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Discover Artificial Intelligence

REVIEW

Opportunities and challenges of integrating artificial intelligence in focus group discussions for health research in India

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Abstract

Background/Aim Focus Group Discussions (FGDs) are important in qualitative research, particularly for exploring collective perspectives, social behaviors, and cultural norms in health research contexts. While FGDs have proven valuable for capturing community perspectives, the integration of Artificial Intelligence (AI) into FGD methodology presents opportunities and challenges, particularly in diverse settings like India. Despite growing adoption of AI-enhanced qualitative research tools globally, limited synthesis exists on effective and ethical integration into health research in linguistically diverse, resource-constrained contexts. This review examines the methodological integration of AI technologies into FGDs, with specific focus on identifying ethical challenges and implementation barriers in Indian health research contexts.

Methods This narrative review employed thematic synthesis to examine scholarly literature on FGDs and AI integration. Literature searches across PubMed, Scopus, Google Scholar, and ScienceDirect (March–April 2025) covered publications from 1940 to 2024. Using purposive selection, 51 studies were included following screening of 1236 records. Data extraction focused on historical development, methodological frameworks, community health applications, digital innovations, Indian context challenges, and ethical considerations.

Results FGDs evolved from 1940s media research through three phases to become foundational in public health. AI innovations include automated moderation, transcription, sentiment analysis, and coding, offering efficiency and broader reach. Indian context challenges include digital infrastructure disparities (38% rural vs. 82% urban internet access), Natural Language Processing limitations across 22 languages, code-switching complexities, algorithmic bias, and ethical concerns regarding privacy and digital literacy.

Conclusion FGDs remain valuable when combined with emerging technologies and cultural sensitivity. Successful AI integration requires addressing digital equity, developing India-specific NLP tools, ensuring methodological rigor, and implementing ethical safeguards. Hybrid human-AI approaches are recommended over full automation.

Keywords Focus group discussions, Public health research, Artificial intelligence, Qualitative methods, India

1 Introduction

Qualitative research methods remain fundamental in exploring complex social, cultural, and behavioural phenomena, especially within the field of community health [1–3]. One of the most widely used qualitative tools, FGDs, has become an indispensable technique for gathering collective viewpoints, stimulating interaction among participants, and generating nuanced understandings of community-based issues [2, 4, 5]. These methods are particularly valuable because they capture the social construction of meaning through group interaction, allowing researchers to observe how beliefs and attitudes are negotiated collectively rather than individually [6, 7]. As public health challenges become increasingly multifaceted and context-dependent [8, 9], there is an increasing demand for methodologies that not only capture rich, contextual data but also adapt to emerging technologies and evolving societal norms [3].

However, it is important to acknowledge that traditional FGD approaches, when conducted with methodological rigor, have successfully captured lived experiences, belief systems, and socio-cultural frameworks for decades [10–12]. The integration of digital and AI technologies does not address inherent inadequacies in traditional FGDs but rather responds to evolving research contexts: geographic dispersal of populations, time and resource constraints, the COVID-19 pandemic's acceleration of virtual research methods, and opportunities for enhanced analytical efficiency [6, 7, 13–15].

The dynamic nature of contemporary public health concerns, particularly in diverse and populous nations like India [8, 16], has underscored the need for qualitative methods that are both methodologically rigorous and contextually adaptable. Issues such as rising non-communicable diseases, emerging infectious threats, mental health challenges, and persistent disparities in health access and education necessitate community-level engagement [4, 17]. Conventional research approaches, including traditionally conducted FGDs, face practical constraints when attempting to reach geographically dispersed or hard-to-reach populations [5, 18].

Despite their long-standing application [10, 11, 19], FGDs have undergone significant methodological transformations, shaped by both technological advancements [6, 7, 20] and a growing awareness of the ethical and logistical complexities involved in qualitative fieldwork [1, 21, 22]. The COVID-19 pandemic accelerated the adoption of virtual platforms [6, 7], and the integration of AI and machine learning tools into the analytical process is enhancing the depth, speed, and accuracy of qualitative data interpretation [3]. However, these innovations introduce critical considerations around access, equity, data privacy, and digital literacy, particularly when working with underserved populations or across linguistically and culturally diverse groups.

This review examines how these methodological innovations resonate with the realities of public health research in India. As one of the most demographically and culturally complex countries in the world [8, 16], India presents a unique set of opportunities and challenges for qualitative research. In this context, FGDs serve as vital tools for understanding community perceptions and shaping participatory policies [8]. However, issues such as linguistic diversity, digital inequality, and varying levels of health literacy complicate the deployment of virtual focus groups or automated analysis techniques.

Given India's rising investment in digital health infrastructure, evident in initiatives like the Ayushman Bharat Digital Mission [9], there is growing appetite for tools that can enhance community engagement. Yet, the successful integration of digital and AI-driven methodologies into focus group practices requires thoughtful adaptation, careful training of moderators, and ethical safeguards sensitive to both technological and socio-cultural contexts.

1.1 Research aim and objectives

Given the rapid integration of AI technologies into qualitative health research and India's unique socio-cultural and infrastructural context, this review addresses the following research question:

"What are the methodological, ethical, and practical challenges of integrating AI-enhanced FGD technologies into health research in India, and how can these challenges be addressed to ensure valid, culturally appropriate, and ethically sound implementation?"

Specific objectives include:

1. To trace the historical evolution of FGD methodology and identify contemporary AI-driven innovations.
2. To examine the functional capabilities and epistemological limitations of AI technologies in conducting and analyzing FGDs.
3. To critically assess implementation barriers specific to the Indian health research context, including digital infrastructure, linguistic diversity, and cultural validity.
4. To identify ethical challenges related to informed consent, data privacy, algorithmic bias, and participant acceptability.
5. To provide evidence-based recommendations for stakeholders to enable contextually appropriate AI-FGD integration.

2 Method

This review employed a narrative synthesis approach [23, 24] to examine scholarly literature and thematic insights on the historical development, evolving methodologies, applications, and future directions of FGDs, with a specific emphasis on their role in community health research. As a narrative review, this study does not employ the systematic rigor defined under PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. A narrative review approach was deemed appropriate for this study because it allows for flexible integration of conceptual, empirical, and theoretical insights across diverse time periods (1940–2024), disciplines (sociology, public health, computer science), and study types (methodological papers, empirical studies, conceptual frameworks). Given the exploratory nature of AI integration in FGDs, an emerging and rapidly evolving field, and the need to synthesize historical, methodological, technological, and contextual dimensions, a narrative approach enables comprehensive thematic synthesis that would be constrained by systematic review protocols [23, 24]. The review also sought to contextualise these developments within the framework of public health challenges in India, evaluating how technological innovations, such as digital tools and AI, are reshaping focus group practices.

2.1 Search strategy

A comprehensive literature search was conducted between March 15, 2025, and April 30, 2025, across multiple electronic databases, including PubMed, Scopus, Google Scholar, and ScienceDirect, covering publications from 1940 to 2024. Additional sources were retrieved from institutional repositories, government reports, and grey literature when deemed relevant. The search strategy used a combination of keywords and Boolean operators, including:

"Focus group discussions" OR "FGDs" OR "group interviews" AND "qualitative research" AND "public health" AND "community health" AND "India" AND "digital focus groups" AND "virtual focus groups" AND "AI in qualitative research".

Additional search strings included: "AI moderation" AND "focus groups"; "sentiment analysis" AND "qualitative data"; "machine learning" AND "thematic coding"; "digital divide" AND "India" AND "health research"; "NLP" AND "Indian languages"; "virtual FGD" AND "COVID-19"; "ethical considerations" AND "AI" AND "public health".

