EDITORIAL

Artificial Intelligence in Health Care: Promise, Progress, and Perils

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Introduction

Artificial intelligence (AI) is a technology that enables computers and machines to simulate human learning, comprehension, problem-solving, decision-making, creativity, and autonomy. AI has rapidly become an indispensable force driving innovation in all facets of health care. Its ability to simulate human cognitive processes, such as learning, pattern recognition, and problem-solving, enables powerful tools that help clinicians diagnose diseases earlier, personalize treatments, expedite drug discovery, optimize healthcare workflows, and empower public health interventions. As the healthcare sector confronts growing patient loads, workforce shortages, rising costs, and the complexity of precision medicine, AI offers transformative solutions that raise important ethical, social, and regulatory challenges.[1] This editorial provides a comprehensive review of AI's evolving role in health care, exploring its applications, benefits, challenges, and future prospects.

AI Transformations across Health Care

The application of AI in clinical diagnosis has witnessed remarkable progress, particularly in the field of medical imaging. Algorithms trained on large datasets can detect anomalies in X-rays, MRIs, and histopathological slides with a sensitivity comparable to that of expert clinicians. The early detection of cancer, cardiovascular abnormalities, and retinal diseases improves prognosis by enabling timely intervention.[2] AI-powered genomic analysis contributes to precision medicine by deciphering the genetic variations that influence disease predisposition and drug response. Machine learning (ML) models integrate multi-omics datasets to develop personalized treatment regimens, optimize efficacy, and minimize adverse effects. Future AI systems could continuously monitor intensive care unit (ICU) patients, analyze vital signs, and predict deterioration (e.g., sepsis) in real time, enabling timely interventions. Additionally, in patient admission, AI can optimize bed allocation by predicting admission rates and assessing acuity and streamlining workflows. Moreover, for triage, ML models can prioritize cases based on severity, thereby enhancing emergency response efficiency. Similarly, AI can alert doctors via integrated systems when anomalies arise, thereby reducing response times. Finally, AI chatbots that leverage natural language processing (NLP) can answer patient queries 24/7, improving satisfaction and reducing staff workload. AI-enabled implantable devices represent a frontier in personalized medicine, integrating ML with bioelectronics to monitor, modulate, and deliver therapies directly to the human body. These "smart" implants, often wireless and minimally invasive, leverage AI algorithms for real-time data analysis, predictive adjustments, and adaptive responses, thereby transforming chronic disease management. For instance, in diabetes care, continuous glucose monitors (CGMs) use AI to predict blood sugar fluctuations and automate insulin delivery using closed-loop pumps.[3]

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Enhanced Clinical Workflows and Decision Support

AI significantly augments healthcare workers by automating tedious administrative tasks, such as documentation, coding, and billing, thereby alleviating clinician burnout and allowing for a greater focus on patient care. Natural language processing plays a pivotal role in facilitating the summarization of extensive clinical notes, extracting critical data points, and enabling voice-assisted documentation, which streamlines record-keeping and reduces manual errors. This is particularly valuable in high-pressure environments, where time efficiency is crucial. Decision support systems further enhance clinical efficacy by synthesizing vast amounts of patient data, including electronic health records, clinical guidelines, and the latest research, to recommend evidence-based interventions for patients with diabetes. These systems assist in medication management by identifying potential drug interactions, flagging contraindications, and dynamically guiding treatment modifications based on real-time patient response. Future advancements may integrate wearable device data and predictive analytics to anticipate complications such as sepsis or cardiac events, thereby enabling proactive care. Additionally, AI-driven tools can prioritize patient cases, optimize resource allocation, and provide real-time alerts to clinicians, fostering a more responsive healthcare ecosystem at the current advancement and beyond. This evolution promises to transform care delivery; however, it requires robust validation to ensure reliability across diverse populations.[4]

Drug Development and Biomedical Research

Insights from *Artificial Intelligence in Health Care: The Hope, the Hype, the Promise, the Peril* (Matheny et al., 2019) underscore this potential, with contributions from authors such as Nigam Shah (Stanford University) and Suchi Saria (Johns Hopkins University) highlighting AI's role in optimizing research workflows. Furthermore, AI transforms clinical trial design by employing predictive analytics to select appropriate cohorts based on genetic, demographic, and disease-specific data, ensuring that trials are more representative and efficient. Current studies demonstrate that AI can predict drug efficacy with 70–80% accuracy, reducing trial costs by 20–30%, and increasing success rates by refining patient selection and endpoint analysis. Recent advancements, such as generative AI, are expected to enable the *de novo* design of novel drug candidates, whereas real-time data integration from wearable devices could enable adaptive trials that dynamically adjust protocols. However, as cautioned by the National Academy of Medicine, challenges such as data biases, regulatory gaps, and ethical concerns regarding patient consent must be addressed to sustain this progress, ensuring equitable access and minimizing risks in this rapidly evolving field.[5]

Disease Surveillance and Precision Public Health

AI tools are transforming disease surveillance by harnessing advanced analytics to process epidemiological and environmental data, enabling the accurate prediction of outbreaks, real-time tracking of disease spread, and identification of high-risk populations. Machine learning models analyze patterns from diverse datasets, such as climate data, travel records, and hospital admissions, to forecast events such as dengue or influenza surges, often with lead times of weeks.

Precision public health further refines this capability by directing resources efficiently and targeting vulnerable populations, such as the elderly or those in low-income areas, with tailored interventions, such as vaccination campaigns or health education, thereby optimizing impact and reducing disparities. The integration of wearable sensors, mobile health apps, and AI-driven analytics enables continuous, real-time monitoring of chronic conditions (e.g., diabetes and hypertension), and health behaviors (e.g., physical activity and sleep patterns), fostering personalized prevention and wellness strategies. AI algorithms process data from devices such as Fitbit or Apple Watch to detect anomalies, trigger early interventions, and promote lifestyle adjustments, potentially lowering healthcare costs by 10–15% through preventive care. These systems could rapidly evolve to predict individual risk profiles using genomic data, thereby enhancing personalized medicine.[6]

In India, the Integrated Disease Surveillance Programme (IDSP) has evolved into a digital surveillance system with the development of an integrated health information platform (IHIP). Leveraging AI, ML, and geographic information systems (GISs) with precise coordinates, the IHIP tracks and investigates cases or clusters of diseases, such as malaria or COVID-19, across urban and rural regions. Launched in 2020 and expanded by 2025, the IHIP integrates data from public health facilities, enabling rapid outbreak response and resource allocation. Future enhancements may include drone-based data collection and AI-powered predictive models to strengthen India's public health infrastructure.

Emerging Horizons: Biotech and Digital Human Models

In a groundbreaking fusion of synthetic biology and digital technology, bioreplicators have emerged as tangible realities, transcending science fiction to enable the seamless electronic transfer of biological fragments across global networks. Drawing from advancements in DNA data storage and bioprinting, these systems encode genetic sequences, such as DNA snippets representing proteins, genes, or even microbial fragments, into binary data streams, allowing instantaneous transmission via the Internet or satellite links, similar to emailing a file. Once received, recipient facilities use enzymatic synthesis or clustered regularly interspaced short palindromic repeats (CRISPR)-based assembly to "print" the biological material in real time, reconstructing viable fragments for research, therapeutics, or even custom organisms. This innovation, as projected in Nature Biotechnology's 2021 outlook, aligns with the sequencing of over 60 million human genomes by 2025, fueling a "DNA of Things" (DoT) paradigm, where biological blueprints are embedded in everyday objects or cloud repositories. For instance, the Fraunhofer Institutes' BIOSYNTH project demonstrates microchip platforms that synthesize DNA from digital blueprints, enabling the mass-scale production of peptides or RNA for drug development. Similarly, innovations that digitize biological systems, such as bio-replication (electronically transmitting and reconstructing biological codes) and digital avatars powered by AI, herald new paradigms in healthcare delivery and human-machine interaction. Brain–computer interfaces enable the direct control of assistive devices through neural signals, enhancing the quality of life of patients with disabilities. Digital avatars with evolving personalities support mental health and chronic disease management by simulating empathetic interactions and personalized coaching, thereby expanding the boundaries of traditional health care.[7]

Ethical, Social, and Technical Challenges

AI thrives on large health datasets encompassing sensitive personal information, such as medical history, genetic profiles, and lifestyle data, which are critical for developing predictive models and personalized treatments. However, this reliance introduces significant risks, including unauthorized data access, breaches, and potential misuse for commercial purposes that must be addressed. Underscores these concerns, noting that inadequate data governance could exacerbate health disparities or erode public trust if sensitive information is exploited. Protecting patient confidentiality demands robust encryption protocols, informed consent models that empower individuals to control data usage, and stringent regulatory frameworks, including adherence to global standards such as the General Data Protection Regulation (GDPR), the Health Insurance Portability and Accountability Act (HIPAA), and country-specific laws such as India's Digital Personal Data Protection Act (2023).[8]

Bias, Fairness, and Equity

Algorithmic bias arises when training datasets lack diversity or inadvertently reflect historical inequities, which is a critical concern in AI applications in health care. This bias can reproduce or magnify existing health disparities, disproportionately affecting racial minorities, women, and underserved groups by skewing the diagnostic accuracy, treatment recommendations, and resource allocation. For instance, models trained on predominantly Caucasian datasets may underperform in Black or Indigenous patients, leading to misdiagnoses in conditions such as hypertension or breast cancer. Ensuring fairness requires transparent model development, in which the decision-making processes of algorithms are openly documented and validated. Continuous audit mechanisms, such as regular bias assessments and post-deployment evaluations, are critical for detecting and rectifying disparities.[9]

Safety, Reliability, and Regulatory Challenges

Despite their promising performance, AI systems in healthcare risk producing erroneous outputs owing to insufficient validation, lack of explainability, or gaps in adapting to evolving medical knowledge, potentially leading to misdiagnoses or inappropriate treatments. For instance, deep learning models may excel in pattern recognition but falter in heterogeneous real-world settings without rigorous clinical validation, as a 2024 review found that 94% of 516 ML studies in health care failed initial clinical tests. "Black box" AI models, where decision-making processes remain opaque, pose significant challenges for accountability, hindering clinicians' ability to understand how outputs are derived and when to trust automated recommendations, which could undermine ethical principles like "do no harm." This opacity raises legal and ethical uncertainties, particularly in high-stakes decisions, as emphasized in the National Academy of Medicine's Artificial Intelligence in Health Care: The Hope, the Hype, the Promise, the Peril, which calls for human-centered AI to avoid overhyping and ensure reliability. Regulatory guidance is evolving to address these concerns; for example, the EU AI Act (2024) introduces risk-based frameworks for AI classification, while international agencies emphasize context-of-use evaluations and explainable AI (XAI) to enhance transparency and meet certification standards. Experts advocate multidisciplinary approaches, including interpretable models and post-deployment audits, to mitigate risks. By integrating XAI techniques, such as those providing clear explanations for cardiovascular imaging decisions, these gaps can be bridged, fostering trust and aligning with World Health Organization (WHO) guidelines for sustainable AI deployment. Addressing these challenges requires ongoing collaboration among developers, clinicians, and regulators to rigorously validate AI and prioritize patient safety in an ever-evolving landscape.[3,10]

Cybersecurity Risks in AI-powered Implantable Devices

AI-powered body-implanted devices, such as pacemakers, insulin pumps, and neuromodulators, emphasize augmented intelligence for equitable outcomes by enabling real-time monitoring and providing adaptive therapies. However, the National Academy of Medicine's Artificial Intelligence in Health Care (Matheny et al.) warns of perils such as biased data exacerbating disparities in diverse populations. However, their wireless connectivity, often via Bluetooth or Internet-linked controllers, introduces profound cybersecurity vulnerabilities, making them susceptible to remote exploitation. Pacemakers and insulin pumps have been demonstrated to be hackable since 2018, with researchers such as Billy Rios and Jonathan Butts remotely altering heart rhythms or overdosing insulin via Bluetooth exploits in Medtronic devices, as shown at Black Hat conferences. The FDA has issued recalls and warnings for such flaws, noting no patient harm to date but highlighting the risks in older models lacking encryption. Hypothetically, these flaws could enable catastrophic biological threats, amplifying concerns about cyber-biosecurity, the intersection of cybersecurity and biosecurity. Cyber-biosecurity experts warn that hacked implants interconnected via hospital networks could serve as vectors for "digital viral pandemics," where malware manipulates biological agents or data to induce widespread harm, as seen in scenarios involving synthetic biology during COVID-19. A modified virus, engineered via synthetic biology, might be remotely "injected" through compromised infusion ports or neuromodulation channels, exploiting subdermal reservoirs to disseminate pathogens and potentially triggering outbreaks with synthetic lethality. By 2025, with over 1 billion projected implants, robust safeguards, such as encrypted protocols, blockchain-verified data, and post-market surveillance, are essential, aligning with WHO and Indian Council of Medical Research (ICMR) guidelines to prevent dystopian scenarios while harnessing AI's potential.

Workforce Implications and Agentic AI in Health Care

While AI automates routine tasks such as scheduling, data entry, and preliminary diagnostics, fears of job displacement persist across various healthcare roles, including administrative staff, radiologists, and general practitioners. The National Academy of Medicine's *Artificial Intelligence in Health Care: The Hope, the Hype, the Promise, the Peril* (Matheny et al.) acknowledges this tension, noting that automation could reduce the demand for certain repetitive tasks, potentially leading to workforce restructuring by 2025, with estimates suggesting that up to 30% of current administrative roles may evolve or diminish. While AI can handle high-volume tasks, it risks eroding the human element in health care if not carefully integrated. Balancing AI integration with the preservation of meaningful clinician-patient relationships is crucial, as AI lacks empathy, compassion, and emotional intelligence—qualities integral to quality care, such as providing comfort during end-of-life discussions or addressing mental health concerns, which remain uniquely human strengths.

Healthcare workers require upskilling in AI literacy to collaborate effectively with technology, ensuring human oversight and ethical application. The need for training programs that equip clinicians with skills in interpreting AI outputs, managing data privacy, and overseeing automated decisions is emphasized, with studies showing a 25% increase in job satisfaction when staff are AI-proficient. This study advocates for continuous professional development and the integration of AI ethics into medical curricula to address biases and ensure equitable care, as well as the importance of interdisciplinary training to bridge gaps between technologists and healthcare providers.[11–13]

The introduction of agentic AI, which is systems capable of autonomous decision-making and adaptive learning, adds a new layer to these dynamics. Unlike traditional AI, agentic AI can proactively adjust treatment plans, coordinate care across teams, and negotiate resource allocation based on real-time data, as seen in emerging prototypes from Johns Hopkins University (Saria et al.) and Stanford (Shah et al.). However, this autonomy raises concerns about accountability, with potential errors in judgment amplifying job displacement fears and ethical dilemmas such as overriding clinician decisions without clear justification.

Regulatory, Implementation, and Societal Barriers

Fragmented regulations, variable legal interpretations, and a lack of global standards create barriers to the broad deployment of AI. Institutional resistance, infrastructural limitations, and high upfront costs disproportionately affect the development of health systems. Ensuring inclusive design, cultural competence, and equitable access is vital to prevent "AI divides" from worsening health inequities globally.[14]

Governance: Building Trustworthy AI

To harness AI's benefits while mitigating its harms, ethical governance frameworks emphasizing transparency, accountability, inclusivity, and safety are urgently needed. International collaboration to establish validated standards, certification processes, and multidisciplinary oversight can foster responsible innovations. Policymakers, healthcare providers, technologists, and patient communities must co-create policies that foster AI that complements human judgment, respects rights, and promotes social good. Policymakers, healthcare providers, technologists, and patient communities must co-create policies fostering AI that complements human judgment, respects rights, and promotes social good.

In response to the growing integration of AI in health care, the Government of India has proactively advanced regulatory frameworks to safeguard data privacy and ethical practices, echoing the National Academy of Medicine's call for balanced innovation and oversight in AI in health care (2019). The Digital Personal Data Protection Act (DPDP Act), enacted in 2023 and bolstered by rules released in early 2025, establishes a comprehensive regime for processing personal data, mandating explicit consent, data minimization, and stringent penalties for data breaches. This legislation profoundly influences AI applications in health care by requiring robust security for sensitive patient data used in diagnostics, predictive analytics, and personalized treatments, thereby mitigating the risks of unauthorized access and bias amplification in algorithms.[15] Complementing this, the ICMR unveiled Ethical Guidelines for the Application of AI in Biomedical Research and Healthcare in 2023, with reaffirmations and expansions noted in 2025. These guidelines outline 10 principles, including fairness, transparency, accountability, and human oversight, to guide AI development in clinical trials, drug discovery, and telemedicine, ensuring equitable access and preventing discriminatory outcomes in diverse populations. Together, these measures foster a trustworthy ecosystem, aligning AI's promise of AI with ethical imperatives to protect vulnerable patients and promote inclusive health advancements. The WHO has also contributed significantly to shaping the ethical landscape of AI in health care, aligning with the balanced approach advocated in AI in health care. In June 2021, the WHO released its Ethics and Governance of AI for Health, a comprehensive guideline updated in 2025 to address emerging technologies and risks, including those posed by implantable devices. This framework outlines six ethical principles—transparency, accountability, inclusiveness, responsiveness, sustainability, and fairness—along with 10 recommendations, such as ensuring human oversight and protecting data privacy, to guide AI development and deployment globally. The 2025 update emphasizes cybersecurity for connected health devices, urging robust safeguards against remote manipulation that could lead to health crises, and promotes equitable access to AI benefits across low- and high-resource settings.[16]

Conclusion and Future Directions

Artificial Intelligence's integration of AI into health care marks one of the most significant technological revolutions in the history of medicine. Its capabilities, from enhanced diagnostics to population health management, offer tangible improvements in outcomes and efficiency. However, these advances do not replace the essential human elements of care: Empathy, ethical reflection, and judgment. Sustained investment in research, education, ethical oversight, and equitable deployment will ensure that AI serves as an adjunct to human expertise rather than as a substitute. As immersive technologies such as digital avatars and brain–computer interfaces mature, the healthcare landscape will increasingly blur digital and biological boundaries, requiring a nuanced understanding and cautious optimism. The future of AI in health care will reflect the collective values, responsibilities, and innovations of society, balancing technological progress with human dignity.

References

1. Pham T. Ethical and legal considerations in healthcare AI: Innovation and policy for safe and fair use. R Soc Open Sci 2025;12(5):241873. DOI: 10.1098/rsos.241873.
2. Pinto-Coelho L. How artificial intelligence is shaping medical imaging technology: A survey of innovations and applications. Bioeng 2023;10(12):1435. DOI: 10.3390/bioengineering10121435.
3. Whicher D, Ahmed M, Israni ST, editors. National Academy of Medicine; The Learning Health System Series. Artificial Intelligence in Health Care: The Hope, the Hype, the Promise, the Peril. National Academies Press (US): Washington (DC): 2023. DOI: 10.17226/27111.
4. Lee C, Britto S, Diwan K, et al. Evaluating the impact of artificial intelligence (AI) on clinical documentation efficiency and accuracy across clinical settings: A scoping review. Cureus 2024;16(11):e73994. DOI: 10.7759/cureus.73994.
5. Qureshi R, Irfan M, Gondal TM, et al. AI in drug discovery and its clinical relevance. Heliyon 2023;9(7):e17575. DOI: 10.1016/j.heliyon.2023.e17575.
6. Olaboye J, Abdul S, Kolawole T, et al. Innovations in real-time infectious disease surveillance using AI and mobile data. Int Med Sci Res J 2024;4(6):647–667. DOI: 10.51594/imsrj.v4i6.1190.
7. Kasoju N, Remya NS, Sasi R, et al. Digital health: Trends, opportunities and challenges in medical devices, pharma and bio-technology. CSI Trans ICT 2023;11(1):11–30. DOI: 10.1007/s40012-023-00380-3.
8. Williamson SM, Prybutok V, Malhotra C, et al. Balancing privacy and progress: A review of privacy challenges, systemic oversight, and patient perceptions in AI-driven healthcare. Appl Sci 2024;14(2):675. DOI: 10.3390/app14020675.
9. Marko JGO, Neagu CD, Anand PB, et al. Examining inclusivity: The use of AI and diverse populations in health and social care: A systematic review. BMC Med Inform Decis Mak 2025;25(1):57. DOI: 10.1186/s12911-025-02884-1.
10. Palaniappan K, Lin EYT, Vogel S, et al. Gaps in the global regulatory frameworks for the use of artificial intelligence (AI) in the healthcare services sector and key recommendations. Healthc (Basel) 2024;12(17):1730. DOI: 10.3390/healthcare12171730.
11. Sauerbrei A, Kerasidou A, Lucivero F, et al. The impact of artificial intelligence on the person-centred, doctor-patient relationship: Some problems and solutions. BMC Med Inform Decis Mak 2023;23(1):73. DOI: 10.1186/s12911-023-02162-y.
12. Anwer MS. Opportunities and challenges of artificial intelligent-powered technology in healthcare. Med Res Arch 2024;12(3). DOI: 10.18103/mra.v12i3.5141.
13. Mohanasundari SK, Kalpana M, Madhusudhan U, et al. Can artificial intelligence replace the unique nursing role? Cureus 2023;15(12): 11–13. DOI: 10.7759/cureus.51150.
14. Gilbert C, Gilbert M. Strategic framework for human-centric AI governance: Navigating ethical, educational, and societal challenges. Int J Latest Technol Eng Manag Appl Sci 2024;13(8):132–141. DOI: 10.51583/ijltemas.2024.130816.
15. Malhotra C, Malhotra U. Putting interests of digital nagriks first: Digital Personal Data Protection (DPDP) Act 2023 of India. Indian J Public Adm 2024;70(3):516–531. DOI: 10.1177/00195561241271575.
16. World Health Organization. Ethics and governance of artificial intelligence for health: WHO guidance 2021. Available from: https://www.who.int/publications/i/item/9789240029200. Last accessed on: 13 September 2025.

ORIGINAL ARTICLE

A Cross-sectional Survey on Awareness, Attitude, and Perception on Organ Donation and Living Donor Liver Transplant among Staff Nurses and Nursing Students

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Abstract

Introduction: Healthcare workers—particularly nurses and nursing students—play a pivotal role in promoting organ donation within the community. Evaluating their awareness of living donor liver transplantation (LDLT) and their attitudes toward organ donation is essential, as LDLT is an increasingly critical treatment option for end-stage liver disease.

Objective: To assess awareness and attitude regarding organ donation and LDLT among nurses and nursing students.

Methods: A cross-sectional survey was conducted across multiple hospitals and nursing colleges, involving 209 nurses and 212 nursing students. Data were collected using a standardized questionnaire and analyzed using descriptive and inferential statistics.

Results: The majority of participants were under 30 years of age—95.2% of nurses and 68.9% of nursing students—with a predominance of female respondents. Both groups demonstrated similar awareness trends, with nursing students performing marginally better overall. Attitudes toward organ donation were generally positive across both groups. Among nurses, awareness levels were significantly associated with age and years of experience, while among nursing students, the setting of training showed significant associations. A moderate negative correlation was found between awareness and attitudes toward organ donation and LDLT in both nurses ($r = -0.443$) and nursing students ($r = -0.389$), with both correlations being statistically significant ($p = 0.000$).

Conclusion: The study found that most participants exhibited good to average awareness and held neutral to positive attitudes regarding organ donation and LDLT. Educational interventions, targeted training sessions, and awareness campaigns within clinical and academic settings are recommended to further strengthen understanding and promote more favorable attitudes, particularly addressing the identified gaps among subgroups.

Keywords: Attitude, Awareness, Living donor liver transplant, Nurses, Nursing students, Organ donation.

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Introduction

In recent years, advancements in medicine and technology have significantly improved the survival rates and quality of life for patients undergoing organ transplantation. Despite this progress, a severe shortage of donor organs persists, with a substantial gap between demand and availability. Although India ranks second after the United States in the number of organ transplants performed, its national organ donation rate remains considerably low.[1,2] As per the World Health Organization (WHO), only 0.001% of the Indian population opts for deceased donor transplantation.[3] Evidence suggests that several factors influence organ donation and promoting deceased donor transplants willingness of the individual, including educational, sociocultural and religious beliefs, family disapproval, and attitude toward organ donation.[4] Majority of the transplants done in India are living donor liver transplantation (LDLT).[5] Nurses play a pivotal role in the organ donation process, with their views potentially influencing individuals' decisions about donation. Additionally, they are well-positioned to contribute to educational initiatives aimed at improving public awareness and attitudes toward organ donation. It is important to assess their own levels of awareness and attitude toward LDLT and deceased donor transplants. This will provide a base for the healthcare system to figure out its preparedness to promote organ donation knowledge and attitude through educational programs. Nursing students, as future healthcare professionals, also play a pivotal role in shaping public awareness and influencing decisions related to organ donation. Assessing their knowledge is essential to ensure that they possess an accurate, evidence-based understanding of the medical, ethical, and legal aspects of organ donation and LDLT. Similarly, evaluating their attitudes is equally important. Positive attitudes can translate into advocacy, compassionate patient care, and a willingness to participate in awareness campaigns. It is essential to develop a competent, compassionate, and proactive healthcare workforce. While several studies have assessed knowledge and attitudes toward organ donation in general, it is particularly important to

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evaluate awareness, attitudes, and preformed opinions of nurses and nursing students regarding LDLT, as it is the more commonly practiced form of organ donation in India.[5]

Objective

The objective of this study was to assess the awareness and attitude regarding organ donation and LDLT among staff nurses and nursing students.

Methods

This cross-sectional survey was conducted from December to February 2025. The exclusion criteria included participants who had been organ donors/recipients, awaiting organs for transplantation for self or first-degree relatives. Using a convenience sampling technique, the questionnaires were distributed to the eligible participants online via Google Forms. The sample size was calculated using Cochran's formula [$n = (Z^2pq)/e^2$], where n = estimated sample size, Z = standard normal deviate, i.e., 1.96 with a confidence level of 95%, p = proportion of individuals in the population with the characteristic of interest (awareness, attitude and perception to organ donation and LDLT), i.e., 60%, e = desired level of precision (0.05), and q = 1–p $(0.04)^2$. With an addition of 10% attrition, the sample size was estimated to be 405. The tools used for data collection included four sections: Section I—sociodemographic tool which contained six variables as mentioned in Table 1, section II—awareness about organ donation, comprising 16 questions with one correct answer related to organ donation and ethical concerns, section III—awareness of live organ donations and procedure of LDLT, consisting nine questions, and section IV—attitudes and perceptions toward organ donation, comprising 17 questions. For the assessment of awareness, 23 multiple-choice questions with a single correct answer were used, with a maximum attainable score of 23. Additionally, one question addressing attitudinal barriers related to concerns preventing individuals from participating in LDLT was included; responses were analyzed based on frequency distribution. To assess overall attitude and perception, responses were categorized as Yes (positive attitude), No (negative attitude), and Not Sure (neutral attitude). All the questions were positively worded. Data were analyzed using descriptive and inferential statistics. The results provided insights into the awareness and attitudes of nurses and nursing students regarding organ donation and LDLT.

Results

Demographic Characteristics of the Participants

Most nurses (95.2%) and nursing students (68.9%) were under 30 years of age. Females were the majority in both groups: 65.6% of nurses and 71.2% of students, which aligns with the general gender trend in the nursing profession. A larger proportion of nurses (83.3%) had completed their graduation, whereas more students were pursuing postgraduate education (29.7%) compared to the nursing staff (13.4%). About 94.3% of nurses were married, while 65.6% of students were unmarried. The two groups were found to be comparable in terms of gender and setting of work (Table 1).

Table 2 shows the awareness of organ donation and LDLT among nurses and nursing students. The areas where nurses performed significantly better are general awareness, nurses: 91.5%, students: 56.8%. This difference may be attributed to their professional exposure. Nurses also demonstrated a better understanding (79%) of the clinical eligibility of brain-dead individuals for organ donation than students (67.9%). For the consent procedure for organ donation in brain death, 87.3% of nurses were aware of and 76.4% of the nursing students. Awareness of the registration process and the national organ donation organization was moderately higher among nurses (69.8%) than among nursing students (ranging from 57.1% to 62.3%). However, nursing students performed better in certain areas, including legal age for organ donation registration (students: 82.1% vs nurses: 75.5%), governing legislation (students: 67.0% vs nurses: 66.0%), liver regeneration time (students: 58.5% vs nurses: 56.1%) and living donor eligibility (students: 55.7% vs nurses: 47.2%). The knowledge gaps in both groups were noticed in misconceptions around organ donation after cardiac arrest (nurses: 41.0%, students: 42.5%), the percentage of liver that can be safely donated (nurses: 41.0%, students: 42.5%), and understanding the risks involved in LDLT (nurses: 74.5%, students: 65.1%).

Table 1: Sociodemographic characteristics of study participants ($n_1 + n_2 = 209 + 212$)

Variables	*Nurses, f (%)*	*Nursing students , f (%)*
1. Age		
<30 years	199 (95.2%)	146 (68.9%)
30–39 years	8 (3.8%)	51 (24.1%)
40–49 years	1 (0.5%)	12 (5.7%)
≥50 years	1 (0.5%)	3 (4%)
2. Gender		
Male	72 (34.4%)	61 (28.8%)
Female	137 (65.6%)	151 (71.2%)
3. Professional education		
Graduation	174 (83.3%)	124 (58.5%)
Post Graduation	28 (13.4%)	63 (29.7%)
Diploma	7 (3.3%)	25 (12.8%)
4. Total years of experience		
<5 years	191 (91.4%)	142 (67.0%)
5–10 years	6 (2.9%)	40 (18.9%)
11–12 years	5 (2.4%)	15 (7.1%)
>20 years	4 (1.9%)	15 (7.1%)
Other	3 (1.4%)	0
5. Setting of work/training		
Govt. hospital/college	81 (38.8)	79 (160)
Private hospital/college	120 (57.4%)	117 (55.2%)
Community health center	1 (0.5%)	9 (4.2%)
Transplant center	4 (1.9%)	7 (3.3%)
Other	3 (1.4%)	0
6. Marital status		
Married	197 (94.3%)	73 (34.5%)
Unmarried	12 (5.7%)	139 (65.6%)

Both groups agreed most strongly on "No history of liver disease or significant chronic illness" as the main criterion for LDLT, but nursing students emphasized it more than nurses (41.9% vs 31.5%). Nurses placed more importance on "Age" than students (26.3% vs 16.2%), which may reflect their greater clinical exposure or awareness of surgical risk factors. Views on "Matching blood type" and "Good overall health" were similar across both groups. A majority in both groups believed there is insufficient awareness of

Table 2: Assessment of awareness regarding organ donation and LDLT among the participants ($n_1 + n_2 = 209 + 212$)

Question	*Nurses n (%)*	*Nursing students n (%)*
Are you aware of organ donation and live donor liver transplant programs?	194 (91.5)	184 (56.8)
Which organs can be donated for transplantation?	189 (89.2)	175 (82.5)
Which of the following statements best describes the primary difference between live and deceased donor organ transplants?	178 (84.0)	177 (83.5)
At what age can a person legally register for organ donation in India?	160 (75.5)	174 (82.1)
What is the main legislation governing organ donation in India?	140 (66.0)	142 (67.0)
What is the main organ donation organization in India?	121 (57.1)	113 (53.3)
Is it acceptable to harvest organs from cardiac arrest people?	107 (50.5)	93 (43.9)
Brain-dead persons are eligible for organ donation.	169 (79.7)	144 (67.9)
People with a past history of alcohol and intravenous drug abuse are not eligible to receive a transplant.	107 (50.5)	103 (48.6)
In India the brain death is legally declared as death.	116 (54.7)	120 (56.6)
What is the time frame for organ donation after cardiac arrest?	110 (51.9)	112 (52.8)
Are you aware of the process for registering as an organ donor in India?	148 (69.8)	132 (62.3)
Who can provide consent for organ donation in the case of a brain-dead patient?	185 (87.3)	162 (76.4)
Do you know about the waiting list system for organ allocation in India?	126 (59.4)	119 (56.1)
How are organs allocated to patients in need?	154 (72.6)	146 (68.9)
Can organs be bought and sold in India?	146 (68.9)	123 (58.0)
Can a living person donate a part of their liver?	189 (89.2)	182 (85.8)
What percentage of the liver can be safely donated by a living donor?	87 (41.0)	90 (42.5)
How long does it take for a donor liver to regenerate after donation?	119 (56.1)	124 (58.5)
Who can be a living liver donor?	100 (47.2)	118 (55.7)
Can liver donation occur after brain death?	156 (73.6)	139 (65.6)
Are you aware of the risks associated with living liver donation?	158 (74.5)	138 (65.1)
Main criteria for becoming a liver donor (a) age	55 (26.3)	35 (16.2)
(b) Good overall health	34 (16.2)	34 (16.0)
(c) Matching blood type with the recipient	54 (25.8)	54 (25.8)
(d) No history of liver disease or significant chronic illness	66 (31.5)	89 (41.9)
Is there sufficient awareness among healthcare workers about liver transplant in India		
Yes	61 (29.1)	6 (31.1)
No	126 (60.2)	124 (58.4)
Not sure	22 (10.5)	22 (10.5)
Concerns for preventing you from liver donation (attitudinal barriers)		
(a) Fear of surgery and complications	59 (28.2)	58 (27.3)
(b) Concern about post-donation health	53 (25.3)	74 (34.9)
(c) Lack of information about the procedure	56 (26.7)	53 (25.0)
(d) Fear of family opposition	36 (17.2)	22 (10.3)
(e) Other (all of the above, I don't know, none of the above, impact on daily life, medical problem may arise, may cause medical surgical condition)	5 (2.3)	5 (2.3)

liver transplant among healthcare workers in India: 0.2% of nurses and 58.4% of nursing students said "No". Only about one-third believed there is sufficient awareness (29.1% nurses and 31.1% students). About 1 in 10 in both groups were unsure.

Both nurses and nursing students perceive a lack of awareness of liver transplant in India and share similar attitudinal barriers to donation, though with some differences. Students were more worried about their health after donation (34.9%). Nurses are more concerned about family opposition (17.2%) than students (10.3%). Fear of complications and lack of information are common barriers in both groups (~25–28%) (Fig. 1).

Table 3 shows that strong positive attitudes were observed on the item for supporting organ donation in both nurses (85.4%) and nursing students (90.1%), showing general endorsement of the concept. A high willingness to donate an organ to a family member was observed among nurses (66.0%) and students (72.2%). Over half of both groups are open to receiving organs (nurses: 55.2%, students: 64.2%) if the need arose. However, very few participants in either group had registered (nurses: 18.4%, students: 15.6%), showing a major gap between attitude and action. Additionally, both groups showed extremely low future intent to register (nurses: 11.8%, students: 10.8%), despite their overall positive attitudes, suggesting barriers to translating intention into action. A mixed opinion was expressed, especially among nurses, to donate the organ of a brain-dead family member who never discussed his preference for organ donation—only 22.6% were positive, indicating emotional/ethical complexity in family decision-making. For the item "Talked to family regarding organ donation", low rates (nurses: 54.2%, students: 47.2%)—discussion within families is lacking, which can hinder actual donation decisions. Knowledge gaps and misconceptions appear to influence both groups. A large proportion of nurses (70.8%) and students (67.5%) feel uninformed, which is a major modifiable barrier. Around half (nurses: 55.7%, students: 53.3%) express fear about the disfigurement or the body image changes post donation, which reveals emotional/misinformation-based barriers. There are personal/moral conflicts: about one-third of both groups report moral hesitation, with slightly more students (58%) than nurses (49.1%) expressing negative views. For the item "Organ donation is against my religious beliefs": Very few (nurses: 12.7%, students: 15.1%) suggest that religion is not a dominant barrier (Fig. 2).

