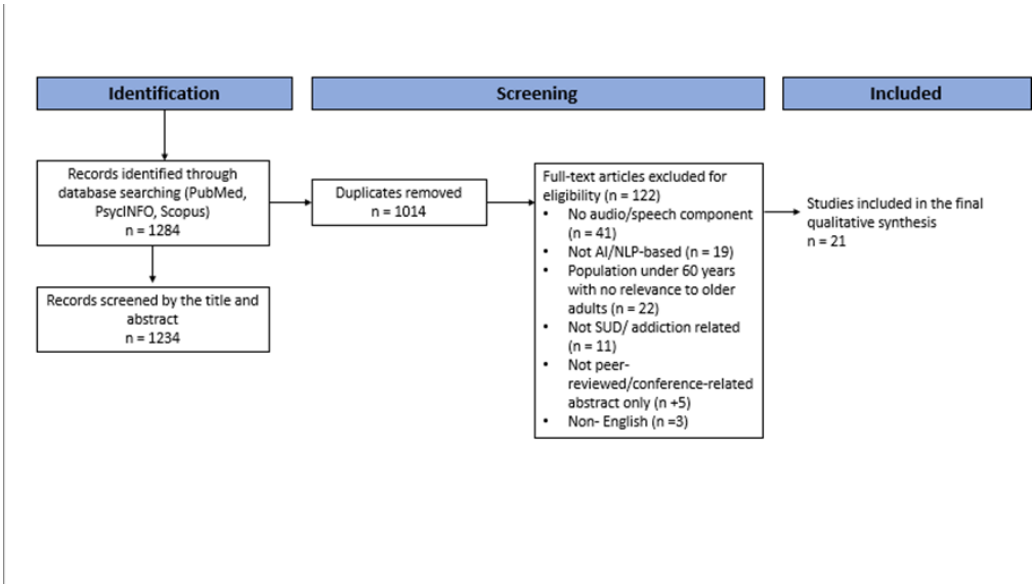

Figure 1
PRISMA Flow Diagram for Systematic Review Selection Process

The initial search across four major databases, PubMed, PsycINFO, Scopus, and IEEE Xplore identified a total of 1,284 records, reflecting how widely research on artificial intelligence, speech analysis, and substance use is distributed across medical, psychological, and engineering fields. To ensure that no relevant studies were missed, an additional 42 records were located through snowballing, which involved manually checking the reference lists of key articles and scanning citations of highly relevant papers. This brought the total number of identified records to 1,326. Once all references were compiled, 312 duplicate entries were removed. These duplicates typically occurred because the same study appeared in multiple databases, which is common in interdisciplinary research. After deduplication, 1,014 unique studies remained and were taken forward for the first level of screening.

In the title and abstract screening stage, these 1,014 records were assessed for broad relevance to the topic. At this point, 892 studies were excluded. Many of these papers focused on unrelated areas such as general speech processing, psychological assessment methods, machine learning unrelated to health, or substance use topics that did not involve AI, audio analysis, or older adults. Some papers examined addiction but did not involve any technological or vocal component, while others were AI-focused but not related to health or SUD. After this filtering, 122 full-text articles were retrieved and reviewed in detail to determine whether they met the predefined inclusion criteria.

During the full-text eligibility review, each article was carefully read to check if it used audio or speech analysis, applied AI or machine learning methods, addressed substance use or addiction, and included or could be applied to adults aged 60 and above. Out of the 122 full-text papers assessed, 101 were excluded for specific methodological and conceptual reasons. The largest group of exclusions (n = 41) consisted of studies that did not include any voice, audio, or speech features, even if they were AI-based. Another set of 19 papers did not use AI or machine learning at all, focusing instead on traditional acoustic analysis or non-digital approaches.

Additionally, 22 studies were excluded because they were conducted entirely in younger populations, with no analysis or discussion relevant to older adults.

Another set of 11 articles were excluded because they were not actually investigating substance use disorders despite appearing in the addiction-related search results. A smaller set of papers were excluded because they were not peer-reviewed publications (n = 5) or were published in languages other than English (n = 3), which could affect the reliability and reproducibility of extraction.