2.2 Inclusion and exclusion criteria

To ensure relevance and quality, inclusion criteria were established as follows:

- Peer-reviewed journal articles, books, book chapters, and methodological guides.
- Publications in English.
- Studies discussing the history, design, implementation, analysis, or innovations in FGDs.
- Literature related to the application of FGDs in community health, public health, or health systems research.
- Studies or reviews that focused on digital or AI-enhanced focus groups, especially in low- and middle-income countries.

Exclusion criteria included:

- Articles that merely mentioned FGDs without methodological discussion or insight.
- Studies focused solely on quantitative methods.
- Non-English literature due to translation limitations.

2.3 Study selection and screening

As a narrative review, this study did not follow a systematic screening protocol. The authors employed a purposive sampling approach to identify relevant literature. A total of 1,236 records were initially retrieved through database searches. Following the removal of 274 duplicate entries, 962 unique studies remained for preliminary screening. The titles and abstracts of these studies were assessed for relevance to the review's objectives. Screening decisions were made collaboratively by the three authors through iterative discussion. In cases of disagreement, consensus was reached through discussion until unanimous agreement was achieved. Based on this screening, 311 articles were identified for full-text review using predefined inclusion and exclusion criteria. After a thorough evaluation, 51 studies met the eligibility criteria and were included in the final synthesis.

2.4 Data extraction and synthesis

A narrative synthesis approach was adopted to critically review and summarise the findings. Rather than following a systematic review model, this method enabled flexible integration of conceptual, empirical, and theoretical insights across time periods and disciplines. Data extraction focused on: (1) historical development of FGDs, (2) methodological frameworks and best practices, (3) applications in community health research, (4) innovations in digital and AI-enhanced FGDs, (5) challenges specific to the Indian context, and (6) ethical and practical considerations.

Thematic synthesis involved three iterative stages [23, 24]: (1) line-by-line coding of findings from included studies, (2) development of descriptive themes through grouping of related codes, and (3) generation of analytical themes that address the research question and objectives. Two authors (MG and CE) independently coded a subset of studies ($n = 10$) to establish consistency, with disagreements resolved through discussion with the third author (DO). This process enabled identification of convergent and divergent perspectives across the literature while maintaining interpretive flexibility appropriate for a narrative review.

2.5 Quality and credibility of sources

Only literature from credible academic sources and reputable organisations was considered. Methodological manuals and foundational texts were prioritised to ensure comprehensive background coverage. Recent innovations and case examples were included from current literature to capture emerging trends in the application of FGDs.

The selected materials were further appraised based on relevance, methodological clarity, and contribution to advancing understanding of FGDs in qualitative health research. Particular attention was paid to literature that integrated FGDs with other methods or discussed cross-cultural and ethical dimensions of conducting group-based research in diverse populations. However, this narrative review did not conduct a formal risk of bias assessment for individual studies, which is acknowledged as a limitation.

Table 1 provides a comprehensive overview of all 51 included studies, detailing authors, year, study type, and key findings relevant to this review. Many included studies are methodological papers, theoretical frameworks, conceptual analyses, or reviews rather than geographically-specific primary empirical studies. These studies contribute methodological guidance, historical analysis, or conceptual frameworks applicable across contexts. This distribution reflects the current state of literature on AI-enhanced FGDs, which is characterized more by methodological innovation than by empirical validation in diverse settings, particularly in Indian contexts.

3 Results

3.1 History of focus group discussions

Focus Group Discussions (FGDs) first emerged in the early 1940s through the pioneering work of sociologists Robert K. Merton and Paul Lazarsfeld. Initially, the method was developed to study how audiences responded to radio programs, with particular attention to how listeners interpreted embedded social and moral messages [10]. These early applications marked a turning point in qualitative research, as they introduced a structured way to capture group perceptions and interpretive responses.

Table 1 Summary of included studies: historical, methodological, and empirical literature on focus group discussions and artificial intelligence ($n=51$)

Sr. No	Author	Year	Study type	Key findings
1	Lee [10]	2010	Historical analysis	The paper seeks to trace how focused interviewing was adopted, disseminated, and adapted within marketing research before re-emerging in sociology in the form of the focus group.
2	Liamputtong [11]	2009	Methods textbook chapter	Book chapter on History and Development of Focus Group Methodology and why it is used in health and social sciences research.
3	Merton [12]	1987	Methodological commentary	Discussion on "How Did We Get from 'Focussed Interviews' to 'Focus Groups'?"
4	Morgan [13]	2021	Bibliographic analysis	This article uses a bibliographic analysis to examine Robert Merton's role in the ongoing history of the focus group.
5	Akyıldız & Ahmed [14]	2021	Methodological review	This study outlines the qualitative research process, focusing on data collection through focus group discussions, and highlights the significance, advantages, and limitations of qualitative research for social science scholars.
6	HERD [15]	2016	Practice guide	Guide on conduct of focus group discussion, pros and cons of using FGDs, key features, major steps and skills, dos and don'ts.
7	Eeuwijk et al. [25]	2017	Methodological manual	How to conduct a focus group discussion?
8	Hennink [26]	2013	Methods textbook	Understanding focus group discussions.
9	Lewis [27]	2003	Literature review	Focus group interviews in qualitative research.
10	Silverman [28]	2024	Methods textbook	To provide a clear and systematic framework for analysing qualitative data, including visual images, interviews, focus groups, and online sources, to effectively address research questions.
11	Barbour [29]	2005	Methodological review	This paper provides an overview of the contribution of medical education research which has employed focus group methodology to evaluate both undergraduate education and continuing professional development.
12	Willis et al. [30]	2009	Critical review	We outline the literature on focus group research, contrasting the 'quick-and-easy' approach with the demands of studies that are designed, conducted and analysed in a methodologically rigorous way to yield high quality public health evidence.
13	Morgan [19]	1997	Methods textbook	The book outlines current social science approaches to focus groups, with expanded discussion on their comparison with individual interviews and their strengths and limitations.
14	Wellings et al. [31]	2000	Methodological case study	This paper reports on focus groups carried out in the general context of three different research projects with the common challenge of generating discussions around sensitive health topics.
15	Wong [32]	2008	Methodological overview	This paper presents a general introduction of the use of focus groups as a research tool within the context of health research, with the intention of promoting its use among researchers in healthcare.
16	Halcomb [20]	2007	Integrative literature review	This integrated literature review seeks to identify the key considerations in conducting focus groups and discusses the specific considerations for focus group research with culturally and linguistically diverse groups.
17	Stevens [33]	1996	Methodological illustration	The author presents investigatory examples to illustrate how focus-group method expands on the possibilities of individual interviewing to explore community interpretations.
18	Kitzinger & Farquhar [34]	1999	Methodological analysis	This work explores how researchers can analyze those crucial, often revealing, points in focus groups where participants discuss difficult or emotionally charged topics.
19	Warr [35]	2005	Methodological discussion	This article discusses and illustrates how sociable interactions from focus groups were analyzed for insights into classed contexts for romantic relationships.
20	Leung and Savithiri [36]	2009	Practice overview	The article is about FGD and its uses in health research.