Tables 4 and 5 show a moderate negative correlation between awareness and attitudes toward organ donation and LDLT among both nurses ($r = -0.443$) and nursing students ($r = -0.389$). These correlations were found to be statistically significant ($p = 0.000$).

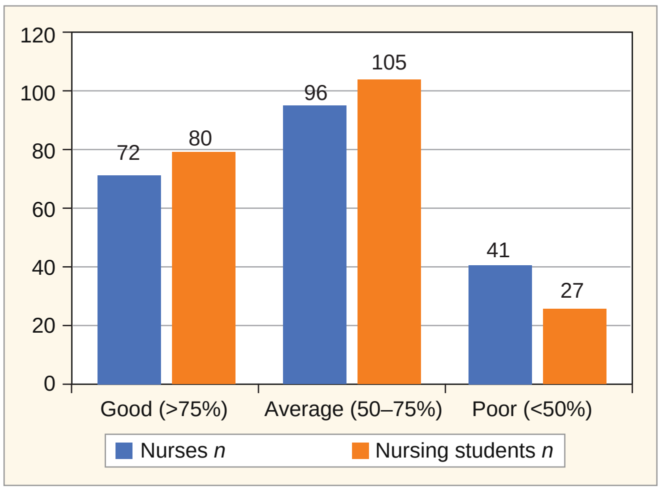

Fig. 1: Bar diagram showing awareness levels among nurses and nursing students

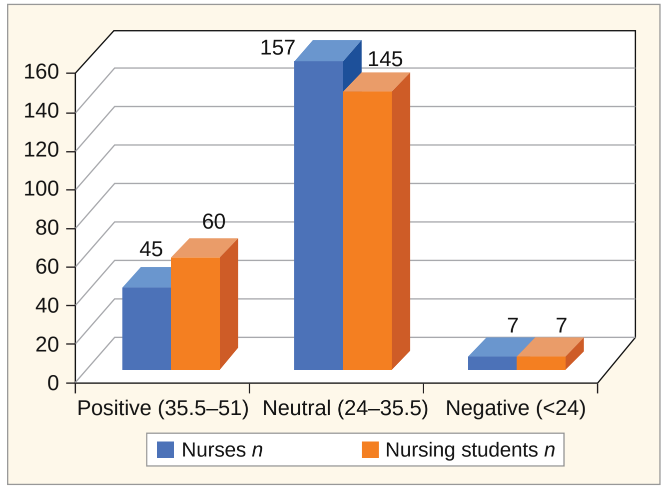

Fig. 2: Bar diagram showing attitude among nurses and nursing students

Table 4: Correlation between awareness and attitudes levels of nurses ($n = 209$)

Variables	*Awareness*	*Attitudes*
Awareness	1	–0.443 (0.000)**
Attitudes	–0.443 (0.00)**	1

$p < 0.05$ significant. **Highly significant

Table 3: Assessment of attitude about organ donation among nurses and nursing students ($n_1 + n_2 = 209 + 212$)

	Nurses, n (%)			*Nursing students, n (%)*		
Item	*Positive*	*Negative*	*Neutral*	*Positive*	*Negative*	*Neutral*
I have thought about doing organ donation	113 (53.3)	65 (30.7)	31 (14.6)	135 (63.7)	45 (21.2)	32 (15.1)
I support organ donation	181 (85.4)	11 (5.2)	17 (8.0)	191 (90.1)	7 (3.3)	14 (6.6)
I'm willing to donate to a family member who is in need of an organ donation	140 (66.0)	27 (12.7)	42 (19.8)	153 (72.2)	19 (9.0)	40 (18.9)
I have already registered as an organ donor	39 (18.4)	143 (67.5)	27 (12.7)	33 (15.6)	164 (77.4)	15 (7.1)
I'm considering myself as a donor in the future	25 (11.8)	184 (86.8)	0	23 (10.8)	189 (89.2)	0
I'm willing to donate the organ of a brain-dead family member who never discussed his preference for organ donation with me	48 (22.6)	83 (39.2)	78 (36.8)	77 (36.3)	70 (33.0)	65 (30.7)
I would like to receive an organ transplant if needed	117 (55.2)	28 (13.2)	64 (30.2)	136 (64.2)	27 (12.7)	49 (23.1)
I would like to donate organ to a stranger in need	96 (45.3)	37 (17.5)	76 (35.8)	98 (46.2)	35 (16.5)	79 (37.3)
Talked to family regarding the decision to donate or not donate	115 (54.2)	56 (26.4)	38 (17.9)	100 (47.2)	79 (37.3)	33 (15.6)
I know someone who donated an organ	77 (36.3)	132 (62.3)	0	94 (44.3)	118 (55.7)	0
I know someone who received an organ	78 (36.8)	131 (61.8)	0	107 (50.5)	105 (49.5)	0
I feel I lack sufficient information about organ donation	150 (70.8)	59 (27.8)	0	143 (67.5)	69 (32.5)	0
I feel organ donation is against my religious beliefs	27 (12.7)	182 (85.8)	0	32 (15.1)	180 (84.9)	0
I would like to be buried or cremated with all my organs intact	65 (30.7)	144 (67.6)	0	68 (32.1)	144 (67.9)	0
There are personal/moral conflicts regarding donating my organs	65 (30.7)	104 (49.1)	40 (18.9)	59 (27.8)	123 (58)	30 (14.2)
I'm scared of the disfigurement or postoperative pain while undergoing the process of donation	118 (55.7)	91 (42.9)	0	113 (53.3)	99 (46.7)	0
I would like to donate an organ to the person whom I choose to	106 (50)	45 (21.2)	58 (27.4)	113 (53.3)	44 (20.8)	55 (25.9)

Table 5: Correlation between awareness and attitudes levels of nursing students ($n = 212$)

Variables	*Awareness*	*Attitudes*
Awareness	1	−0.389 (0.000)**
Attitudes	−0.389 (0.000)**	1

$p < 0.05$ significant. **Highly significant

Table 6: Association between awareness of organ donation and LDLT among nurses with demographic variables ($n = 209$)

Sociodemographic characteristic	*Mean ± SD*	*f*	*df*	*p-value*
1. Age		0.427	208	0.734
<30 years	14.34 ± 4.6			
30–39 years	15.63 ± 3.2			
40–49 years	18			
≥50 years	23			
2. Gender		0.11	208	0.731
Male	14.25 ± 5.10			
Female	14.48 ± 4.36			
3. Professional education		0.138	208	0.871
Graduation	14.36 ± 4.77			
Post Graduation	14.46 ± 3.99			
Diploma	15.29 ± 2.98			
4. Total years of experience		2.552	208	0.040*
<5 years	14.41 ± 4.62			
5–10 years	17.67 ± 2.94			
11–12 years	15.40 ± 3.97			
> 20 years	8.50 ± 4.20			
Other	13.33 ± 2.08			
5. Setting of work		0.352	208	0.842
Govt. hospital	14.51 ± 4.5			
Private hospital	14.29 ± 4.6			
Community health center	16			
Transplant center	13.25 ± 6.07			
Other	17.00 ± 4.35			
6. Marital status		0.613	208	0.435
Married	14.34 ± 4.6			
Unmarried	15.42 ± 3.3			

*$p < 0.05$ significant

Table 6 shows the association between awareness and demographic variables. Among nurses, awareness levels differed significantly across total years of experience, with p-value of 0.040, showing that awareness increased with increasing years of professional experience.

As shown in Table 7, age, working in transplant centers, and being unmarried were significantly associated with higher awareness of organ donation among nursing students.

As all p-values are greater than 0.05, none of the socio-demographic variables (age, gender, education, experience, work setting, or marital status) showed a statistically significant association with nurses' and nursing students' attitude scores toward organ donation and LDLT (Tables 8 and 9).

Table 7: Association between awareness with demographic variables among nursing students ($n = 212$)

Sociodemographic characteristic	*Nursing students Mean ± SD*	*f*	*df*	*p-value*
Age				
<30 years	14.82 ± 4.10	2.67	211	0.049*
30–39 years	15.53 ± 2.93			
40–49 years	17.92 ± 2.84			
≥50 years	14.67 ± 5.50			
Gender				
Male	14.66 ± 4.5	1.47	211	0.226
Female	15.36 ± 3.5			
Professional education				
Graduation	14.80 ± 4.05	1.64	211	0.180
Post Graduation	15.70 ± 3.46			
Diploma	14.76 ± 4.1			
Total years of experience				
<5 years	15.04 ± 3.91	1.878	211	0.134
5–10 years	14.53 ± 3.78			
11–12 years	16.33 ± 1.87			
>20 years	16.87 ± 4.51			
Setting of training				
Govt. hospital	15.86 ± 3.44	0.675	211	0.001**
Private hospital	14.87 ± 3.98			
Community health center	11 ± 3.64			
Transplant center	17.43 ± 1.90			
Marital status				
Married	14.81 ± 3.99	3.298	211	0.039
Unmarried	15.92 ± 3.43			

*$p < 0.05$ significant. **0.001 level of significance

Table 8: Association between attitudes with demographic variables among nurses ($n = 209$)

Sociodemographic characteristic	*Nurses mean ± SD*	*f*	*df*	*p-value*
1. Age				
<30 years	27.12 ± 5.21	1.659	208	0.177
30–39 years	26.25 ± 3.05			
40–49 years	25			
≥50 years	16			
2. Gender				
Male	26.54 ± 5.70	0.934	208	0.335
Female	27.27 ± 4.88			
3. Professional education				
Graduation	27.14 ± 5.22	2.218	208	0.111
Post Graduation	27.29 ± 4.90			
Diploma	23 ± 3.83			
4. Total years of experience				
<5 years	27.07 ± 5.13	0.512	208	0.727
5–10 years	28.67 ± 5.16			
11–12 years	24.80 ± 1.48			
>20 years	25.25 ± 10.9			
Other	26.33 ± 2.30			

(Contd...)

Table 8: *(Contd...)*

Sociodemographic characteristic	*Nurses mean ± SD*	*f*	*df*	*p-value*
5. Setting of works				
Govt. hospital	27.01 ± 4.96	1.215	208	0.306
Private hospital	26.94 ± 5.15			
Community health center	19			
Transplant center	31 ± 9.09			
Other	27.67 ±5.85			
6. Marital status				
Married	27.03 ± 5.28	0.016	208	0.898
Unmarried	26.83 ± 3.15			

*$p < 0.05$ significant

Table 9: Association between attitudes with demographic variables among nursing students ($n = 212$)

Sociodemographic characteristic	*Nursing students Mean ± SD*	*f*	*df*	*p-value*
1. Age				
<30 years	26.67 ± 5.2	0.94	211	0.420
30–39 years	25.41 ± 4.1			
40–49 years	25.58 ± 4.1			
≥50 years	27.33 ± 3.0			
2. Gender				
Male	26.62 ± 6.7	0.327	211	0.568
Female	26.19 ± 4.0			
3. Professional education				
Graduation	26.64 ± 5.33	0.959	211	0.413
Post Graduation	25.57 ± 4.33			
Diploma	27.00 ± 5.63			
4. Total years of experience				
<5 years	26.69 ± 5.25	1.409	211	0.241
5–10 years	24.90 ± 4.48			
11–12 years	26.13 ± 4.32			
>20 years	26.73 ± 3.17			
5. Setting of works				
Govt. hospital	26.08 ± 4.07	1.527	211	0.209
Private hospital	26.36 ± 5.37			
Community health center	29.33 ± 6.94			
Transplant center	24.43 ± 2.4			
6. Marital status				
Married	26.80 ± 5.29	2.074	211	0.128
Unmarried	25.36 ± 4.13			

*$p < 0.05$ significant

Discussion

The current study aimed at assessing awareness, attitude, and perception of organ donation and LDLT among staff nurses and nursing students. As frontline healthcare providers and future practitioners, these groups play a critical role in influencing public opinion and decision-making on organ donation.[6] Understanding their knowledge and mindset of these professionals is essential for developing effective education and advocacy strategies.

General Awareness on Organ Donation

Both groups showed similar trends in awareness, with nursing students performing marginally better than nurses. The knowledge gaps in both the groups were noticed in misconceptions around organ donation after cardiac arrest (nurses: 41.0%, students: 42.5%). The areas where nurses performed significantly better are general awareness (nurses: 91.5%, students: 56.8%). This difference may be attributed to their professional exposure. Nurses performed significantly better understanding (79%) of clinical eligibility of a brain-dead person for organ donation than 67.9% of the students. For the consent procedure for organ donation in brain death, 87.3% of the nurses were aware to 76.4% of the nursing students. Awareness of the registration process and the national organ donation organization was moderately better among nurses (69.8%) than among nursing students (57.1–62.3 and 53.3%).

Awareness of LDLT and Attitudinal Barriers

The areas where nurses performed better included knowledge of the percentage of liver that can be safely donated (nurses: 41.0%, students: 42.5%) and understanding of the risks involved in LDLT (nurses: 74.5%, students: 65.1%). However, in legal age for organ donation registration (students: 82.1% vs nurses: 75.5%), governing legislation (students: 67.0% vs nurses: 66.0%), and liver regeneration time (students: 58.5% vs nurses: 56.1%), the nursing students performed better. Both nurses and nursing students perceived a lack of awareness of liver transplant in India (only one-third, 29.1% nurses, 31.1% students felt that there is sufficient awareness) and shared similar attitudinal barriers to donation, though with some differences: students are more worried about health after donation (34.9%). Previous literature has similarly noted that nursing students often report fear of medical consequences and insufficient procedural understanding as key deterrents to organ donation.[6,7] Nurses are more concerned about family opposition (17.2%) than students (10.3%). This may reflect increased familial and societal responsibilities typically associated with older, working professionals. Despite this, both groups reported a relatively low frequency of this concern, which may indicate growing social acceptance of organ donation or underreporting due to social desirability bias. Fear of complications and lack of information are common barriers in both groups (~25–28%). Previous studies have emphasized that adequate knowledge significantly improves attitudes and willingness to donate.[8,9] For the liver donor eligibility, the majority of both nurses and students correctly identified "no history of liver disease or significant chronic illness" as the most important criterion (31.5 and 41.9%, respectively), reflecting a general awareness of the importance of donor health status, although nursing students emphasized this criterion more strongly, potentially due to theoretical knowledge. Nurses more frequently cited "age" (26.3%) as an important criterion compared to students (16.2%). This may reflect their clinical exposure and understanding of the surgical and physiological risks associated with older donors. Both groups gave comparable importance to "matching blood type" (25.8%) and "good overall health" (around 16%), indicating a baseline understanding of essential compatibility factors. Similar findings have been observed in earlier studies where nurses demonstrated moderate knowledge of transplant protocols but lacked depth in specific eligibility criteria.[8]

The present study examined two distinct yet essential stages in the professional nursing continuum—practicing nurses and nursing students—to explore the impact of differences in clinical exposure, the gap between theoretical knowledge and practical application, and the preparedness of the future nursing workforce to organ donation and LDLT. However, due to the limited availability of studies comparing both groups simultaneously on their awareness and attitudes toward organ donation and LDLT, direct comparisons with existing literature were not feasible. Similar results were obtained in a comparable study conducted in Hong Kong, among undergraduate and postgraduate nursing students found that they possessed only average knowledge about organ donation and transplantation. The study highlighted the need for more educational and promotional resources on the topic.[6] Another study involving nurses in Hong Kong revealed similar findings, indicating a lack of knowledge and awareness concerning tissue and organ donation. It emphasized the need for education on key aspects such as brain death and appropriate communication strategies for approaching families about organ donation.[8] Likewise, a survey conducted at Tehran University of Medical Sciences in Iran assessed nurses' knowledge and attitudes toward organ and tissue donation. The findings suggested that targeted educational programs can significantly improve nurses' understanding and commitment to the donation process, potentially leading to higher donation rates.[9]

Attitude on Organ Donation and LDLT

Generally positive attitudes toward organ donation and LDLT among both nurses and students were noted in the present study. However, nurses showed a slightly more positive attitude (27.0) compared to students (26.3). The results are consistent with a study done on nurses in western India, wherein 89.4% had a favorable attitude and 10.6% had a highly favorable attitude toward organ donation.[7]

Correlations among Awareness and Attitude among the Participants

In the present study, a moderate negative correlation was observed between awareness and attitudes toward organ donation and LDLT among both nurses ($r = -0.443$) and nursing students ($r = -0.389$), and these correlations were found to be statistically significant ($p = 0.000$). This highly significant correlation needs to be explored further through longitudinal studies interpreted very cautiously. Higher awareness among healthcare workers may be associated with more realistic or cautious attitudes as concerns about medical, ethical, or procedural issues that the general public or less-informed individuals may overlook.

Strengths of the Study

An online survey was employed to encourage participation and ensure representation of nurses from diverse cultural and demographic backgrounds.

Limitations

The present study utilized an online survey method, which may have introduced certain limitations. Due to the distribution of the survey link through various informal channels, it was not possible to apply a specific statistical sampling technique. Consequently, nurses without access to digital devices such as smartphones, those unable to access Google Forms, or those unfamiliar with its use were excluded, resulting in potential selection bias. Additionally, the descriptive nature of the study limits the ability to establish causal relationships. Data were collected using self-report tools, which may have introduced response bias.

Conclusion

The findings reveal that while both groups display a generally positive attitude toward organ donation and LDLT, there are notable gaps in awareness and understanding, particularly in areas involving clinical criteria, procedural knowledge, and legal frameworks. A statistically significant negative correlation between awareness and attitudes suggests that higher awareness may be associated with more cautious or reserved attitudes, possibly due to increased understanding of the medical and ethical complexities involved in organ donation and LDLT. Hence, it is recommended to integrate structured education on organ donation and LDLT into nursing curricula and continuing professional development. Increasing clinical exposure for nursing students, particularly through rotations in transplant units, can help bridge the gap between theoretical knowledge and practice. Regular awareness programs and workshops should be conducted to address persistent knowledge gaps and attitudinal barriers, such as fear of complications and lack of information.

Declaration

The authors declare that this work is their original creation and has not been published/submitted for publication anywhere else.

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References

1. Vipin K, Sharma R, Kumar A. Impact of green corridors in organ donation: A single-center experience. Indian J Transplant 2018; 12(2):110–112. DOI: 10.4103/ijot.ijot_11_18.
2. Press Information Bureau. Dr. Harsh Vardhan presides over the 10th Indian Organ Donation Day, May 30, 2020. Available from: https://pib.gov.in.
3. Donate Life. Need for organ donation in India–Organ donation information in India | Donate Life, June 1, 2020. Available from: https://www.donatelife.org.in.
4. Issac A, Devi S, Khan A, et al. Knowledge, attitude, willingness, and factors influencing organ donation decision-making in India. Int J Commun MedPubl Health 2025;12(1):374–381. Available from: http://www.ijcmph.com.
5. Narasimhan G. Living donor liver transplantation in India. Hepatobiliary Surg Nutr 2016;5(2):127–132. DOI: 10.3978/j.issn.2304-3881.2015.09.01.
6. Tam WW, Suen LK, Chan HY. Knowledge, attitudes and commitment toward organ donation among nursing students in Hong Kong. Transplant Proc 2012;44(5):1196–1200. DOI: 10.1016/j.transproceed.2012.01.108.
7. John P, Priyadarsini P. Knowledge and attitude of nurses on organ donation in Western India. Indian J Continuing Nurs Educ 2023;24(1):68–73. DOI: 10.4103/ijcn.ijcn_106_22.
8. Ozdag N. The nurses' knowledge, awareness and acceptance of tissue organ donation. EDTNA/ERCA J 2001;27(4):201–206. DOI: 10.1111/j.1755-6686.2001.tb00179.x.
9. Aghayan HR, Arjmand B, Emami-Razavi SH, et al. Organ donation workshop: A survey on nurses' knowledge and attitude toward organ and tissue donation in Iran. Int J Artif Organs 2009;32(10):739–744. DOI: 10.1177/039139880903201007.

ORIGINAL ARTICLE

Determinants of Multimorbidity in Community-dwelling Older Adults: A Decision-tree-based Analysis

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Abstract

Aims and background: The aging population represents a critical group from a public health perspective. This cross-sectional study aims to understand the determinants and health conditions associated with multimorbidity in a sample of community-dwelling older adults.

Materials and methods: A sample of 1,100 individuals aged 60 and above was drawn from the population in Dibrugarh district, Assam, India. The highest recorded health conditions and the presence of multiple chronic conditions are identified. A heat map of dyads and triads is generated using the descriptive statistics tool, and factors responsible for the number of health conditions occurring concurrently in the sample are identified through a Classification and Regression Tree (CRT) decision-tree model in IBM SPSS Statistics 27.

Results: Among the 25 health conditions reported, hypertension, arthritis, and gastritis graced the top three spots individually. In terms of co-occurring conditions, the most significant dyad was hypertension and diabetes. Hypertension, diabetes, and heart disease constituted the prime triad. As per the decision tree, education, income, and body mass index have been found to influence multimorbidity the most. The model is 70.6% accurate.

Conclusion: Noncommunicable diseases (NCDs) dominate the multimorbidity burden in the population studied. Health policies directed toward older adults need to be strengthened to equip them with the changing lifestyles and risk factors associated therewith.

Clinical significance: Consideration of sociocultural realities influencing multimorbidity leads to better health outcomes for patients undergoing treatment and targeted preventive interventions for those perceived to be at risk.

Keywords: Classification and regression tree, Decision-tree model, Dyads and triads, Multimorbidity, Population aging.

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Introduction

The countries of the world have been undergoing a demographic transition, albeit at varied rates.[1,2] The global population is progressing toward a low-fertility and low-mortality society.[3,4] Birth rates have been brought down drastically because the chances of survival of infants have risen by multitudes, primarily due to the success of vaccination programs worldwide.[5] Life expectancy has been stretched considerably due to skyrocketing medical technology. The share of older people in the global population has been growing steadily, whereas the share of youth is declining. Population aging is now a major issue in the developed world. The developing world is following suit. The economic implications of a graying population are far-reaching, as a sizeable amount of resources is needed to sustain the dependent population, who require more healthcare and contribute the least to the economy. This can be countered by reducing the healthcare burden and increasing labor-force participation of the elderly.[6,7] As such, the optimum health and well-being of older adults now demand a priority position in policy making.

The world population has witnessed a near doubling of the share of people aged 65 and above over the last 50 years, between 1974 and 2024, spiking from 5.5 to 10.3%. The next doubling, following the United Nations population projections, is expected to occur in 2074, at 20.7%. Within the same period, the number of persons aged 80 and above is projected to more than triple.[8] The elderly population in India is growing at a decadal growth rate of 41%. The population of the elderly will exceed that of children (0–15 years) by 2046 and account for 20% of the total population by 2050. Even more alarming is the fact that more than 40% of the elderly in India belong to the poorest wealth quintile.[9] These statistics highlight the real population bomb – the silver tsunami.[10]

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Conflict of interest: None

People are now living longer lives. However, their quality-of-life warrants research. Accompanying technological advances are some social changes that contribute to a lowering of the quality of life among older adults. The nuclearization of the family structure and employment-induced migration of the youth have led to elderly individuals living alone, often bereft of love and care. An increasing number of older adults live subpar lives.[11–15] Health-related quality of life includes social and mental well-being in addition to the physical health. But the impact of compromised physical health is quite significant. The development of multiple chronic conditions is a natural consequence of aging.[16] Multi-morbid older adults have greater dependency on caregivers, which often leads to high caregiver burden and strained relationships, a defining factor in deteriorating social and mental health. As such, multimorbidity has become one of the focal points of research in elderly health.[17–19]

The term multimorbidity refers to the co-occurrence of two or more health conditions, which may or may not be related. With significant demographic changes, an epidemiological transition is also becoming evident in the global population, with degenerative and human-induced diseases overriding infectious diseases as the major drivers of morbidity and mortality.[20] This shift is also seen in the elderly population. Noncommunicable diseases (NCDs) are on the rise and now account for an increasing morbidity among older adults compared to past decades. In the case of India as well, the share of NCDs in morbidity of older adults is alarming, particularly in urban populations.[21] A rural–urban disparity has been found in NCD prevalence among the elderly in India. Two significant predictors of this increasing rural–urban variability in the occurrence of NCDs have been found to be the level of education and current working status.[22] Hypertension is the most significant NCD among the elderly in urban India.[21,23] Researchers also found that the north-eastern and southern states of the country had higher shares of older adults at high-risk for NCDs.[24]

This study is an attempt at tracing the multimorbidity pattern, unearthing the probable determinants of multimorbidity, and also to single out health conditions that dominate the burden of multimorbidity in a sample of older adults aged 60 and above in Dibrugarh district, Assam. The district is divided into seven revenue circles and seven community development blocks. The boundaries of the revenue circles and CD blocks often overlap. The seven revenue circles are – Dibrugarh East, Dibrugarh West, Chabua, Tengakhat, Naharkatia, Tingkhong, and Moran (Fig. 1). The district has three statutory towns and six census towns. The urban population comprises only 18.38% of the total population.[25]

The population in the selected region is quite diverse socio-culturally and thus, can present a far detailed overview of precursors of multimorbidity. Some rural areas in the district have developed a semi-urban character, due to proximity to urban areas, and the multimorbidity burden in these areas is found to be quite higher than in the typical villages. Thus, the spilling effect of urbanization and associated health conditions is also noteworthy.

This study has been carried out with the following objectives:

- To assess the multimorbidity pattern in the sample population.
- To single out the health conditions that dominate the multimorbidity burden.
- To determine the effects of factors like location, gender, working status, marital status, ethno-linguistic group, age-group, education, income, and body mass index (BMI) on multimorbidity.

Materials and Methods

This is a cross-sectional study, the data for which were collected from a sample of community-dwelling older adults aged 60 and above. The research was conducted according to the ethical guidelines of the authors' affiliated university. According to the 2011 Census, the total population of older adults above the age of 60 in the district is 89,368 persons. The 2011 data has been considered because the census for the year 2021 could not be conducted due to the coronavirus disease-2019 (COVID-19) pandemic. Also, since many mortality cases from COVID-19 were of older adults, even a

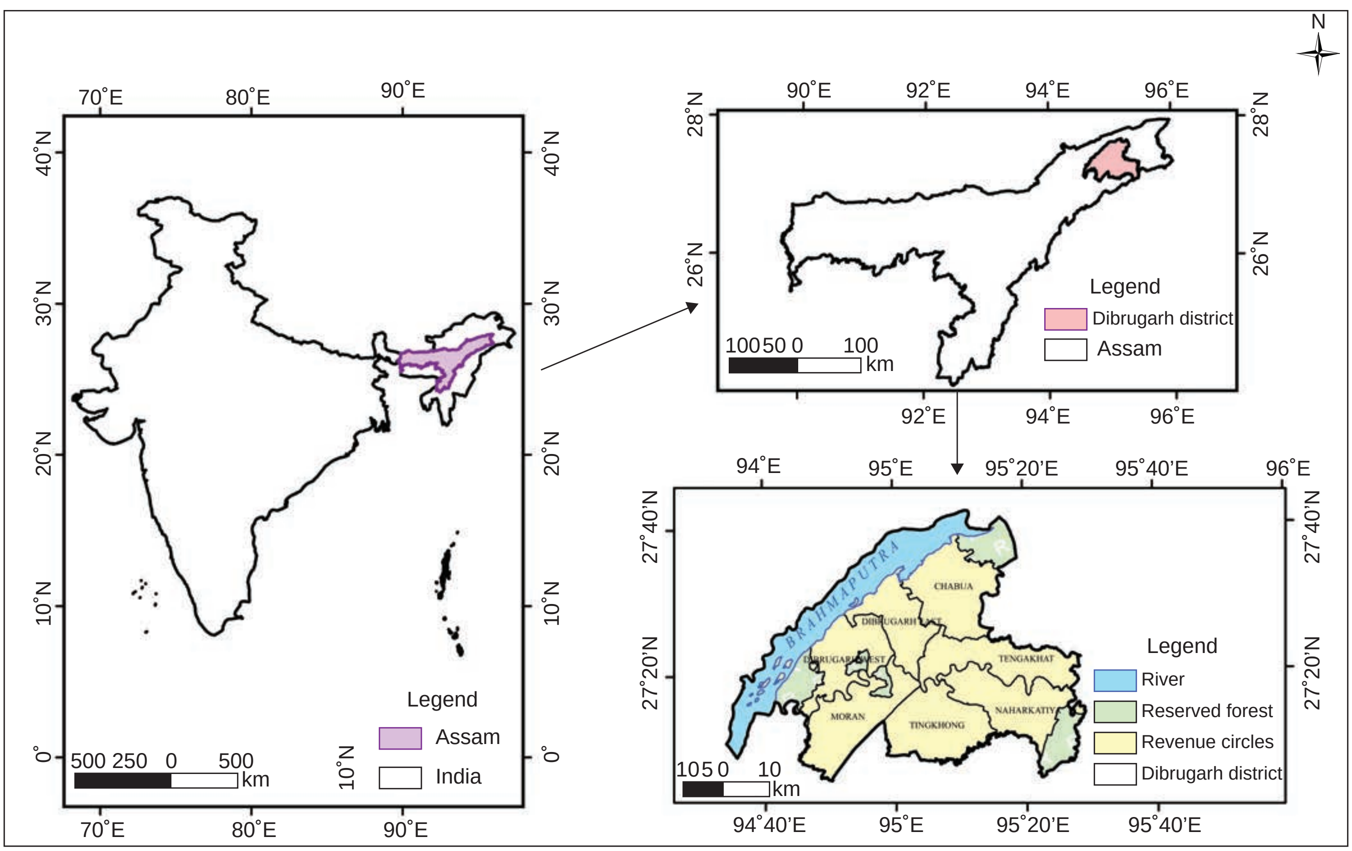

Fig. 1: Location map of the study area

projected population would not be accurate. The sample size has been determined as follows:[26]

$$n = N/[1 + N(e)^2]$$

where,

n = sample size, N = universe, e = confidence interval.

The sample size was calculated as 1097.47, at a 97% confidence interval. Therefore, a total of 1,100 samples were determined for the study. The samples were spread out to better account for spatial variation. Since a huge portion of the total population is rural, the samples are selected in such a way that reflects the rural character. The cluster sampling technique was employed for the selection of samples.

For the rural sample, villages were selected from each of the seven CD blocks. Then, households were selected from each village, followed by the selection of individuals for interview. A total of 39 villages were selected for the rural sample. These include – Dinjan TE, Balijan TE, Polonga Gaon, Komar Gaon, Dighala Gaon, Bogibeel Gaon, Lepetkata Gaon, Rawomari Gaon, Kotoha Gaon, Gabharujan Gaon No. 2, Niz Lahoal, Mohanbari Hindu Gaon, Lahoal Patra Gaon, Dibrual Changmai, Japi Sajia Gaon, Duliajan No. 2, Jutlibari Borhula, Hukuta, Boragadhai, Chapatali No. 4, Borpathar No. 2, Puwali Pather, Ahomgaon No. 1, Bukahula, Nunghunia No. 3, Gozpuria Gaon, Baghtoli Sonowal Gaon, Tiloibari Gaon, Faltutola Gaon, Kapahuwa Gaon, Ghuronia, Sachoni, Ushapur, Tipamia No. 2, Kachalu Pather No. 2, Latomoni, Bailong Bhati, Nabhakatia No. 2, and Lonboi No. 341 Nlr.

A similar process was followed for the urban sample. Urban areas were selected from each of the seven revenue circles for better representation. However, as urban population comprises a low proportion of the total population in the district, all the urban areas (11 in number), namely, Dibrugarh (MB), Chabua (TC), Naharkatiya (TC), Barbari AMC Area (CT), Duliajan Oil Town (CT), Moran (CT), Namrup (CT), Niz-Mankata (CT), Sarupathar Bengali (CT), Tekela Chiring Gaon (OG), and Mahpowalimara Gohain Gaon (OG), were selected from the seven revenue circles for the urban sample.

The respondents were asked about the health conditions that they suffer from. In addition to this, the demographic and socio-economic profile of the respondents was generated through questions on location, age-group, gender, marital status, ethno-linguistic group, education, monthly household income, and working status. Respondents were grouped into rural and urban based on location. Five age-groups were identified – 60–69, 70–79, 80–89, 90–99, and 100–109 years. During the survey, older adults belonging to the two genders – male and female were reported. Three categories were created with regard to marital status – single, married, and widowed. A number of ethno-linguistic groups were found during the survey. These include – Ahom, Assamese, Bengali, Bihari, Bodo-Kachari, Deori, Marwadi, Mising, Nepali, Odia, Punjabi, Sonowal Kachari, and Tea tribe. Educational levels recorded in the sample population were – no education, primary, matriculate, higher secondary, graduate, and master's. The monthly household income of the respondents (in INR) was recorded within five groups – below 15,000, 15,000–30,000, 30,000–45,000, 45,000–60,000, and above 60,000. Respondents were divided into two categories based on working status – working and non-working. Additionally, height and weight information were also obtained. Weight (in kg) was divided by the square of height (in meters) to get BMI value. The BMI categories were created as – underweight (BMI < 18.5), healthy weight ($18.5 \leq$ BMI ≤ 24.9), overweight ($25 \leq$ BMI ≤ 29.9), and obese (BMI ≥ 30).

Prevalence of multimorbidity has been assessed through a heat map and identification of dyads and triads of health conditions in the sample population. For the identification of dyads and triads, the authors used frequency tables within descriptive statistics in IBM SPSS Statistics 27. A decision tree has been created to fulfill the third objective of the study. A decision tree is a non-parametric classification method often used to predict disease prognosis and outcomes, as well as associated risk factors.[27,28] Here, it has been used to gauge the effects of socio-cultural variables on multimorbidity in older adults, in addition to some direct indicators like age and BMI. Decision trees are employed instead of regression due to the presence of significant outliers in the data, which are not a result of measurement errors, but rather a natural consequence of the nature of the data. Decision trees are robust and can handle outliers better as they split the data based on certain criteria, thus incorporating extreme values in the analysis and maintaining the accuracy of the model at the same time. They are particularly useful when meaningful sub-groups are present in the data.

For the purpose of this study, a decision tree was created in IBM SPSS Statistics 27 to determine the factors that played major roles as probable causative agents of multimorbidity. The choice of the method of tree formation is directed by the nature of the dependent variable. The Classification and Regression Tree (CRT) method is used to determine the factors influencing the number of health conditions in the sample population and also the importance of individual health conditions. It is used when the dependent variable is a scale variable, e.g., the number of health conditions. It has a better predictive power than other methods. Predicted value at each node has been assessed to gain an understanding of the patterns originating from the data.

The CRT method produces binary splits. The maximum tree depth for a CRT model is 5. The maximum number of cases at the parent node is set as 6, and that for the child node is set as 3. The trees are pruned to avoid overfitting. For pruning, the maximum difference in risk (standard errors) is set as 2. The impurity measure selected is the Gini coefficient, which finds splits that maximize the homogeneity of child nodes with respect to the value of the target variable.

Results

At the onset, an understanding of the number, types, and patterns of health conditions prevalent in the sample population is essential. A total of 25 health conditions were reported by the sample population (Fig. 2). Along with their shares, these include – hypertension (27%), arthritis (12%), gastritis (11.82%), hypotension (7%), diabetes (6.64%), hypothyroidism (5%), rheumatism (4.64%), elevated uric acid (3.45%), fatty liver disease (2.82%), heart disease (2.45%), cataract (2.27%), neuropathy (2.18%), and osteoporosis (1.81%). The remaining 12 health conditions affect less than 1% of the total sample population.

The number of health conditions occurring concurrently in the sample population gives an idea of the prevalence and degree of multimorbidity in the sample population. A minimum of 0 and a maximum of 6 health conditions were reported. Of the sample population, 59.09% have at least one health condition, and 23.53% are multimorbid, i.e., they exhibit two or more co-occurring health conditions. The shares of the sample population with two, three, four, five, and six health conditions are 16.09, 4.36, 2.4%, 0.36, and 0.27%, respectively.