After this rigorous and stepwise filtering process, 21 studies met all inclusion criteria and were selected for the final narrative synthesis. These were the studies that provided reliable, relevant, and methodologically sound evidence on how audio-assisted AI tools have been used to detect substance use, monitor relapse risk, or support intervention efforts.

IV. Discussion

The country is undergoing rapid demographic ageing, with the proportion of persons aged 60 years and above expected to rise steeply in the coming decades, crossing 300 million by 2050 (Government of India, 2021; United Nations, 2022). Community-based studies indicate that substance use among older Indians is not rare. In fact, substance use disorders (SUDs) in later life have historically received far less attention than substance use in adolescents and younger adults, yet global evidence now shows that harmful use of alcohol, tobacco, prescription sedatives, opioids, and other substances among older adults is both common and clinically significant (Lin et al., 2023; Yarnell et al., 2020). Community-based evidence from India indicates that substance use among older adults remains significant, with alcohol and tobacco use being particularly prevalent, and patterns shaped by gender and sociocultural factors (Laslett et al., 2020; Parasuraman et al., 2021). Narrative reviews from Indian geriatric mental health literature further suggest that clinicians can expect a rising number of elderly patients with SUDs, highlighting age-specific patterns such as late-onset use driven by loneliness, chronic pain, or bereavement, along with complex interactions between substances and prescribed medications (Sarkar et al., 2015).

Older adults present with unique vulnerabilities such as pharmacokinetic and pharmacodynamic changes, multimorbidity, polypharmacy, cognitive decline, frailty, and social stressors including bereavement and isolation all interacting with substance use and thereby complicating both diagnosis and treatment (Lin et al., 2023). Despite this, older adults are often excluded from clinical trials, and screening tools such as CAGE or AUDIT and treatment models are rarely tailored to their specific needs. They were largely developed and validated in younger populations, and may show reduced sensitivity and specificity in elders, especially when cognitive impairment or multimorbidity is present (Yarnell et al., 2020).

On the other hand, the past decade has witnessed incredible growth and advancements of digital health and artificial intelligence (AI) applications, including the use of vocal biomarkers, wherein the health-related signals are extracted from speech and voice data. A growing body of work indicates that acoustic and prosodic features of voice can carry clinically relevant information about cardiometabolic disease, respiratory function, neurodegenerative disorders, depression, and anxiety (Fagherazzi et al., 2021). Large digital cohorts such as Colive Voice have demonstrated that smoking status can be predicted from ecological audio recordings, providing proof-of-concept that everyday speech contains signatures of long-term exposures such as tobacco (Ayadi et al., 2024). This suggests that the human voice can serve as a non-invasive and effective biomarker especially in contexts where access to laboratory tests or specialists is limited. Importantly, voice-based tools can also be integrated into technologies that older adults already use, such as telephone calls, interactive voice response (IVR) systems, or simple smartphone apps, potentially overcoming literacy barriers and complex user interfaces. As a result, SUD in older adults is often detected only after complications arise, falls, confusion, delirium, arrhythmias, or functional decline that get misattributed to "normal ageing" rather than alcohol misuse, sedative dependence, or prescription interactions.

Our systematic review sits at the intersection of these two trends, the rising need to improve late-life SUD detection and the emerging potential of audio-assisted AI. The studies included in this review collectively highlight three consistent themes, first, the feasibility and accuracy of speech-based AI in detecting intoxication and substance exposure, second, the utility of voice analytics for relapse prediction and third, the early development of voice-enabled therapeutic interventions that could be adapted for older populations.