Table 1 (continued)

Sr. No	Author	Year	Study type	Key findings
21	Zhang et al. [37]	2024	AI innovation study	This study introduces the "Focus Agent," a Large Language Model (LLM) powered framework that simulates both the focus group and acts as a moderator.
22	Anis [38]	2024	Pilot study	We explored methods to gather thick data quickly using a 1.5-hour online discussion with $N = 100$ respondents.
23	Stafford et al. [39]	2024	Experimental account	Evidence that participants in online focus groups may have been providing LLM generated responses, with preventative measures.
24	Halliday et al. [40]	2021	Implementation study (Australia)	Describes an entirely online approach to recruiting for and facilitating virtual FGDs within the pharmacy profession.
25	Rupert et al. [41]	2017	Comparative study (USA)	Comparison of in-person and virtual focus group discussions.
26	Cheng et al. [42]	2009	Comparative study	Compares the effectiveness of online audio and face-to-face FGD methods.
27	Nyumba [43]	2018	Application review	Assesses the strength and weaknesses of FGD technique based on its application in conservation.
28	Bailey et al. [44]	2021	Qualitative study (UAE)	Identifies best practices that facilitate achieving enrollment and retention targets in biomedical cohort studies.
29	Altaras [45]	2024	Multi-country evaluation (Sub-Saharan Africa)	Outreach training combined with supportive supervision improved malaria service delivery quality across 11 countries.
30	Lakshmi [46]	2023	Empirical FGD study (India)	16 FGDs with adults with diabetes in rural Tamil Nadu showed limited knowledge and poor practices around diabetes prevention.
31	Chutke et al. [47]	2022	Empirical FGD study (India)	4 FGDs with 45 primary healthcare workers identified multilevel barriers to preconception care in rural India.
32	Hwang [48]	2008	Methodological review	Discusses how qualitative data analysis software enhances data organization while emphasizing that analytical insight depends on the researcher.
33	Kim [49]	2020	HCI experimental study	The chatbot improved discussion efficiency and balanced participation by prompting quieter participants.
34	Herdiyanti [50]	2024	Ethical analysis	Highlights concerns related to data privacy, consent, accuracy, and power dynamics in AI-based transcription tools.
35	Keen [7]	2022	Methodological reflection	Virtual qualitative methods offered increased flexibility but raised challenges related to rapport building and digital access.
36	Mc Duff et al. [51]	2013	Technical dataset study	Introduced a large dataset of spontaneous facial expressions for affect recognition research.
37	Hasan & Ahmed [52]	2023	Computational study (Bangladesh)	Demonstrated how NLP techniques identify emotions in marginalized groups.
38	Gupta [53]	2023	Methodological guide	Provides practical strategies for coding, theme development, and interpretation of FGD data.
39	Yuxio [54]	2024	Experimental study	AI-assisted translation tools improve teaching efficiency but face integration and training challenges.
40	Osborne [55]	2023	Landscape analysis	Examined social interaction features in VR meeting platforms and their influence on engagement.
41	Bajpai [56]	2020	Conceptual paper (India)	Explores how AI and ICT can enhance healthcare delivery in India while noting infrastructure challenges.
42	Ramya [57]	2023	Review (India)	Explores AI applications in Indian languages and highlights NLP development challenges.
43	Singh [58]	2010	Review (India)	Examines disparities in access to digital technologies in India and emphasizes need for inclusive policies.
44	Das [59]	2024	Review (India)	Outlines current status of AI integration in Indian healthcare and presents a future roadmap.
45	Sato [60]	2024	Review (India)	Examines how ICT can bridge the digital divide in rural India.
46	Marda [61]	2018	Policy analysis (India)	Outlines a framework for AI policy in India, discussing limitations of data-driven decision-making.
47	Petersson [62]	2022	Qualitative study (Sweden)	Healthcare leaders identified organizational, ethical, and technical challenges to AI implementation.

Table 1 (continued)

Sr. No	Author	Year	Study type	Key findings
48	Pradhan [63]	2021	Review (India)	Highlights AI applications in diagnostics and hospital management while addressing implementation challenges.
49	Chettri [64]	2025	Review (India)	Examines barriers and opportunities for implementing trustworthy AI in Indian healthcare.
50	Sindakis [65]	2024	Review (India)	Examines digital revolution in rural India and strategies to bridge technology adoption gap.
51	Farhud [66]	2021	Review (Iran)	Explores ethical challenges of AI in medicine including privacy, bias, and informed consent.

During World War II, Merton further refined the FGD method to assess the effectiveness of wartime propaganda. He examined how various messages shaped public opinion, demonstrating the power of group discussions to uncover deeper insights into collective attitudes and behavioural shifts. This period marked a significant expansion of FGDs beyond media analysis, establishing their value in a range of fields including market research, sociology, and public health [11].

The evolution of FGDs can be understood across three distinct phases. The first phase, spanning from 1941 to 1956, laid the groundwork for the method in early social science research. The second phase, between 1965 and 1985, witnessed the widespread adoption of FGDs in marketing research, where consumer opinions and preferences became a central focus. The third and ongoing phase began in the mid-1980s, when social scientists reignited interest in FGDs, recognising their potential to generate rich, context-sensitive qualitative data [12].

While Lazarsfeld was instrumental in introducing the group format, it was Merton's systematic development of FGD techniques that elevated the method into a reliable and respected research tool. What began as a modest innovation has since grown into a foundational qualitative approach, cited in over 5,000 academic articles by 2020 [13], and continues to play a vital role in understanding group dynamics, community beliefs, and collective decision-making processes.

3.2 The FGD method

A FGD is a widely used qualitative research method that involves a small group of 8 to 12 participants engaging in a guided, in-depth conversation about a specific topic. These discussions are moderated by a trained facilitator whose role is to encourage the free flow of ideas, manage group dynamics, and ensure that all participants have an opportunity to share their perspectives. FGDs are particularly effective in exploring participants' attitudes, perceptions, experiences, opinions, and beliefs, creating a space for interaction that often reveals not just individual viewpoints but also how ideas are formed and negotiated within groups [14].

One of the strengths of FGDs lies in their ability to capture both consensus and diversity of thought. The conversation usually follows a semi-structured outline designed to cover all key areas while allowing flexibility for new themes to emerge. This structure helps maintain focus while also accommodating the organic development of ideas, making FGDs a powerful tool for collecting rich, context-specific data from communities [15].

FGDs can generally be categorized into two types based on participant composition. Natural groups consist of individuals who already share some social connection, such as family members, coworkers, or community members, bringing familiarity that may enhance comfort and openness. On the other hand, expert groups are composed of participants selected for their specialised knowledge or experience related to the topic of discussion. Depending on the research objectives, these groups may be homogeneous, sharing similar backgrounds, or heterogeneous to capture a range of perspectives [25].

Creating a safe and inclusive environment is essential for the success of any FGD. Participants must feel respected, heard, and free from judgment to engage meaningfully. Skilled moderation is critical in establishing this atmosphere, with moderators expected to balance time, ensure equal participation, and guide the conversation constructively. The recruitment of participants is often done through purposive or convenience sampling, using community outreach, social media, or online platforms to identify individuals who meet the study criteria [25, 26].

A typical FGD structure includes an initial ice-breaker to establish rapport, a brief introduction to the discussion topic, a series of flexible and open-ended questions, and a closing session where participants are thanked for their contributions. Each of these components contributes to a well-rounded and ethically sound data collection process, enabling researchers to delve deeply into community views and social processes [25, 27].

3.3 Research questions and number of focus group sessions

To generate meaningful and analytically useful data from FGDs, the formulation of questions is a critical component. Questions must be precise, focused, and closely aligned with the study objectives. Well-crafted, specific questions help guide the discussion, encouraging participants to share relevant insights and experiences. In contrast, overly broad or vague questions can lead to disorganised conversations and fragmented data, making the process of coding and thematic analysis more complex and less reliable [28].

The number of FGD sessions required is not fixed but varies according to several factors, including the research goals, the scope of the inquiry, and the diversity of the participant pool. In studies involving heterogeneous populations, multiple sessions may be necessary to ensure a comprehensive representation of perspectives. For example, if the study seeks input from various demographic groups (e.g., by gender, age, or profession), separate FGDs may be required for each subgroup to capture the full range of experiences and avoid dominance by any particular voice.

Practical considerations such as time, budget, and participant availability can also influence how many sessions are feasible. Despite these constraints, it is important to aim for data saturation, a point at which additional discussions no longer yield new insights or themes. Saturation serves as a benchmark for determining when the data collection process can justifiably conclude, ensuring that the findings are robust and well-substantiated [29]. In essence, the effectiveness of FGDs depends not only on the quality of interaction during sessions but also on thoughtful planning regarding the number of discussions and the clarity of questions posed. Together, these factors shape the depth, reliability, and utility of the data generated.