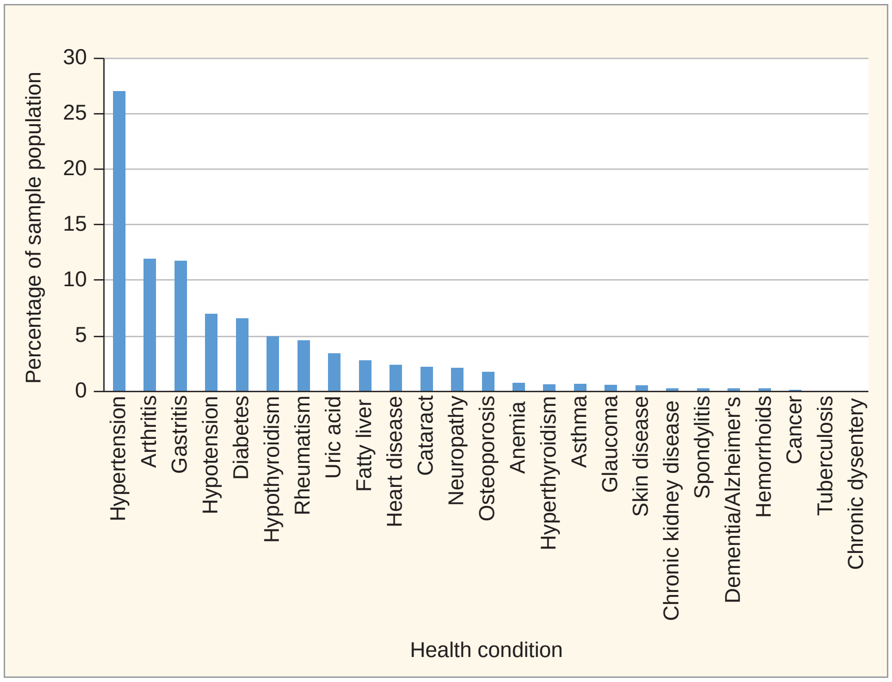

Fig. 2: Shares of individual health conditions in the sample population

	Hypertension	Arthritis	Gastritis	Hypotension	Diabetes	Hypothyroidism	Rheumatism	Uric Acid	Fatty liver	Heart disease
Hypertension	297	40	27	0	51	33	16	14	11	21
Arthritis	40	132	19	12	10	8	1	6	5	7
Gastritis	27	19	130	14	5	6	9	5	6	3
Hypotension	0	12	14	77	1	0	7	1	1	0
Diabetes	51	10	5	1	73	12	4	9	6	14
Hypothyroidism	33	8	6	0	12	55	5	4	1	7
Rheumatism	16	1	9	7	4	5	51	0	1	2
Uric acid	14	6	5	1	9	4	0	38	9	3
Fatty liver	11	5	6	1	6	1	1	9	31	0
Heart disease	21	7	3	0	14	7	2	3	0	27

Fig. 3: Heat map of the top 10 individual and co-occurring health conditions in the sample population with at least one health condition

Out of the sample population with at least one health condition (N = 650), the top 10 individual and co-occurring health conditions are presented as a heat map (Fig. 3). All of these health conditions are chronic NCDs. The blue gradation in the map represents individual health conditions of respondents with at least one health condition. The red gradation represents the co-occurring health conditions. The figures in the map are the number of respondents exhibiting the particular health condition(s).

The most significant dyads among respondents with at least one health condition are – hypertension and diabetes (7.85%), hypertension and arthritis (6.15%), hypertension and hypothyroidism (5.08%), hypertension and gastritis (4.15%), hypertension and heart disease (3.23%), arthritis and gastritis (2.92%), hypertension and rheumatism (2.46%), hypertension and uric acid (2.15%), diabetes and heart disease (2.15%), and gastritis and hypotension (2.15%). Hypertension occurs in 70% of the top 10 dyads, followed by gastritis (30%). Arthritis, diabetes, and heart disease each account for 20% of occurrences in the top 10 dyads.

The triads are of higher importance as these basically refer to greater than 2 co-occurring conditions and represent sections of the population who belong to a high-risk category. The unholy trinity – hypertension, diabetes, and heart disease – is at the peak among the triads, with a share reaching 2% of respondents with at least one health condition. The other significant triads, in order of their shares, are – hypertension, diabetes, and hypothyroidism (1.69%); hypertension, arthritis, and diabetes (1.23%); hypertension, arthritis, and heart disease (1.07%); and hypertension, hypothyroidism and heart disease (1.07%). Hypertension occurs in 100% of the top five triads. Diabetes and heart disease each account for 60%, and arthritis and hypothyroidism each account for 40% of shares in the top five triads.

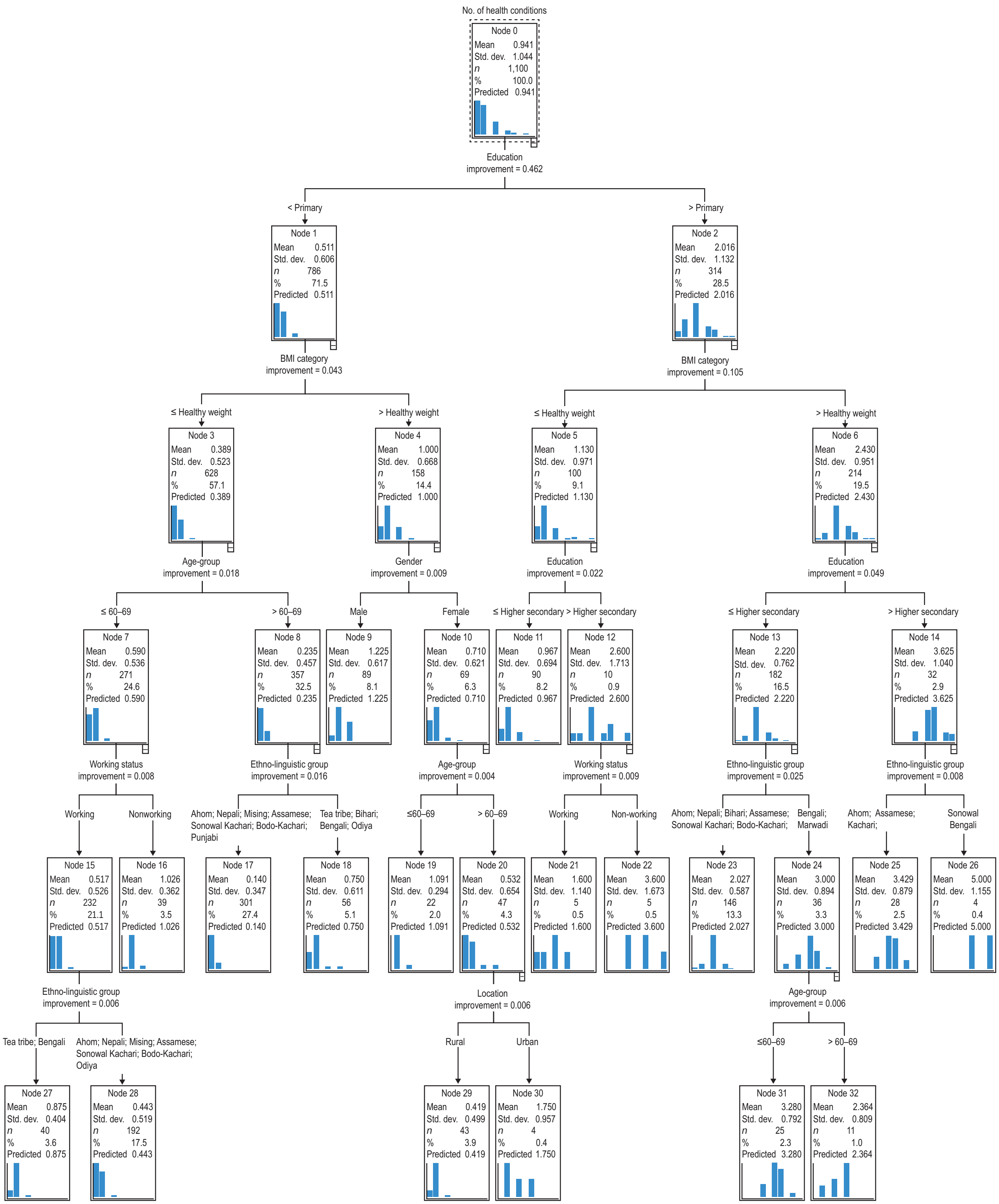

Fig. 4: CRT decision tree

In order to unearth causative relationships, the data were fed into a CRT decision-tree model (Fig. 4). The dependent variable is the number of health conditions occurring concurrently in the sample population. In this case, all the 1,100 cases are considered for the analysis. The independent variables are – location, age-group, gender, marital status, ethno-linguistic group, education, monthly household income, and working status.

A detailed tree with 32 nodes gives a clear idea of the relationships overall and which factors influence multimorbidity in further sub-groups. Each node produces a predicted number of health conditions. The mean or predicted number of health conditions at node 0, which is the parent node, is 0.941. This is the mean for the total sample. The branching continues up to the leaf nodes. The first split in the tree is based on education. This is the parent node. As such, education is the defining variable of multimorbidity. The branching continues up to the leaf nodes.

The nodes with significant predicted values for the number of co-occurring health conditions are identified and then traced in the tree to form meaningful associations. The predicted value of 5 at Node 26 is the highest among all the nodes in the tree. Thus, respondents with a BMI above the healthy weight category, education above the higher secondary, and belonging to the Bengali ethno-linguistic group are likely to be the most multi-morbid. This node comprises 0.4% of the total sample population. Node 17 bears the lowest predicted value at 0.14. Trailing the tree to node 17 reveals that respondents with education equal to or below primary, BMI equal to or below the healthy weight category, belonging to the age-group greater than 60–69, and ethno-linguistic groups Ahom, Nepali, Mising, Assamese, Sonowal Kachari, Bodo-Kachari, and Punjabi, are likely to have the lowest morbidity. This node comprises 27.4% of the total sample population. This node comprises the highest share of the sample population.

The importance of the dependent variables is presented in Figure 5. As evident from the tree and importance chart, education seems to be the most influential factor (normalized importance = 100%), followed by income category (normalized importance = 65.3%) and BMI category (normalized importance = 58.7%). Factors with normalized importance less than 50% but greater than 10% include ethno-linguistic group, location, and age-group. Working status, marital status, and gender had very little effect on multimorbidity. The model has a risk estimate of 0.294 with a standard error of 0.018. This means that it predicts 29.4% of the outcomes incorrectly. Therefore, the model is 70.6% accurate.

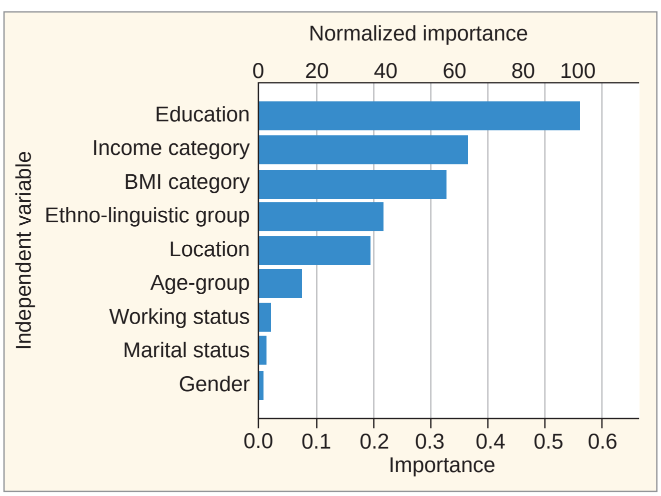

Fig. 5: Normalized importance chart

Discussion

All the major health conditions self-reported by the sample population are noncommunicable chronic diseases, with diabetes, heart disease, and hypertension having a stronghold on the overall burden of multimorbidity. Other studies have also found these associations to hold true.[29–31] Thus, better healthcare and introduction of healthier lifestyles, promoting increased mobility and simpler diets, can help reduce the burden of multimorbidity and nudge older adults toward active and healthy aging.

The independent variables with the highest influence on multimorbidity in the sample population turned out to be education, monthly household income, and BMI category. Higher levels of education, income, and BMI have been found to have associations with multimorbidity in older adults in studies of a similar nature.[32–36] As such, well-educated, affluent, and obese older adults are more likely to be multi-morbid compared to their counterparts. Thus, adults belonging to these groups need early screening and intervention to prevent the development of multiple chronic conditions in later stages of life.

Conclusion

This study delineated causative factors responsible for multi-morbid conditions and the health conditions dominating multimorbidity in older adults. The model generated results with a fairly acceptable risk. The burden of NCDs in the population studied seems quite significant. These are lifestyle-induced conditions that were almost non-existent around two centuries ago. Health policies directed toward older adults need to be strengthened to equip them with the changing lifestyles and risk factors associated therewith. Adults who are obese and have higher levels of education and income need to be vigilant about the development of chronic conditions, and should try to adopt healthier lifestyles to ward off the development of multiple chronic conditions that may vastly reduce life expectancy and quality of life. Future research could aim at developing a workable policy framework for the management of multimorbidity, considering the results generated in this study as the base.

Clinical Significance

Multimorbidity goes beyond biological factors. It is deeply ingrained in social and cultural realities. Herein lies the clinical significance of this study. The habits adopted throughout the life course due to cultural influences and particular lifestyles play a major role in interactions with risk factors of multimorbidity and the development of chronic conditions in later life. This knowledge can aid clinicians in designing preventive screening and treatment plans for patients, each with their unique socio-cultural profile. Such an approach leads to better health outcomes for those undergoing treatment and targeted preventive interventions for those perceived to be at risk.

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References

1. Coale AJ. Demographic transition. In: Eatwell J, Milgate M, Newman P. Social Economics. London: Palgrave Macmillan; 1989. pp. 16–23.
2. Kirk D. Demographic transition theory. Popul Stud 1996;50(3): 361–387. DOI: 10.1080/0032472031000149536.
3. GBD 2021 Fertility and Forecasting Collaborators. Global fertility in 204 countries and territories, 1950–2021, with forecasts to 2100: A comprehensive demographic analysis for the Global Burden of Disease Study 2021. Lancet 2024;403(10440):2057–2099. DOI: 10.1016/S0140-6736(24)00550-6.
4. Tupy ML, Bailey R. 2023. Available from: https://humanprogress.org/trends/global-death-rate-is-falling/.
5. Shattock AJ, Johnson HC, Sim SY, et al. Contribution of vaccination to improved survival and health: Modelling 50 years of the Expanded Programme on Immunization. Lancet 2024;403(10441):2307–2316. DOI: 10.1016/S0140-6736(24)00850-X.
6. Tang B, Li Z, Hu S, et al. Economic implications of health care burden for elderly population. Inquiry 2022;59:469580221121511. DOI: 10.1177/00469580221121511.
7. Niewiadomska A, Sobolewska-Poniedziałek E. Utilising the professional potential of the elderly in the process of construction of silver economy in Poland. Acta Scientiarum Polonorum. Oeconomia 2015;14(1):81–91. Available from: https://aspe.sggw.edu.pl/article/view/463/429.
8. United Nations Population Fund. https://www.unfpa.org/; 2024. Available from: https://www.unfpa.org/ageing.
9. International Institute for Population Sciences and United Nations Population Fund. India Ageing Report 2023. New Delhi; 2023.
10. Maples MF. Spirituality, Wellness and the “Silver Tsunami”: Implications for Counseling; 2007. Available from: https://manifold.counseling.org/system/resource/d/1/d/d1dffcc4-1c5c-461c-a6e7-1b17e6a91d70/attachment/8db5bdfc8e15bb8ef0b1fd1ee5e096e4.pdf.
11. Wani A, Ganaie S, Shafi A. Family transition and older adults: Does age still matter? Working with Older People 2025;29(1):105–116. DOI: 10.1108/WWOP-02-2024-0010.
12. Taqui AM, Itrat A, Qidwai W, et al. Depression in the elderly: Does family system play a role? A cross-sectional study. BMC Psychiatry 2007;7:57. DOI: 10.1186/1471-244X-7-57.
13. Lamichhane S. Qualitative study on youth out-migration and its impact on elderly parents. Tri-Chandra J Anthropol 2024;1(1):15. DOI: 10.3126/tja.v1i1.67960.
14. Khanal P, Rai S, Chalise HN. Children’s migration and its effect on elderly people: A study at old age homes in Kathmandu. Am J Gerontol Geriatr 2018;1(1). Available from: https://www.remedypublications.com/american-journal-of-gerontology-and-geriatrics-abstract.php?aid=2031.
15. He C, Ye J. Lonely sunsets: Impacts of rural–urban migration on the left-behind elderly in Rural China. Popul, Space Place 2013;20(4):352–369. DOI: 10.1002/psp.1829.
16. Fabbri E, Zoli M, Gonzalez-Freire M, et al. Aging and multimorbidity: New tasks, priorities, and frontiers for integrated gerontological and clinical research. J Am Med Dir Assoc 2015;16(8):640–647. DOI: 10.1016/j.jamda.2015.03.013.
17. Ding TYG, De Roza JG, Chan CY, et al. Factors associated with family caregiver burden among frail older persons with multimorbidity. BMC Geriatr 2022;22(1):160. DOI: 10.1186/s12877-022-02858-2.
18. Giovannetti ER, Wolff JL, Xue QL, et al. Difficulty assisting with health care tasks among caregivers of multimorbid older adults. J Gen Intern Med 2012;27(1):37–44. DOI: 10.1007/s11606-011-1831-5.
19. Ploeg J, Garnett A, Fraser KD, et al. The complexity of caregiving for community-living older adults with multiple chronic conditions: A qualitative study. J Comorb 2020;10:1–12. DOI: 10.1177/2235042X20981190.S.
20. Omran AR. The epidemiologic transition: A theory of the epidemiology of population change. Milbank Q 2005;83(4):731–757. DOI: 10.1111/j.1468-0009.2005.00398.x.
21. Chobe M, Chobe S, Dayama S, et al. Prevalence of non-communicable diseases and its associated factors among urban elderly of six Indian states. Cureus 2022;14(10):e30123. DOI: 10.7759/cureus.30123.
22. Chauhan S, Kumar S, Patel R, et al. Burden of communicable and non-communicable diseases-related inequalities among older adults in India: A study based on LASI survey. BMC Geriatr 2022;22(1):790. DOI: 10.1186/s12877-022-03481-x.
23. Ramanujam K, Thakur J, Koralla RT, et al. Non-communicable diseases and risk factors profiling among geriatric population residing in Hyderabad city, India. Arch Gerontol Geriatrics Plus 2025;2(2):100153. DOI: 10.1016/j.aggp.2025.100153.
24. Roy S, Maheshwari V, Basu S. Prevalence of multiple non-communicable diseases risk factors among self-reported healthy older adults living in community dwelling in India: Evidence from the Longitudinal Ageing Study in India. Clin Epidemiol Global Health 2024;28. DOI: 10.1016/j.cegh.2024.101680.
25. Directorate of Census Operations. Assam. District Census Handbook – Village and Town Wise Primary Census Abstract (PCA). New Delhi; 2011.
26. Yamane T. Statistics: An Introductory Analysis, 2nd Edition, New York: Harper and Row; 1967.
27. Kumaran M, Pham TM, Wang K, et al. Predicting the risk factors associated with severe outcomes among COVID-19 patients–decision tree modeling approach. Front Public Health 2022;10:838514. DOI: 10.3389/fpubh.2022.838514.
28. Moon M, Lee SK. Applying of decision tree analysis to risk factors associated with pressure ulcers in long-term care facilities. Healthc Inform Res 2017;23(1):43–52. DOI: 10.4258/hir.2017.23.1.43.
29. Anushree KN, Mishra PS. Prevalence of multi-morbidities among older adults in India: Evidence from national Sample Survey organization, 2017-18. Clin Epidemiol Global Health 2022;15. DOI: 10.1016/j.cegh.2022.101025.
30. Sinclair AJ, Abdelhafiz AH. Multimorbidity, frailty and diabetes in older people-identifying interrelationships and outcomes. J Pers Med 2022;12(11):1911. DOI: 10.3390/jpm12111911.
31. Forman DE, Maurer MS, Boyd C, et al. Multimorbidity in older adults with cardiovascular disease. J Am Coll Cardiol 2018;71(19):2149–2161. DOI: 10.1016/j.jacc.2018.03.022.
32. Nagel G, Peter R, Braig S, et al. The impact of education on risk factors and the occurrence of multimorbidity in the EPIC-Heidelberg cohort. BMC Public Health 2008;8:384. DOI: 10.1186/1471-2458-8-384.
33. Feng X, Kelly M, Sarma H. The association between educational level and multimorbidity among adults in Southeast Asia: A systematic review. PLoS One 2021;16(12):e0261584. DOI: 10.1371/journal.pone.0261584.
34. Kumar A, Singh B. Modeling the spectrum and determinants of multimorbidity risk among older adults in India. PLoS One 2025;20(5):e0323744. DOI: 10.1371/journal.pone.0323744.
35. Chauhan S, Patel R, Kumar S. Prevalence, factors and inequalities in chronic disease multimorbidity among older adults in India: Analysis of cross-sectional data from the nationally representative Longitudinal Aging Study in India (LASI). BMJ Open 2022;12(3):e053953. DOI: 10.1136/bmjopen-2021-053953.
36. Khan MR, Malik MA, Akhtar SN, et al. Multimorbidity and its associated risk factors among older adults in India. BMC Public Health 2022; 22(1):746. DOI: 10.1186/s12889-022-13181-1.

ORIGINAL ARTICLE

Echoes of Pain and Shadows of Vision: A Narrative Visit to an Old Age Home in India

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Abstract

Background: Geriatric health is an emerging concern in India, where the elderly population is rapidly increasing. During a visit to an old age home, it was observed that the most common health complaints among residents were joint pain and blurring of vision. This study narrates the lived experiences of the elderly, their dependency on symptomatic relief, and highlights the need for policy interventions.

Methods: A narrative observational approach was used, focusing on direct interactions with residents, documenting their expressions, and comparing findings with national data.

Results: The majority of residents complained of musculoskeletal pain and age-related visual decline. Requests for diclofenac gel ("tube de do doctor sahab") and eye drops reflected the heavy burden of chronic morbidity. Three thematic challenges emerged: Limited access to specialized geriatric care, dependency on quick symptomatic relief, and psychosocial neglect.

Conclusion: The voices of the elderly demand more than temporary relief. There is a pressing need to strengthen the National Programme for Health Care of the Elderly (NPHCE), ensure accessible geriatric medicines, promote preventive eye and joint health services, and provide psychological support. The narrative highlights that aging with dignity requires empathy-driven, patient-centered care beyond pharmacological solutions.

Keywords: Arthritis, Cataract, Geriatric health.

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Introduction

Population aging is a global phenomenon, with India projected to have over 300 million elderly citizens by 2050.[1] The demographic shift is accompanied by a surge in chronic noncommunicable diseases (NCDs), sensory impairments, and functional disabilities.[2] Old age homes, though not the traditional model of eldercare in India, are increasingly becoming necessary due to urbanization, migration, and weakening family support systems.[3] During a visit to an old age home in North India, a recurring theme emerged among the residents-complaints of persistent joint pain and blurring of vision. These ailments, while seemingly simple, profoundly affect quality of life. The repetitive requests for diclofenac gel, locally referred to as "tube," and eye drops illustrate the daily struggles and unmet needs of the elderly. This study attempts to transform a personal observational narrative into a reflection supported by evidence and public health policy relevance.

Methods

This study adopts a narrative, observational approach. The visit to the old age home was conducted as part of a community health outreach activity. Elderly residents were engaged in informal conversations where their primary health complaints were recorded. Observations included the frequency of specific health demands, nonverbal cues, and psychosocial contexts.

The findings from the visit were compared with published national data on geriatric health problems in India.[4,5] Policy documents, including the National Programme for Health Care of the Elderly (NPHCE), were reviewed to identify existing gaps.[6] This integration of lived experience with secondary evidence forms the basis of the present narrative analysis.

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Conflict of interest: None

Observations

The old age home housed approximately 70 residents, mostly above 65 years of age. The common theme across conversations was joint pain and blurring of vision (Table 1). The phrase "tube de do doctor sahab" echoed repeatedly as elderly individuals lined up for diclofenac gel. Similarly, requests for eye drops highlighted the unmet need for eye care services.

Other common issues included hypertension, diabetes, hearing difficulties, and signs of psychosocial loneliness.

Results

The observations revealed three thematic results:

- Musculoskeletal morbidity dominates: The overwhelming demand for topical analgesics highlights a silent epidemic of arthritis and degenerative joint disease.[7]
- Visual impairment as a barrier to independence: Blurring of vision, likely from untreated cataracts and presbyopia, restricts mobility, and autonomy.[8]

Table 1: Common health problems among elderly residents in an old age home, North India

Health problem	*Frequency/observation*	*Resident expressions (local phrases)*	*Clinical implication*
Joint pain/arthritis	Very common	"Tube de do doctor sahab"	High prevalence of musculoskeletal pain
Blurring of vision	Common	Requests for "eye drop" and "chasma nhi laaye"	Suggests cataract/age-related decline
Hypertension/diabetes	Present in many	"BP ki dava" and "sugar ki dava"	Chronic disease burden
Hearing difficulty	Noted in some	Leaning in to hear	Impaired social engagement
Psychological issues	Implied	Loneliness, dependency	Needs psychosocial support

Source: Field Observations, 2025

Table 2: Policy gaps vs identified needs in geriatric care

Policy gaps	*Needs identified*
Limited reach of NPHCE	Universal access to geriatric health care at primary level
Inadequate eye care services	Regular cataract screening and provision of spectacles
Lack of dedicated arthritis clinics	Community-based physiotherapy and joint care services
Focus on medicines only	Holistic care including mental health and social support
Weak supply chain for essential drugs	Uninterrupted supply of geriatric medicines at old age homes

Source: Integrated Field Observations and Policy Review, 2025

- Psychosocial neglect: Loneliness, expressed indirectly, indicates a gap in emotional, and social well-being beyond physical health concerns.[9]

These findings mirror national surveys including Longitudinal Aging Study in India (LASI), which reports arthritis and visual impairment among the top morbidities in geriatric population.[10]

Discussion

This narrative visit underscores that geriatric health is not only biomedical but also social and emotional. The repeated requests for "tube" and "eye drop" reflect the limited access to comprehensive geriatric care. While these small medical interventions provide temporary relief, they do little to address the underlying pathologies.

The NPHCE was launched to address these very concerns. However, its reach remains limited. Integrating geriatric services into primary health care, training health workers in elder care, and ensuring uninterrupted supply of essential geriatric medicines are urgently needed (Table 2).

From an empathetic standpoint, the voices of the elderly resonated strongly. Behind every request for a "tube" lies a story of aching knees that make prayer difficult, of stiff joints that hinder holding a grandchild, and of blurred eyes that struggle to see familiar faces. Aging, thus, is not just a biological process but also a journey of dignity, dependence, and resilience.

Conclusion

The visit to the old age home revealed more than medical symptoms; it exposed the lived realities of the elderly in India. Joint pain and visual impairment were not mere clinical entities but daily obstacles to dignity, independence, and participation in life. The metaphorical chorus of "tube de do doctor sahab" and "chasma nhi laaye" was not just a plea for pain relief but a cry for sustained attention to geriatric health. If India is to honor its aging population, health systems must integrate empathy with efficiency, policies with practice, and relief with resilience. Aging with dignity is not a privilege but a right. Strengthening geriatric care, both medically and socially, is the path forward to ensure that the twilight years of life are filled not with suffering but with peace, companionship, and care.

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References

1. Bloom DE, Chatterji S, Kowal P, et al. Macroeconomic implications of population ageing and selected policy responses. Lancet 2015;385(9968):649–657. DOI: 10.1016/S0140-6736(14)61464-1.
2. Beard JR, Officer AM, Cassels AK. The world report on ageing and health. Gerontologist 2016;56(Suppl 2):S163–S166. DOI: 10.1093/geront/gnw037.
3. Dey AB, Soneja S, Nagarkar KM, Jhingan HP, et al. Geriatric health care in India: Current status and way forward. Indian J Med Res. 2019;150(6):575–583. PMID: 31805129.
4. Ingle GK, Nath A. Geriatric health in India: Concerns and solutions. Indian J Community Med 2008;33(4):214–218. DOI: 10.4103/0970-0218.43225.
5. Rathore FA, Mansoor SN. Geriatric care in low-resource settings: Challenges and prospects. J Coll Physicians Surg Pak 2020;30(2):123–125. DOI: 10.29271/jcpsp.2020.02.123.
6. National Programme for Health Care of the Elderly (NPHCE): Operational Guidelines. New Delhi: Ministry of Health and Family Welfare; 2011. Available from: https://dghs.mohfw.gov.in/national-programme-for-the-health-care-of-the-elderly.php [Last accessed November, 2025].
7. Sharma MK, Swami HM, Bhatia V. A community-based study of morbidities in the elderly in Chandigarh. Indian J Community Med 2003;28(4):165–170.
8. Murthy GV, Gupta SK, John N, et al. Current status of cataract blindness and vision 2020: The right to sight initiative in India. Indian J Ophthalmol 2008;56(6):489–494. DOI: 10.4103/0301-4738.41411.
9. Chatterjee S, Prasad S, Roy S. Mental health of the elderly: Status, challenges, and way forward in India. J Geriatr Ment Health 2018;5(2):112–120. PMID: 30510681.
10. International Institute for Population Sciences (IIPS), NPHCE, MoHFW. Longitudinal Ageing Study in India (LASI) Wave 1, 2017–2018, India Report. Mumbai: IIPS; 2020. Available from: https://www.iipsindia.ac.in/lasi [Last accessed November, 2025].

ORIGINAL RESEARCH

A Public Health Intervention for Homoeopathy in Geriatric Healthcare

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Abstract

Background: India has about 112 million elderly people with 71% of them living in rural areas. The elderly suffer from multiple physical, social, psychological, and economic problems with unmet needs in all domains of health. The objective is to screen the elderly population in rural areas for their psycho-socio-medical need using a questionnaire, to identify prevalent diseases, and to provide homoeopathic treatment.

Materials and methods: A door-to-door survey was undertaken in villages having a predominant scheduled caste population for screening of the elderly population for their psychosocial need using a predefined questionnaire and sensitizing community living elderly at the doorstep using a preidentified integrated care tool-brief (ICT-BRIEF) questionnaire. The elderly suffering from any disease and intended to take homoeopathic treatment were referred to geriatric outreach clinics conducted in villages weekly. The elderly reporting was assessed for their daily activities using the Katz index and followed up fortnightly for 6 months.

Results: A total of 4,123 elderly individuals were screened for their psycho-socio-medical needs, and 929 cases were treated in the outpatient department (OPD). Of these, 361 patients completed follow-up visits lasting more than 1 month. The musculoskeletal system was identified as the most commonly affected, with *Rhus toxicodendron* and *Bryonia alba* being the most effective homoeopathic remedies.

Conclusion: The findings from this program highlight the potential of homoeopathy as a complementary treatment modality in geriatric care. Future research should focus on randomized controlled trials (RCTs) to validate these findings, particularly for conditions like multimorbidity and musculoskeletal disorders.

Keywords: Community medicine, Geriatrics, Homoeopathy, Multimorbidity.

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Background

Aging is a process that focuses on optimizing health, participation, and security to improve quality of life in later years. With advancements in medical care, the global geriatric population has been steadily rising. Older adults are living longer and often managing multiple chronic conditions.[1] Understanding and managing their needs over time is an integral part of defining successful aging.[2] By 2030, one in six people in the world will be aged 60 years or over. By 2050, the world's population of people aged 60 years and older will double (2.1 billion). The number of persons aged 80 years or older is expected to triple between 2020 and 2050 to reach 426 million.[3] The elderly in India currently comprise a little over 10% of the population, translating to about 104 million, and are projected to reach 19.5% of the total population by 2050.[4]

The elderly suffer with multiple physical, social, psychological, and economic problems with unmet needs in all domains of health.[5] Health care utilization and support service needs are increasing among older adults. Due to the increasing population size and number of comorbidities among older adults, it is unrealistic to address their health needs solely on either an individual disease or condition-related basis; thus, a public health intervention is required.[2]

This subjective and psychosocial (i.e., psychological and social) aspect of health goes beyond a medical diagnosis and reflects a growing need to better understand the population health continuum for older adults and how to integrate successful aging into that model. Major diseases are diabetes, hypertension, and coronary artery disease (CAD). Very few seek treatment for common

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Conflict of interest: None

age-related complaints – sleep, fall, forgetfulness, isolation, and depression unless these activities of daily living (ADL).[6]

Homoeopathy is an acceptable and recognized alternative medical health care system in India, with over three lakh registered homoeopathic practitioners in the country, providing homoeopathic treatment in public and private settings. Homoeopathy is known to be useful in the treatment of geriatric conditions like osteoarthritis, benign prostrate hypertrophy, and multimorbidity.[7] These are individual disease-based studies based on clinical care approaches with varying level of evidence generated, however, the evidence generated is sufficient enough to explore the utility of homoeopathy in geriatric populations in public health settings.

Central Council for Research in Homoeopathy (CCRH) is an autonomous body of the Ministry of Ayush, Government of India, undertaking, and developing research on homoeopathy. A major activity of CCRH is undertaking public health care programs in research mode. This involves the development and implementation of public health care programs targeting specific populations. The data generated is recorded to identify the program usefulness and its implications in the public health care of the country.

Under this activity, CCRH undertook a public health care program for the geriatric population under scheduled caste sub plan (SCSP) to screen the elderly for their unmet psychosocial and medical needs and document their response to the homoeopathic treatment.

Materials and Methods

Study Setting and Participants

This study was conducted through eight institutes/units located in different states under the aegis of CCRH viz. Dr. D. P. Rastogi Central Research Institute for Homoeopathy, Noida; Regional Research Institutes for Homoeopathy at Mumbai, Gudivada, Siliguri; Drug Proving Unit, Bhubaneswar; Clinical Research Units for Homoeopathy at Siliguri, Puducherry, Tirupati and Patna in the identified villages having predominated scheduled caste population (Supplementary information, Table 1).[8] Special geriatric health camps were organized in these villages on a weekly basis. The program was undertaken in two phases:

Phase – I: A Cross-sectional Survey

The objective was to screen the elderly population in villages for their psychosocial and medical need and assess their functional status. The research fellows who were homoeopathic graduate doctors went door-to-door in the identified villages to screen the elderly population for their psychosocial needs using a preidentified integrated care tool-brief (ICT-BRIEF) questionnaire.[9] The elderly suffering from any disease and intending to take homoeopathic treatment were referred to geriatric mobile outpatient department (OPD) camps.

Inclusion and Exclusion Criteria

Persons residing in the identified villages aged 60 years or above of both sexes were included in the study. Patients who could not understand the questions being asked or refused to participate in the survey were excluded.

Assessment Parameters

The ICT-BRIEF is a concise, culturally appropriate self-assessment or caregiver-assisted instrument designed to screen the unmet psychosocial and medical needs of older Indian adults. Developed by researchers at the All-India Institute of Medical Sciences (AIIMS), New Delhi, the tool encompasses 30 items across various domains, including physical and functional health, psychological and mental well-being, geriatric syndromes, financial security, social involvement, elder abuse, health perception, and life satisfaction. It requires only 15–20 minutes to complete, making it practical for diverse settings such as hospitals, communities, and old-age homes. By improving health literacy and facilitating early identification of health issues, the ICT-BRIEF aids in enhancing health-seeking behavior, preventing frequent hospitalizations, and assisting individuals and their families in prioritizing care plans.[9]

Sample Size

There was no fixed sample size, and it was attempted to include all eligible persons residing in the identified villages.