Speech-Based Detection of Substance Use

Speech production is a complex neurocognitive-motor process involving coordination between the respiratory system, phonatory control and articulators. Psychoactive substances interfere with these domains in highly specific ways leading to distinctive and reproducible acoustic distortions. These distortions referred to as vocal fingerprints form the scientific basis for speech-driven detection models (Fagherazzi et al., 2021). Among these, the alcohol detection has most compelling evidence, as a controlled laboratory trial (Suffoletto et al., 2023) demonstrated that spectral features extracted from brief smartphone recorded speech samples could

distinguish intoxicated from sober adults with 98% accuracy, indicating how alcohol impairs vowel articulation, formant stability, spectral distribution and prosodic rhythm even before slurring is perceptible to human listeners. Similarly, findings from another study (Agurto et al., 2020) showed that MDMA intoxication could be classified against placebo with high sensitivity and specificity because the drug reliably alters temporal dynamics, emotional tone and linguistic organisation of spontaneous speech. Chronic substance exposure particularly tobacco use has also shown to leave long-term acoustic signatures (Ayadi et al., 2024).

Speech Markers in Relapse Prediction and Monitoring

The second theme revolves around relapse prediction and longitudinal monitoring which emerges as a critical frontier for management of chronic substance use disorders in older adults who often require sustained, proactive follow-up rather than periodic clinic-based evaluations. Evidence from a longitudinal study demonstrated that linguistic and acoustic patterns captured during early abstinence in individuals with cocaine use disorder could predict future drug use behavior including cravings, abstinence duration and frequency of relapse for up to 12 months outperforming standard clinical self-report tools (Agurto et al., 2023). These findings indicate that speech encodes stable or semi-stable markers of relapse vulnerability such as emotional dysregulation, impaired cognitive control, negative affect and internal stress that are not fully captured by self-report. Broader psychiatric literature reinforces this interpretation, indicating that vocal biomarkers can detect depression and anxiety with high accuracy often from voice samples as short as 20-120 seconds using features such as fundamental frequence, jitter, shimmer, spectral tilt, speech rate and pause structure (Fagherazzi et al., 2021; Low et al., 2020; Menne et al., 2024; Liu et al., 2024).

Early work on Layered Voice Analysis (LVA) and related stress-sensitive systems in the addiction context points in the same direction.

Voice-Based Digital Interventions in Substance Use Care

The third theme emerging from this review identifies the potential of voice-based AI interventions to augment psychosocial care for SUDs in older adults, even though direct trials with this population are not yet available. Evidence from adjacent mental health fields demonstrates that voice-enabled virtual coaches and relational agents can successfully deliver structured, evidence-based therapies. For example, the virtual voice-based coach 'Lumen' was designed to deliver an eight-session problem-solving treatment (PST) program for adults with mild to moderate depression and anxiety. Pilot and follow-up trials have shown that Lumen use was associated with reductions in depressive and anxiety symptoms and changes in neural indices of cognitive control, with feasibility and acceptability demonstrated in diverse patient groups (Kannampallil et al., 2022; Lv et al., 2023; Ronneberg et al., 2024). In parallel, relational and text-based conversational agents such as Woebot have shown that individuals are willing to disclose highly personal information to digital agents and can experience clinically meaningful benefit, early randomized trials in young adults found significant reductions in depressive symptoms after brief engagement with Woebot's

CBT-informed conversations (Fitzpatrick et al., 2017), and later work extending Woebot for Substance Use Disorders (W-SUDs) reported reduced frequency of substance-use occasions and improved confidence and cravings among adults seeking help for SUDs, with good feasibility and user engagement (Prochaska et al., 2021; Prochaska et al., 2023). Although India lacks direct trials evaluating voice-based AI interventions for SUDs in older adults, a rapidly expanding body of Indian digital-health and tele-psychiatry research provides a strong foundation for their feasibility and cultural acceptance. India has already demonstrated large-scale success with digital mental health delivery, the e-Sanjeevani telemedicine platform, which has delivered over 100 million teleconsultations, has proved that older adults are willing and able to use voice-based and audio-supported telehealth services, even in rural and low-literacy populations (MoHFW, 2023).