3.3.1 Applications and considerations

FGDs are a powerful qualitative tool for uncovering the collective beliefs, attitudes, and social norms that shape human behaviour, especially within communities. Their value lies not only in capturing individual viewpoints, but also in revealing the group dynamics and shared understandings that emerge through interaction. As a flexible method, FGDs can be used independently or incorporated into a broader mixed-methods approach. In multi-method research designs, FGDs serve various functions: they help refine research instruments, validate or expand upon findings from surveys or interviews, and provide a participatory forum for feedback and collaborative interpretation of results [30].

However, the applicability of FGDs is context-dependent. Morgan [19] highlights that FGDs are not suitable in every research situation. If participants are uncomfortable, feel unsafe, or harbour expectations about the outcomes that cannot realistically be met, the quality of discussion can be compromised. Similarly, FGDs are less effective when the research requires quantifiable data or when participants are unable or unwilling to speak freely, such as in highly sensitive, politicised, or traumatic contexts [19, 31]. These limitations underscore the need for careful consideration of the method's appropriateness relative to the research question and population.

In public health, FGDs play a particularly vital role due to the complexity of social determinants influencing health behaviours and outcomes. They are frequently used to explore how people perceive illness, respond to health risks, and make decisions about care-seeking and treatment. For example, FGDs are especially effective in examining community responses to chronic conditions, understanding stigma related to HIV/AIDS or mental health, and investigating maternal and reproductive health beliefs. Importantly, they also help capture the views and challenges of healthcare providers, offering a more holistic view of health system performance [30, 32].

When applied in culturally diverse or underserved communities, FGDs require additional layers of preparation and ethical sensitivity. Researchers must be attuned to local norms, languages, and communication styles, as misinterpretation or perceived insensitivity can damage trust and skew results. Power dynamics within communities and among participants may also influence who speaks and whose opinions dominate. As such, building a culturally competent research team, often with the inclusion of bilingual facilitators, community health workers, and local experts, is critical for fostering inclusive dialogue and ensuring that all voices are equitably represented [20, 29].

Ethical considerations are paramount in the use of FGDs. Prior to data collection, researchers must obtain informed consent and ensure that participants are aware of their rights, including the right to withdraw at any point. Maintaining confidentiality is also essential, especially given the group setting where privacy cannot be fully guaranteed. Transcripts should be anonymized, and any identifying information should be securely stored in accordance with ethics board approval and relevant data protection regulations. Ultimately, researchers have a duty to ensure that no participant is exposed to physical, psychological, social, or economic harm as a result of their involvement in the study [25].

3.3.2 Data analysis and challenges

Analysing data from FGDs presents a distinct set of methodological complexities that set it apart from individual interviews. One of the primary challenges lies in the transcription process, particularly when multiple participants speak simultaneously or interrupt one another. Overlapping speech, fragmented sentences, and dynamic exchanges make it difficult to capture a coherent and complete textual representation of the conversation. As such, transcription for FGDs demands a high level of detail and accuracy, often requiring the use of high-quality audio recordings alongside comprehensive field notes to preserve the context and interaction patterns [25].

Unlike interviews that centre on one participant's narrative, FGDs generate data on three interrelated levels: the individual responses, the interactions between participants, and the overall group dynamics. Each layer offers unique insights, and the richness of the data lies not only in what is said but also in how it is said, to whom, and in what sequence. For example, researchers must pay attention to when participants agree or disagree, how they build on each other's points, or how social hierarchies and peer influences shape the direction of the conversation. These layers require a nuanced approach to analysis that accounts for both the content and the social context of the discussion.

In addition to verbal content, non-verbal cues such as body language, facial expressions, gestures, and tone of voice are essential for interpreting meaning. These cues often reveal underlying sentiments or tensions that may not be explicitly articulated. For instance, a hesitant tone, a pause before responding, or a subtle gesture might indicate discomfort, uncertainty, or disagreement, especially when discussing sensitive or personal topics.

To navigate this complexity, Stevens [33] proposes a set of analytic questions designed to help researchers interpret group-level meanings. These questions encourage analysts to examine who speaks when, who responds to whom, and how group consensus or divergence emerges. Such an approach facilitates a deeper understanding of how knowledge, beliefs, and attitudes are collectively negotiated within the group.

Furthermore, Kitzinger and Farquhar [34] highlight the importance of identifying "sensitive moments" in the discussion, instances where participants reveal deeply personal insights, shift tone, or exhibit emotional responses. These moments often open windows into public health issues that are otherwise difficult to access, such as stigma surrounding mental illness, experiences of discrimination, or discomfort in discussing sexual health. Analysing these interactions with care and reflexivity can yield powerful, nuanced insights that enhance the overall value of the research.

3.3.3 Evidence and Insights

Within the hierarchy of evidence, studies that produce generalisable findings are often regarded as offering the highest level of empirical robustness. These studies, typically grounded in quantitative methodologies, are valued for their ability to apply findings across populations or contexts. However, qualitative methods like FGDs also play a vital role, particularly when conducted with methodological rigour and situated within a well-defined conceptual framework. When FGDs are designed and analysed with precision, they can yield credible, trustworthy insights that extend beyond mere description, and in certain cases, offer transferable knowledge applicable to similar groups or settings [30].

The strength of FGDs lies in their ability to uncover context-specific meanings, community-level interpretations, and collective reasoning, dimensions that are often missed in purely quantitative research. These rich, grounded narratives can inform policy and practice, especially in areas like public health, where the social, cultural, and emotional dimensions of health behaviours matter just as much as statistical trends.

Nonetheless, Warr [35] offers an important methodological caution: triangulating FGD findings with other forms of data, such as surveys or interviews, should not be approached as a simple means of validating findings. FGDs operate through qualitatively different mechanisms of knowledge construction. Participants often co-create meaning in real time, influenced by group dynamics, social norms, and conversational cues. These interactive processes produce data that are shaped by the social setting in which they emerge and may not align neatly with individually obtained responses.

Despite this, we contend that when the purpose and methodological rationale for triangulation are clearly articulated, the integration of FGDs into broader mixed-methods research can yield deeper and more layered insights. For example, while a survey may quantify the percentage of individuals hesitant about vaccines, FGDs can explain the why, revealing fears, cultural beliefs, or social pressures underlying those statistics. The added complexity of managing and interpreting multiple data sources is outweighed by the potential to inform more holistic and context-sensitive policy responses [30].

3.3.4 Advantages and limitations of focus groups

FGDs are widely recognised as an efficient and resource-effective qualitative research method. They allow for the simultaneous engagement of multiple participants, offering a cost- and time-efficient alternative to conducting numerous individual interviews. In a single session, researchers can collect a wide array of perspectives, particularly useful when exploring complex social issues, community behaviours, or shared experiences. This efficiency is one of the reasons FGDs are frequently used in public health, education, market research, and development studies [15, 30].

A core strength of FGDs lies in the richness of data generated through group interaction. Unlike one-on-one interviews, FGDs foster real-time dialogue among participants, prompting reflections, disagreements, and elaborations that may not surface in isolation. This interactive environment often leads to deeper insights, as participants build upon or challenge each other's responses, helping researchers understand how group norms, values, and social processes shape opinions and behaviours [11]. According to Ezzy [21], the group dynamic is not a bias to be eliminated, but rather a vital dimension to be studied, one that influences how knowledge is constructed and shared during the discussion.

Another notable advantage of FGDs is their flexibility. They can be tailored to a wide variety of research contexts, population groups, and settings. Whether conducted in-person, online, or via hybrid models, FGDs adapt well to different environments and timelines. They are especially beneficial in exploratory research, needs assessments, programme evaluations, and studies involving vulnerable populations, provided that ethical and methodological considerations are carefully addressed [15, 30, 36].