Data Management and Analysis

The questionnaire was administered to all elderly individuals, regardless of their health status, and real-time data was recorded in pen-paper mode. The data was entered into an MS Excel sheet for analysis. Descriptive statistics was used to present the socio-demographic characteristics and health-related variables and data were presented as frequencies (percentage). Chi-square test was used to analyze associations between categorical variables.

Phase – II: Homoeopathic Treatment to Elderly Population Reporting in Geriatric Health Camps OPD

The objective was to identify diseases prevalent among the elderly, evaluate the effectiveness of homoeopathy, and monitor and document improvements in health outcomes and quality of life among the elderly participants.

Study Design

Prospective observational cohort study.

Study Settings

In the selected villages, outreach clinics were organized on a weekly basis wherein the patients were provided care in their local settings and, if need be, in home-care settings. The doctors, pharmacists, and supporting staff would travel to the villages and organize treatment camps in predesignated places with limited infrastructure. The medicines were dispensed from these treatment camps itself. The data of all cases reported in the outreach clinics was recorded in pen-paper format and maintained with the treating doctors. All doctors were homoeopathic postgraduates.

Assessment Tool

The Katz index of independence in ADL is a standardized tool developed by Sidney Katz in 1963 to assess functional status in older adults by evaluating their ability to independently perform six basic activities: bathing, dressing, toileting, transferring, continence, and feeding. It is widely used in geriatrics to determine levels of dependence and monitor changes in functional ability over time, aiding in clinical decision-making and care planning. The tool has been validated across diverse cultural and linguistic settings, demonstrating its reliability and utility in both clinical and research contexts.[10]

Sample Size

There was no predetermined fixed sample size, as treatment was offered to all eligible participants meeting the inclusion criteria.

The sample included all patients reporting to the geriatric OPD who provided informed consent.

Interventions

Individualized homoeopathic medicines were prescribed. The homoeopathic medicines were procured from a good manufacturing practices (GMP) certified pharmaceutical company. All the medicines used were pharmacopeial preparations as per Homoeopathic Pharmacopeia of India.

Data Collection

Data was collected using a standardized case recording format. Voluntary informed consent was obtained from all participants. A detailed case history was documented, including demographic, clinical, and treatment-related details, ensuring consistency and reliability. All the cases were analyzed based on homoeopathic principles. All participants were followed up fortnightly for 6 months. None of the medication which the patients were already taking were stopped. The treatment response was independently assessed as improved, status quo, or worse.

Data Management and Statistical Analysis

All collected data, including follow-up information, was compiled and entered into Microsoft® Excel. The data was then cleaned, managed, and organized. The statistical analysis and interpretation were conducted using SPSS version 20.0. Data were represented as number (%) as appropriate, *p*-value less than 0.05 was considered statistically significant. Demographic variables were compared between two age subgroups (60–70 and >70) years using Chi-square test. Similarly, categorical domain data were compared using Chi-square test for statistical significance.

Results

Phase – I: A Cross-sectional Survey

Socio-demographic Details

In the door-to-door survey, 5,000 households were approached. The screening was conducted for 4,123 participants, and 877 did not provide consent. The mean age of the participants was 67.24 ± 6.98 years. The majority of participants were female (58%) compared to male (42%). The rural population predominated across both age-groups, comprising 76% of individuals (Table 1).

Psychosocial and Medical

The ICT-BRIEF questionnaire is a subjective assessment based on self-reported information provided by the respondent. The assessment comparing the health outcomes of those between the ages of 60–70 years and those over 70 are given in Table 2.

The study identified significant differences between the two age-groups (60–70 and >70 years) across most variables. Individuals over 70 years of age showed a higher prevalence of poor eyesight (57% compared to 54%), poor hearing capacity (47% compared to 33%), difficulty chewing (66% compared to 48%), difficulty swallowing (35% compared to 30%), trouble dressing (31% compared to 28%), challenges with toileting (42% compared to 47%), difficulty sitting (25% compared to 21%), and nervousness or restlessness (56% compared to 59%).

On the other hand, individuals aged 60–70 years had a higher percentage of individuals going outside the house four or more times a week (31% compared to 25%) and had a lower percentage of trouble sleeping (66% compared to 61%).

Table 1: Sociodemographic characteristics of participants

Demographic variables	*Total n (%)*	*60–70 years n = 3,169 n (%)*	*>70 years n = 954 n (%)*	*p-value*
Gender				
Male	1,786 (42)	1,307 (41)	479 (50)	<0.01
Female	2,337 (58)	1,862 (59)	475 (50)	
Residence				
Rural	3,172 (76)	2,481 (78)	691 (72)	<0.000
Urban	951 (24)	688 (22)	263 (28)	
Living arrangements				
No response	39 (1)	29 (1)	10 (1)	<0.000
Living with spouse	1,010 (24)	831 (26)	179 (19)	
Living with children	2,718 (66)	2,050 (65)	668 (70)	
Alone	271 (7)	206 (7)	65 (6)	
With relative	43 (1)	27 (1)	16 (2)	
Old age home	39 (1)	23 (1)	16 (2)	
Occupation				
No response	55 (1)	44 (2)	11 (1)	<0.000
Not working	2,798 (67)	2,052 (65)	746 (78)	
Daily wages	445 (11)	389 (12)	56 (6)	
Self-employed	308 (7)	268 (8)	40 (4)	
Salaried/ pensioner	302 (7)	216 (7)	86 (9)	
Other	214 (5)	199 (6)	15 (2)	
Education				
No response	87 (2)	72 (2)	15 (2)	<0.632
Illiterate	2,333 (56)	1,788 (56)	545 (57)	
Schooling	1,517 (37)	1,161 (37)	356 (37)	
Graduate	145 (3)	115 (4)	30 (3)	
Postgraduate to above	40 (1)	32 (1)	8 (1)	
Family history				
Nil	2,584 (62)	1,945 (60)	639 (67)	<0.020
Heart attack	67 (2)	55 (2)	12 (1)	
Diabetes	279 (7)	210 (7)	69 (7)	
Hypertension	254 (6)	211 (7)	43 (5)	
Obesity	73 (2)	62 (2)	11 (1)	
Stroke	17 (1)	14 (1)	3 (1)	
Cancer	46 (1)	38 (1)	8 (1)	
Chronic respiratory diseases (COPD)	799 (19)	632 (20)	167 (17)	
Habits				
Regular exercise	380 (9)	298 (9)	82 (9)	<0.237
Yoga	359 (8)	291 (9)	68 (7)	
Both	28 (1)	22 (1)	6 (1)	
None	3,354 (82)	2,556 (83)	798 (83)	

Chi-square test is used to analyze the association between socio-demographic factors and the two age categories; a *p*-value of < 0.05 is considered statistically significant

Table 2: ICT-BRIEF comparison between persons of 60–70 years and more than 70 years

ICT-BRIEF	*60–70 years (n = 3,169) n (%)*	*>70 years (n = 954) n (%)*	*p-value*
Eyesight			
Good	1,449 (45)	400 (42)	0.114
Poor	1,709 (54)	551 (57)	
Blind	11 (1)	3 (1)	
Hearing capacity			
Good	2,102 (66)	494 (52)	<0.01*
Poor	1,060 (33)	453 (47)	
Deaf	7 (1)	7 (1)	
Difficulty in chewing			
Never	1,528 (48)	325 (34)	<0.01*
Sometimes	1,530 (48)	546 (57)	
Always	111 (4)	83 (9)	
Difficulty in swallowing			
Never	2,202 (69)	603 (63)	<0.01*
Sometimes	948 (30)	334 (35)	
Always	19 (1)	17 (2)	
Difficulty in eating? (%)			
Never	1,854 (58)	463 (49)	<0.01*
Sometimes	1,255 (40)	459 (48)	
Always	60 (2)	32 (3)	
Difficulty in dressing			
Never	2,246 (71)	625 (66)	<0.01*
Sometimes	891 (28)	298 (31)	
Always	32 (1)	31 (3)	
Difficulty in toileting			
Never	1,505 (47)	403 (42)	0.002*
Sometimes	1,440 (45)	458 (48)	
Always	224 (7)	93 (10)	
Difficulty in sitting on the floor/chair			
Never	883 (28)	189 (20)	<0.01*
Sometimes	1,634 (52)	523 (55)	
Always	652 (21)	242 (25)	
Frequency of leaking urine			
Never	2,296 (72)	662 (69)	<0.01*
Sometimes	821 (26)	259 (27)	
Always	52 (2)	33 (3)	
Complete evacuation when you pass motion			
Never	1,769 (56)	489 (51)	<0.01*
Sometimes	1,318 (42)	410 (43)	
Always	82 (3)	55 (6)	
During a typical week, if weather permits, do you go outside the house			
Four or more times/week	974 (31)	238 (25)	<0.01*
Less than four times	1,639 (52)	498 (52)	
Never	556 (18)	218 (23)	

(Contd...)

Table 2: *(Contd...)*

ICT-BRIEF	*60–70 years (n = 3,169) n (%)*	*>70 years (n = 954) n (%)*	*p-value*
In last 6 months have you experienced any weight loss without any effort			
Don't know	958 (30)	327 (34)	0.131
No	1,905 (60)	528 (56)	
Less than 3 kg	240 (8)	77 (8)	
More than 3 kg	34 (1)	11 (1)	
More than 5 kg	32 (1)	11 (1)	
Number of medications			
0	1,783 (56)	520 (55)	0.354
3	1,029 (32)	321 (33)	
5	127 (4)	30 (3)	
7	224 (7)	80 (8)	
10+	6 (1)	3 (1)	
Admitted in hospital in last 1 year			
No	2,354 (74)	734 (77)	0.288
Don't remember	190 (6)	50 (5)	
1–3 times	617 (19)	166 (17)	
More than three times	8 (1)	4 (1)	
History of fall/slip during last 6 months			
No	2,378 (75)	700 (72)	0.253
Don't remember	211 (7)	70 (7)	
1–2 times	559 (17)	172 (18)	
More than two times	21 (1)	12 (1)	
Do you enjoy the things the way you did 2 weeks before			
Always	1,270 (40)	411 (43)	0.237
Often	1,486 (47)	429 (45)	
Never	413 (13)	114 (12)	
Nervousness and/or restlessness			
Never	1,242 (39)	379 (40)	0.013*
Often	1,855 (59)	537 (56)	
Always	72 (2)	38 (4)	
Forgetfulness			
Never	1,019 (32)	288 (30)	<0.01*
Often	2,034 (64)	603 (63)	
Always	116 (4)	63 (7)	
During past 1 month, do you have trouble falling asleep or staying asleep			
Not during past month or less than once/week	2,105 (66)	586 (61)	0.01*1
1–5/week	675 (21)	231 (24)	
Almost everyday	343 (11)	113 (12)	
No response	46 (1)	24 (3)	
With whom you can share your feelings			
Family/relatives	2,780 (88)	856 (90)	0.219
Friends/any other	172 (5)	46 (5)	
Don't know	217 (7)	52 (5)	

(Contd...)

Table 2: *(Contd...)*

ICT-BRIEF	*60–70 years (n = 3,169) n (%)*	*>70 years (n = 954) n (%)*	*p-value*
Do you have somebody to help you during your times of crisis			
Family/relatives	2,846 (90)	882 (92)	0.048
Friends/any other	188 (6)	40 (4)	
Don't know	135 (4)	32 (3)	
Can you rely on your family in time of medical emergency			
Strongly	1,827 (58)	586 (61)	0.005*
Somewhat/most likely	891 (28)	270 (28)	
Not at all/don't know	451 (14)	98 (10)	
How competent are you to manage your financial matters			
Strongly competent	1,087 (34)	357 (37)	0.105
Sometimes	1,230 (39)	334 (35)	
Often/always	821 (26)	257 (27)	
Don't know comments	31 (1)	6 (1)	
Feel secure in your house? (%)			
Always/most often	2,540 (80)	770 (81)	0.777
Neutral/sometimes	554 (17)	159 (17)	
Never	75 (2)	25 (3)	
Feel secure outside your house			
Always/most often	1,989 (63)	626 (66)	0.194
Neutral/sometimes	776 (24)	224 (23)	
Never	404 (13)	104 (11)	
Have you ever been harassed physically			
Always/most often	230 (7)	70 (7)	0.074
Neutral/sometimes	700 (22)	178 (19)	
Never	2,239 (71)	706 (74)	
Have you ever been harassed mentally			
Always/most often	213 (7)	57 (6)	0.005*
Neutral/sometimes	848 (27)	209 (22)	
Never	2,108 (67)	688 (72)	
Do you feel neglected at your home			
Always/most often	199 (6)	56 (6)	0.575
Neutral/sometimes	1,013 (32)	291 (31)	
Never	1,957 (62)	607 (64)	
How do you rate your health			
Good	1,131 (36)	326 (34)	0.644
Normal	1,979 (62)	608 (64)	
Bad	59 (2)	20 (2)	
How satisfied are you with your life			
Strongly satisfied	744 (24)	224 (24)	0.001*
Slightly satisfied	1,680 (53)	463 (49)	
Don't know	331 (10)	108 (11)	
Slightly dissatisfied	327 (10)	107 (11)	
Strongly dissatisfied	87 (3)	52 (5)	

Chi-square test is used to analyze the association between the factors and the two age categories; a *p*-value of < 0.05 is considered statistically significant

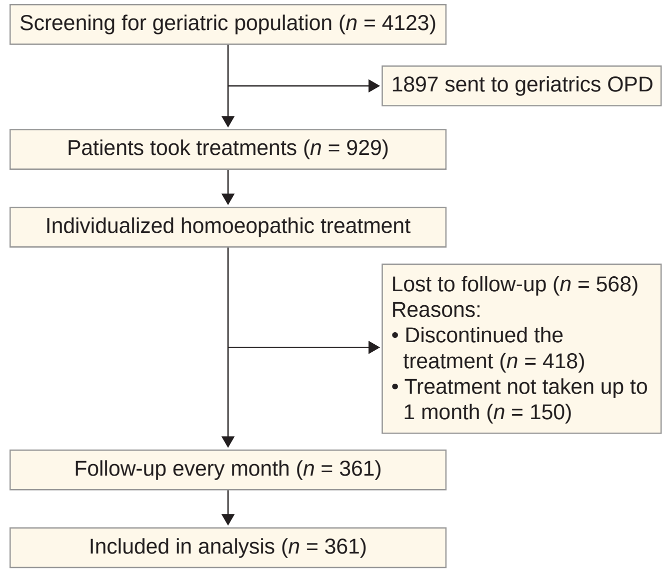

Fig. 1: Study flow diagram

Overall, the study reveals that those over 70 are more likely to experience worse health outcomes than people between 60 and 70 years old, especially regarding eyesight, hearing ability, mobility, and mental health.

This study revealed that, in addition to its reliability, the ICT-BRIEF questionnaire exhibits remarkable internal coherence. It addressed the majority of aspects essential to an elderly person's health.

Phase – II: Homoeopathic Treatment to Elderly Population Reporting in Geriatric Health Camps OPD

Out of the 4,123 persons screened, 1,897 cases were referred to geriatrics OPD, and 929 participants took homoeopathic treatment. Five hundred sixty-eight participants didn't have the complete follow-up (418 had zero follow-up and 150 patients had less than 1-month follow-up), and 361 had more than one follow-up over a period of more than 1 month (Fig. 1). Centre-wise information of the treated patients and socio-demographic details is given in Supplementary information (Table 1).

Socio-demography

Of the 929 cases who took treatment, 77.9% were in the age-group of 60–70 years (Table 3).

System Affected

The most frequently reported complaints were musculoskeletal disorders, particularly joint pain, followed by multimorbidity, skin, respiratory, and neurological disorders (Fig. 2).

The highest affected system is the musculoskeletal system (630 cases) out of which osteoarthritis ($n = 141$) emerged as the most prevalent condition, followed by stiffness of joints ($n = 11$), arthralgia ($n = 17$), spondylosis ($n = 11$), and sciatica ($n = 5$).

Multimorbidity, which reflects the co-occurrence of multiple chronic conditions, is the second most common category, with 103 cases, such as the co-occurrence of osteoarthritis with vertigo and combinations like atopic dermatitis with osteoarthritis, reflecting the complexity of managing multiple chronic conditions in older adults.

Table 3: Sociodemographic characteristics of treated patients

Demographic variables	*60–70 years (n = 724) n (%)*	*>70 years (n = 205) n (%)*	*p-value*
Gender			
Male	245 (34)	97 (47)	0.00041
Female	479 (59)	108 (53)	
Residence			
Rural	625 (86)	165 (80)	0.03857
Urban	99 (14)	40 (20)	
Living arrangements			
No response	8 (1)	4 (2)	0.04659
Living with spouse	209 (29)	40 (20)	
Living with children	469 (65)	147 (72)	
Alone	31 (4)	14 (7)	
With relative	6 (1)	0 (0)	
Old age home	1 (1)	0 (0)	
Occupation			
No response	8 (1)	3 (1)	0.0002
Not working	500 (69)	155 (76)	
Daily wages	98 (14)	13 (6)	
Self-employed	61 (8)	13 (6)	
Salaried/pensioner	18 (2)	16 (8)	
Other	39 (5)	5 (2)	
Education			
No response	18 (2)	2 (1)	0.26878
Illiterate	464 (64)	138 (67)	
Schooling	223 (32)	57 (28)	
Graduate	16 (2)	5 (2)	
Postgraduate to above	3 (1)	3 (1)	
Family history			
Nil	453 (63)	142 (69)	0.240883037
Heart attack	10 (1)	1 (0)	
Diabetes	37 (5)	11 (5)	
Hypertension	19 (3)	10 (5)	
Obesity	22 (3)	4 (2)	
Stroke	7 (1)	2 (1)	
Cancer	15 (2)	1 (0)	
Chronic respiratory diseases (COPD)	161 (22)	36 (18)	
Habits			
Regular exercise	48 (7)	10 (5)	0.07086
Yoga	44 (6)	4 (2)	
Both	4 (1)	2 (1)	
None	628 (87)	189 (92)	

Dermatological conditions follow closely, with 74 cases, suggesting the notable prevalence of contact dermatitis ($n = 16$) which results from prolonged exposure to irritants or age-related skin changes. These findings highlight the importance of addressing skin health as part of holistic geriatric care.

Respiratory conditions (59 cases) and neurological disorders (25 cases) are moderately represented, indicating areas where additional medical attention might be required. Gastrointestinal (17 cases), genitourinary (13 cases), and ophthalmological conditions (8 cases) are less frequent but remain clinically relevant. This distribution highlights the diverse health challenges faced by the geriatric population.

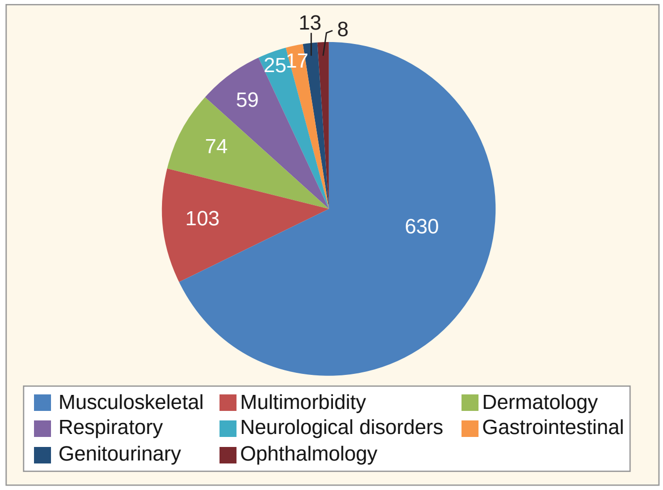

Fig. 2: Classification of affected system

These findings highlight the importance of integrating cognitive and psychological support into geriatric care. Overall, the study demonstrates the multi-faceted health challenges faced by older adults, necessitating comprehensive and multi-disciplinary approaches to ensure effective management and improved quality of life.

Treatment Response

System-wise treatment response was recorded as improved, status quo, or worse (Fig. 3). Musculoskeletal disorders showed the highest improvement (190), status quo (47), and worsening in (8) cases. In multimorbidity conditions, there was an improvement in 27 cases, with no reported worsening. Dermatological, respiratory, and neurological conditions showed favorable outcomes, with improvement in most cases. Gastrointestinal conditions had a relatively lower improvement rate, with seven cases improving and two worsening. Ophthalmological and genitourinary conditions also demonstrated positive outcomes, with improvements in most cases and minimal worsening. These findings highlight the overall effectiveness of interventions, particularly for musculoskeletal and multimorbid conditions.

Homoeopathic Medicines Used

Homoeopathic treatment is symptom-based, with prescriptions guided by the recorded symptoms in Materia Medica. Medicines were prescribed following the fundamental principles of homoeopathy. The most frequently indicated homoeopathic medicines were *Rhus toxicodendron* (prescribed in 69 cases), Bryonia alba (prescribed in 45 cases), Sulphur (prescribed in 32 cases), *Lycopodium clavatum* (prescribed in 22 cases), *Calcarea carbonica* (prescribed in 14 cases), and Arsenicum album (prescribed in 14 cases). The treatment response with individual medicines was also recorded (Fig. 4).

System-wise Distribution of Medicines

Rhus toxicodendron was the most frequently prescribed remedy, with 58 cases in musculoskeletal conditions, showing improvement in 46 patients, and six cases of improvement in multimorbidity.

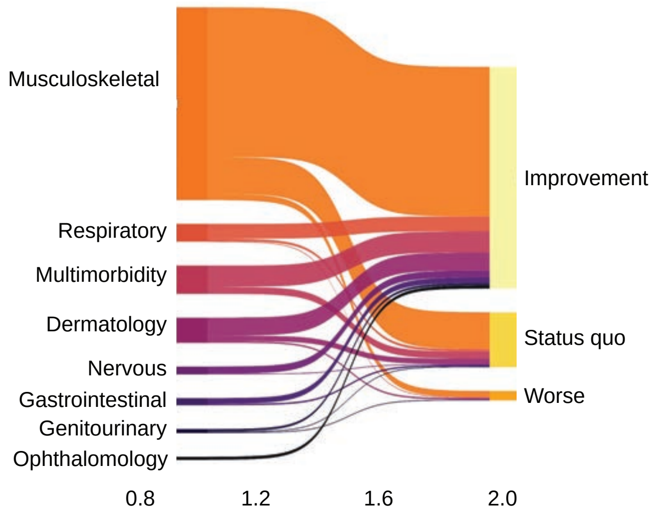

Fig. 3: Treatment response

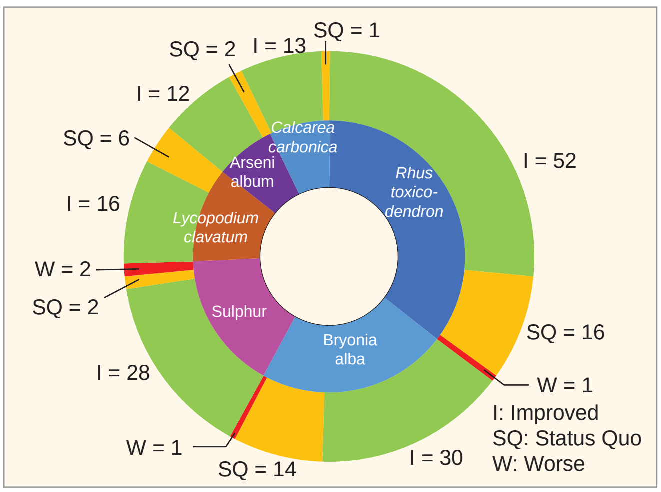

Fig. 4: Homoeopathic medicines used

Bryonia alba was also commonly used (43 cases), with 30 patients experiencing improvement. Sulphur demonstrated positive outcomes across multiple conditions, with 10 cases of improvement in the musculoskeletal system, eight in multimorbidity, and nine in dermatological conditions. Additionally, *Lycopodium clavatum* and Arnica montana were prescribed, showing varying degrees of success (Table 4).

Katz Index ($n = 361$)

The baseline mean Katz index score assessing disability-adjusted life year (DALY) of the study participants ($n = 361$) was 5.5180 ± 0.82012, and at 6 months, it was 5.4848 ± 0.86949 (Table 5). The change in scores was analyzed using a paired *t*-test, which showed no statistically significant difference ($t = 1.378$, $p = 0.169$). This indicates that the participants retained a high level of independence in ADL throughout the study.

Table 4: System-wise distribution of medicines

Medicine	*Prescribed*	*Improvement*	*Status quo*	*Worse*
Musculoskeletal system				
Rhus toxicodendron	58	46	11	1
Bryonia alba	43	30	12	1
Lycopodium clavatum	15	11	4	0
Sulphur	11	10	1	0
Arnica montana	9	6	2	1
Arsenic album	1	1	0	0
Multimorbidity				
Sulphur	9	8	1	0
Rhus toxicodendron	9	6	3	0
Natrum muriaticum	7	5	2	0
Lycopodium clavatum	5	3	2	0
Bryonia alba	2	0	2	0
Arsenic album	1	1	0	0
Dermatological conditions				
Lycopodium clavatum	1	0	1	0
Sulphur	11	9	0	2
Natrum muriaticum	7	5	2	0
Rhus toxicodendron	1	0	1	0
Arsenic album	4	3	1	0
Gastrointestinal system				
Rhus toxicodendron	1	1	0	0
Lycopodium clavatum	1	1	0	0
Respiratory system				
Arsenic album	8	7	1	0
Natrum sulphuricum	3	2	1	0
Nervous system				
Sulphur	1	1	0	0

Table 5: Change in Katz index

Baseline (Mean ± SD)	*6 months (Mean ± SD)*	*t-value*	*p- value*
5.5180 ± 0.82012	5.4848 ± 0.86949	1.378	0.169

Values are presented as mean ± standard deviation (SD); paired *t*-test is used to analyze the difference in the Katz index between baseline and 6 months; *p*-value of < 0.05 is considered statistically significant

Discussion

The study aimed to assess the psychological, social, and medical needs of the elderly in rural areas through a questionnaire, identify prevalent diseases, and evaluate treatment responses. This study provides valuable insights into the healthcare needs and treatment outcomes of the geriatric population screened and treated. Among the 4,123 participants screened, 929 individuals opted for treatment, with 361 participants completing more than 1 month of follow-up. These results underscore the challenges in maintaining consistent follow-ups in geriatric populations, potentially due to factors such as mobility limitations, caregiver availability, and socioeconomic constraints. The findings reveal a predominance of rural participants across both age-groups, highlighting the need for targeted healthcare services in rural areas. Living arrangements showed a significant proportion of participants living with children, underscoring the dependence on family support in older age. Illiteracy and low educational attainment were notable, particularly in the over 70 age-group, emphasizing the need for accessible and tailored health education interventions for this demographic.

The survey results confirm the high prevalence of musculoskeletal disorders among geriatric individuals, followed by multimorbidity. These findings align with existing literature that highlights the burden of chronic conditions and their impact on functional independence in older adults. Multimorbid cases presented complex combinations of diseases, such as osteoarthritis with vertigo, illustrating the intricate nature of managing geriatric health. Chronic obstructive pulmonary disease (COPD) also emerged as a significant concern, particularly among those aged 60–70 years, consistent with the increased susceptibility to respiratory conditions in this age-group.

Homoeopathic medicines are prescribed on the basis of their symptomatic indications as recorded in the *Materia medica* and are usually independent of the name of the disease. One medicine can be prescribed in multiple conditions and a single condition may require prescribing different medicines in different persons. As such instead of identifying usefulness of a single drug in a single disease condition, the overall treatment effect with homoeopathy is recorded and reported. The treatment outcomes indicate a promising role for homoeopathic interventions in managing geriatric health conditions. Musculoskeletal disorders showed the highest improvement rates, with 190 cases demonstrating significant clinical benefits and only eight cases worsening. This is consistent with the efficacy of remedies like *Rhus toxicodendron* and *Bryonia alba* in addressing musculoskeletal complaints.[11] Multimorbid conditions also responded favorably, with 27 cases showing improvement and none worsening, suggesting the potential of individualized homoeopathic treatment in addressing complex chronic conditions. Dermatological, respiratory, and neurological conditions demonstrated favorable outcomes, reflecting the adaptability of homoeopathic principles to diverse health concerns in geriatrics. The minimal worsening across all systems underscores the safety profile of homoeopathic treatments in older adults.

The quality of life was measured by the Katz index, which remained static throughout the study. This indicates that the participants retained a high level of independence in ADL despite their underlying health conditions. This finding underscores the potential of homoeopathic treatment not only to manage symptoms effectively but also to help maintain functional independence in older adults.

The analysis of prescribed medicines highlights the effectiveness of frequently used remedies such as *Rhus toxicodendron*, *Bryonia alba*, *Sulphur*, *Lycopodium clavatum*, *Calcarea carbonicum*, and *Arsenic album*. These remedies showed substantial improvement rates, particularly in musculoskeletal and dermatological conditions. The findings emphasize the importance of individualized remedy selection based on the principles of homoeopathy, which appears to be instrumental in achieving positive outcomes across various conditions. The program also underscores the need for further investigation into optimizing prescriptions for conditions with lower response rates, such as gastrointestinal disorders.

A key strength of this program is its focus on a large, diverse geriatric population, providing a comprehensive overview of their health profile and treatment outcomes. The systematic categorization of conditions and outcomes offers valuable insights into the practical applications of homoeopathic interventions. This program highlights a high degree of external validity, cultural contextuality, and acceptance of people for homoeopathic treatment in outreach settings.

However, the analysis is limited by incomplete follow-ups in a significant portion of participants, which may have introduced biases in outcome assessment. Additionally, the absence of a control group limits the ability to draw definitive conclusions about the efficacy of homoeopathic treatments compared to conventional care. The pragmatic public health approach fails to meet the required levels of evidence of a randomized, controlled clinical trial, and may exhibit bias due to treatment expectations.

The findings from this program highlight the potential of homoeopathy as a complementary treatment modality in geriatric care. Future research should focus on RCTs to validate these findings, particularly for conditions like multimorbidity and musculoskeletal disorders.

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Declaration of Ethics

This study was conducted in accordance with the requirements of the Declaration of Helsinki (World Medical Association, 2013. The study was approved by the Central Ethics Committee of CCRH and was registered in the Clinical Trial Registry of India (CTRI/2019/10/021688 [Registered on: 16/10/2019]).

Availability of Data

The data is available with the primary author and corresponding author on request.

Supplementary Materials

The Supplementary Table 1 is available on the website www.hppi.in.

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References

1. Varma S, Sareen H, Trivedi JK. The Geriatric Population and Psychiatric Medication. In: Psychopharmacology Today: Some Issues (A.R. Singh and S.A. Singh eds.), MSM, 8, 2010, pp. 30–52.
2. Tkatch R, Musich S, MacLeod S, et al. Population health management for older adults: Review of interventions for promoting successful aging across the health continuum. Gerontol Geriatr Med 2016;2. DOI: 10.1177/2333721416667877.
3. Ageing and Health, WHO Fact sheet, 1 October 2022. Available from: https://www.who.int/news-room/fact-sheets/detail/ageing-and-health.
4. Aayog N. Senior Care Reforms in India – Reimagining the Senior Care Paradigm: A Position Paper. Government of India; 2024.
5. Adhikari P. Geriatric health care in India-Unmet needs and the way forward. Arch Med Health Sci 2017;5(1):112. DOI: 10.4103/2321-4848.208215.
6. Homoeopathy: Science of Gentle Healing. Central Council for Research in Homoeopathy, Ministry of Ayush; Chapter 3, New Delhi: Chauhan Art Press: Updated edition; 2019.
7. Long L, Ernst E. Homeopathic remedies for the treatment of osteoarthritis: A systematic review. Br Homeopath J 2001;90(1):37–43. DOI: 10.1054/homp.1999.0449.
8. Ministry of Law. Notification No S.R.O. 385, dated 10 August 1950. Gazette of India, Extraordinary, Part II, Section 3. 1950 Aug 10. p. 163.
9. Chatterjee P, Rebok GW, Dwivedi SN, et al. Development of integrated care tool – BRIEF for screening the unmet psychosociomedical needs of older Indians. Indian J Public Health 2019;63:51–57. DOI: 10.4103/ijph.IJPH_187_18.
10. Katz S, Ford AB, Moskowitz RW, et al. Studies of illness in the aged. The index of ADL: A standardized measure of biological and psychological function. JAMA 1963;185(12):914–919. DOI: 10.1001/jama.1963.03060120024016.
11. Mohanty N, Sahoo AR, Gautam P, et al. A randomised placebo-controlled clinical trial of homeopathic medicines on osteoarthritis. Hom Links 2023;36(01):12–15. DOI: 10.1055/s-0043-1766115.

ORIGINAL RESEARCH

Knowledge, Attitude and Utilization of Complementary and Alternative Therapies among Healthcare Workers: A Cross-sectional Assessment

Varsha Sharma[1], Sunita Srivastava[2], Monika Maan[3]

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Abstract

Introduction: Available literature consistently highlights that the use of complementary and alternative medicine (CAM) is more prevalent among healthcare workers than in the general population. This trend has significant implications for the integration of CAM into routine clinical practice, particularly in developing countries where CAM often remains the most accessible and affordable form of care. Therefore, it is essential to assess healthcare workers' knowledge, attitudes, and utilization of CAM to identify gaps and provide targeted training that can enhance safe and effective practice.

Research methodology: A cross-sectional descriptive survey was conducted among 100 healthcare workers—including doctors, nurses, technicians, pharmacists, and physiotherapists—employed at a multispecialty hospital in a developing country. Total enumerative sampling was applied to the conveniently selected participants.

Results: Among 100 healthcare workers, nurses were the largest group (43%). Complementary and alternative medicine prevalence was 54% for natural products/nutritional supplements and 57% for mind–body practices, with supplements and yoga being the most common. Over half (53%) had poor knowledge, and most (87%) showed negative attitudes toward CAM. Nurses had higher odds of using nutritional supplements (AOR = 4.35, $p = 0.03$), technicians of yoga (AOR = 8.17, $p = 0.019$), and pharmacists of massage therapy (AOR = 16.00, $p = 0.003$). Participants with <1 year of experience were less likely to use massage than those with >5 years (AOR = 0.17, $p = 0.005$).

Conclusion: Complementary and alternative medicine use was common among healthcare workers, particularly nutritional supplements and yoga. However, knowledge and attitudes toward its use were largely poor and negative.

Keywords: Attitude, Ayurveda, Complementary and alternative therapies, Cross-sectional study, Doctors, Healthcare workers, Homeopathy, Knowledge, Unani, Utilization.

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Introduction

Therapies that are usually not considered part of the conventional medicine are known as complementary and alternative medicines (CAM). These approaches are claimed to offer many health benefits; however, they are not based on scientific evidence.[1] It includes therapies as Ayurveda, Homeopathy, Unani, Siddha, Mind-body practices, Yoga, Acupressure, Massage, Spiritual healing, and Chiropractic therapies. For the purpose of this study, any form of medical therapy that is not included in modern scientific guidelines or not recommended by major scientific associations has been classified under CAM.

Complementary and alternative medicine's utilization in developed and developing countries has almost doubled in recent years, particularly where long-term treatment is required. The utilization rate of CAM in India ranges from 32 to 63% in chronic medical conditions.[2]

A survey revealed that although most of the doctors agreed that CAM therapies held promise for the treatment of disease, many were not comfortable in counseling patients about CAM treatment. The doctors who personally used CAM reported feeling better after using it and had a belief in the beneficial role of CAM, recommended CAM as a therapy to patients to a greater extent so that the use of CAM was found to be more common among doctors than patients.[3] While half of the physicians recognized that CAM could be potentially beneficial, they also expressed concerns about its safety, fearing it could lead to increased side effects from allopathic medications or even worsen the patient's condition.[2] Despite the overall positive attitude of healthcare professionals toward CAM, their knowledge about it remains limited. However, there is a notable lack of communication between healthcare providers (HCPs) and patients regarding CAM.[4]

The recognition by the Government of India and easy availability of CAM, including the Indian Systems of Medicine in India have contributed to its widespread use. Although CAM has

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been practiced in India for thousands of years, there is limited literature available on the extent of its use, and attitudes of patients utilizing CAM services—and none among doctors in India.[3]

There are very few published studies documenting the extent of knowledge, attitude, and utilization of CAM among HCP in the Indian population. That is why this is the study was carried out to find out the knowledge, attitudes, and utilization of CAM products among HCPs. This article reports pilot study findings as part of a larger research project.