Similarly, the NIMHANS Centre for Addiction Medicine has developed and evaluated telephone-delivered brief interventions for alcohol use and tobacco cessation, finding that structured phone-based counselling, motivational interviewing, and follow-up calls significantly reduce substance-use frequency and improve treatment adherence demonstrating that audio-first models are both effective and scalable in Indian addiction care (Benegal et al., 2020; Murthy et al., 2021). These studies, though not AI-driven, establish that Indian patients including older adults respond positively to voice-centric therapeutic contact. Parallel evidence from the NIMHANS Virtual Knowledge Network (VKN) and Tele-MANAS national mental health helpline further shows that seniors and caregivers frequently prefer voice calls over app-based or text-based interfaces, citing comfort, cultural familiarity, and reduced technological burden. Additionally, Indian trials of mobile-based tobacco cessation programs such as m-Cessation revealed that older adults engaged most consistently with IVR-based (Interactive Voice Response) and voice-prompt counselling, compared with SMS or smartphone-based interventions (Gururaj et al., 2019). Research on geriatric digital adoption in India indicates that seniors show far higher acceptance of voice notes, phone calls, and IVR menus than text-heavy interfaces, largely because voice aligns with oral communication norms, overcomes literacy barriers, and is easier for

those with declining vision or limited digital exposure (Chatterjee & Singh, 2021; Rashid et al., 2022). When combined, these Indian studies strongly suggest that voice-first, AI-enabled companions could be culturally and practically well-suited for older adults with SUD capable of delivering motivational interviewing prompts, craving-management strategies, medicine reminders, and emotional support using the same modalities that older Indians already trust and use.

Real-world deployment of these ideas is beginning to take shape in digital health platforms. One digital tool under development, called RAE (Realize, Analyze, Engage), although not solely voice-based, aims to combine various digital biomarkers including physiological stress indicators) to detect high-risk moments for individuals in recovery and deliver real-time interventions. While RAE focuses on wearables and stress signals, one can imagine integrating voice biomarkers into such a system. Extending these ideas, one can envision voice-based companions that deliver motivational interviewing-style check-ins, coping skills, and personalised feedback to older adults in recovery particularly those who are home-bound or living in rural areas. Because voice is a natural mode of interaction, such tools may be more acceptable and less effortful for elders than text-heavy apps.

Within this global evidence base, our review specifically highlights how these developments might map onto the Indian context and geriatric care. However, India faces a dual challenge, firstly, an ageing population with an underappreciated burden of SUDs, and large geographical and socioeconomic disparities in access to specialist addiction and mental health care (Mundada et al., 2013; Sarkar et al., 2015). Audio-assisted AI offers several theoretical advantages here. Voice-based screening and monitoring can be delivered over basic mobile phones, which have high penetration even in rural areas; this is critical in settings where smartphone ownership and digital literacy among older adults may be limited. Voice-first interfaces can also overcome literacy barriers, enabling elders who cannot read or write fluently to still engage with digital health tools. Furthermore, many older Indians already use voice notes (e.g., on WhatsApp) or interact with IVR systems for banking or government services, suggesting that the modality itself is not entirely unfamiliar. At the same time, the review points to substantial gaps and challenges that must be addressed before audio-assisted AI can be responsibly integrated into geriatric SUD care in India.

A key limitation of the current evidence is the almost complete absence of studies that specifically involve older participants (≥60 years) or Indian and other LMIC populations. Most of the included studies used adult samples with mean ages in the 20s to 50s, and vocal models were trained on languages such as American English or European languages (Agurto et al., 2020, 2023; Suffoletto et al., 2023; Ayadi et al., 2024). Ageing is associated with characteristic changes in voice, sometimes termed presbyphonia, including reduced loudness, altered pitch, instability, and tremor, which can confound acoustic measurements if models are not explicitly trained on older voices (Jaqua, 2022; Fagherazzi et al., 2021). It is therefore unsafe to assume that models developed in younger cohorts will perform equivalently in seniors. Voice-AI tools for SUD in India will require training and validation on datasets that include older adults with diverse health conditions, both with and without SUD, to ensure that sensitivity and specificity remain acceptable. A related issue is linguistic and cultural adaptation. India is one of the most linguistically diverse countries in the world, with dozens of major languages and thousands of dialects. Models trained on English speech may not generalise to Hindi, Bengali, Tamil, Marathi, or other Indian languages without careful adaptation. Future work will need to build a large, representative voice corpora in Indian languages, including elders with varying education levels, to ensure that AI systems are not biased towards urban, English-speaking, or relatively affluent groups. On the positive side, India's familiarity with voice technologies has grown (e.g., many Indians use voice notes on WhatsApp or interact with phone voice assistants). The government's Digital India initiative even includes programs like Bhashini to drive AI in local languages. This environment bodes well for acceptance of voice-based health tools if designed with local languages in mind. In rural or low-literacy settings, voice-first interfaces can bridge the digital divide, as they do not require reading or typing.