Despite these advantages, FGDs are not without limitations. The presence of others can affect how participants express themselves. Dominant voices within the group may steer the conversation, suppressing alternative views and limiting the diversity of responses. Shy or marginalised individuals may hesitate to speak up, especially when the topic is sensitive or controversial. This underscores the importance of skilled moderation; the facilitator must manage group dynamics, encourage balanced participation, and ensure a safe, respectful environment for all contributors. Without this, the data gathered may be skewed or incomplete.

Another limitation concerns the nature of the setting. FGDs are often conducted in structured environments, which can feel artificial and may influence participant behaviour. People may provide socially desirable answers, conform to perceived group norms, or withhold personal insights due to the public nature of the discussion. This can lead to discrepancies between expressed opinions in the group and actual behaviours or beliefs in private settings.

Furthermore, while FGDs provide rich, contextual data, the generalisability of their findings is limited. The sample sizes are typically small and purposively selected, meaning they are not statistically representative of larger populations. As such, the insights derived from FGDs are best understood as in-depth explorations rather than generalisable conclusions. Researchers must therefore be cautious in extending findings beyond the group without triangulating with other methods or contextual evidence.

3.4 The use of AI in conducting focus group discussions

Artificial Intelligence (AI) is revolutionizing the way FGDs are conducted, offering innovative solutions to traditional challenges. One notable advancement is the development of AI-powered virtual focus groups, where AI personas simulate human participants. These AI-generated personas are crafted using machine learning algorithms that analyze extensive datasets to emulate the behaviors, preferences, and responses of specific target demographics [37]. This approach enables researchers to conduct FGDs without the logistical complexities and costs associated with recruiting human participants, thereby accelerating the research process and reducing expenses. However, while AI personas can provide preliminary insights, they may not fully capture the depth and nuance of human emotions and experiences [37].

Another significant application of AI in conducting FGDs is the use of AI-led moderation [37, 38]. AI systems can now facilitate text and voice-based user interviews, guiding discussions, posing relevant questions, and probing deeper into topics based on participant responses [38]. This method ensures consistency in questioning and can adapt in real-time to the direction of the conversation. For instance, platforms like Wondering have developed AI-led user interviewing methodologies that approach human-level ability in moderating discussions and extracting useful information [17]. Such AI-led moderation can be particularly beneficial in scaling research efforts, allowing for simultaneous sessions and broader participant reach. Nevertheless, the absence of human moderators may impact the ability to navigate complex group dynamics and understand subtle social cues, which are often critical in qualitative research [39].

Table 2 provides a detailed comparison between traditional and digital FGDs, highlighting differences in accessibility, data collection, and participant engagement. These comparative observations are drawn from multiple studies examining virtual versus in-person FGD modalities [40–43], though it is important to note that the relative advantages and disadvantages depend heavily on research context, participant characteristics, and available infrastructure. The table synthesizes findings from empirical comparisons rather than presenting universally applicable claims.

The comparative features presented reflect general trends identified across studies [40–43] and may not apply uniformly across all contexts. Researchers should assess the appropriateness of each modality based on their specific research objectives, participant characteristics, and available resources.

Table 2 Comparative overview of traditional vs. digital FGDs

Feature	Traditional FGDs	Digital/Virtual FGDs
Venue [41]	Conducted in physical locations such as community halls or clinics	Conducted through online platforms such as Zoom, MS Teams, or WhatsApp
Participant recruitment [40]	Relies on in-person outreach, community leaders, and local organisations	Digital invitations through emails, online ads, and social media channels
Time and cost efficiency [41]	High logistical costs; more time needed for coordination	Lower costs; faster scheduling; often free or low-cost platforms
Accessibility [40, 42]	Limited to those able to travel to central locations	Broader reach including remote, home-bound, or dispersed populations (though constrained by digital access)
Group interaction quality [40, 42]	Richer interaction with body language, facial expressions, and informal bonding	Limited non-verbal cues; screen fatigue may reduce engagement (though some studies report comparable interaction quality with proper facilitation)
Moderator's role [40,41,43]	In-person guidance, managing group flow, observing behaviour	Digital moderation through screen; less effective for real-time interpersonal cues (requires enhanced verbal facilitation skills)
Data recording [40,41,43]	Manual audio recordings; separate note-takers often required	Automatic recording, transcription, and data storage via platform features
Participation barriers [40,4141]	Travel time, physical mobility, and location-based exclusions	Digital literacy, access to devices, internet connectivity (particularly challenging in resource-constrained settings)
Technical support required [40,43]	Minimal, usually a recorder and notepad	Requires stable internet, functional devices, software setup, and tech support

3.5 The use of AI for focus group discussion analysis

AI has significantly enhanced the analysis of data derived from FGDs by automating transcription and facilitating in-depth qualitative analysis. AI-powered transcription tools can swiftly convert audio recordings into text with high accuracy, even across diverse accents and speaking styles [45]. This automation reduces the time and potential errors associated with manual transcription, allowing researchers to focus more on data interpretation. For example, Krisp is an AI-powered meeting transcription tool that has proven helpful to researchers conducting FGDs by providing accurate and timely transcriptions [18].

Beyond transcription, AI-driven analytical tools can identify patterns, themes, and sentiments within the transcribed data [46, 47, 53]. These tools employ natural language processing (NLP) techniques to code responses, detect emerging trends, and visualize data relationships. Software like ATLAS.ti leverages AI to assist researchers in organizing and analyzing qualitative data, offering features such as auto-coding, sentiment analysis, and data visualization [48, 53]. By utilizing such tools, researchers can achieve a more nuanced understanding of group dynamics and participant perspectives. However, while AI can process large volumes of data efficiently, the interpretation of complex human emotions and cultural contexts still benefits from human oversight to ensure accuracy and depth [48].

Table 3 explores the spectrum of AI and digital tools currently transforming FGD methodology, from automated transcription to virtual moderation and real-time summarisation. However, it is critical to note that these tools have primarily been developed and validated in Western, English-language contexts. Their epistemological assumptions about language structure, sentiment expression, and communication patterns may not align with the linguistic and cultural realities of multilingual, high-context settings like India [56, 57, 61]. Furthermore, the functional descriptions provided represent

Table 3 Innovations in FGD methodology – tools and their functions

AI/Digital tool	Primary function in FGDs	Example/Platform	Limitations in Indian context
AI chatbot moderator [49,56]	Guides discussions, probes responses, and maintains flow without human intervention	Wondering, GPT API	Limited understanding of cultural communication norms, code-switching, and contextual meanings
Emotion recognition software [51,61]	Identifies participant emotions through facial expressions and tone	Affectiva, microsoft azure emotion API	Cultural differences in emotional expression may lead to misinterpretation
Voice-to-text transcription [18,45, 50,56,57]	Instantly transcribes recorded dialogue into text	Otter.ai, google speech-to-text, krisp	Poor accuracy with Indian accents, regional languages, and code-switching
Sentiment analysis tools [52,61]	Detects mood, tone, and participant sentiment across themes	IBM watson, lexalytics	May misclassify indirect communication styles common in Indian discourse
Auto-coding software [46,47, 48,53]	Automatically identifies themes, patterns, and key terms in transcripts	NVivo, MAXQDA, ATLAS.ti	Requires cultural contextualization; may miss culturally-specific concepts and idioms
AI-based translation tools [54,57]	Enables multilingual discussions with real-time translation	DeepL, google translate API, lokalise	Limited accuracy for many Indian languages; struggles with colloquialisms and context-dependent meanings
Virtual reality FGDs [55]	Simulates real-world settings for immersive discussion	Mozilla hubs, unreal VR	High infrastructure requirements limit accessibility in resource-constrained settings
AI-powered participant screening	Screens for eligibility and group matching based on pre-determined variables	Qualtrics AI, surveymonkey genius	May embed selection biases based on Western demographic categorizations
Real-time discussion summarisation [50]	Live summarisation of key themes as the FGD progresses	Fireflies.ai, assemblyAI	May oversimplify complex cultural narratives or miss nuanced discussions

While these tools offer functional capabilities that can enhance FGD methodology, their application in culturally diverse, multilingual settings requires careful validation, cultural adaptation, and ongoing researcher oversight. The limitations column reflects challenges identified in the literature that require attention before widespread adoption in Indian health research contexts

technological capabilities rather than validated applications in diverse cultural contexts. The cultural validity, accuracy in non-English languages, and ethical implications of these tools in Indian health research contexts require empirical examination [56, 57].