Objectives of the Study

Primary Objective

To assess knowledge, attitudes, and utilization of selected CAM among HCPs.

Secondary Objectives

- To find the association of knowledge and attitudes regarding CAM with selected socioprofessional variables of HCPs.
- To determine the associated factors for utilization of selected CAM therapies.

Research Methodology

The study adopted a quantitative approach with a descriptive cross-sectional design. The target population consisted of healthcare workers, including doctors, nurses, technicians, pharmacists, and physiotherapists, while the accessible population included all healthcare workers in these categories employed at a multispecialty hospital. Healthcare workers who were on long leave or unwilling to participate were excluded. Data collection tools included a demographic data sheet, a structured knowledge assessment tool, an attitude assessment tool on CAM modalities, and a tool to assess utilization of selected CAM practices. All tools were developed by the primary researcher under the supervision of a guide and validated by nine experts from the fields of hepatology (3), psychiatry (1), an AYUSH expert (1), and medical-surgical nursing (4). Language validity was ensured by a Hindi language expert, and reliability was confirmed using the test–retest method and Cronbach's alpha, which yielded high values of 0.96, 0.92, and 0.99, respectively.

The variables in the study included categorical variables such as demographic characteristics and utilization of selected CAM, and continuous variables such as attitude and knowledge. Knowledge was operationally defined as awareness of CAM modalities, including their risks and benefits, and was measured using a structured knowledge assessment tool developed by the researcher. This tool contained two subscales—natural products/supplements and mind–body practices—with a total of 22 items. Scores ranged from 0 to 22 and were categorized as good knowledge (17–22), average knowledge (13–16), and poor knowledge (below 13). Attitude was operationally defined as the perception and utilization of CAM, measured using a structured tool consisting of 18 items across three domains, including nine positive and nine negative statements. Scores ranged from 9 to 45, with higher scores indicating a more positive attitude toward CAM and lower scores reflecting a negative attitude. Utilization was defined as the actual use of CAM therapies, which were grouped under natural products such as Ayurveda, Siddha, Unani, Homeopathy, and nutritional supplements, and mind–body practices such as acupuncture, yoga, massage, spiritual healing, and chiropractic therapy. The tool captured details of type, duration, frequency, reasons for use, and perceived effectiveness, and utilization was expressed in terms of frequency and percentage. For the purpose of this study, HCP referred to any qualified professional directly or indirectly involved in patient care, including doctors, nurses, pharmacists, technicians, and physiotherapists employed at the selected research setting.

Ethical Considerations

The ethical permission for the study was obtained from the competent authorities (CONEC/ILBS/MSc/01/24/016). All the ethical principles as per Declaration of Helsinki were followed. Voluntary participation was ensured, with the freedom to withdraw from the study at any point in time.

Data collection was carried out from 1st to 6th September 2025 at a selected superspecialty hospital, after obtaining approval and permission from the competent authorities. A total of 100 healthcare professionals were recruited as participants. Each was approached individually and provided with a participant information sheet (PIS) outlining the purpose, objectives, procedures, relevance of the study, and details of data usage. Adequate time was given to review the information, and participants were encouraged to ask questions. After clarifying all queries, written informed consent was obtained from those willing to participate. Participation was entirely voluntary and based on informed decision-making, and completion of the questionnaire required approximately 5 minutes.

Data Analysis

Data was analyzed using SPSS (v.30). Frequency, percentage, mean, and standard deviation were used to describe the variables. The distribution of normality of scores across the four study variables was examined using histograms. The socioprofessional scores were normally distributed (Mean = 15.45, SD = 2.13), utilization showed a normal distribution normal (Mean = 21.44, SD = 11.13), with most scores between 10 and 30 and attitude scores followed a fairly normal distribution (Mean = 55.08, SD = 4.54). Hence, parametric tests were applied. Chi-square test, one-way ANOVA, and *t*-tests were used to find the association. Univariate and multivariate logistic regression analysis was done to assess the predictors of utilization of CAM among the healthcare workers.

Results

For the demographic variables (Fig. 1), more than one-fourth of the study participants were nurses (43%).

Description of Types of CAM Therapies Used by HCPs

Out of 100 participants, the most commonly used therapies (Fig. 2) were nutritional supplements (33%), yoga (30%), and massage (29%), followed by Ayurveda (22%).

Overall Prevalence of CAM Use among HCPs

The prevalence of CAM use in natural products and nutraceuticals was 23%; however, it was 35% in mind-body practices (Table 1).

Description of Utilization of CAM

Utilization of CAM varied across modalities. Nutraceuticals were most common (24% ever, 9% current), followed by Ayurveda (16%, 6%) and Homeopathy (13%, 2%), Siddha (1%) and Unani (6%) had minimal uptake. Most used CAM occasionally and for <1 year, with

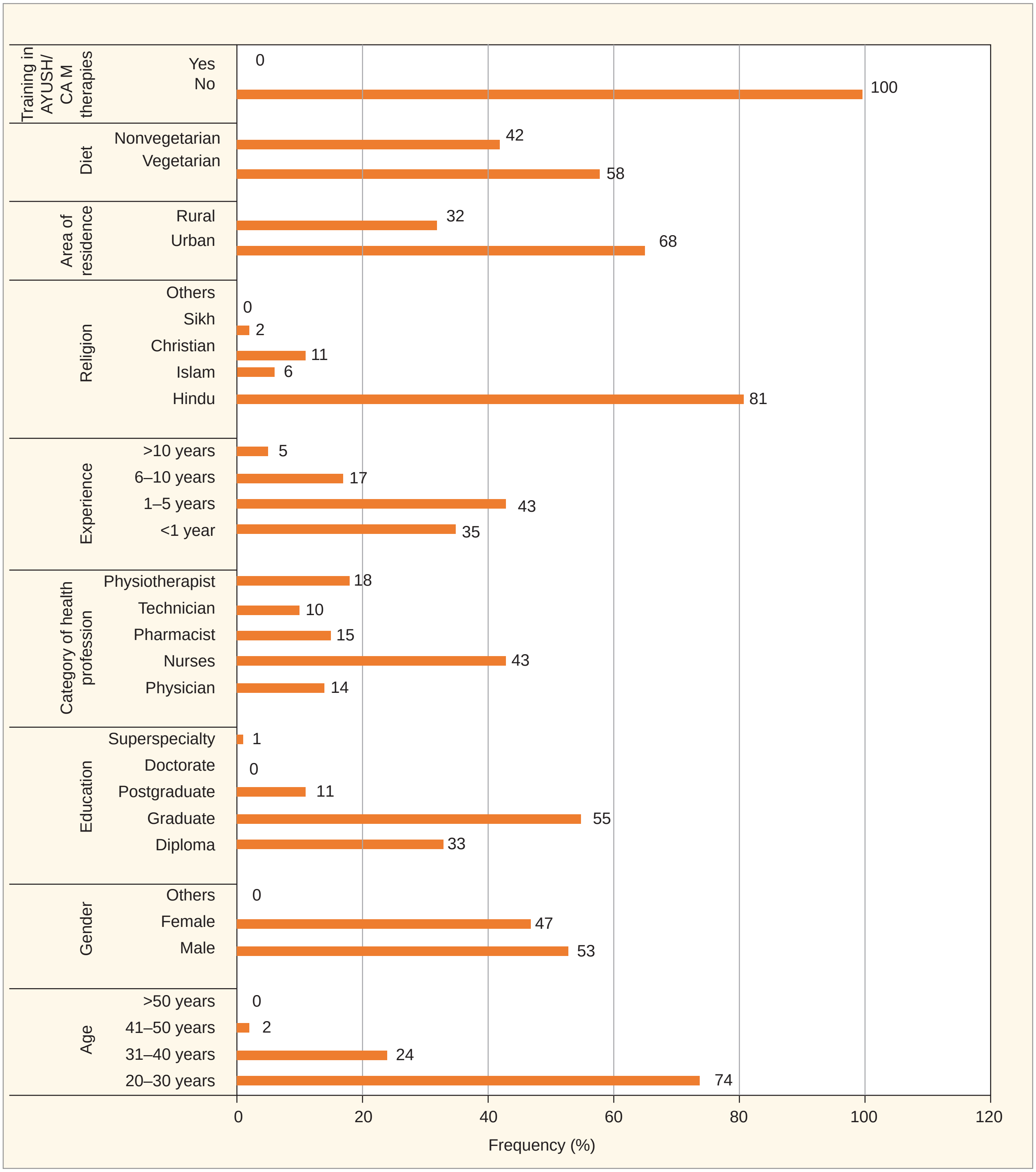

Fig. 1: Bar graph showing the frequency and percentage distribution of socioprofessional characteristics of the study participants

higher familiarity for nutraceuticals and lower for traditional CAM therapies.

The main reasons for CAM use were improving well-being and managing long-term conditions, with family, friends, and HCP as key influences. Yoga (19% ever, 11% current) and massage (17% ever, 12% current) were most popular, while acupuncture, spiritual healing, and chiropractic therapy were less common. Most participants used these therapies occasionally, with perceived benefits mainly in overall health and treatment outcomes (Table 2).

The assessment of knowledge regarding CAM revealed that a majority (53%) of the respondents demonstrated a poor level of knowledge, followed by 29% who had an average level of knowledge, while only 18% of participants showed a good level of knowledge. The overall mean knowledge score was 11.68 ± 5.7 (Fig. 3).

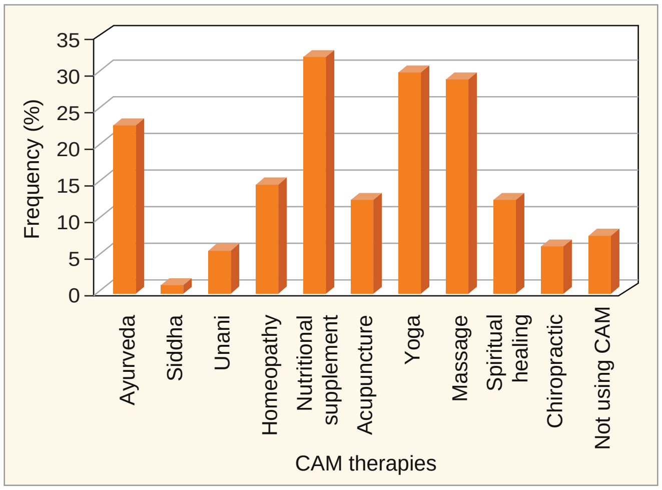

Fig. 2: Bar graph showing the frequency and percentage distribution of utilization of CAM among participants

The assessment of attitude towards CAM revealed that an overwhelming majority of respondents exhibited a negative attitude (87%), while only a small proportion expressed an ambivalent attitude (13%), and none were categorized as having a positive attitude. The overall mean attitude score was 55.15 ± 4.6, which falls within the negative category range (18–61) (Fig. 4).

Table 3 presents the association of socioprofessional variables with knowledge and attitude toward CAM, analyzed using one-way ANOVA. Results showed a highly significant difference in knowledge across professional categories (F = 4.70, p = 0.002). Similarly, attitude also varied significantly by professional category (F = 3.92, p = 0.005). The null hypothesis was rejected, indicating that nurses and technicians demonstrated more favorable attitudes towards CAM compared to physicians and pharmacists. However, none of the variables associated significantly with utilization.

Table 1: Prevalence of CAM (natural products and nutraceuticals) use among healthcare workers (n = 100)

CAM practice	*Used in past (%)*	*Presently using (%)*	*Never used (%)*
Natural products and nutraceuticals	23	31	46
Mind–body practices	35	22	43

Table 2: Frequency and percentage distribution of utilization of natural products and nutraceuticals among participants (n = 100)

Natural products/Nutraceuticals	*Ayurveda f (%)*	*Siddha f (%)*	*Unani f (%)*	*Homeopathy f (%)*	*Nutraceuticals f (%)*
History					
Ever used	16	01	–	13	24
Using presently	06	0	06	02	09
Never used	78	99	94	85	67
Duration					
< 1 year	16	01	06	11	18
>1 year	06	–	–	04	15
How frequently do you use CAM?					
Never	78	99	94	85	68
Rarely	7	–	01	07	05
Sometimes	12	01	05	03	12
Often	3	–	–	05	08
Always	0	–	–	–	07
How much do you know about CAM?					
A lot	09	–	–	02	20
Some	12	01	06	10	08
Very little	78	99	94	87	71
None	–	–	–	–	
Reason for using CAM					
An acute illness/condition	03	–	01	05	04
To treat long-term condition	09	–	04	04	08
To improve well being	11	01	01	06	21
Any reference/influence for using CAM products					
No	–	–	–	–	05
Social media	02	–	02	–	01
Colleagues, friends, family member, doctor	18	01	04	15	26
Perceived effectiveness					
Effectiveness of treatment	09	–	02	08	11
Improvement in overall health	11	01	–	03	14
Usefulness of experience	02	–	04	02	06

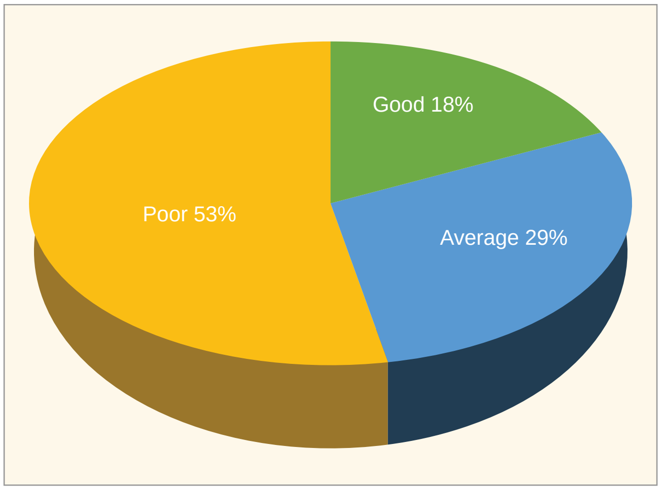

Fig. 3: Pie chart showing percentage distribution of level of knowledge on CAM among participants

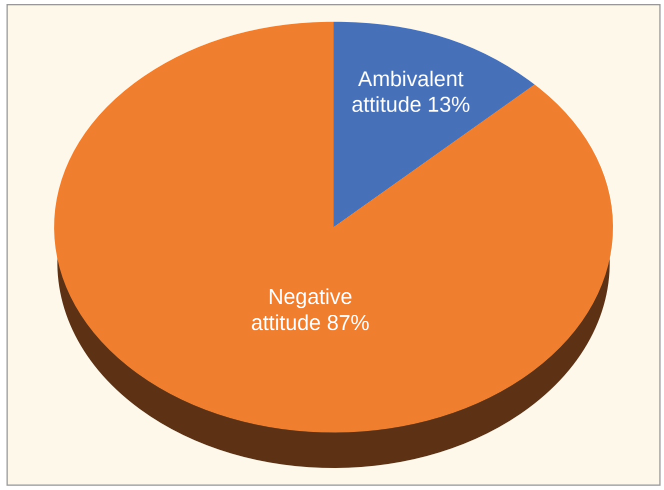

Fig. 4: Pie chart showing percentage distribution of attitude on CAM among participants

Table 3: Association of socioprofessional variable with knowledge and attitude ($n = 100$)

Socioprofessional variable category	*Knowledge (mean ± SD)*	*df F-test/t-test (p-value)*	*Attitude (mean ± SD)*	*df F-test/t-test (p-value)*
Age-group (years)				
20–30	10.84 ± 5.94	2, 97	55.59 ± 4.1	2, 97
31–40	13.84 ± 4.38	4.37 (0.15)	53.63 ± 5.8	1.82 (0.16)
41–50	21.00 ± 1.41		57.00 ± 2.8	
> 50	–		-	
Gender				
Male	11.79 ± 6.15	98	54.42 ± 4.94	98
Female	11.34 ± 5.35	0.15 (0.69)	55.98 ± 4.16	2.88 (0.93)
Others	-		-	
Education				
Diploma	11.85 ± 5.14	3, 98	55.94 ± 3.81	3, 96
Graduate	11.64 ± 5.82	0.26 (0.85)	54.82 ± 4.74	1.75 (0.16)
Postgraduate	10.27 ± 7.68		55.27 ± 5.79	
Doctorate	–		-	
Superspecialty	14.00		46.00	
Category of health professional				
Physician	13.93 ± 4.90	4, 95	53.36 ± 4.78	4, 95
Nurses	12.12 ± 5.16	4.70	56.72 ± 3.54	3.92
Pharmacist	13.40 ± 5.09	(0.002)**	52.00 ± 5.04	(0.005)**
Technician	11.80 ± 5.00		55.60 ± 4.55	
Physiotherapist	6.83 ± 5.77		55.17 ± 5.20	
Experience (years)				
<1	9.74 ± 6.04	3, 96	54.74 ± 4.57	3, 96
1–5	11.86 ± 5.33	3.36 (0.22)	55.45 ± 4.67	1.15 (0.33)
6–10	13.00 ± 5.40		54.76 ± 4.59	
>1	17.20 ± 4.38		52.40 ± 4.66	

**$p < 0.01$ = highly significant

Univariate logistic regression showed that most socio-professional variables—age, gender, education, and years of experience—were not significantly associated with the CAM category of natural products and nutraceuticals. The category of health professional was the only variable significantly associated with Unani use ($p = 0.006$), indicating that utilization differed across professional groups. For other CAM modalities, no statistically significant associations were observed (Table 4). For the CAM category of mind-body practices, most socio-professional variables—age, gender, and education—were not significantly associated with the use of any CAM modality ($p > 0.05$). Category of health professional was significantly associated with the use of nutritional supplements ($p = 0.045$), yoga ($p = 0.018$), and massage ($p = 0.007$), indicating differences in utilization across

Table 4: Univariate logistic regression between selected socioprofessional variables and utilization of CAM therapies among participants

	Ayurveda			Siddha			Unani			Homeopathy		
	Never used	*Used*		*Never used*	*Used*		*Never used*	*Used*		*Never used*	*Used*	
Category	*f (%)*	*f (%)*	*p-value*	*f (%)*	*f (%)*	*p-value*	*f (%)*	*f (%)*	*p-value*	*f (%)*	*f (%)*	*p-value*
Age-group (years)												
20–30	57 (74)	17 (73.9)	1.000	74 (74.7)	0	0.260	71 (75.5)	3 (50)	0.335	63 (74.1)	11 (73.3)	1.000
> 30	20 (26)	06 (26.1)	–	25 (25.3)	1 (100)	–	23 (24.5)	3 (50)	–	22 (25.9)	4 (26.7)	–
Gender												
Male	44 (57.1)	09 (39.1)	0.157	52 (52.5)	1 (100)	1.000	49 (52.1)	4 (66.7)	0.681	48 (56.5)	5 (33.3)	0.159
Female	34 (42.9)	13 (60.9)	–	47 (47.5)	0	–	45 (47.9)	2 (33.3)	–	37 (43.5)	10 (66.7)	–
Education												
Diploma	25 (32.5)	8 (34.8)	0.208	33 (33.3)	0	1.000	33 (35.1)	0	0.63	30 (35.3)	3 (20)	0.521
Graduate	45 (58.4)	10 (43.5)	–	54 (54.5)	1 (100)	–	49 (52.1)	6 (100)	–	45 (52.9)	10 (66.7)	–
Above and postgraduate	7 (9.1)	5 (21.7)	–	12 (12.1)	0	–	12 (12.8)	0	–	10 (11.8)	2 (13.2)	–
Category of health professional												
Physician	13 (16.9)	01 (4,3)	0.379	14 (14.1)	0	0.570	14 (14.9)	0	0.006*	11 (12.9)	3 (20)	0.695
Nurses	32 (41.6)	11 (47.8)	–	43 (43.4)	0	–	43 (45.7)	0	–	36 (42.4)	7 (46.7)	–
Pharmacist	11 (14.3)	04 (17.4)	–	15 (15.2)	0	–	11 (11.7)	4	–	13 (15.3)	2 (13.3)	–
Technician	9 (11.7)	01 (4.3)	–	10 (10.1)	0	–	9 (9.6)	1	–	10 (11.8)	0	–
Physiotherapist	12 (15.6)	26 (21.1)	–	17 (17.2)	1 (100)	–	17 (18.1)	1	–	15 (17.6)	3 (20)	–
Experience (years)												
<1	30 (39.0)	5 (21.7)	0.269	35 (35.4)	0	1.000	32 (34)	3 (50)	0.433	27 (31.8)	8 (53.3)	0.057
1–5	32 (41.6)	11 (47.8)	–	42 (42.4)	1 (100)	–	40 (42.6)	3 (50)	–	36 (42.4)	7 (46.7)	–
> 5	15 (19.5)	7 (30.4)	–	22 (22.2)	0	–	22 (23.4)	0	–	22 (25.9)	0	–

$^{*}p < 0.05$ = significant

Table 5: Multivariate logistic regression between selected socioprofessional variables and utilization of CAM therapies among participants

Variables	*Category*	*COR (95% CI)*	*AOR (95% CI)*	*p-value*
Unani	Category of HCPs			
	Physician	0.000	0.007	0.999
	Nurses	0.000	0.007	0.998
	Pharmacist	6.182 (0.60–62.83)	6.182 (0.60–62.83)	0.124
	Technician	1.889 (0.10–33.89)	1.889 (0.10–33.89)	0.666
	Physiotherapist	1	1	–
Nutritional supplements	Category of HCPs			
	Physician	3.750 (0.73–19.14)	3.750 (0.73–19.14)	0.112
	Nurses	4.348 (1.09–17.22)	4.348 (1.09–17.22)	0.03*
	Pharmacist	0.769 (0.11–5.33)	0.769 (0.11–5.33)	0.791
	Technician	1.250 (0.17–0.09)	1.250 (0.17–0.09)	0.826
	Physiotherapist	1	1	–
Yoga	Category of HCPs			
	Physician	2.625 (0.566–12.17)	2.625 (0.566–12.17)	0.218
	Nurses	1.203 (0.32–4.43)	1.203 (0.32–4.43)	0.781
	Pharmacist	0.538 (0.08–3.45)	0.538 (0.08–3.45)	0.514
	Technician	8.167 (1.41–47.01)	8.167 (1.41–47.01)	0.019*
	Physiotherapist	1	1	–
Massage	Category of HCP			
	Physician	2.182 (0.31–15.28)	2.182 (0.31–15.28)	0.432
	Nurses	2.750 (0.54–13.92)	2.750 (0.54–13.92)	0.221
	Pharmacist	16.000 (2.59–98.77)	16.000 (2.59–98.77)	0.003**
	Technician	3.429 (0.456–25.271)	3.429 (0.456–25.271)	0.227
	Physiotherapist	1	1	–
	Experience (years)			
	<1	1	1	–
	1–5	2.60 (0.824–8.202)	2.60 (0.824–8.202)	0.103
	>5	6.00 (1.69–21.21)	6.00 (1.69–21.21)	0.005**

$^{*}p < 0.05$ = significant; $^{**}p < 0.01$ = highly significant; 1 = reference

professional groups, with nurses showing higher use. Years of experience was significantly associated only with massage use ($p = 0.016$), suggesting participants with <1 year experience used it less than more experienced groups. No significant associations were observed for spiritual healing or chiropractic practice with any socioprofessional variable (Table 5).

Bivariate and multivariable logistic regression analyses were performed to examine the association between socioprofessional variables and CAM utilization among participants ($n = 100$). Crude odds ratios (COR) were obtained from bivariate models, and adjusted odds ratios (AOR) were calculated after controlling for all socioprofessional variables (Table 5).

Unani Therapy

No professional category was significantly associated with utilization of Unani therapy ($p > 0.05$). Nurses had significantly higher odds of using nutraceuticals compared to physiotherapists COR = 4.35, 95% CI: [1.09, 17.22], $p = 0.03$; AOR = 4.35, 95% CI: (1.09, 17.22), $p = 0.03$.

Yoga

Technicians reported significantly greater yoga use than physiotherapists, AOR = 8.17, 95% CI: [1.41, 47.01], $p = 0.019$. No other categories showed significant differences.

Massage Therapy

Pharmacists had the highest odds of massage use, COR = 16.00, 95% CI: [2.59, 98.77], $p = 0.003$; AOR = 16.00, 95% CI: [2.59, 98.77], $p = 0.003$, suggesting a stronger association after adjustment.

Professional Experience

Participants with <1 year of experience were significantly less likely to use massage therapy compared to those with >5 years, AOR = 6.00, 95% CI: [1.69–21.21], $p = 0.005$.

Discussion

This study highlights widespread utilization and significant knowledge and attitude gaps. The finding that over half of healthcare professionals actively use CAM therapies, particularly nutritional supplements and yoga, aligns with prior research globally and in developing countries, where CAM remains a vital component of healthcare due to cultural acceptance, accessibility, and affordability.[5] Several studies have reported a higher prevalence of CAM use among males, such as in a study by Noor et al.,[6] whereas our study found a more balanced gender distribution. Similarly, another study observed that younger populations tend to be the primary CAM users, contrasting with our findings, where age-groups were more evenly represented.[7]

The study results concur with the findings of Tahir et al.,[4] who reported that while healthcare workers hold generally positive attitudes toward CAM's potential benefits, their knowledge remains insufficient, posing challenges for safe patient counseling and integration into clinical practice. Likewise, another study showed high CAM prevalence in healthcare settings but highlighted disparities in knowledge shaped by factors such as education level and urban vs rural practice environments.[5] Our study's observations about the influence of professional role and experience in CAM utilization mirror similar trends reported by another study, documenting higher CAM use among nurses and allied health staff compared to physicians and pharmacists, reflecting differences in patient contact and cultural openness to holistic practices.[8]

The predominant use of supplements and mind–body practices such as yoga within our study echoes findings from studies in developing countries, where supplements and spiritual modalities often represent the preferred CAM avenues due to their familiarity and perceived holistic benefits.[6] The study, though reporting somewhat higher knowledge levels among healthcare workers in other settings, similarly underscores the gap between actual knowledge and use or recommendation of CAM, reinforcing the global nature of this disconnect.[9]

The notable predominance of negative attitudes in this study contrasts with some literature suggesting generally positive or ambivalent attitudes in other contexts, such as Ethiopia where more than half of HCPs favored CAM integration.[4,9] This difference may reflect varying regulatory environments, cultural acceptance, and institutional support for CAM practices.

The association of years of experience with CAM use, particularly decreased use of massage therapy among less experienced workers, highlights the role of professional socialization and clinical exposure in normalizing CAM use.[9] This emphasizes the need for early, evidence-based CAM education to familiarize newer health workforce members with CAM principles, benefits, and contraindications, thereby promoting safe clinical integration.

This study reinforces key findings in recent literature, showing that while CAM use among HCPs is widespread, significant gaps in knowledge and predominantly negative attitudes remain. These gaps hinder the effective and safe integration of CAM into health care.

Strengths and Limitations of the Study

The inclusion of multiple professional categories enhances representativeness within the research setting and using total enumerative sampling technique minimizes selection bias. The chosen topic of CAM use among the healthcare workers has a practical relevance. Limitations include single-center study with cross-sectional design and a relatively smaller sample size; convenience-based selection of the research setting limits generalizability.

Conclusion

Healthcare workers demonstrated varying knowledge, attitudes, and use of CAM, highlighting the need for targeted training to ensure safe integration into clinical practice—especially in developing countries where CAM is widely accessible.

Declaration

The authors declare that this work is their original creation and has not been published or submitted for publication elsewhere.

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References

1. Barnes PM, Bloom B, Nahin RL. Complementary and alternative medicine use among adults and children: United States, 2007. Natl Health Stat Report 2008;(12):1–23. PMID: 19361005.
2. Kunnoor NS, Rathore R. Physicians perception on complementary and alternative medicine (CAM): A cross sectional survey at Tertiary Care Hospital in India. Med Chem 2015;5(5):197–202. Available from: https://www.hilarispublisher.com/open-access/physicians-perception-on-complementary-and-alternative-medicinecam-a-cross-sectional-survey-at-tertiary-care-hospital-in-india-2161-0444-1000264.pdf.
3. Roy V, Gupta M, Ghosh R. Perception, attitude and usage of complementary and alternative medicine among doctors and patients in a tertiary care hospital in India. Indian J Pharmacol 2015;47(2):137–142. DOI: 10.4103/0253-7613.153418.
4. Tahir AH, Tanveer M, Shahnaz G, et al. Knowledge, attitude, and perceptions of healthcare professionals towards complementary and alternative medicine: A cross-sectional survey from twin cities of Pakistan. BMC Complement Med Ther 2023;23(1):432. DOI: 10.1186/s12906-023-04187-2.
5. Denu MK, Buadu MAE, Adrah F, et al. Traditional complementary and alternative medicine (TCAM) use among PLHIV on antiretroviral medication. AIDS Res Ther 2024;21(1):84. DOI: 10.1186/s12981-024-00673-w.
6. Noor S, Begum A, Siddiqua SA, et al. Utilization of complementary and alternative medicine (CAM) among chronic disease patients in a government hospital outpatient department in Hyderabad. J Young Pharm 2025;17(2):427–433. DOI: 10.5530/jyp.20251572.
7. Alwhaibi M, Sambamoorthi U. Sex differences in the use of complementary and alternative medicine among adults with multiple chronic conditions. Evid Based Complement Alternat Med 2016;2016:2067095. DOI: 10.1155/2016/2067095.
8. Gyasi RM, Abass K, Adu-Gyamfi S, et al. Nurses' knowledge, clinical practice and attitude towards unconventional medicine: Implications for intercultural healthcare. Complement Ther Clin Pract 2017;29:1–8. DOI: 10.1016/j.ctcp.2017.07.00.
9. Sarman A, Uzuntarla Y. Attitudes of healthcare workers towards complementary and alternative medicine practices: A cross-sectional study in Turkey. Eur J Integr Med 2022;49:102096. DOI: 10.1016/j.eujim.2021.102096.

ORIGINAL RESEARCH

India's Healthcare Future: Igniting Transformation with Artificial Intelligence

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Abstract

In India, Artificial intelligence (AI) in health care is at a nascent stage; however, the growing interest of many innovators and entrepreneurs, supportive government policies, AI adoption in public and private sectors, and support of start-up accelerators have boosted India's start-up ecosystems and *inter alia* promoted the use of AI in the health care sector. In the past few years, AI has revolutionized health care in India by addressing critical challenges related to accessibility, affordability, and diagnostic accuracy. This article aims to explore recent advancements in the AI-driven health care sector and examine challenges to ensure the ethical and scalable adoption of AI in health care, with the overarching goal of building India into a global leader in AI adoption and an exporter of AI solutions across the health care ecosystem worldwide.

Keywords: Artificial intelligence adoption, Artificial intelligence in health care, Artificial intelligence, Data security and data privacy, Digital health, Health care technology, Health-tech and Med-tech Start-ups, National health programmes, Public health management.

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Introduction

India's health care system has traditionally depended on paper-based, manual processes across all levels, placing a substantial burden on health care personnel, especially those working in the field. A severe shortage of medical and paramedical professionals further led to uneven access, out-of-pocket expenditures, and high treatment costs, particularly in rural areas. Service delivery especially diagnostics, was costly and time-consuming, and data management was fragmented, with limited digital infrastructure.

Digital health has gained the limelight as a way to overcome data reporting, access, and other challenges. The Ministry of Health and Family Welfare (MoHFW), Government of India, has progressively built a digital health ecosystem since 2012.

Starting with the Clinical Establishments Rules of 2012 mandating electronic health records (EHRs), MoHFW introduced EHR standards in 2013 and 2016 to ensure data interoperability with the objective of introducing a uniform standard-based system for the development and maintenance of EHR by health care providers.[1,2]

The National Health Portal launched in 2015 further expanded digital access to health information, followed by the National Health Policy (2017), which advocated extensive deployment of digital tools for improving the efficiency and outcome of the health care system. National Health Profile 2015 stated that "Recognizing the integral role of technology (eHealth, mHealth, Cloud, Internet of things, wearables, etc.) in the health care delivery, a National Digital Health Authority (NDHA) will be set up to regulate, develop, and deploy digital health across the continuum of care."[3–5]

In 2019, MoHFW launched eSanjeevani: Telemedicine services aiming towards digital health equity to achieve Universal Health Coverage (UHC), which has served more than 370 million (37 crores) patients till April 2025. Also, the National Digital Health Blueprint, published in 2019, outlined the need of having interoperable data systems.[6]

In 2020, National Health Stack and National Digital Health Mission (NDHM) first introduced unique health IDs and piloted them in six Union Territories.[7,8] Further, renamed NDHM—Ayushman Bharat Digital Mission (ABDM), rollout in 2021 was backed by an allocation of ₹1,600 crore budget reflecting the Government's commitment towards building a strong digital infrastructure.[9]

Subsequently, the Digital Personal Data Protection Act, 2023 bolstered much-needed infrastructure and privacy concerns.[10] By 2024, ABDM's microsites and integrations with schemes like UWIN, Poshan Abhiyan, National Viral Hepatitis Control Program, e-Sanjeevani 2.0, Aarogya Setu, RCH ANMOL, TB Nikshay, COWIN, e-Hospital, and many others have enhanced public and private sector engagements.[11]

The digital foundation created in India has enabled and supported Artificial intelligence (AI) adoption to leverage vast datasets for automated diagnostics (e.g., tuberculosis screening), predictive analytics, and significant cost reduction. There are significant developments, and health care technologies are re-defining the way from identifying new treatments, and developing medical devices for improving patient experiences.

Recent Developments: AI in Health Care

India's health care landscape is witnessing a surge in specialized AI and health tech applications across diverse domains, enhancing accessibility and health outcomes. For preventive care, the use of AI for health risk prediction, nutrition coaching, and promoting lifestyle

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changes is gaining popularity. Wearables using ballistocardiography can track sleep apnea and heart failure. Portal diagnostic devices with AI-enabled quick reporting have nationwide deployment potential for real-time monitoring of chronic diseases. It is projected that improved access to smartphones and internet connectivity could help in a widespread adoption of AI-based technology and mobile-based innovations across the country. Use of AI in diagnostics promises to be a game changer. Thermal imaging detects breast cancer, while portable ECGs with cloud-based AI identify cardiac arrhythmias. Prospects in diagnostics include integrating multimodal imaging for comprehensive screening and AI-based tele-diagnostics, potentially reducing diagnostic costs and issues related to access, infrastructure, and trained HR.

For infectious diseases, portable polymerase chain reaction (PCR) devices diagnose tuberculosis, and AI pathogen detection identifies sepsis, which can enhance rural access. Future advancements may leverage acoustic AI for non-invasive screening, expanding reach to remote areas. In tuberculosis detection and management, AI-powered X-ray analysis, cough sound analysis, and handheld X-ray devices enable rapid screening, and federated learning and biosensors could further improve privacy and sensitivity.

In mental health, AI chatbots provide emotional support, and teleconsultation platforms address anxiety, with the potential to reach millions of users across all age groups. The use of AI in oncology employs technology for lung cancer detection and tumor recurrence monitoring, improving survival rates; future AI-driven liquid biopsies could personalize treatments. Surgical robotics further improves precision in minimally invasive procedures, reducing recovery times, and wider adoption could lower surgical costs.