Beyond technical performance, our review underscores important ethical and implementation considerations. Voice data are intrinsically identifiable and can reveal sensitive health and emotional information. Using audio-AI to infer SUD status or relapse risk raises pressing questions about privacy, consent, data ownership, and potential stigma. Older adults may have lower digital literacy and may not fully understand how their data are being processed unless explanation is particularly clear and accessible. It will be essential to obtain informed consent in a way that accounts for possible cognitive impairment or power imbalances within families, and to align any deployment with India's emerging data protection and health-data governance frameworks.

Despite the current evidence gaps, the review identifies several urgent and coherent directions for future research that are necessary to translate audio-assisted AI into safe and effective tools for geriatric addiction care. First, there is a critical need to develop and validate speech-and audio-based SUD detection models specifically in older adults, using prospective designs, larger and more diverse samples, and ecological voice recordings that reflect real-world variability rather than controlled laboratory speech. Second, progress

will depend on creating multilingual, culturally grounded Indian voice datasets that include elders with and without SUDs, spanning dialects, literacy levels, and health conditions, given that acoustic patterns and expressive norms vary substantially across Indian languages. Third, researchers should design and evaluate pilot implementations of voice-based screening and monitoring tools embedded within existing national programmes, such as the National Programme for Health Care of the Elderly (NPHCE), Tele-MANAS, district de-addiction centres, or community-based ASHA-led geriatric outreach, to assess feasibility, integration challenges, and clinical utility in real-world Indian settings. Fourth, the success of such technologies will depend on co-designing voice-enabled interventions with older adults themselves, along with caregivers, community-health workers, and clinicians, to ensure high acceptability, usability, and cultural resonance particularly given the stigma, generational norms, and digital literacy barriers common in this population. Finally, the rapid expansion of voice biomarker research necessitates robust ethical, legal, and governance frameworks, including clear protocols for consent, data protection, model transparency, algorithmic fairness, and the role of human oversight, which must be shaped through multidisciplinary stakeholder consultations. Advancing these priorities will require close collaboration among geriatric psychiatrists, addiction specialists, speech scientists, AI researchers, ethicists, legal scholars, and public-health policymakers to move the field from promising early studies toward deployable, equitable, and context-appropriate solutions for India's ageing population.

V. Conclusion

The human voice is emerging as a powerful frontier in digital health, and its application to substance use disorders in the elderly holds significant promise. Through this systematic review, we have synthesized evidence that audio-assisted AI, analyzing speech and acoustic patterns with machine learning, can facilitate early detection, continuous monitoring, and personalized intervention for SUDs among older adults. For India's rapidly growing elderly population, which faces unique challenges in SUD identification and treatment, such innovations could be transformative. Voice-based algorithms have shown the ability to detect substance-induced changes with striking accuracy and to potentially predict relapse by picking up subtle stress or craving-related cues. Moreover, voice-interactive AI systems offer a user-friendly medium to deliver therapy and support, lowering barriers like literacy and mobility that often hinder older patients from receiving consistent care. However, realizing this potential in practice will require careful bridging of gaps. Alongside technical development, robust ethical frameworks must guide implementation. Such human-centered AI solutions, if scaled, could relieve suffering, reduce stigma and ultimately weave into a sustainable clinical practice that addresses SUDs among the elderly with greater precision and compassion. The promise is undeniable, but it will take continued research, ethical mindfulness, and policy support to fully harness audio-based AI as a tool for healthier, happier aging free from substance-related harm in India.

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