3.6 Issues with the use of AI for conducting and analyzing FGDs in India

In the Indian context, the integration of AI in conducting and analyzing FGDs presents unique challenges. India's vast cultural and linguistic diversity means that AI systems must be adept at understanding and processing multiple languages, dialects, and cultural nuances [56, 57]. Many AI tools are primarily trained on data from Western contexts, which may limit their effectiveness in accurately interpreting Indian languages and the socio-cultural intricacies inherent in Indian FGDs. For instance, certain expressions or sentiments prevalent in Indian discourse might be misinterpreted or overlooked by AI systems not tailored to this context.

Additionally, the digital divide in India poses a significant barrier. While urban areas may have access to advanced technological infrastructure, rural regions often lack the necessary resources and connectivity [58–60]. Implementing AI-driven FGDs in such areas may exclude valuable perspectives from underrepresented communities, leading to biased or incomplete research outcomes. Ensuring inclusivity requires addressing these infrastructural disparities and considering hybrid models that combine AI capabilities with traditional methods.

Ethical considerations also come to the forefront with AI integration. Concerns regarding data privacy, informed consent, and the potential for AI to perpetuate existing biases are particularly pertinent in India, where data protection laws are still evolving [59, 61]. Researchers must navigate these issues carefully, ensuring that AI applications adhere to ethical standards and respect participant rights [59, 61]. Moreover, transparency in how AI tools operate and make decisions is crucial to maintain trust and credibility in the research process.

3.6.1 Digital infrastructure and the digital divide

The digital divide in India represents a fundamental barrier to equitable implementation of AI-enhanced FGDs. While urban centers like Mumbai, Delhi, and Bangalore have robust internet connectivity and digital infrastructure, rural and semi-urban areas face significant challenges [58, 60]. According to recent data, only 38% of rural households have internet access compared to 82% in urban areas [58].

This disparity creates several practical challenges for virtual FGDs:

- Unreliable internet connectivity leads to frequent disconnections during sessions.
- Limited smartphone penetration in rural areas restricts participant recruitment.
- High data costs prohibit extended participation in video-based discussions.
- Lack of technical support in local languages complicates platform navigation.

These infrastructure limitations risk systematically excluding perspectives from underserved communities, precisely those populations most vulnerable to health inequities. A hybrid model combining in-person FGDs with selective AI-enhanced analysis may offer a more inclusive approach in resource-constrained settings [59].

Furthermore, the assumption that digital FGDs are universally "more accessible" overlooks the reality that for many Indian communities, traveling to a central physical location may actually be more feasible than accessing reliable internet, acquiring appropriate devices, or developing the digital literacy needed to participate effectively in virtual discussions. Researchers must carefully assess context-specific barriers before defaulting to digital modalities.

3.6.2 Natural language processing limitations with Indian languages

India's linguistic diversity, with 22 officially recognized languages and hundreds of dialects, poses unique challenges for AI-powered FGD tools. Most NLP models are trained predominantly on English, with limited representation of Indian languages [56, 57]. Even for widely spoken languages like Hindi, Tamil, and Bengali, AI tools struggle with:

- **Code-switching**: Indian speakers frequently mix English with regional languages mid-sentence, which confuses most NLP algorithms.
- **Dialectal variations**: The same language can have vastly different vocabulary and pronunciation across states.
- **Cultural idioms and expressions**: AI may misinterpret culturally-specific phrases or metaphors.
- **Accent recognition**: Speech-to-text tools trained on Western accents often fail to accurately transcribe Indian English or regional language speakers.

Consider a common Hindi-English code-switched statement: “Hum log regular exercise karte hain par diet maintain nahi kar paate.” An AI tool trained primarily on English may fail to capture the nuance of “maintain nahi kar paate” (unable to maintain), potentially missing critical insights about barriers to healthy eating. Similarly, culturally-specific health concepts like “garmi” (heat-related ailments in Ayurveda) or “pet kharab” (stomach upset with cultural connotations) may be mistranslated or misinterpreted by generic AI tools.

Development of India-specific NLP models through academic-government-industry partnerships is essential to address these limitations [57]. Initiatives like AI4Bharat at IIT Madras are beginning to develop open-source NLP tools for Indian languages, but widespread availability and validation for research contexts remain limited.

3.6.3 Ethical challenges: consent, privacy, and algorithmic bias

The integration of AI into FGD research in India raises several ethical concerns that require careful consideration:

Informed consent I. *in digital settings*: Participants may not fully understand how AI processes their data, particularly in communities with low digital literacy. Researchers must ensure consent procedures clearly explain AI’s role in transcription, analysis, and data storage [61]. Traditional written consent forms may be insufficient; verbal explanations in participants’ primary languages, with opportunities for questions, should be standard practice.

II. *Data sovereignty and privacy*: India’s evolving data protection landscape creates uncertainty about how FGD data should be stored, who can access it, and how long it can be retained. The Digital Personal Data Protection Act (2023) imposes new obligations on researchers, but implementation guidelines remain unclear [61]. Key questions include: Where should data be stored physically? Can cloud services based outside India be used? How should data be protected if AI analysis occurs on third-party platforms? Researchers need clear institutional policies addressing these concerns.

III. *Algorithmic bias*: AI models trained on Western datasets may embed cultural biases that misrepresent Indian contexts. For instance, sentiment analysis tools may misclassify expressions of disagreement as negative sentiment in cultures where indirect communication is normative [61]. In hierarchical Indian social structures, participants may express disagreement through subtle linguistic cues (e.g., “perhaps we could also consider.“) that AI trained on Western directness may miss entirely. Similarly, cultural norms around expressing emotion, such as restraint in discussing personal health issues with strangers, may be misinterpreted as disengagement by AI affect recognition systems.

IV. *Community mistrust*: In some communities, particularly among marginalized groups, there is skepticism about technology and data collection. The introduction of AI moderation may exacerbate concerns about surveillance and misuse of personal information [62]. Building trust requires transparent communication, community involvement in research design, and demonstrated data protection safeguards. Researchers should consider involving community leaders or trusted health workers as intermediaries to explain the technology and its purpose.

3.6.4 Participant readiness and acceptability

The success of AI-enhanced FGDs depends not only on technological capability but also on participant comfort and readiness:

I. *Age-related digital literacy gaps*: Older adults may struggle with virtual platforms, requiring additional orientation and technical support [62]. Pre-session practice calls, simplified interfaces, and availability of technical support in local languages are essential accommodations.
II. *Gender disparities in technology access*: In many Indian communities, women have less access to personal devices and may face restrictions on digital communication [64]. Virtual FGDs may inadvertently exclude women's voices unless researchers provide devices or arrange women-only group sessions in community centers with provided technology.
III. *Cultural preferences for face-to-face interaction*: Some communities value the social dynamics and trust-building that occur in physical gatherings, viewing virtual formats as impersonal [64]. The communal nature of Indian social life, where discussions over chai often build rapport and trust, may be difficult to replicate in digital environments. Researchers report that virtual FGDs sometimes feel more like structured interviews than the dynamic group interactions that characterize traditional FGDs.