Genomics is another critical area with futuristic use and global demand that uses AI for genetic risk profiling, aiding cancer prevention, with future prospects in rare disease sequencing for personalized medicine. AI retinal imaging for diabetic retinopathy screening, integrated with national blindness prevention programs, with the potential for automated glaucoma detection, is a key technological area in ophthalmology.

Artificial intelligence-based teleconsultation, teleradiology, and telepathology during emergency medical services and portable ventilators for critical care, with future integration into mobile units are enhancing trauma response. Artificial intelligence is accelerating drug discovery by analyzing molecular structures to predict drug candidates. Moreover, AI is playing a crucial role in clinical trials, hospital management, health care service delivery, research, and the medical devices industry as well.

These technologies collectively democratize health care, with future innovations poised to reduce costs, enhance scalability, and address India's diverse health needs through localized, data-driven solutions.

Challenges in Widespread AI Adoption

The adoption of AI in health care holds immense potential to revolutionize patient care, diagnostics, and operational efficiency, but it is fraught with significant challenges that must be addressed to ensure safe and effective implementation. Artificial intelligence systems require access to vast amounts of sensitive patient data; therefore, ensuring data privacy and security is of paramount importance. Protecting patient confidentiality while mitigating cybersecurity risks are critical priorities. Meeting requirements of global regulations like the Health Insurance Portability and Accountability Act (HIPAA) in the U.S. and the General Data Protection Regulation (GDPR) in Europe further complicates the deployment and usability of AI solutions across countries.[12,13] Another hurdle is data quality and standardization. Incomplete, inaccurate, or siloed data across disparate health care systems can lead to unreliable AI predictions or diagnoses. The lack of universal standards for medical data formats and terminology exacerbates this issue, hindering AI's ability to integrate and analyze information consistently across regions and countries.

Regulatory challenges also pose significant barriers. The absence of uniform global regulations for AI in health care results in varying standards for testing and implementation, creating uncertainty for developers and providers. Regulating AI models are complicated by their dynamic nature, as they continuously evolve with new data, requiring ongoing regulatory scrutiny. Limited guidance from authorities in many regions further complicates compliance for developers.

Additionally, the integration of AI into health care workflows is challenging due to resistance from health care professionals who may lack trust or understanding of AI tools. Effective adoption requires comprehensive training and education, as well as interoperable systems that seamlessly integrate with existing health care IT infrastructure, such as EHRs.

Furthermore, result validation and explainability are critical for building trust. Artificial intelligence decisions must be transparent and understandable to health care providers, particularly for critical decisions, as opaque "black-box" models can undermine confidence.[14] Both patients and providers may hesitate to rely on AI for life-threatening conditions, necessitating efforts to ensure ethical, accurate, and fair outcomes.

The cost and accessibility of AI implementation present additional obstacles. High development and maintenance costs can be prohibitive, especially for smaller hospitals or clinics, while low-resource settings may lack the technological infrastructure needed to deploy AI solutions. Human oversight is another concern, as over-reliance on AI risks diminishing the human element in patient care, potentially compromising care quality. The long-term impact and safety of AI systems remain uncertain, as many have not been tested over extended periods to evaluate their efficacy and reliability. Overdependence on AI increases the risk of disruptions from system failures or bugs, underscoring the need for robust contingency plans, including alternative AI systems and enhanced capacity building for health care professionals.

On the other hand, start-ups and health-tech/med-tech companies that are developing or have already developed technology without proper clinical validation, technology assessment and meeting regulatory compliances and/or without accessing the market demand and supply, user requirements, global import/export restrictions, funding opportunities, novelty of the product, peer reviewed feedback with experts from health care, IT domains, etc. at proof of concept stage itself, usually facing challenges in scaling-up technology. Addressing these multifaceted challenges is essential to unlocking AI's transformative potential in health care while ensuring patient safety and trust.

Way Forward

To overcome the challenges of AI adoption in health care and to align with global best practices, a strategic and collaborative approach is essential. The following suggestions may provide a way forward for AI adoption and for addressing key barriers, while leveraging successful frameworks from around the world.

- Strengthening Data Privacy and Security: Adopting robust encryption, anonymization techniques, secure data-sharing protocols, data minimization, and user consent are critical for strengthening data privacy and security in India. In addition, regular audits and compliance with national and global regulations like HIPAA and GDPR need to be prioritized.
- Improving Data Quality and Standardization: High-quality, standardized data are the backbone of AI innovations. Building an interoperable ecosystem for secure data exchange among various stakeholders at the national level, as well as adopting global standards widely used in the U.S. and Europe like HL7 FHIR (Fast Health care Interoperability Resources) can facilitate seamless data integration across systems globally. In the global market, such an initiative will also support global innovations and scalability of AI technology.[15]
- Establishing Clear Regulatory Frameworks Based on feasible Provisions of National and Global Regulations: In the European Union, the AI Act provides a risk-based approach to AI governance. Similarly, the FDA's AI/ML-based framework, named "Software as a Medical Device (SaMD)," offers a model for regulating AI technologies and also emphasizes continuous monitoring and validation of AI tools.[16] Therefore, it is high time to adopt uniform regulations and harmonized regulatory guidelines in the country to ensure AI systems are safe, ethical, and effective within and across borders. As per the Indian constitution, health is a state's subject and therefore, engagement of states to understand local needs and priorities is needed. Regulatory sandboxes, like those in the UK and Singapore, allow developers to test AI innovations under controlled conditions. A similar sandbox can regulate dynamic AI models in India as well.
- Facilitating Technological Adoption and Capacity Building of Health care Workforce: To foster the adoption of AI in the health care sector, health care providers need comprehensive and periodic training programs on relevant technologies. Building trust among end users and ensuring that tools align with clinical needs are prerequisites for technology adoption by health care workers and patients. A model like the UK's NHS Digital Academy, which equips clinicians with digital and AI literacy, may be adopted.[17]
- Addressing Cost and Accessibility: To make AI affordable, public–private partnerships (PPPs) can subsidize costs for smaller health care facilities. Exploring PPP in health care AI ecosystems in India can be a game changer in ensuring the affordability of technology solutions so that people facing access issues, especially in difficult and hard-to-reach areas of rural India can get benefits from AI innovations; however, the technology must be safe, effective, and clinically validated. Canada's Pan-Canadian AI Strategy is one example of PPP in the sector.[18] Similarly, open-source AI platforms can lower barriers to entry. There is a need to deliberate on how the PPP model can support start-ups and facilitate the adoption of AI in health care.
- Maintaining Human Oversight: Artificial intelligence should not replace human decision-making and must act as an enabler. The American Medical Association's guidelines on AI emphasize the importance of clinician oversight, ensuring the human element remains central to care.[19] Therefore, clinicians' insights must be duly sought and considered at each stage of AI development and market access to avoid any error and, AI training models should focus on collaborative AI–human workflows.
- Ensuring Long-Term Safety and Resilience: There is a strong need to assess AI's efficacy and safety through clinical validations. Building resilience against technological failures requires robust contingency plans. Capacity building should focus on training health care workers to operate independently of AI when needed.
- Building Global Collaboration: Global collaboration and cross-learning from best practices are critical to facilitate AI adoption in health care. There is a need to explore knowledge-sharing through platforms like the International Medical Device Regulators Forum (IMDRF) and WHO's Digital Health Technical Advisory Group, which can facilitate knowledge-sharing and harmonized standards.[20,21]
- Fostering Health-tech Innovation through Government Initiatives: Start-ups and health-tech companies could seek support of Medtech Mitra for getting handholding support like fostering partnership between health care and IT experts, conducting pre-clinical/clinical evaluation, clinical validation, licensing and regulatory compliances, Health Technology Assessment (HTA), and so on.[22] In addition, Atal Innovation Mission (AIM) of NITI Aayog is established to create and promote a culture of innovation and entrepreneurship across schools, educational organizations, research institutes, and industries, and therefore, start-ups may also take support of AIM.[23]

Conclusion

To fully harness the transformative potential of AI in health care, India or any other country, must prioritize robust "AI in Health care" policy, strategy and regulatory frameworks that address critical challenges while fostering innovation. Establishing harmonized regulations is essential to ensure AI systems are safe, ethical, and effective across jurisdictions. Data privacy must be safeguarded through stringent compliance with national and global standards like GDPR and HIPAA, coupled with advanced encryption and anonymization techniques to protect sensitive patient information. There is a strong need to promote data standardization and interoperability to enable seamless integration of health data for AI applications. By investing in clinician training, PPPs, and regulatory sandboxes, governments can enhance trust, accessibility, and human oversight in AI-driven health care. Through collaborative international efforts and continuous monitoring of AI's long-term impact, governments can create an ecosystem that balances innovation with patient safety, ensuring equitable and resilient health care systems for the future.

While governments lay the foundational framework, the private sector, particularly start-ups and health-tech/med-tech companies, plays a crucial role in developing and deploying these AI solutions. However, they need to do a thorough assessment of end-user needs, understand existing market-ready technologies, ensure AI-enabled technology is clinically validated to avoid false-positive and false-negative outcomes, consider health technology assessment (HTA) results, and an analysis of both national and global health care technology markets. By taking these steps in the start-up journey, the developed AI-enabled health technology can be scaled efficiently and quickly across both public and private health care systems worldwide, bringing about positive transformations in the health care ecosystem.

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Declaration

The views expressed herein are those of the author alone and do not represent those of any government agency, institution, or employer.

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References

1. Ministry of Health and Family Welfare, Government of India. The Clinical Establishments (Registration and Regulation) Act, 2010. New Delhi: Government of India; 2012. Available from: http://clinicalestablishments.gov.in/WriteReadData/386.pdf.
2. Ministry of Health and Family Welfare, Government of India. Electronic Health Record (EHR) Standards for India, Version 2. New Delhi: Government of India; 2016. Available from: https://mohfw.gov.in/sites/default/files/17739294021483341357.pdf.
3. Press Information Bureau (PIB). National Health Portal launched. Ministry of Health & Family Welfare. 2014. Available from: https://www.pib.gov.in/newsite/PrintRelease.aspx?relid=113443.
4. Ministry of Health and Family Welfare, Government of India. National Health Policy 2017. New Delhi: Government of India; 2017. Available from: https://mohfw.gov.in/sites/default/files/9147562941489753121.pdf.
5. Central Bureau of Health Intelligence (CBHI). National Health Profile (NHP) of India – 2015. Ministry of Health and Family Welfare, Government of India; 2015. Available from: https://cbhidghs.mohfw.gov.in/publications/national-health-profile.
6. Ministry of Health & Family Welfare. eSanjeevani. Government of India; 2019. Available from: https://esanjeevani.mohfw.gov.in/#/.
7. NITI Aayog. Comments Invited for Creation of National Health Stack. Press Information Bureau; 2018. Available from: https://www.pib.gov.in/PressReleasePage.aspx?PRID=1538061.
8. National Health Authority. About ABDM, 2021. Available from: https://nha.gov.in/NDHM.
9. Press Information Bureau. Cabinet Approves Implementation of Ayushman Bharat Digital Mission with a Budget of Rs.1600 Crore for Five Years; 2022. Available from: https://www.pib.gov.in/PressReleasePage.aspx?PRID=1801322.
10. The Digital Personal Data Protection Act, 2023, No. 22 of 2023. The Gazette of India: Extraordinary, Part II, Section 1. Ministry of Law and Justice; 2023. Available from: https://www.meity.gov.in/static/uploads/2024/06/2bf1f0e9f04e6fb4f8fef35e82c42aa5.pdf.
11. National Health Authority. ABDM Microsites- Building a Macro-level Digital Health Ecosystem in India. Ayushman Bharat Digital Mission; 2023. Available from: https://abdm.gov.in:8081/uploads/Addl_CEO_letter_and_Microsite_Guidelines_7d16822da9.pdf.
12. Health Insurance Portability and Accountability Act of 1996. Available from: https://www.govinfo.gov/app/details/PLAW-104publ191.
13. European Union. General Data Protection Regulation (GDPR), Chapter 5: Transfers of Personal Data to Third Countries or International Organisations. 2016. Available from: https://gdpr-info.eu/chapter-5/.
14. Hassija V, Batra P, Singh V, et al. Interpretability of Black-Box Models: A Review on Explainable Artificial intelligence (XAI). 2023. Available from: https://iris.uniroma1.it/retrieve/7048d899-3bf4-4706-8033-2a97d3ee0f15/Hassija_Interpreting_2023.pdf.
15. HL7 International. HL7 FHIR, 2023. Available from: https://hl7.org/fhir/.
16. International Medical Device Regulators Forum. Software as a Medical Device (SaMD): Key Definitions. IMDRF; 2013. Available from: https://www.imdrf.org/sites/default/files/docs/imdrf/final/technical/imdrf-tech-131209-samd-key-definitions-140901.pdf.
17. NHS England. NHS Digital Academy. 2017. Available from: https://digital-transformation.hee.nhs.uk/digital-academy/programmes.
18. Innovation, Science and Economic Development Canada. Pan-Canadian Artificial intelligence Strategy. Government of Canada; 2017. Available from: https://ised-isde.canada.ca/site/ai-strategy/en.
19. American Medical Association. AMA Principles for Augmented Intelligence Development, Deployment, and Use. 2023. Available from: https://www.ama-assn.org/system/files/ama-ai-principles.pdf.
20. International Medical Device Regulators Forum. About IMDRF. 2011. Available from: https://www.imdrf.org/about.
21. WHO Digital Health Technical Advisory Group - Membership 2019. Available from: https://www.who.int/groups/dh-tag-membership.
22. Indian Council of Medical Research. MedTech Mitra. 2023. Available from: https://medtechmitra.icmr.org.in/.
23. Atal Innovation Mission (AIM) | Government of India's Flagship Initiative 2016. Available from: https://aim.gov.in/.

REVIEW ARTICLE

Correlates of Anemia in Children Under Five: A Meta-analysis of 1.39 Million Cases in India

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Abstract

Context: To help children grow healthily, early detection and prevention of anemia are necessary.

Objective: The present meta-analysis focused on estimating the pooled prevalence and key risk factors of anemia among children (under 5 years) in this population.

Evidence acquisition: The present study searched PubMed/Google Scholar for studies published (2000–2025), reporting anemia prevalence. A total of 24 studies had 13,90,567 children were included. Data analyses using common/random-effects models were used to estimate pooled prevalence and associated risk factors. Heterogeneity (I^2), subgroup analysis, and publication bias (Egger's test) were assessed. The Newcastle–Ottawa Scale (NOS) was used for quality assessment.

Results: Among 24 studies, the pooled prevalence of anemia among children under five was 62.2% (95% CI: 53.4–70.2%) under the random-effects model. Inter-state prevalence varied from 4.7 to 92.9%, with Uttar Pradesh reporting the highest pooled estimate (77.4%). Toddlers (12–35 months) were identified as a high-risk age-group for anemia, stunting, under-nutrition, and severe anemia in mothers, with almost triple the likelihood of an anemic child. Low iron biomarkers are the best diagnostic parameter for anemia. Heterogeneity was present across studies ($I^2 > 75\%$) with no significant publication bias ($p = 0.203$).

Conclusion: Overall, the study showed anemia continues to affect a large proportion of Indian children, with significant interstate and demographic disparities. Policymakers must target vulnerable groups, significant risk factors, and region-specific strategies to reduce the anemia burden in early childhood.

Keywords: Anemia, Iron deficiency, Meta-analysis, Systematic review, Under-five children.

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Introduction

Anemia in children under 5 years old is a key global public health issue, especially in countries with low to middle incomes. It has been linked to decreased cognitive and motor development, greater susceptibility to infections, poor school performance, and an increased risk of mortality.[1,2] According to the World Health Organization (WHO), "anemia in this age range as hemoglobin (Hb) concentration of <11.0 g/dL, and its prevalence is regarded as an important indication of population health and nutritional status."[3]

India contributes significantly to the global burden of childhood anemia. According to the National Family Health Survey (NFHS-5), the prevalence of anemia among children under age 5 year increased from 59% in 2015–2016 to 67% in 2019–2021.[4] This alarming increase happened despite the adoption of large-scale national initiatives such as the Anemia Mukt Bharat (AMB) project, as well as long-standing interventions through the Integrated Child Development Services (ICDS) and National Iron Plus project (NIPI).[5,6] Such trends highlight the ongoing problem of controlling anemia and call for a rethinking of intervention options.

Several studies carried out in various Indian states have found quite differing anemia prevalence among children, ranging from less than 40% to more than 80%, depending on the population examined, geographical setting, sampling methods, and diagnostic criteria utilized.[7–9] Several risk factors have been identified, including maternal anemia, insufficient nutritional intake, stunting, infections, poor sanitation, socioeconomic level, and limited access to health care.[10,11] However, there is limited synthesis of prevalence data and associated risk variables that use standardized meta-analytic methodologies that bring together findings from various states.

As a result, the purpose of this study is to fill this gap by conducting a systematic review and meta-analysis of available literature on anemia among children aged under 5 years in India.

Objectives

- To estimate the pooled prevalence of anemia among children aged 6–59 months in India.
- To identify regional variations in prevalence and key risk factors contributing to childhood anemia in this population.

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Methodology

Search Eligibility

Protocol and Registration

This systematic review and meta-analysis followed the PRISMA 2020 standards.[12] A formal protocol was created beforehand to guide this assessment process. However, the protocol was not registered with PROSPERO, which is not obligatory due to the study focusing on observational studies.

Study Design

This is a systematic review and meta-analysis that follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 recommendations.

Eligibility Criteria

Studies were selected based on the following criteria given in Table 1.

Search Strategy

Information Source and Search Strategy

"A systematic search was carried out to find relevant studies that reported the prevalence and/or related risk factors for anemia among children under the age of five in India. The databases searched were PubMed, Scopus, Web of Science, and Google Scholar, and the time span covered was 2000–2025. The search approach used a combination of Medical Subject Headings (MeSH) and free-text phrases. Boolean operators (AND/OR) were employed to assure complete recovery." An optimal search string for PubMed was as follows: "*(((((((prevalence) OR (proportion)) OR (incidence)) OR (frequency)) OR (prevalent)) OR (frequence)) OR (occurrence)) AND ((((((anaemia) OR (anemia)) OR (bloodlessness)) OR (iron-deficiency anaemia)) OR (iron-poor blood)) OR (anaemic)) AND (((India) OR (Bharat)) OR (Hindustan)) OR (southAsia)) OR (Indian subcontinent)) OR (Kerala)) OR (Karnataka)) OR (Tamil Nadu)) OR (Andhra Pradesh)) OR (Arunachal Pradesh)) OR (Assam)) OR (Bihar)) OR (Chhattisgarh)) OR (Goa)) OR (Gujarat)) OR (Haryana)) OR (Himachal Pradesh)) OR (Jharkhand)) OR (Madhya Pradesh)) OR (Maharashtra)) OR (Manipur)) OR (Meghalaya)) OR (Mizoram)) OR (Nagaland)) OR (Odisha)) OR (Punjab)) OR (Rajasthan)) OR (Sikkim)) OR (Telangana)) OR (Tripura)) OR (Uttar Pradesh)) OR (Uttarakhand)) OR (West Bengal)) OR (Jammu)) OR (Kashmir)) OR (Ladakh)) OR (Pondicherry)) OR (Delhi)) OR (Andaman)) OR (Nicobar Islands)) OR (Chandigarh)) OR (Orissa)) OR (Dadra)) OR (Nagar Haveli)) OR (Daman)) OR (Diu)) OR (North India)) OR (South India)) OR (Northeast India)) OR (Central India)) OR (East India)) OR (West India)).*"

Table 1: Inclusion and exclusion criteria for study selection

Criteria	*Inclusion*	*Exclusion*
Population	Children aged under 5 years in India	Adults, adolescents, or non-Indian populations
Geographic scope	India	Studies outside India
Study type	Cross-sectional, cohort study	RCTs, editorials, protocols
Outcomes	Prevalence of anemia/age-group/odds/risk ratios for associated factors	No anemia-related outcomes reported
Publication year	2000–2025	Before 2000
Language	English	Non-English

Additional search adjustments included risk factor-related keywords such as "dietary diversity," "socioeconomic status," "maternal anemia," "malnutrition," "sanitation," and "child infections." Filters were used to restrict the results to observational studies (cross-sectional or cohort), published in English, and with a target population of 0–5 years. Duplicates were eliminated, and titles and abstracts were checked for relevancy. The full texts of possibly relevant studies were examined using the predefined inclusion criteria.

Data Extraction

The following data were extracted into a standardized Excel. Study ID, authors, year, country/state, publication details, study design, total sample size and number/anemia cases, prevalence (%) of anemia in defined age-group, age-group(s) studied, diagnostic tool used and anemia cutoff, Risk factors analyzed, effect sizes (ORs, PRs), and 95% CIs, hemoglobin mean if available.

Quality Assessment

The Newcastle-Ottawa Scale (NOS), which was developed for cross-sectional investigations, was used to assess the risk of bias in the included observational studies. The studies were rated as high (7–9), moderate (4–6), or low ($\leq$3) in quality. Studies with significant bias were removed or examined in sensitivity and subgroup analysis.

Data Synthesis and Statistical Analysis

Data analysis was carried out in R 4.3.2/R Studio using the *meta* and *metafor* packages. Due to the expected heterogeneity, the pooled prevalence and odds ratios were estimated using a random-effects model. The I^2 statistic was used to quantify heterogeneity, with values of 25, 50, and 75% indicating low, moderate, and high levels, respectively.[13] The Egger's regression test and funnel plots were used to assess publication bias. The findings were shown as pooled effect sizes with 95% confidence intervals. the p-value <0.05 was considered statistically significant.

Results

Initial database searches yielded a total of 2,318 records (2,218 from PubMed and 100 from Google Scholar's first five pages). After deleting duplicates, only 156 articles were left for title and abstract screening. Of these, 40 full-text papers were assessed, with 14 being removed due to a lack of prevalence or population data. Finally, the quantitative synthesis consisted of 24 studies (Fig. 1).

Study Characteristics

The examined studies included 13,90,567 children under five from various locations in India. The study designs were largely cross-sectional, utilizing both primary and secondary data. WHO criteria were used to determine prevalence (Hb < 11 g/dL), and anemia was measured using HemoCue, cyanmethemoglobin, and colorimetric techniques. Table 2 highlights essential characteristics, risk differences, and effect sizes from several studies.

Pooled Prevalence of Anemia

Figure 1 demonstrates that the pooled prevalence of anemia among children is high. Using a common-effects model using data from 24 studies with a total sample size of 13,90,567 children, the

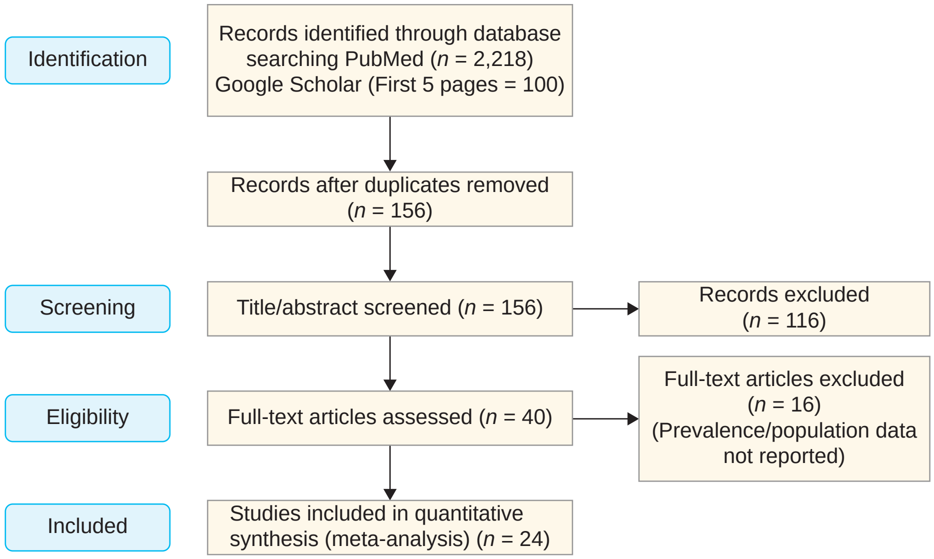

Fig. 1: PRISM diagram for study selection process

Table 2: Summary of studies on childhood anemia and associated risk factors in India

Author	*Year*	*Location*	*Sample Size*	*Prevalence (%)*	*Anemia cases*	*Age-group (months)*	*Risk factors (contrast)*	*Effect sizes*
Bharati et al.[14]	2015	India	35,591	64.7	23,011	6–59	Maternal education (higher vs none)	0.74
Gosdin et al.[15]	2018	Bihar	5,664	68.8	3,893	6–18	Gender (female vs male); caste (OBC vs SC); dietary diversity (adequate vs inadequate); household hunger (high vs low)	0.77; 0.68; 0.87; 1.47
Kalhan et al.[16]	2022	Haryana	170	62.4	106	12–36	Iron supplementation (regular vs none); supplementary nutrition (received vs none); socioeconomic status (upper vs lower); birth order (first vs ≥ third)	6.63; 3.98; 15.43; 13.8
Kumar et al.[17]	2014	New Delhi	1,000	69.6	696	6–30	Plasma folate (linear β); Vitamin B12 (linear β); homocysteine (linear β); stunting (linear β); household income (linear β)	0.35; 0.26; 0.39; 0.10; 0.24
Awasthi et al.[18]	2003	Uttar Pradesh	1,200	70	840	36–60	Underweight (anemia associated); stunted (anemia associated); wasted (anemia associated)	1.66; 1.41; 0.91
Mishra et al.[19]	2016	Uttar Pradesh	4,556	73.9	3,369	6–59	Age (13–24 months vs ref); stunting (stunted vs non-stunted); maternal anemia (anemic vs non-anemic); residence (rural vs urban)	6.05; 4.83; 2.77; 1.78
Sharma et al.[20]	2019	Uttar Pradesh	365	92.9	339	48–71	Stunting (mild anemia vs non-anemic); stunting (moderate anemia vs non-anemic); wasting (moderate anemia vs non-anemic); zinc deficiency (rural vs urban)	36.6; 13.9; 3.7; 2.84
Kumar et al.[21]	2020	Uttar Pradesh	32,103	63.2	20,300	6–59	Maternal education (higher vs none—urban); maternal education (higher vs none—Rural); Maternal anemia (non-anemic vs anemic—urban); maternal Anemia (non-anemic vs anemic—rural); child age-group (48–59 months vs 6–11 months—urban); child age-group (48–59 months vs 6–11 months—rural)	2.16; 1.53; 1.79; 1.84; 2.43; 3.11

(Contd...)

Table 2: *(Contd...)*

Author	*Year*	*Location*	*Sample Size*	*Prevalence (%)*	*Anemia cases*	*Age-group (months)*	*Risk factors (contrast)*	*Effect sizes*
Nair et al.[22]	2023	Telangana	476/316	66.4/47.8	316/151	6–12/29–56	Maternal anemia (Anemic vs non-anemic); Iron biomarker (≥1.9 vs <1.9); Inflammation marker CRP (≥5 vs <5); Child age (29–35 months vs older)	3.31; 2.21; 3.77; 5.29; 4.38; 1.92
Arora et al.[23]	2025	India	1,75,289	68	1,19,197	6–59	Maternal literacy (literate vs illiterate); maternal BMI (underweight vs normal); maternal diet (high vs low diversity); residence (rural vs urban); wealth index (richer vs poorest)	0.77; 1.46; 0.95; 0.95; 0.67
Majumder et al.[10]	2025	India	58,345	79	45,693	6–23	Minimum dietary diversity (met vs unmet); maternal anemia (anemic vs non-anemic); maternal education (higher vs none/low); wealth index (richest vs poorest); recent diarrhea (yes vs no); child sex (female vs male)	0.91; 1.70; 0.70; 0.80; 1.10; 0.90
Singh et al.[24]	2025	India	2,08,007	68	1,41,645	6–59	Child age (12–23 months vs ref); birth order (≥4 vs first-born); maternal anemia (anemic vs non-anemic); maternal education (higher vs lower)	1.10; 1.06; 1.04; 0.94
Das et al.[25]	2024	Odisha	69	82.4	57	0–59	Maternal anemia (descriptive)	NA
Roy et al.[26]	2024	India	1,83,855	66.8	1,23,462	6–59	Never eats fruits (never vs any); never eats fish (never vs any); daily soft drink intake (daily vs seldom/never); Maternal anemia (severe/moderate/mild vs non-anemic); maternal education (no/primary/secondary vs higher); age at first birth (19–29 years vs <19)	1.14; 1.18; 1.12; 2.45; 1.99; 1.48; 1.42; 1.18; 1.07; 0.76
Joshi et al.[27]	2024	India	1,77,695	67	1,19,058	6–59	Mother age (15–19 vs ref); mother education (uneducated vs higher); mother anemia (non-anemic vs anemic); birth order (first child vs higher); religion (Hindu vs other); caste (SC vs general); media exposure (none vs exposed)	2.43; 1.29; 0.60; 0.73; 1.27; 1.11; 1.08
Yadav et al.[28]	2024	India	11,237	40.5/30.0	4,557/3,635	12–59	Age (1 year vs older); maternal education (no schooling vs educated); IFA in pregnancy (<100 tablets vs ≥100); recent illness (yes vs no); iron deficiency (deficient vs sufficient); zinc deficiency (deficient vs sufficient); unsafe feces disposal (unsafe vs hygienic)	1.90; 1.40; 1.30; 1.20; 2.20; 1.30; 1.10
Larson et al.[29]	2024	India	1,238	56	692	6–59	Ferritin, RBC folate, CRP, AGP, retinol, β-thalassemia trait, maternal anemia (Ferritin–β Hb per unit ferritin)	0.9
Singh et al.[7]	2023	India	1,52,752	67.1	1,02,372	6–59	Maternal education (no schooling vs higher); maternal anemia (mild/moderate/severe vs none); household wealth (poorest vs richest)	1.31; 1.45; 1.96; 2.54; 1.07

(Contd...)

Table 2: *(Contd...)*

Author	*Year*	*Location*	*Sample Size*	*Prevalence (%)*	*Anemia cases*	*Age-group (months)*	*Risk factors (contrast)*	*Effect sizes*
Sreeramareddy et al.[30]	2020	India	28,351	69.5	19,715	6–59	Household wealth (poorest vs richest); maternal education (no formal vs higher); maternal anemia (anemic vs non-anemic); residence (rural vs urban)	2.06; 1.19; 2.37; 1.32
Kumar et al.[31]	2021	India	26,910	4.7	1,265	6–59	Parental education (both educated vs none/low); parental employment (Both employed vs one/none); caste (ST vs others)	0.69; 1.40; 1.62
Chandran et al.[32]	2021	Madhya Pradesh	20,102	69.6	14,015	6–59	Maternal age (15–19 vs older); maternal education (no education vs literate); maternal anemia (mild/moderate/severe vs non-anemic); caste (ST vs general); birth weight (VLBW vs normal); nutritional status (severe stunting vs normal)	2.08; 2.25; 1.43; 1.98; 1.85; 1.88; 4.28; 3.19
Sarna et al.[33]	2020	India	7,044	41.6	2,930	12–48	Iron deficiency (deficient vs normal); vitamin A deficiency (yes vs no); inflammation (present vs absent)	1.87; 1.22; 1.37
Sarna et al.[34]	2019	India	1,94,127	59.4	1,15,298	6–59	Household wealth (poorest vs richest); caste (SC/ST vs others); residence (rural vs urban); maternal anemia (anemic vs non-anemic); maternal education (no education vs literate)	1.55; 1.35; 1.13; 1.74; 1.22
Baranwal et al.[35]	2014	India	52,868	61	32,191	0–59	Toilet facility (present vs absent); pucca housing (pucca vs kutcha); clean cooking fuel (clean vs biomass); smoking exposure (exposed vs not); female child (female vs male); age (6–23/24–59 vs ref); Caste (SC vs general); religion (Hindu vs others); primary education (primary vs none); wealth (poor vs richest); media exposure (TV vs No TV)	0.89; 0.87; 0.87; 1.15; 1.05; 0.80; 0.73; 1.31; 1.60; 0.92; 1.06; 0.91

pooled prevalence of anemia was estimated to be 64.6% (95% CI: 64.56–64.72%). Given the variability across the included studies, a random-effects model was also used, providing a somewhat lower but more cautious prevalence estimate of 62.2% (95% CI: 53.4–70.2%) (Fig. 2).

The prevalence rates reported across different studies range from 4.7 to 92.9%, indicating regional and methodological variations. The study found significant heterogeneity ($p < 0.05$), with an $I^2 = 99.9\%$, a $\tau^2 = 0.8686$, and an $H = 37.67$, indicating that most of the observed variation in anemia prevalence was real.

Subgroup Analysis by Region

Figure 3 displays a subgroup analysis by geographic region, revealing significant variance in anemia prevalence among states. In Uttar Pradesh, the aggregated prevalence from four studies was found to be 77.4% (95% CI: 61.9–87.9%), showing a very high burden. In comparison, the Telangana subgroup (two studies) revealed a much lower prevalence of 57.5% (95% CI: 44.2–69.7%). The single research investigation from Odisha found the most significant prevalence of 82.6% (95% CI: 71.8–89.9%). While 15 national studies found a pooled prevalence of 54.9% (95% CI: 42.3–66.9%), indicating a reduced burden when averaged across all regions. The random-effects model revealed statistically significant between-group heterogeneity ($Q = 22.10$, $df = 7$, $p = 0.0024$), confirming that geographical differences contribute significantly to overall variation in anemia prevalence estimates.