To address these challenges, researchers should consider:

- Pre-session technology training in participants' primary languages.
- Blended approaches with human facilitators present during AI-moderated sessions.
- Clear communication about AI's role and limitations.
- Options for participants to opt out of AI recording while still participating.
- Providing devices and data packages where necessary.
- Flexibility in scheduling to accommodate participants' daily routines and responsibilities.

Table 4 examines the capacity gaps hindering effective AI-FGD implementation in India, along with actionable strategies to address linguistic, infrastructural, ethical, and educational limitations. These gaps were identified through synthesis of literature on AI

Table 4 Capacity gaps in AI-FGD integration in India

Challenge area	Gap description	Suggested strategy
Local language AI Models [56,57]	Lack of training data for many Indian dialects	Build local NLP datasets through academic-government partnerships
AI literacy among researchers [62,63]	Limited knowledge of AI tools among public health and social science scholars	Incorporate AI tools training in health research methods curricula
Access to reliable digital infrastructure [60,64]	Poor internet and device access in many rural or underserved areas	Invest in mobile-first platforms and provide tech support in local languages
Participant ldiness for AI-led FGDs [62,64]	Distrust or confusion about AI moderation among rural or older populations	Use blended human-AI facilitation with clear participant orientation sessions
AI regulation and ethical guidelines [59,61]	No India-specific ethical codes for AI use in qualitative research	Form regulatory taskforces with academics, tech experts, and ethics boards
Training materials for hybrid FGDs [44]	Few resources tailored for Indian contexts or local cultures	Co-develop regionally adapted training with NGOs and local universities
Interdisciplinary collaboration [65]	Lack of coordination between health researchers and AI developers	Create interdisciplinary consortia focused on digital qualitative methods
Cost of AI tools and licensing [59,66]	Proprietary platforms may be unaffordable for small research teams	Promote open-source, subsidised, or publicly funded AI research tools

adoption in Indian healthcare and represent systemic challenges that require multi-stakeholder collaboration to address.

4 Discussion

The findings of this review reveal fundamental methodological, epistemological, and ethical tensions in integrating AI technologies into FGD research, particularly in India's linguistically diverse and infrastructurally constrained context. Rather than merely cataloguing challenges, this discussion interprets their implications for research validity, cultural appropriateness, and the epistemic authority of AI-mediated qualitative inquiry.

4.1 Epistemological implications of AI-mediated FGDs

The historical trajectory from Merton and Lazarsfeld's 1940s radio audience research [10, 11] to contemporary AI-enhanced platforms represents not technological progression but epistemological transformation. Traditional FGDs derive their validity from human moderators' ability to navigate cultural nuances, power dynamics, and emergent group processes [10–15]. AI-led moderation [37, 38, 17] fundamentally alters this epistemological foundation by substituting algorithm-driven conversation management for human judgment.

This substitution raises critical questions about knowledge production mechanisms. While AI systems can extract information efficiently [17], they operate without cultural competence, contextual sensitivity, or ethical judgment that skilled human moderators provide [39, 43]. In health research contexts requiring discussion of sensitive topics, this absence is not merely a technical limitation but an epistemological deficiency that compromises data validity [14, 31, 32].

The comparative studies [40–42] demonstrate that modality selection cannot be reduced to technical optimization but must account for what forms of knowledge each approach can reliably produce. Halliday et al.'s [40] success with geographically diverse pharmacy professionals and Cheng et al.'s [42] finding of richer non-verbal data in face-to-face settings reveal that different modalities access different dimensions of social reality. The critical question is not "which is better" but "which epistemological trade-offs are acceptable for specific research objectives."

4.2 Cultural validity and algorithmic interpretation

Beyond functional capabilities, AI analytical tools face fundamental cultural validity challenges that directly threaten research credibility. Sentiment analysis and emotion recognition software [51, 52], trained predominantly on Western datasets, embed epistemological assumptions about emotional expression, communication directness, and disagreement that systematically misrepresent high-context cultural settings [61].

This is not a technical glitch requiring better training data, it reflects deeper questions about whether algorithmic interpretation can achieve cultural validity in contexts where meaning emerges from implicit social cues, hierarchical positioning, and collective negotiation processes [52, 61]. Hasan and Ahmed's [52] demonstration of misclassified stress and discrimination expressions in Bangladesh exemplifies how technical accuracy (correct pattern identification) diverges from interpretive validity (culturally appropriate meaning-making).

In India's context, where 22 official languages, hundreds of dialects, and pervasive code-switching create irreducible linguistic complexity [46, 47, 56, 57], AI tools do not merely struggle with accuracy, they fundamentally cannot access the cultural-semantic frameworks necessary for valid interpretation. The Hindi-English example illustrates not a translation problem but an interpretive impossibility: the phrase encodes hierarchical family structures, gendered decision-making norms, and healthcare access patterns that algorithmic processing cannot contextualize without ethnographic understanding.

4.3 Digital infrastructure and epistemic exclusion

The digital divide [58–60] creates not just access barriers but systematic epistemic exclusion with profound implications for research representativeness and validity. When only 38% of rural households have internet access compared to 82% urban [58], AI-enhanced FGDs systematically privilege urban, educated, digitally literate voices, precisely those already over-represented in health research.

This is not peripheral to research validity, it constitutes fundamental sampling bias that undermines claims to community representation. The paradox is acute: technologies marketed as accessibility-enhancing actually compound existing marginalization by creating new participation prerequisites (devices, connectivity, digital literacy) that disproportionately exclude vulnerable populations most affected by health inequities.

The assumption that digital FGDs universally improve access overlooks material realities: for many Indian communities, traveling to a central location remains more feasible than acquiring devices and connectivity. This infrastructural constraint transforms into epistemic constraint, systematically excluding perspectives that could challenge dominant health narratives or reveal community-specific health beliefs and practices.

4.4 Ethical challenges beyond procedural compliance

Ethical concerns [39, 50, 61, 62, 66] extend beyond procedural compliance (obtaining consent, protecting privacy) to fundamental questions about power, representation, and interpretive authority in AI-mediated research. Herdiyanti's [50] observation that participants may not understand AI data processing raises questions about whether consent can be truly informed when the technology itself operates as a "black box."

India's evolving data protection landscape [61] creates regulatory uncertainty, but more fundamentally, it exposes tensions between innovation imperatives and participant protection in contexts where power asymmetries (researcher-participant, urban-rural, digital-analog) already compromise genuine voluntariness. The Digital Personal Data Protection Act (2023) imposes obligations but provides limited implementation guidance, particularly regarding cross-border data transfer when AI processing occurs externally.

Algorithmic bias [52, 59, 61, 62] poses particular risks in India's hierarchical social structures, where AI trained on Western directness may systematically misinterpret culturally normative indirect disagreement as consensus, silencing dissenting voices and producing false unanimity. This threatens not just data accuracy but research legitimacy, if AI systematically misrepresents marginalized voices, research claims to community representation become epistemically unfounded.

4.5 Toward methodologically hybrid, contextually grounded integration

Synthesizing across evidence, appropriate AI integration requires rejecting technological solutionism in favor of methodologically hybrid, contextually grounded approaches that preserve human expertise while selectively leveraging AI capabilities.

First, successful implementations [40, 43] retained human moderation, suggesting AI should augment rather than replace human judgment. Bailey et al.'s [44] recruitment and retention findings underscore that human connection remains essential, particularly with vulnerable populations. This points toward hybrid models where AI handles logistical functions (transcription, initial coding) while human researchers maintain responsibility for cultural interpretation, ethical judgment, and participant relationship management.

Second, methodological rigor cannot be sacrificed for technological efficiency. Willis et al.'s [30] caution against "quick-and-easy" FGDs applies equally to AI variants, quality depends on thoughtful design and skilled facilitation regardless of technological mediation. Altaras et al.'s [45] finding that training and supervision, not technology alone, improved service quality demonstrates that human capacity building matters more than technological sophistication.

Third, participatory co-design with communities is essential. Successful integration requires involving communities in technology adaptation, developing local language capacity, and building researcher competencies, not imposing externally developed solutions [44, 45, 65].

Fourth, ethical frameworks must evolve beyond procedural compliance toward substantive protection of epistemic authority and interpretive legitimacy. This requires India-specific governance addressing data sovereignty, algorithmic transparency, and participatory oversight mechanisms that give communities meaningful control over how AI processes their narratives [61, 64, 66].

5 Limitations of the review

This narrative review has several important limitations that must be acknowledged:

I. *Methodological approach*: As a narrative rather than systematic review, this study did not employ the structured search strategy, formal screening process, or risk of bias assessment defined under PRISMA guidelines [22]. While efforts were made to include a wide range of peer-reviewed and grey literature, the absence of systematic inclusion/exclusion criteria and comprehensive bias assessment may limit reproducibility. The "structured yet flexible" narrative synthesis approach allows for selective integration of content, which may inadvertently introduce selection bias. Future systematic reviews employing PRISMA protocols could provide more rigorous assessment of specific aspects of AI-enhanced FGDs, such as transcription accuracy across languages or ethical outcomes in diverse settings.

II. *Language limitations*: Restricting the review to English-language publications is a significant limitation given India's vast cultural and linguistic diversity. This exclusion potentially overlooks crucial context-specific insights from regional publications in Hindi, Tamil, Telugu, Bengali, and other Indian languages. Indigenous applications of FGDs documented in state-level publications or regional journals may have been missed, limiting the generalizability of findings in such a diverse country. For example, innovative adaptations of FGDs for tribal communities or region-specific methodological developments published in regional languages would not have been captured.

III. *Temporal scope*: The review spans publications from 1940 to 2024, an extremely broad timespan that introduces inconsistencies in terminology, scope, and context across the reviewed literature [12]. Direct comparison or synthesis of findings is complicated by the evolution of both FGD methodology and technological capabilities over this 84-year period. Earlier literature may not reflect contemporary ethical standards or technological realities, while recent studies may lack the longitudinal perspective of foundational works. The dramatic shift from analog audio recording to AI-powered analysis represents just one dimension of this evolution that complicates synthesis.

IV. *Western-centric AI literature*: Much of the literature on AI-enhanced qualitative research originates from Western contexts, with limited empirical studies from Indian settings [56, 61]. This creates uncertainty about the transferability of findings to India's unique socio-cultural landscape. The review identifies challenges related to Indian languages and digital infrastructure, but the limited availability of India-specific empirical studies means these discussions remain somewhat speculative.

V. *Absence of implementation guidance*: While the review highlights significant challenges in implementing AI-enhanced FGDs in India (digital divide, linguistic diversity, ethical concerns), it does not provide detailed, prescriptive solutions. The focus remains largely descriptive rather than prescriptive, which may limit its immediate utility for researchers seeking practical implementation strategies. Development of concrete implementation frameworks would require primary research on successful adaptations in diverse Indian contexts.

VI. *No meta-analysis*: As a narrative review, this study cannot provide the quantitative synthesis or effect size estimates that would be possible in a systematic review or meta-analysis. The inability to pool findings across studies means conclusions rely on qualitative synthesis and expert interpretation rather than statistical aggregation. Questions such as "How much does AI transcription accuracy improve with Hindi-specific training?" or "What percentage of rural Indian participants can feasibly engage in virtual FGDs?" cannot be answered quantitatively from this review.

VII. *Study type distribution*: Of the 51 included studies (Table 1), a significant proportion are methodological papers, conceptual frameworks, or reviews rather than primary empirical research. Specifically, many studies are categorized as "Methods," "Review," or "Conceptual/Policy Analysis" rather than reporting primary data collection in specific geographic regions. This distribution reflects the current state of literature on AI-enhanced FGDs, a field characterized more by methodological innovation and theoretical development than by empirical validation in diverse settings. The absence of country/region information for many studies indicates that they are not geographically specific primary studies but rather methodological contributions applicable across contexts. This limits the evidence base for making context-specific recommendations for Indian health research settings.

Despite these limitations, this review provides a comprehensive overview of FGD evolution and identifies critical considerations for future research, particularly in diverse, resource-constrained settings like India. It serves as a foundation for more targeted systematic reviews and primary research addressing specific aspects of AI-enhanced FGDs in Indian contexts.

6 Conclusion

FGDs remain vital in qualitative health research for exploring collective beliefs and culturally embedded health behaviors. In India's linguistically diverse, hierarchically complex context, FGDs offer culturally sensitive approaches to understanding health perceptions.

However, AI integration into FGD methodology presents fundamental methodological, epistemological, and ethical challenges that cannot be resolved through technical optimization alone. Digital infrastructure disparities, NLP limitations across 22 languages, cultural validity gaps in algorithmic interpretation, and ethical concerns regarding consent, privacy, and bias create systematic barriers to valid, appropriate implementation.

Successful integration requires rejecting technological solutionism in favor of methodologically hybrid approaches that preserve human expertise while selectively leveraging AI capabilities. Critical priorities include: developing India-specific NLP tools and training datasets; investing in digital infrastructure as research equity imperative; building researcher competencies in culturally grounded AI interpretation; establishing robust ethical governance addressing algorithmic transparency and data sovereignty; and conducting primary research on successful implementations in diverse Indian contexts.

Ultimately, AI-enhanced FGDs should augment, not replace, traditional approaches. The goal is not efficiency alone but maintaining methodological rigor, cultural validity, and ethical integrity while adapting to evolving research landscapes.

6.1 Recommendations for stakeholders

Table 5 summarizes evidence-based recommendations for researchers, AI developers, ethics committees, and funders/policymakers to enable contextually appropriate AI-FGD integration.

Table 5 Evidence-based recommendations for stakeholders

Stakeholder	Recommendations
Researchers	Conduct pilot testing of AI tools with India-specific datasets before full implementation
	Use hybrid approaches combining human expertise with AI assistance
	Ensure robust informed consent procedures in participant's primary languages
	Develop cultural competency in interpreting AI-generated outputs
	Document AI tool limitations alongside findings
	Consider traditional FGDs as gold standard where participants lack digital access
AI developers	Invest in training datasets including Indian languages and code-switching patterns
	Collaborate with social scientists and linguists on cultural communication nuances
	Design tools with adjustable sensitivity to dialectal variations
	Implement transparent algorithms allowing researcher oversight
	Develop low-bandwidth options for resource-constrained settings
	Provide technical support in multiple Indian languages
	Prioritize open-source models allowing institutional customization
Ethics committees	Develop specific guidelines for AI-enhanced qualitative research
	Require detailed data management plans addressing cross-border transfer
	Ensure consent procedures explain AI processing in accessible language
	Consider digital literacy requirements in risk assessment
	Establish standards for algorithmic transparency
	Address data sovereignty concerns in international collaborations
	Create expedited review for AI tool modifications
Funders & policymakers	Invest in digital infrastructure in underserved regions
	Fund development of India-specific NLP tools
	Support interdisciplinary collaborations (computer scientists, linguists, health researchers)
	Establish national guidelines for AI use in health research
	Subsidize AI tool access for academic/non-profit researchers
	Support capacity building programs for researchers
	Commission primary research on successful AI-FGD implementations

Author contributions
MG conceptualized the study, conducted data extraction and analysis, and drafted the manuscript. CE contributed to data extraction. DO reviewed the manuscript, provided critical input, and assisted in its revision. All authors approved the final version of the manuscript.

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