Risk Factors for Anemia

A meta-analysis of effect size from reviewed articles showed several significant predictors of anemia in Indian children. The strongest association was seen for children aged 12–35 months, with a pooled adjusted odds ratio (aOR) of 6.62 (95% CI: 5.60–13.58), showing that children in this age range are at significantly higher risk than other age-groups. Stunting was also strongly associated with anemia (pooled aOR = 3.32, 95% CI: 1.98–7.78), which shows the interrelated nature of chronic undernutrition and hemoglobin deficiency. Other significant predictors included undernutrition (composite index) (aOR = 3.71, 95% CI: 2.12–7.70) and low iron biomarkers, such as serum ferritin/transferrin receptor levels (aOR = 4.21, 95% CI: 2.23–9.71). Maternal severe anemia emerged as

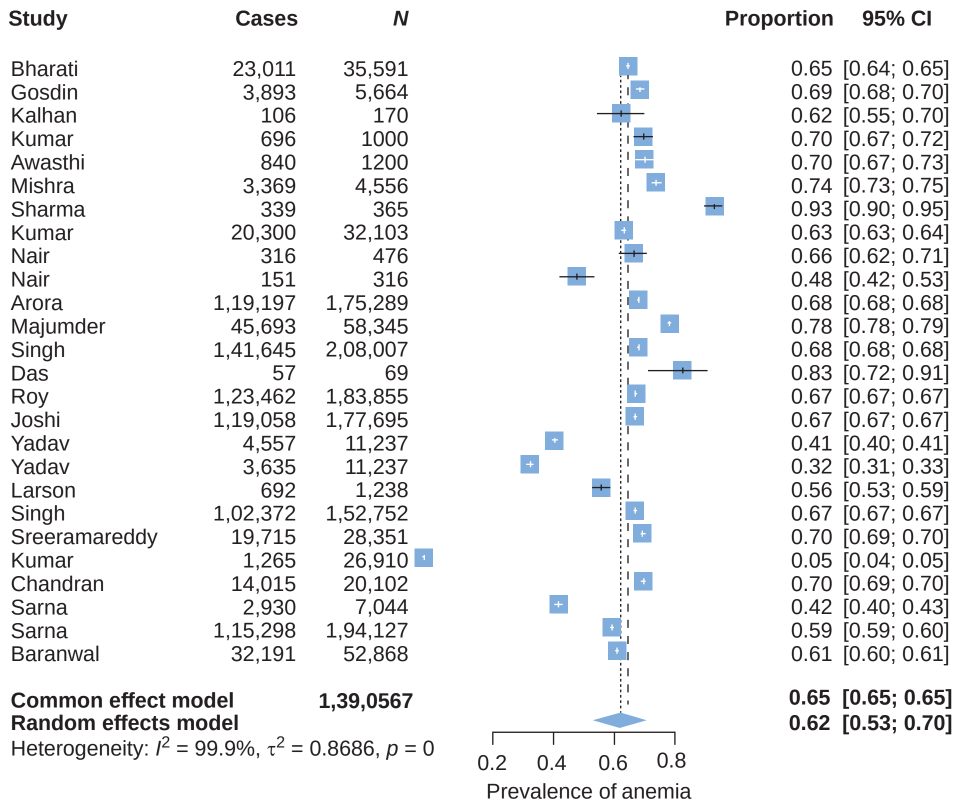

Fig. 2: Pooled prevalence of anemia among children under 5 years in India

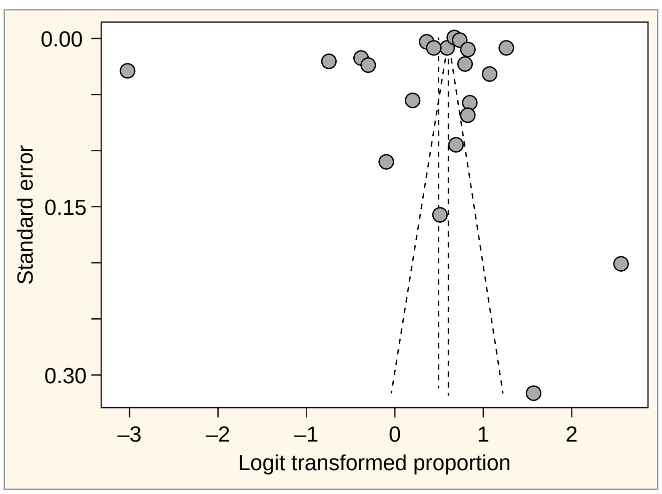

Fig. 3: Subgroup analysis of prevalence of anemia among children under 5 years in India

Table 3: Important predictors of anemia among children under five in India

Risk factor	*Pooled OR*	*95% CI*	I^2	*p-value*
Maternal severe anemia	2.45	2.27–2.64	75.30%	<0.001
Child age (12–35 months)	6.62	5.60–13.58	96.30%	<0.001
Stunting	3.32	1.98–7.78	86.20%	<0.001
Undernutrition (composite)	3.71	2.12–7.70	85.90%	0.02
Low iron biomarkers	4.21	2.23–9.71	95.90%	0.005
Low maternal education	2.01	1.60–2.52	80.0%	<0.001

CI, confidence interval; I^2, inconsistency index indicating between-study heterogeneity; OR, odds ratio; $p < 0.05$ considered significant

a significant upstream determinant (aOR = 2.45, 95% CI: 2.27–2.64), underscoring the intergenerational risk of poor maternal health on child outcomes. Heterogeneity across studies was significant (I^2 = 75.3–96.3%, $p < 0.05$), showing variation in study settings, demographic variables, and measurement approaches (Table 3).

Publication Bias

In Figure 4, the funnel plot showed mild asymmetry, primarily among smaller studies. However, Egger's regression test was not statistically significant ($t = -1.31$, $p = 0.203$), indicating no strong evidence of publication bias, which indicated asymmetry presented due to heterogeneity across studies in sample size and other factors.

Discussion

The findings provided compelling evidence of the significant burden of anemia among children under the age of five in India,

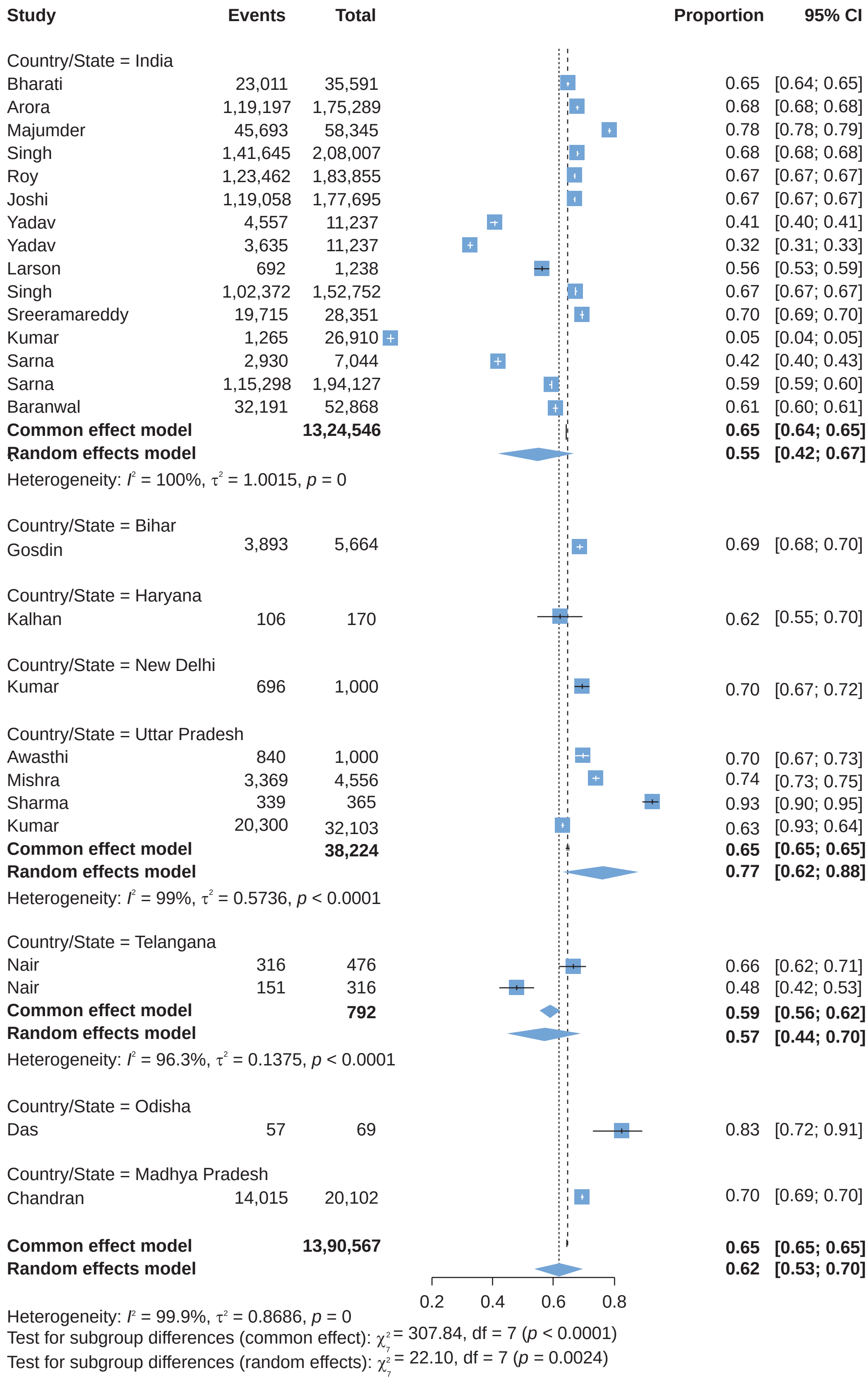

Fig. 4: Funnel plot of studies included in meta-analysis

based on data from over 1.39 million children across 24 studies. The overall pooled prevalence was calculated to be 64.6% (95% CI: 64.56–64.72%) (common-effects model) and 62.2% (95% CI: 53.4–70.2%) (random-effects model). The result is consistent with the Global Nutrition Report and NFHS-5 (2019–2021), both of which underscore childhood anemia as a major public health issue in India.[4,36] Heterogeneity ($I^2 = 99.9\%$) observed across studies reflects the variation in socioeconomic and demographic settings, dietary patterns, maternal health, and regional disparities. Kumar et al.[31] found the lowest reported prevalence (4.7%) in households experiencing the "triple burden" of anemia, where anemia was present in the child, mother, and father at the same time, because the study represented a more restricted subgroup rather than the general under-five population. The highest (92.9%) was observed in Uttar Pradesh-based primary data, reflecting acute regional disparity.[20]

The sub-group analysis found significant inter-state differences, confirming that anemia prevalence is not uniformly distributed across India. Uttar Pradesh reported a high anemia prevalence of 77.4% which aligns with recent regional reports on poor maternal and child health indicators in UP.[37] However, Telangana showed a lower pooled estimate (57.5%), reflecting improvements in public nutrition schemes such as POSHAN Abhiyaan.[38] Odisha, representing a tribal-dense children, reported the highest single-state burden (82.6%), emphasizing the vulnerability of particularly vulnerable tribal groups in remote districts.[25] The pooled prevalence of 54.9% at the national level based on 15 studies suggests that aggregating data at the macro level may cover subnational heterogeneity in anemia prevalence.

Further, risk factor synthesis depicts the top six correlates of anemia among children under five, in which child age (12–35 months) emerged as the vulnerable age-group with 6.62 times higher risk than other age-groups under age five, consistent with known vulnerability during rapid growth phases, high nutrient demands, and sub-optimal complementary feeding.[39] Stunting was another important predictor, with 3.32 times the odds of anemia compared to no stunting, indicating the correlation between chronic undernutrition and anemia. This is consistent with biological evidence that linear growth slowing changes iron metabolism and immunity.[40] Low iron indicators (ferritin/transferrin saturation) were associated with 4.21 times greater odds of anemia in Indian children, indicating iron deficiency as the primary cause.[29,33]

Undernutrition and maternal severe anemia have a significant impact on anemia, highlighting intergenerational effects. This supports earlier research showing that maternal micronutrient deficiencies directly affect child hematological development and postnatal anemia risk.[26,30] Low maternal education was 2.01 times increase the odds of childhood anemia, aligning with maternal literacy improves feeding practices, healthcare-seeking behavior, and compliance with iron-folic acid (IFA) supplementation programs.[14,34]

Hence, overall, the meta-analysis supports the urgent need for targeted anemia control programs for under five age-group in high-burden states such as Uttar Pradesh and Odisha. Interventions must concentrate on children aged 12–35 months/the malnourished group/mothers with anemia/low education. While India has adopted ambitious programs like Anemia Mukt Bharat, the persistently high anemia rates shown in the analysis recommend a gap in implementation, uptake, or effectiveness.[5]

Conclusion

In summary, this study demonstrates that child anemia with a pooled prevalence of 62.2% is the most important public health concern in India. With decades of national nutritional initiatives, the load remains significant, predominantly in north-eastern regions such as Uttar Pradesh/Odisha. The study offers several insights into the population. Child anemia has several risk factors, such as anemia among mothers, child stunting, a lack of nutritional diversity, a vulnerable age-group of 12–35 months, low maternal education, and low iron biomarkers. These findings underline the inter-generational and multifaceted characteristics of child anemia, advocating for synchronized interventions that target maternal health, household nutrition, sanitation, and socioeconomic profile.

Limitations

This study has some limitations. This study used a cross-sectional design, and the diversity in hemoglobin assessment methodologies and anemia classifications may have introduced measurement bias. Confounding factors such as infections, parasite burden, and hereditary hemoglobinopathies were included due to the scarcity of studies.

Policy Implications

From last two decades, there has been growing trend seen among anemia in all age-groups especially in childrens which lead to be the reason of national embarrassment for India. Among all developing countries, our country was the first to establish a national-level anemia program in 1970, the National Nutritional Anemia Prophylaxis Program (NNAPP).[41] Nutritional Anemia Prophylaxis Program (NNAPP) launched to target pregnant/lactating women, children aged 6–59 months. Later on, eleventh five year plan launched on time based aim to reducing anemia prevalence up to 50% by 2012.[42] Further, in 2018, The government started the Anemia Mukt Bharat plan with specially focused on reducing anemia prevalence by three percent points per year among children/adolescents/women of reproductive age and pregnant women between 2018 and 2022.[5] Conversely, childhood anemia prevalence increase by 8.5%.[43] Due to inter/intra-state variations, the goal of national policies is unlikely to be reached. Improvement in translation policy relating to health and nutrition may improve the performance. Anemia prevention through targeting these risk factors and controlling them together is essential to bridge the existing knowledge and implementation gap.

References

1. Stevens GA, Finucane MM, De-Regil LM, et al. Nutrition Impact Model Study Group (Anaemia). Global, regional, and national trends in haemoglobin concentration and prevalence of total and severe anaemia in children and pregnant and non-pregnant women for 1995–2011: A systematic analysis of population-representative data. Lancet Glob Health 2013;1(1):e16–e25. DOI: 10.1016/S2214-109X(13)70001-9.
2. Black RE, Victora CG, Walker SP, et al. Maternal and Child Nutrition Study Group. Maternal and child undernutrition and overweight in low-income and middle-income countries. Lancet 2013;382(9890):427–451. DOI: 10.1016/S0140-6736(13)60937-X. Erratum in: Lancet 2013;382(9890):396.
3. WHO. Haemoglobin concentrations for the diagnosis of anaemia and assessment of severity. Vitamin and Mineral Nutrition Information System. Geneva: World Health Organization; 2011. Available from http://www.who.int/vmnis/indicators/haemoglobin.pdf.

4. International Institute for Population Sciences (IIPS) and ICF. National Family Health Survey (NFHS-5), India, 2019–2021: Compendium of Key Indicators. Mumbai: IIPS; 2021.
5. Ministry of Health and Family Welfare. Anemia Mukt Bharat Strategy Document. Government of India; 2018.
6. Kapil U. Integrated Child Development Services (ICDS) scheme: A program for holistic development of children in India. Indian J Pediatr 2002;69(7):597–601. DOI: 10.1007/BF02722688.
7. Singh SK, Lhungdim H, Shekhar C, et al. Key drivers of reversal of trend in childhood anaemia in India: Evidence from Indian demographic and health surveys, 2016–2021. BMC Public Health 2023;23:1574. DOI: 10.1186/s12889-023-16398-w.
8. Preethi V, Hemalatha V, Arlappa N, et al. Trends and predictors of severe and moderate anaemia among children aged 6-59 months in India: An analysis of three rounds of National Family Health Survey (NFHS) data. BMC Public Health 2024;24(1):2824. DOI: 10.1186/s12889-024-20328-9.
9. Kanjilal B, Mazumdar PG, Mukherjee M, et al. Nutritional status of children in India: Household socio-economic condition as the contextual determinant. Int J Equity Health 2010;9:19. DOI: 10.1186/1475-9276-9-19.
10. Majumder K, Sarkar M, Mallick R, et al. Unveiling the nexus between minimum dietary diversity and anemia among children aged 6–23 months in India: Evidence from NFHS-5 (2019–2021). Cogent Social Sci 2025;11(1):2438845. DOI: 10.1080/23311886.2024.2438845.
11. Goswami S, Acharjee R, Dey S. Determinants of anaemia among children aged under five years in Assam, India. Int J Contemp Pediatr 2020;7(11):2157–2162. DOI: 10.18203/2349-3291.ijcp20204550.
12. Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ 2021;372:n71. DOI: 10.1136/bmj.n71.
13. Higgins JP, Thompson SG, Deeks JJ, et al. Measuring inconsistency in meta-analyses. BMJ 2003;327(7414):557–560. DOI: 10.1136/bmj.327.7414.557.
14. Bharati S, Pal M, Chakrabarty S, et al. Socioeconomic determinants of iron-deficiency anemia among children aged 6 to 59 months in India. Asia Pac J Public Health 2015;27(2):NP1432–NP1443. DOI: 10.1177/1010539513491417.
15. Gosdin L, Young MF, Engle-Stone R, et al. The co-occurrence of anaemia and stunting in young children. Matern Child Nutr 2018;14(3):e12597. DOI: 10.1111/mcn.12597.
16. Kalhan M, Garg S, Sharma S, et al. Prevalence of anemia among toddlers (12–36 months) in urban area of district Rohtak, Haryana. J Family Med Prim Care 2022;11(6):2532–2536. DOI: 10.4103/jfmpc.jfmpc_1469_21.
17. Kumar T, Taneja S, Yajnik CS, et al. Prevalence and predictors of anemia in a population of North Indian children. Nutrition 2014;30(5):531–537. DOI: 10.1016/j.nut.2013.09.015.
18. Awasthi S, Das R, Verma T, et al. Anemia and undernutrition among preschool children in Uttar Pradesh, India. Indian Pediatr 2003;40:985–990. PMID: 14581738.
19. Mishra N, Kumar S, Parveen K. Essential determinants of anaemia among children of Uttar Pradesh (India): Evidence from National Family Health Surveys. Indian J Community Health 2016;28(3): 254–259.
20. Sharma U, Yadav N. Prevalence and risk factors of anemia and zinc deficiency among preschoolers of Allahabad District. Indian J Public Health 2019;63(1):79–82. DOI: 10.4103/ijph.IJPH_342_17.
21. Kumar A, Gulati BK, Sahu D, et al. Socioeconomic determinants of anaemia in preschool children in Uttar Pradesh: Evidence from NFHS-4 survey. Int J Community Med Public Health 2020;7(11):4461–4466. DOI: 10.18203/2394-6040.ijcmph20204745.
22. Nair KM, Balakrishna N, Rao BSN, et al. Characterisation of anaemia and associated factors among infants and pre-schoolers from rural India. Public Health Nutr 2023;26(8):1779–1792. DOI: 10.1017/S1368980015002050.
23. Arora P, Bhatia M, Dwivedi LK. Co-occurrences of forms of child undernutrition in India: Insights from the National Family Health Survey. Nutrients 2025;17(6):977. DOI: 10.3390/nu17060977.
24. Singh M, Carvalho AM, Barik S, et al. Coexistence of anemia with stunting, wasting, and underweight among children aged 6–59 months: Insights from the National Family Health Survey. Research Square 2025. DOI: 10.21203/rs.3.rs-6437332/v1.
25. Das A, Ghosal J, Khuntia HK, et al. Malnutrition and anemia among particularly vulnerable tribal groups of Odisha, India: Needs for context-specific intervention. Indian J Community Med 2024;49(3):519–528. DOI: 10.4103/ijcm.ijcm_452_23.
26. Roy TB, Das P, Das T. Unique contribution of maternal factors and its association with anemia among under-5 children in Indian context. Glob Soc Welf 2024;11:45–60. DOI: 10.1007/s40609-023-00289-4.
27. Joshi A, Tanwar D, Dubey PK, et al. Unveiling the spatial pattern and determinants of child anaemia in India: National Family Health Survey-5 chronicles (NFHS-5). Scr Med 2024;55(2):137–148. DOI: 10.5937/scriptamed55-47571.
28. Yadav K, Ramaswamy G, Puri S, et al. Prevalence and determinants of anemia due to micronutrient deficiencies among children aged 12–59 months in India: Evidence from Comprehensive National Nutrition Survey, 2016–18. PLOS Glob Public Health 2024;4(1):e0002095. DOI: 10.1371/journal.pgph.0002095.
29. Larson LM, Thomas T, Kurpad AV, et al. Predictors of anaemia in mothers and children in Uttar Pradesh, India. Public Health Nutr 2024;27(1):e30. DOI: 10.1017/S1368980024000028.
30. Sreeramareddy CT, Shankar RP, Chuni N. Socioeconomic determinants of anemia in young children in India. Child Youth Serv Rev 2020;119:105546. DOI: 10.1542/peds.2009-3108.
31. Kumar P, Chauhan S, Patel R, et al. Anaemia among mother–father–child pairs in India: Examining co-existence of triple burden of anaemia in a family. BMC Public Health 2021;21(1):1341. DOI: 10.1186/s12889-021-11408-1.
32. Chandran V, Kirby RS. Social determinants of anemia among children in Madhya Pradesh: Evidence from NFHS-4. Int J Environ Res Public Health 2021;18(6):3105. PMID: 33802946.
33. Sarna A, Porwal A, Ramesh S, et al. Characterisation of the types of anaemia prevalent among children and adolescents aged 1–19 years in India: A population-based study. Lancet Child Adolesc Health 2020;4(8):515–525. DOI: 10.1016/S2352-4642(20)30094-8.
34. Sarna A, Porwal A, Ramesh S, et al. Socioeconomic determinants of anemia among children in India. Public Health 2019;175:90–98. DOI: 10.1016/j.puhe.2019.06.007.
35. Baranwal A, Baranwal A, Roy N. Association of household environment and prevalence of anemia among children under-5 in India. Front Public Health 2014;2:196. DOI: 10.3389/fpubh.2014.00196.
36. Development Initiatives. (2021). 2021 Global Nutrition Report. Available from: https://globalnutritionreport.org/reports/2021-global-nutrition-report/.
37. Mandal S, Behera J, Shit B, et al. Regional disparity of anemia among children and its determinants: A study of National Family Health Survey-5. Indian J Public Health 2024;68(3):450–453. DOI: 10.4103/ijph.ijph_943_23.
38. NITI Aayog. Transforming Nutrition in India: POSHAN Abhiyaan: A Progress Report. New Delhi: NITI Aayog; 2018. Available from: https://www.niti.gov.in/sites/default/files/2020-02/POSHAN_Abhiyaan_first_progress_report_6_Feb_2019.pdf. [Last accessed August, 2025].
39. Dewey KG, Adu-Afarwuah S. Systematic review of the efficacy and effectiveness of complementary feeding interventions in developing countries. Matern Child Nutr 2008;4 Suppl 1:24–85. DOI: 10.1111/j.1740-8709.2007.00124.x.
40. Kinyoki DK, Osgood-Zimmerman AE, Pickering BV, et al. Mapping child growth failure across low- and middle-income countries. Nature 2020;577(7789):231–234. DOI: 10.1038/s41586-019-1878-8.
41. Kapil U, Chaturvedi S, Nayar D. National nutrition supplementation programmes. Indian Pediatr 1992;29:1601–1613. PMID: 1291517.
42. Planning Commission. Eleventh Five Year Plan (2007–2012). New Delhi: Government of India; 2008. Available from: https://www.niti.gov.in/sites/default/files/2023-08/11th_vol1.pdf.
43. Kurpad, AV, Sachdev HS. Childhood and adolescent anemia Burden in India: The way forward. Indian Pediatr 2022;59:837–840. DOI: 10.1007/s13312-022-2639-6.

REVIEW ARTICLE

Government Initiatives to Address Maternal Mortality in India: A Review

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Abstract

In India, the maternal mortality rate (MMR) decreased from 384 in 2000 to 103 per 100,000 live births in 2020. According to available data, MMR in India has declined by 6.36%, which remains higher than the global average decline in maternal mortality. The main causes of maternal death include hypertensive disorders of pregnancy, hemorrhage, obstetric complications, and pregnancy-related infections. This paper aims to assess the trends and causes of maternal mortality in India. It also sheds light on the government's health programs and schemes aimed at reducing maternal deaths.

We analyzed the MMR from 2004 to 2025 and identified contributing factors using nationally published data, including the Sample Registration System (SRS), National Family Health Survey (NFHS), WHO, UNICEF, the Ministry of Health and Family Welfare (MoHFW) annual reports, and official websites. India aimed to achieve SDG 3 by 2020 to reduce maternal deaths to 100 per 100,000 births. The Indian Government adopted various strategies to lower MMR by implementing and strengthening interventions and programs, such as Janani Suraksha Yojana (JSY), Pradhan Mantri Surakshit Matritva Abhiyan (PMSMA), Janani Shishu Suraksha Karyakram (JSSK), PMMVY, LaQshya, the Reproductive and Child Health (RCH) portal, and Birth Waiting Homes. The operationalization of First Referral Units and Surakshit Matritva Aashwasan has contributed to increased institutional deliveries, better delivery and postdelivery care, more regular ANC contacts, improved diet, screening of high-risk pregnancies, and comprehensive care from early ANC through the child's first immunization.

Keywords: Antenatal care, Health facility, Maternal mortality ratio, Sustainable development goals.

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Introduction

Women significantly play an important role in society in raising children and shaping the country's future. Almost 50% of the Indian population is women, and 22.2% are of reproductive age.[1] During reproductive age, women are the most vulnerable group and they need good health services. Due to a lack of good health services, we lose these women, i.e., a huge loss of families and society.[2] There was a global maternal mortality rate (MMR) decline of around 40%, from 328 deaths to 197 deaths per 100,000 live births from 2000 to 2020.[3–5] This is around a 2.1% reduction in the annual average rate of MMR.[6,7]

The Bhore Committee reported that MMR in India during the 1940s was around 2,000. The Sample Registration System (SRS) was over 800 during 1970, over 500 during 1980, and more than 400 in 1990. Maternal mortality rate in India declined from 254 to 113 in 2004–2018.[8,9]

National Rural Health Mission (NRHM) and the Reproductive and Child Health (RCH) program are taking several initiatives to reduce the MMR in India. Still, some contributing factors to MMR include maternal age, education, socioeconomic status, and environmental conditions. The current challenge for the government is to identify gaps in health services, society, and individual accessibility and utilization of health facilities.[10]

Methodology

We selected national data to observe the MMR and cause distribution in India. We extracted MMR estimates from 2004 to 2021 of India based on individual states, major regions, National Family Health Survey (NFHS), SRS, government reports, Rural Health Statistics bulletin from Census, and Health Management Information System.

The NFHS analyzed trends in maternal health Indicators. It provides information about trends in four or more antenatal care visits, full immunization, and institutional childbirth at government facilities in rural and urban.[11]

We have considered the WHO, UNICEF, Ministry of Health and Family Welfare (MoHFW) annual official reports, and websites to assess the reach of government efforts to pregnant women by gathering information on improvement in maternal health. Additionally, we used literature reviews on the causes of death data.

Maternal Mortality Trends in India: According to the Registrar General of India, Sample Registration System (RGI-SRS) report MMR has reduced over the years that is 254 during 2004–2006, 103 in 2017–2019, 97 in 2018–2020, 93 in 2019–2021, and 88 in 2020–2025 as shown in Table 1.[12] So it can be analyzed that there is progressive reduction in the MMR ratio as indicated in Table 1 and Figure 1.

Table 1: Registrar General of India, SRS data on MMR in India (2004–2022)

Year	*MMR per 100,000 live births*
2004–2006	254
2007–2009	212
2010–2012	178
2011–2013	167
2014–2016	130
2015–2017	122
2016–2018	113
2017–2019	103
2018–2020	97
2019–2021	93
2020–2022	88

MMR, maternal mortality rate

Source: SRS (2004–2022)[13]

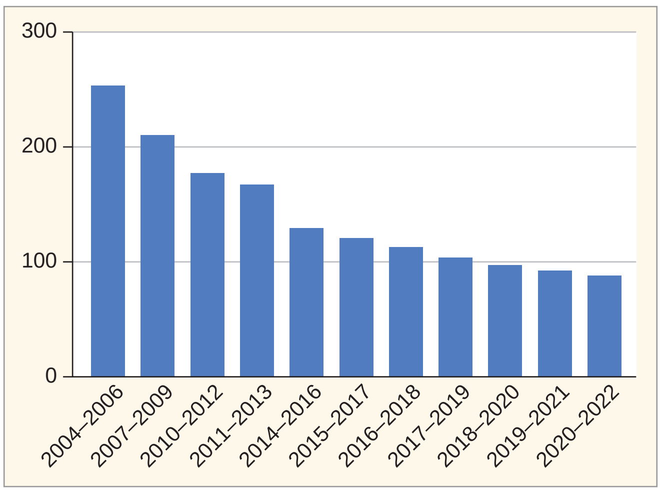

Fig. 1: Registrar General of India, SRS, yearly data on reduction in the MMR in India (2004–2022)

Intrastate Disparities in MMR

The SRS has been categorized into different groups, namely, empowered action group states comprising Andhra Pradesh, Assam, Bihar, Chhattisgarh, Rajasthan, Jharkhand, Odisha, Madhya Pradesh, Southern States Kerala, Telangana, Karnataka, Tamil Nadu, Uttar Pradesh, Uttarakhand, and other states covering the remaining states/UTs. According to 2020–2022 SRS data, the state with the highest MMR is 159 in Madhya Pradesh, followed by 141 in Uttar Pradesh, 136 in Odisha, 125 in Assam, 105 in West Bengal, 104 in Uttrakhand, 92 in Punjab, 91 in Bihar, 89 in Haryana, 87 in Rajasthan, 81 in other states, 58 in Karnataka, 55 in Gujarat, 50 in Jharkhand and Telangana, 47 in Andhra Pradesh, 38 in Tamil Nadu, 36 in Maharashtra, and 18 in kerala, as shown in Figure 2.[7,13]

Major Causes of Maternal Mortality in India

The International Classification of Diseases-10 divides the causes of maternal mortality into direct obstetric deaths (i.e., incorrect treatment, omissions), indirect obstetric deaths (deaths from a previously existing disease).[14]

Say et al. study in 2014 reported that from 2003 to 2009, all maternal deaths, around 73%, were attributable to direct obstetric causes, and 27% of deaths were caused by indirect causes.[15] The prime reasons for maternal mortality, in descending order, are as follows: Postpartum hemorrhage 27%, hypertension 14%, sepsis 11%, abortion 8%, and embolism 3%.[15,16]

According to WHO 2019, major causes of maternal death were maternal infections, hypertension-related disorders of pregnancy such as preeclampsia and eclampsia, severe hemorrhage, unsafe abortion, cardiac conditions, diabetes mellitus, and HIV/AIDS.[16,17]

A study by Montgomery et al. in 2014 reported that maternal mortality in India is almost 80% due to direct obstetric causes.[18] The same study also reported that obstetric complications lead to over 20%, and obstetric hemorrhage causes around 25% of total maternal mortality.[18] Similarly, a study demonstrated that the major cause of maternal mortality was obstetric, 47% due to hemorrhage, especially in poorer states, hypertensive disorders of pregnancy were around 7%, and pregnancy-related infection was 12%.[19] A similar report of the Million Death Study by SRS in 2021 reported that the prime reason for maternal death in India is obstetric hemorrhage, unsafe abortions, excessive bleeding, childbirth, or soon after delivery.[13]

Kaur et al. reported that socio-cultural, individual and family level, and healthcare systems, such as gender (male) child preference, home delivery, lack of antenatal care, danger signs of pregnancy, lack of knowledge about family planning, and non-availability of doctors at the time of consultation in the emergency, were major causes of maternal death.[11,19] Similarly, a study by Hamal et al. reported that caste/ethnicity, economic condition, education, religion, gender, and cultural beliefs were major contributing factors of maternal health in India.[20]

Results and Discussion

In India, maternal health programs during the post-independence era are the Reproductive Child Health (RCH I), Child Survival and Safe Motherhood Programme (CSSM), and NRHM. These programs are implemented in different ways, like the establishment of blood storage units, training of skilled birth attendants, First Referral Units (FRUs), and demand-side financing programs.[21]

Institutional delivery of babies is promoted in the Janani Suraksha Yojana (JSY). It was launched in 2005 by the government of India to reduce newborn and maternal deaths in India. This is a 100% sponsored program by the government of India that integrates cash assistance, ensuring safe delivery, emergency obstetric care, and post-delivery care.[14] The institutional delivery has also increased among rural families, which is the key outcome of this scheme (JSY). Janani Suraksha Yojana assigns Accredited Social Health Activists (ASHA) workers who are major contributors to promoting and encouraging institutional deliveries in rural areas. According to the NFHS, institutional births have increased from 40.8% in 2005–2006 (NFHS-3), 78.9% in 2015–2016 (NFHS-4), to 88.6% in 2019–2021 (NFHS-5). Around 7.39 lakhs beneficiaries availed facilities in 2005–2006, the scheme provides benefits to more than 1 crore beneficiaries every year, as shown in Figure 3.[22]

The Indian Government launched Janani Shishu Suraksha Karyakram (JSSK) in 2011, providing free facilities for pregnant women and newborns. The scheme focuses on cashless deliveries, free medicines and consumables, cashless cesarean sections, free diagnostics and treatment, and dietary support during hospital stays in government hospitals.[23]

Janani Shishu Suraksha Karyakram also offers additional benefits such as exemption from user charges, free blood supply,

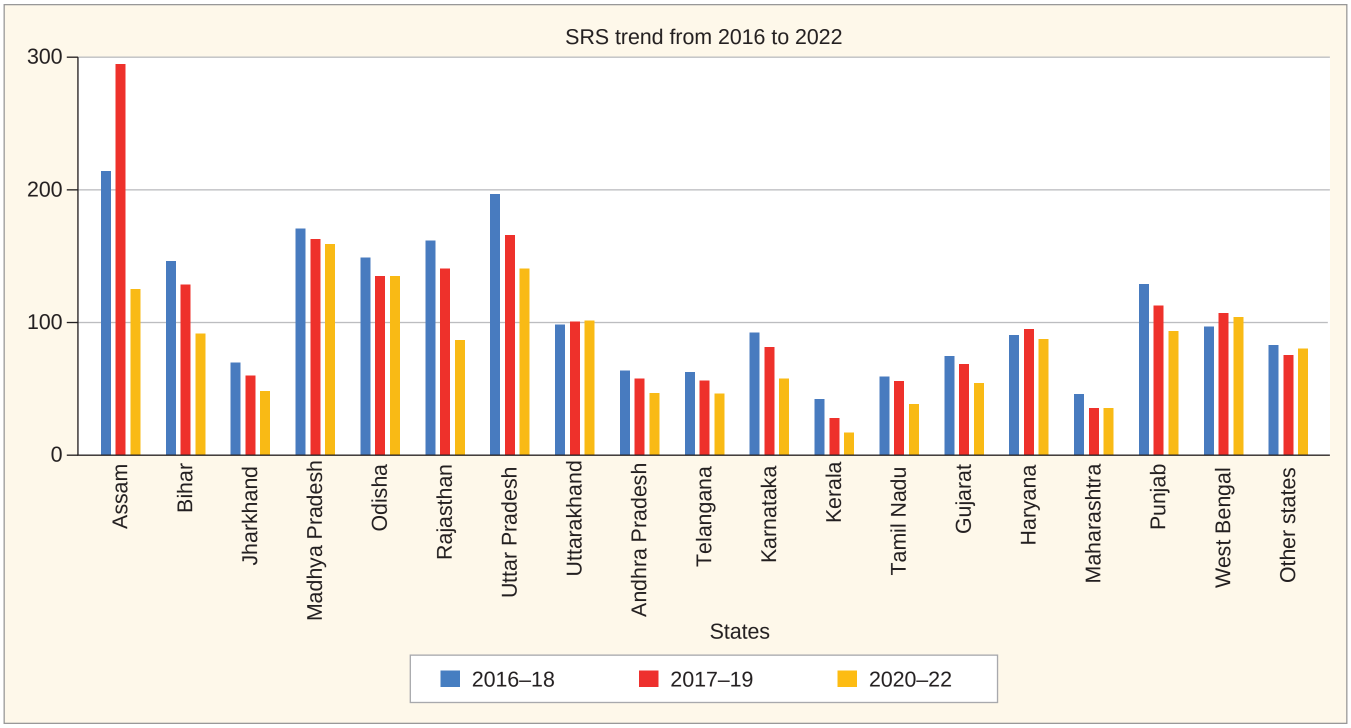

Fig. 2: The SRS data on state-wise MMR in India (SRS 2022)

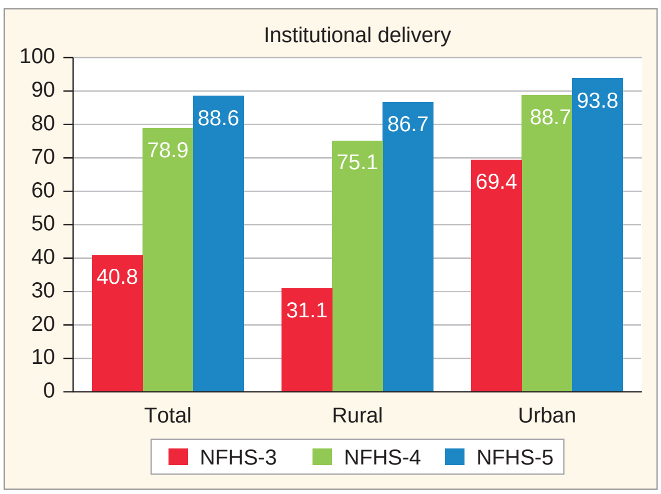

Fig. 3: Trends of NFHS data for institutional delivery in rural and urban India

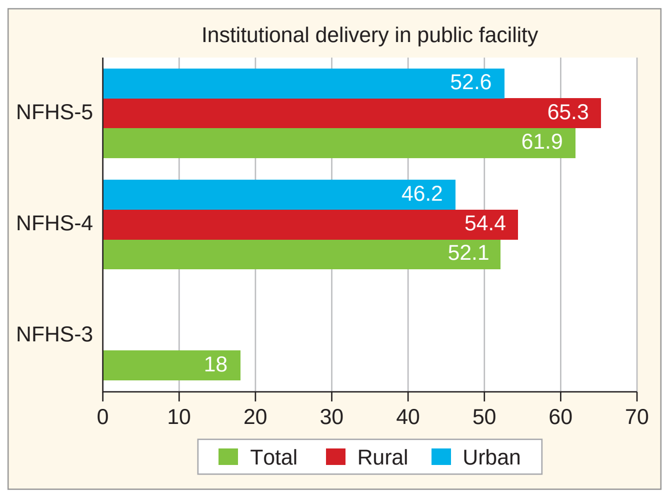

Fig. 4: National Family Health Survey data on institutional delivery in public facilities in rural and urban India

transportation from home to hospital, free interfacility transport in case of referrals, and free drop-off from hospital to home after 48 hours of delivery through Khusiyon Ki Sawari and 104 ambulance services. The scheme was revised in 2013 to fill gaps during the antenatal and postnatal periods, as well as for ill infants.[23,24]

Pregnant mothers are utilizing government health facilities through the JSY and JSSK programs, with more than 1.34 crore mothers delivering in government hospitals in 2018–2019. National Family Health Survey-5 reports that institutional births in public facilities increased from 52.1 to 61.9% (Fig. 4).[25,26]

In 2013, the RMNCH+A (Reproductive, Maternal, Newborn, Child, and Adolescent Health) was introduced to address causes of mortality in women and children, as well as to prevent delays in accessing and utilizing healthcare facilities.[22] The RMNCH+A program was developed to promote an understanding of the "continuum of care" to ensure equal focus on other age groups, such as pregnancy, childbirth, the newborn period, children, and adolescents. Facilities should be available within the community, referral hospitals, and outpatient health services. The referral hospital, including skilled care at birth, childbirth, management of pregnancy complications, emergency obstetric care, the immediate postpartum period, blood transfusion, hysterectomy, induction or augmentation of labor, cesarean section, and assessment of maternal and fetal health—including nutritional status (four antenatal care visits) at outpatient health facilities.[11] Additionally, community-level information and counseling should focus on birth

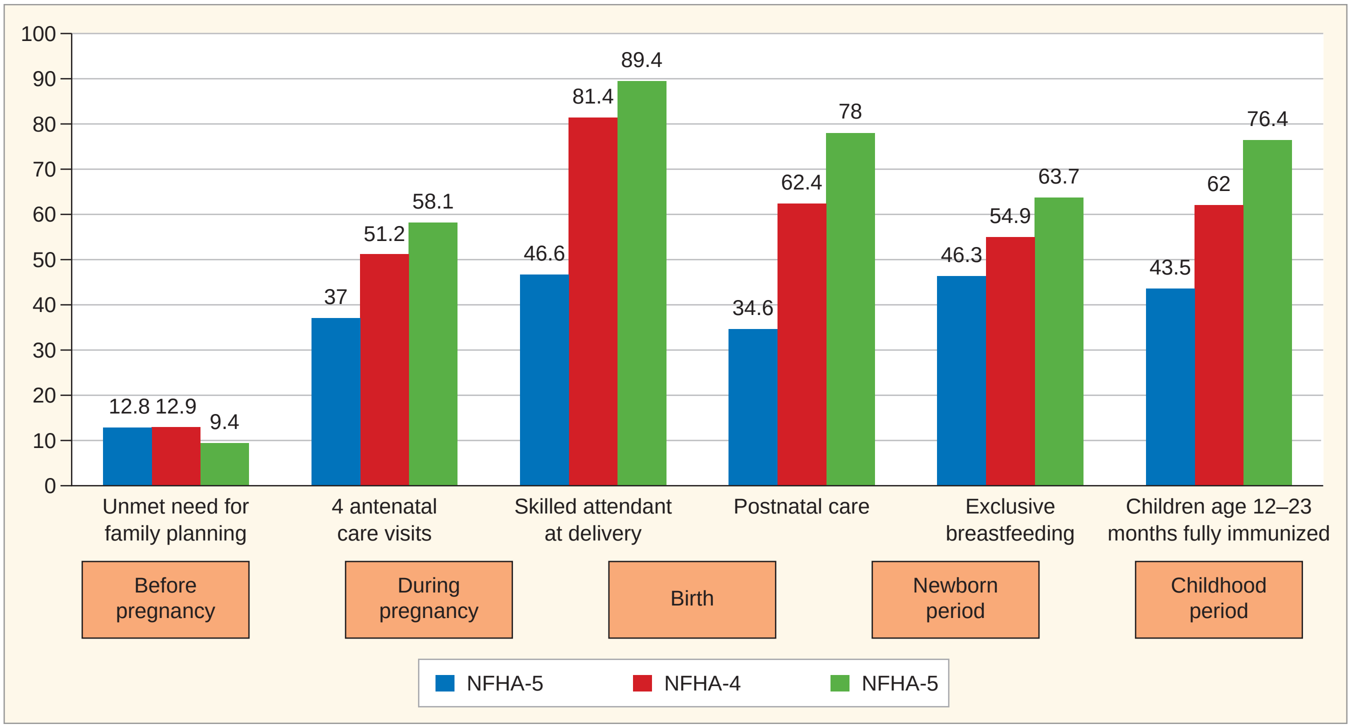

Fig. 5: National Family Health Survey trends on coverage (%) along the continuum of care in various life stages

planning, clean delivery, emergency preparedness, recognizing danger signs, maintaining warmth, and promoting immediate and exclusive breastfeeding, along with early care for neonates.[21]

Data shows improvements in hospital coverage across different life stages (before pregnancy), such as the unmet need for family planning decreasing from 12.8 (NFHS-3) to 9.4% (NFHS-5). During pregnancy, at least four or more antenatal care visits increased from 37 (NFHS-3) to 58.1% (NFHS-4).[22] The rate of deliveries assisted by skilled attendants at health facilities rose from 46.6 (NFHS-3) to 89.4% (NFHS-5).[25] Postnatal care increased from 34.6 (NFHS-3) to 78% (NFHS-5). Exclusive breastfeeding of newborns improved from 46.3 (NFHS-3) to 63.7% (NFHS-5), and the full immunization rate for children aged 1–2 years increased from 43.5 (NFHS-3) to 76.4% (NFHS-5), as shown in Figure 5.[22,25]

The Pradhan Mantri Surakshit Matritva Abhiyan (PMSMA) is a new scheme launched by the Indian Government in 2016 to provide regular antenatal care (ANC) to expectant women on the 9th day of each month. According to data, under PMSMA, 3.02 crore antenatal check-ups have been carried out, and 25.46 lakh at-risk pregnancies have been identified across states and union territories up to 2021.[11,24] In 2017, the Indian Government introduced the PMMVY, which offers cash transfers of Rs. 5,000 to expectant mothers' accounts in three installments: Rs. 1,000 for early registration; Rs. 2,000 for receiving at least one ANC within 6 months of pregnancy; and Rs. 2,000 after birth registration and the completion of the first immunization cycle for the first live born child.[27]

Another program, LaQshya, introduced in 2017, aims to benefit every pregnant woman and newborn delivered in government hospitals. It ensures adequate human resources and infrastructure, availability of essential equipment, capacity building of healthcare workers, adherence to clinical guidelines, and improved quality of care for pregnant women in labor rooms and maternity operation theaters.[11] National certification for LaQshya had been targeted for 1110 labor rooms and 808 operating theaters till 31st December 2024.[28]

A new initiative, Surakshit Matritva Aashwasan (SUMAN), launched in 2019, aims to offer a wide range of quality services in maternal and newborn healthcare. These services will be free of charge, with a strict policy against delays. Management of any complications is guaranteed, respect for mothers will be upheld, and their preferences, dignity, and feelings will also be safeguarded.[28]

Conclusion

India has achieved remarkable success in reducing MMR. The Sustainable Development Goal 3 (SDG 3) target can be met on time if the decline continues at the same rate. Some states (Tamil Nadu, Telangana, Jharkhand, Andhra Pradesh, Kerala, and Maharashtra) have already reached the SDG 3 target. The Indian Government has taken several initiatives to lower MMR by implementing and strengthening various interventions and programs, including JSY, JSSK, PMSMA, and Pradhan Mantri Matru Vandana (PMMVY). These efforts have helped increase institutional deliveries, improve delivery and postdelivery care and diet, maintain regular ANC contacts, and screen high-risk pregnancies, from early ANC through the child's first immunization.

References

1. PIB. Data on marital status and fertility and head of household released. 2011. Available from: http://www.censusindia.gov.in/. [Last accessed on 30 December 2024].
2. Sharma S, Mohanty P, Omar R, et al. Determinants and utilisation of maternal health care services in urban slums of an industrialised city in western India. J Fam Reprod Health 2020;14(2):95–101. DOI: 10.18502/jfrh.v14i2.4351.

3. UNICEF. Maternal mortality. 2025. Available from: https://data.unicef.org/topic/maternal-health/maternal-mortality/. [Last accessed on 6 May 2025].
4. UNICEF. Maternal health. 2021. Available from: https://www.unicef.org/media/123406/file/Health_Results_2021_Maternal_Newborn_Adolescent_Health.pdf. [Last accessed on 13 February 2025].
5. PIB. MMR of India declined from 384 in 2000 to 103 in 2020: UN MMEIG 2020 report. Ministry of Women and Child Development, Government of India. 2024. Available from: https://www.pib.gov.in/PressReleasePage.aspx?PRID=2003432. [Last accessed on 27 February 2025].
6. Ministry of Health and Family Welfare. National Health Policy 2017. Available from: https://mohfw.gov.in/sites/default/files/Annual%20Report%202019-2020%20English.pdf. [Last accessed on 8 May 2025].
7. Suresh N. Maternal mortality in India. 2025. Available from: https://www.dataforindia.com/maternal-mortality/. [Last accessed on 28 January 2025].
8. Joe W, Sharma S, Sharma J, et al. Maternal mortality in India: a review of trends and patterns. 2015;1–32. Available from: https://iegindia.org/upload/publication/Workpap/wp353.pdf. [Last accessed on 14 May 2025].
9. UNICEF. Maternal health. 2019. Available from: https://www.unicef.org/india/search?query=Maternal+health&created%5Bmin%5D=&created%5Bmax%5D=. [Last accessed on 25 June 2025].
10. Meh C, Sharma A, Ram U, et al. Trends in maternal mortality in India over two decades in nationally representative surveys. Int J Obstet Gynaecol 2021;550–561. DOI: 10.1111/1471-0528.16888.
11. Verma R, Verma L. A literature review on emerging factors affecting antenatal care utilisation of pregnant women. Int J Food Nutr Sci 2022;11(6):58–66. DOI: 10.4103/ijfans_161_22.
12. PIB. India's success in reducing maternal mortality. 2025. Available from: https://www.pib.gov.in/PressReleasePage.aspx?PRID=2113800. [Last accessed on 25 June 2025].
13. Sample Registration System. Special bulletin on maternal mortality in India 2017–2022. 2025. Available from: https://censusindia.gov.in/nada/index.php/catalog/45569. [Last accessed on 2 July 2025].
14. WHO. Counselling for maternal and newborn health care. 2013;13:978–992. ISBN: 9789241547628.
15. Say L, Doris C, Gemmil A, et al. Global causes of maternal death: A WHO systematic analysis. Lancet Glob Health 2014;2:323–333. DOI: 10.1016/S2214-109X(14)70227-X.
16. Vora KS, Mavalankar DV, Ramani K, et al. Maternal health situation in India: a case study. J Health Popul Nutr 2009;27(2):184–201. DOI: 10.3329/jhpn.v27i2.3363.
17. WHO. Maternal mortality fact sheet. 2025. Available from: https://www.who.int/news-room/fact-sheets/detail/maternal-mortality. [Last accessed on 29 May 2025].
18. Montgomery AL, Ram U, Kumar R, et al. Maternal mortality in India: causes and healthcare service use based on a nationally representative study. PLoS One 2014;9(1):1–11. DOI: 10.1371/journal.pone.0083331.
19. Kaur M, Gupta M, Purayil VP, et al. Contribution of social factors to maternal death in urban India: use of care pathway and delay models. PLoS One 2018;1–18. DOI: 10.1371/journal.pone.0203209.
20. Hamal M, Dieleman M, Brouwere VD, et al. Social determinants of maternal health: A scoping review of factors influencing maternal mortality and maternal health service use in India. Public Health Rev 2020;1–24. DOI: 10.1186/s40985-020-00125-6.
21. WHO. WHO recommendations on antenatal care for a positive pregnancy experience. 2016. Available from: https://www.who.int/publications/i/item/9789241549912. ISBN: 9789241549912. [Last accessed on 15 February 2025].
22. Ministry of Health and Family Welfare. National Family Health Survey-4 (NFHS-4). Int Inst Pop Sci 2017;1–167. Available from: https://dhsprogram.com/pubs/pdf/fr339/fr339.pdf.
23. Chandrakar A, Panda S, Soni P, et al. Awareness regarding Janani Shishu Suraksha Karyakram (JSSK) among mothers: A community-based cross-sectional study in the rural area of Raipur district, Chhattisgarh. Int J Res Med Sci 2017;10:4374–4379. DOI: 10.18203/2320-6012.ijrms20174561.
24. PIB. Benefits to women under PMKVY. 2021. Available from: https://pib.gov.in/PressReleseDetail.aspx?PRID=1781676. [Last accessed on 2 April 2025].
25. Ministry of Health and Family Welfare. National Family Health Survey-5 (NFHS-5). Int Inst Pop Sci 2021;1(1):1–715. Available from: https://www.dhsprogram.com/pubs/pdf/FR375/FR375.pdf. [Last accessed on 12 May 2025].
26. Salve HR, Charlette L, Kankaria A, et al. Improving access to institutional delivery through Janani Shishu Suraksha Karyakram: Evidence from rural Haryana, North India. Indian J Community Med 2016;42(2):73–76. DOI: 10.4103/0970-0218.205223.
27. GOI, Ministry of Women and Child Development. Available from: https://pmmvy.wcd.gov.in/; https://wcd.delhi.gov.in/wcd/pradhan-mantri-matru-vandana-yojana-pmmvy. [Last accessed on 30 June 2025].
28. Ministry of Health and Family Welfare. Annual report 2024–2025. Available from: https://mohfw.gov.in/sites/default/files/Final%20Printed%20English%20AR%202024-25.pdf. [Last accessed on 30 August 2025].

REVIEW ARTICLE

Air Pollution in Metropolitan Cities: Emerging Trends, Health Burden, and Pathways to Clean Air

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Abstract

Urban air pollution imposes a massive and largely preventable burden of disease in India's metropolitan regions. Rapid migration, motorization, industrial expansion, and construction have escalated emissions, while seasonal patterns (e.g., winter stagnation, agricultural residue burning) amplify pollutant build-up. Recent studies confirm that both short-term spikes and long-term exposures to $PM_{2.5}$, NO_2, ozone, and other pollutants significantly raise risks of cardiovascular disease, respiratory morbidity, cancers, adverse perinatal outcomes, and neurological/metabolic disorders. Digital tools (AI/ML forecasting, low-cost sensors, geospatial compliance monitoring) are emerging in India as scalable supports for intervention. This review describes the current metropolitan airpollution landscape in India, elaborates on the biological and epidemiologic evidence of harm, and systematically outlines strategies to reduce emissions and exposure at the individual, organizational, and policy levels. For each strategy, we discuss rationale, implementation considerations, and challenges, with attention to equity, climate co-benefits, and digital innovation.

Keywords: Air pollution, Climate co-benefits, Health impacts, Metropolitan cities, $PM_{2.5}$, Policy interventions.

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Introduction

India is among the nations urbanizing at a fast pace. Each year, numerous people migrate to cities seeking educational, employment, and lifestyle opportunities. Metropolitan boundaries expand relentlessly, incorporating peri-urban areas into city limits. This influx intensifies demands on transport, energy, housing, infrastructure, and job opportunities. This leads to more vehicles, more industries, more construction, and more emissions. The resulting rise in ambient pollutant concentrations degrades air quality, elevates carbon footprints, and threatens public health.

Air pollution ranks among the top environmental threats to health globally. The World Health Organization (WHO) identifies ambient (outdoor) air pollution as a major cause of mortality, attributing millions of premature deaths to it annually, and also a cause for morbidity and disability adjusted life years (DALY).[1] In metropolitan settings, high population density gives rise to higher emission sources and maximizes exposure. Addressing air pollution in Indian cities must become a public health priority with the aim of protecting health, addressing inequities, and pursuing sustainable urban development.

Current Situation in Metropolitan Cities in India

National Burden

A recent analysis in *The Lancet Planetary Health* estimated that India suffers ~1.5 million excess deaths annually attributable to ambient air pollution, if benchmarked by WHO guideline exposures (0–5 μg/m^3).[2] That aligns with other recent studies showing that long-term $PM_{2.5}$ exposure in India correlates with an estimated 3.8 million deaths over 2009–2019 under national standards, and ~16.6 million deaths (24.9% of all mortality) if compared with WHO guideline levels.[3] Jaganathan et al.[3] used a difference-in-differences approach to estimate that each 10 μg/m^3 increase in annual $PM_{2.5}$ raises mortality by 8.6% (95% CI: 6.4–10.8).

In ten Indian cities, de Bont et al.[4] applied causal modeling and found that a 10 μg/m^3 rise in $PM_{2.5}$ over 2 days increased daily mortality by 1.4%, but locally generated pollution had a stronger effect (3.6% increase). Their integrated exposure–response analysis estimated 7.2% of daily deaths attributable to $PM_{2.5}$ above the WHO 24-hour guidelines.[4]

Thus, both chronic and acute exposure in Indian metro cities exert substantial mortality and morbidity burdens.

City and Seasonal Trends

Cities like Delhi remain among the world's worst in air quality. In 2024, a study rated Delhi's air quality crisis as one of the most extreme severity globally, driven by industrial emissions, vehicle traffic, deforestation, construction dust, and seasonal stubble burning.[5] The city's air quality index (AQI) mostly stays in "severe" or "hazardous" ranges.

For instance, on November 18, 2024, Delhi recorded its worst pollution episode in years, with a 24-hour AQI of ~491 (classified "severe plus") and extremely elevated $PM_{2.5}$.[6] Regional smog episodes between India and Pakistan in late 2024 (the "2024 India–Pakistan smog") resulted from aggregated emissions from stubble

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burning, vehicular emission, construction dusts and meteorological stagnation, with satellite imagery showing massive smog plumes and $PM_{2.5}$ concentrations exceeding 900 µg/m^3 in some zones.[7]

A longitudinal analysis from 2014 to 2023 in five populous Indian cities (Mumbai, Delhi, Hyderabad, Chennai, Kolkata) found that $PM_{2.5}$ time series show long-memory characteristics, that is, in addition to immediate impact, there are shocks having potentially lasting effects rather than rapid reversion to baseline.[8]

Additionally, a 2025 study on real-time monitoring emphasized that ambient pollution continues to pose an urgent challenge in India, with gaps in data granularity and public access.[9]

Though there is a National Clean Air Programme (NCAP) launched in 2019 (targeting a 30% reduction in particulate pollution by 2024, later revised to 40% by 2026), progress remains uneven. By December 2023, only 931 out of a planned 1,500 manual ambient monitoring stations were operational; emissions-based interventions lag.[10]

Thus, Indian metropolitan cities confront a dual problem: persistently high baseline pollution levels and extreme episodic peaks of pollutants during winters or smog events, compounding health risks.

Sources of Urban Air Pollution in India

Understanding emission sources is critical to designing interventions.

- Transport: Vehicles (diesel, petrol, compressed natural gas, diesel buses, two- and three-wheelers) emit nitrogen oxides (NOx), fine particulate matter less than 2.5 microns ($PM_{2.5}$), particulate matter less than 10 microns (PM_{10}), carbon monoxide (CO), and volatile organic compounds (VOCs). Non-exhaust sources (brake/tire wear, road dust resuspension) also contribute significantly—especially in congested metros.
- Energy and industry: Coal and gas power plants, refineries, cement plants, metal processing, chemical industries, and brick kilns emit sulfur dioxide (SO_2), NOx, fine and coarse particles, and trace metals. The brick kiln sector alone contributes 8–14% of total air pollution in India.[11]
- Residential and commercial: Use of solid fuels such as firewood, kerosene, or biomass for cooking and heating remains common in peri-urban zones, while diesel backup generators in urban facilities emit PM and NOx when grid supply falters.
- Construction and demolition: Heavy construction and real estate activity produce fugitive dust and resuspend soil/road dust, especially during the building of high-rise structures and infrastructure.
- Open burning: Agricultural residue burning (e.g., stubble burning in states like Punjab and Haryana) and municipal solid waste burning (especially in informal dumps) add seasonal and local pollutant surges.
- Transboundary and episodic: Wildfire smoke or smoke from distant pollution sources travels into city airsheds. Seasonal wind patterns may transport pollutants across states or even countries.[12]

Emerging approaches combine satellite-based detection and geospatial methods to locate sources such as brick kilns and to monitor compliance.[11] A recent geospatial machine learning (ML) pipeline identified over 30,600 brick kilns across the Indo-Gangetic plain (IGP) states and assessed compliance in the Delhi airshed.[11]

Harmful Effects of Air Pollution

Air pollution affects the human body through oxidative stress, systemic inflammation, autonomic imbalance, endothelial dysfunction, and epigenetic changes. Details are elaborated as follows:

Cardiovascular Disease

Chronic and acute exposures to $PM_{2.5}$ and NO_2 provoke systemic inflammation, raise blood coagulability, promote atherogenesis, and destabilize plaques, leading to acute health conditions. Many observational studies link air pollution exposure to increased incidence of myocardial infarction, stroke, heart failure, arrhythmias, hypertension, and sudden cardiac death. Cardiovascular causes account for a majority of pollution-related excess mortality.[4,13,14]

In India, de Bont et al.[4] found that short-term $PM_{2.5}$ surges raised mortality—partly via cardiovascular deaths—even at moderate exposure ranges. The steep slopes at lower exposures suggest even incremental improvements yield health gains.

Respiratory Disease

Inhaled fine particles penetrate deep into alveoli, provoke airway inflammation, reduce mucociliary clearance, aggravate asthma and COPD, reduce lung function growth in children, and increase the risk of pneumonia and acute lower respiratory infections. Especially in Indian cities, high baseline pollutant levels exacerbate respiratory morbidity.[15,16]

Children and the elderly manifest higher sensitivity. Long-term exposure decreases lung function trajectories and may predispose to the onset of chronic respiratory disease in later life.

Cancer

Fine particulate matter includes carcinogenic components (e.g., black carbon, polycyclic aromatic hydrocarbons, trace metals). Epidemiologic evidence links $PM_{2.5}$ exposure with lung cancer risk; some studies also show associations with gastrointestinal cancers and leukemia under high exposure regimes.[17]

Maternal, Perinatal, and Child Health

Maternal exposures to elevated $PM_{2.5}$ and NO_2 in pregnancy appear to increase risks of low birth weight, preterm birth, intrauterine growth restriction, and small-for-gestational-age infants. Exposure in utero may impair neurodevelopment, leading to long-term deficits in cognition, behavior, and lung growth.[18,19]

Neurological, Cognitive, and Metabolic Effects

Emerging evidence implicates long-term pollution exposure in neurodegenerative diseases (Alzheimer's, Parkinson's), cognitive decline, stroke, depression, and autism. Mechanisms involve neuroinflammation, blood–brain barrier disruption, microvascular injury, and oxidative stress.[20,21]

In metabolic health, studies show associations with insulin resistance, type 2 diabetes incidence, dyslipidemia, and non-alcoholic fatty liver disease, possibly via systemic oxidative stress and inflammatory pathways.

Equity and Vulnerability

Air pollution burden is distributed unequally. Children, pregnant women, the elderly, outdoor workers, those with underlying illnesses, especially cardio-pulmonary disease, and economically disadvantaged communities face disproportionate exposure and limited access to mitigation. Urban spatial planning often places the low-income population in urban slums, closer to highways, industrial zones, and polluting sources.[1,22]

India's large informal workforce (construction, street vending, waste pickers) works outdoors and experiences the highest exposures with minimal protection.

Collectively, the burden is huge. According to the *State of Global Air 2024*, ambient pollution accounted for ~8.1 million deaths globally in 2021, and noncommunicable diseases (heart disease, COPD, diabetes, lung cancer) formed ~90% of that burden.[23]

Strategies to Reduce Air Pollution in Metropolitan Cities in India

Preventive strategies can be planned at three levels (individual, organizational, policy/system) to mitigate the menace of air pollution. The strategies are explained below:

Individual Level

- Adopt cleaner commuting and mobility choices
  - Decreasing private vehicle use and preferring public transport, cycling, and walking (especially on low-traffic routes) reduces vehicular emissions and personal exposure. In Indian metro cities, transport is often a dominant contributor to urban emissions.
  - *Implementation:* Local civic groups can promote cycling/pedestrian infrastructure. People can join carpool networks, schedule trips to avoid peak hours, and prefer electric two- or three-wheelers when possible. Also, avoid idling vehicles, conduct periodic emission control testing, and maintain vehicles to reduce emissions.
- Avoid exposure during high-pollution episodes
  - Pollution levels in cities often spike (e.g., in winter). Avoiding outdoor activity during such episodes reduces peak-dose exposure and protects the individual from harmful effects.
  - *Implementation*: Use air quality index apps and government warnings to plan activities. Keep windows closed when ambient levels are hazardous. Use personal masks (N95/FFP2) indoors briefly. Adjust schedules (e.g., exercise in the mornings). Employers/schools can adopt "smog days" to reduce outdoor activity.
- Use indoor air filtration and cleaner household energy
  - Indoor air often reflects outdoor infiltration plus indoor sources. HEPA filters significantly reduce indoor $PM_{2.5}$ levels. Clean cooking/heating energy (LPG, electricity) eliminates a key source of indoor pollution.
  - *Implementation*: Households can install portable or central air cleaners with HEPA filters. Ensure sealing of windows and doors. Subsidy programs (e.g., Ujjwala scheme) should be implemented widely, leading to the transition remaining biomass/kerosene users to cleaner fuels. Promote rooftop solar or clean electric heating/cooking.
- Engage in civic advocacy and community action
  - Structural change depends on political will. Informed citizens can influence policy, demand clean-air measures, and sustain accountability.
  - *Implementation*: Participate in local environment committees, public hearings, and petitions. Demand real-time open data, green zones, low-emission vehicle policies, and stricter industrial regulation. Use social media and local media to raise awareness.
- Behavioral substitution where possible
  - Certain choices reduce personal emissions (e.g., shorter showers, reducing use of polluting solvents, smoking). Less direct but cumulative impact.
  - *Implementation*: Use energy-efficient appliances, properly dispose of waste (avoid open burning at home).

Organizational/Workplace Level

- Green fleet and commute programs
  - Organizational travel (employee commutes, work-related transport) contributes to urban emissions and employee exposure. Electrifying fleets, encouraging public or pooled vehicles, and promoting alternative commuting reduce both.
  - *Implementation*: Organizations can transition to electric or hybrid vehicles over time, set up charging infrastructure, and offer incentives/subsidies for employees to use public transit or bicycles. Promote staggered shifts or remote work to reduce peak travel.
- On-site emission and energy control
  - Many institutions (offices, hospitals, schools) maintain diesel backup generators or inefficient heating systems, contributing to local emissions. Reducing those improves local air quality and protects occupants.
  - *Implementation*: Replace generators with battery-based or cleaner fuel alternatives. Use clean electricity for heating/cooking. Monitor emissions regularly, maintain equipment, and apply emission controls (filters, scrubbers).
- Indoor air quality management
  - People spend most of their time indoors. In polluted cities, reducing indoor concentrations is critical for exposure control.
  - *Implementation*: Design buildings with mechanical ventilation and filtration (e.g., MERV/HEPA filters). Use positive-pressure clean rooms in sensitive zones (e.g., neonatal, elderly wards). Schedule tasks (e.g., lab work, cleaning) when ambient pollution is lower. Provide indoor air cleaners in high-risk zones.
- Operational planning and scheduling
  - Outdoor workers (construction, landscaping, utility repair) face the highest exposure. Adjusting their schedules reduces risk.
  - *Implementation*: Avoid assigning heavy outdoor tasks during pollution peaks (morning/evening in winter). Provide suitable respiratory protection (certified masks) when tasks are unavoidable. Rotate workforce, provide breaks indoors, and monitor air quality.
- Monitoring, transparency, and resilience planning
  - Organizations must understand their emission footprint and exposure risk to act effectively. Transparent reporting supports accountability.
  - *Implementation*: Deploy low-cost sensors alongside reference monitors to map exposure gradients on premises. Publish emission and exposure reports annually. Participate in city-wide monitoring networks. Develop pollution-response plans: designate clean-air zones on campus, reduce outdoor events on high-pollution days, and plan for business continuity.

Policy/System Level

At the city, state, and national scale, systemic policies produce the largest, sustained impacts.

- Implementing stricter vehicular emission standards and low-emission zones (LEZs)/congestion pricing
  - Transport remains a predominant emission source in metros; older vehicles disproportionately pollute.

- *Implementation*: Phase in tighter standards for vehicles, impose retrofit or scrappage schemes for older vehicles, establish LEZs and congestion pricing in core city areas. Charge entry fees for high-emissions vehicles. Penalize non-compliance. Examples: London's ULEZ, Singapore's ERP. India can scale this across city regions.
- Accelerated electrification and clean fuel incentives
  - Electric vehicles (EVs) eliminate tailpipe emissions; fuel switching reduces CO_2 and co-pollutant emissions.
  - *Implementation*: Subsidies, tax breaks, and rebates for EV purchase; mandates for public transport fleets to become EV; build charging infrastructure; encourage battery swapping. Promote CNG/LNG in heavy vehicles as an interim step. Penalize high-emission vehicles via higher registration taxes.
- Clean energy transition and industrial emissions control
  - Power plants, heavy industry, and brick kilns contribute major pollutant loads.
  - *Implementation*: Phase out or retrofit coal plants with modern flue-gas desulphurization, particulate control. Promote renewable sources of energy (solar, wind, hydro). Impose and enforce emission limits for industries, with stringent penalties. Offer subsidies or feed-in tariffs for clean energy. Israel-style cap-and-trade has proven effective: a pilot cap-and-trade for particulate matter in Gujarat's Surat region showed 20–30% emission reductions with lower cost than conventional regulation.[24,25]
- Integrated urban planning, green infrastructure, and land-use zoning
  - Urban form influences travel demand, dispersion, and exposure gradients. Green spaces and vegetation help filter and diffuse pollutants.
  - *Implementation*: Promote transit-oriented development (TOD), mixed-use planning to shorten travel, buffer zones (tree belts) along highways and industrial areas. Mandate green roof/vertical gardens. Restrict polluting industries near residential zones. Enforce dust-control protocols during construction. Use "green walls" and urban wetlands for pollutant capture.
- Robust regulatory frameworks, air quality standards, and enforcement
  - Policies must rest on legally enforceable standards. Without regulatory teeth and monitoring, many measures remain aspirational.
  - *Implementation*: Align national ambient air quality standards (e.g., NAAQS) with WHO guideline levels progressively. Strengthen permitting, ensure implementation of continuous emissions monitoring systems (CEMS) in industries with the potential of causing pollution. Ensure public reporting and real-time publication of air-quality data. Empower regulatory bodies (CPCB, SPCBs) for penalties, closure orders, and periodic compliance audits.
- Early-warning systems, health protection, and surveillance
  - Despite mitigation, pollution spikes will persist. Protecting health requires anticipatory systems and health-system readiness.
  - *Implementation*: Install real-time forecasting using AI/ML (e.g., Rautela et al.;[26] Naveed et al.).[27] Issue action-based advisories (graded response action plans, GRAP) to schools, workplaces, and citizens. Create sentinel surveillance of pollution-linked illnesses (respiratory clinics, hospital admissions, birth registries). Prepare health systems (training, resources, respiratory care capacity). Mandate closure of schools/events during extreme pollution days.
- Economic incentives, penalties, and market mechanisms
  - Regulatory tools alone may not suffice. Economic instruments shift behavior and investment.
  - *Implementation*: Provide subsidies for clean energy technology, tax credits for pollution control equipment. Impose pollution taxes, emission trading, or cap-and-trade schemes for particulate and NOx emissions. Use "polluter pays" principles, congestion tolls, and differential tariffs for industrial discharges.
- Sentinel surveillance and data-driven policy cycles
  - Monitoring pollution-linked disease trends helps assess intervention impacts and guide resource allocation.
  - *Implementation*: Build surveillance systems in metropolitan health networks that track hospital admissions, outpatient visits, birth outcomes, and mortality temporally aligned with pollution events. Link these data to air-quality data for policy evaluation. Develop dashboards for decision makers.
- Digital innovations and compliance monitoring
  - Traditional regulatory monitoring often lacks spatial coverage and real-time responsiveness.
  - *Implementation*: Leverage low-cost sensor networks combined with reference monitors to map intra-city pollution gradients and hotspots. Apply AI/ML forecasting models and urban digital twins to predict AQI and guide interventions.[26,27] Use satellite and geospatial analytics to detect noncompliance (e.g., unauthorized brick kilns).[11] Integrate social media analytics (e.g., Twitter) to crowd-source pollution detection and awareness.[28]

Evidence of Effectiveness and India-relevant Examples

- London's ULEZ and congestion pricing zones demonstrated measurable declines in NO_2 and PM, and associated improvements in cardiovascular markers and respiratory health.[29]
- In India, the Gujarat cap-and-trade experiment in Surat pioneered a novel emissions market for particulates, achieving 20–30% emissions reductions at lower cost.[24,25]
- The NCAP has catalyzed source apportionment studies (though only ~37 of 131 nonattainment cities completed these by 2023).[10]
- AI/ML forecasting models in India, such as those by Rautela et al.,[26] improve real-time response potential.
- Naveed et al.[27] built a digital twin model for AQI forecasting in smart city settings.
- Abdelmalek et al.[30] used ML for hourly AQI prediction with promising accuracy.
- Patel et al.[11] developed scalable geospatial detection of brick kilns, enabling targeted compliance actions.
- Sidhu et al.[31] used ML models (Random Forest, XGBoost, LSTM) to predict AQI variability across North Indian states, including stubble burning influence.

These examples show that combined regulatory, economic, infrastructural and digital strategies can yield measurable air-quality and health dividends.

Challenges, Enablers, and Equity Considerations

Challenges

- Political economy and vested interests: Fossil-fuel industries and vehicle manufacturing sectors may resist strict regulation.

- Institutional capacity and financing gaps: Many municipal agencies and state bodies lack technical and financial resources to implement, enforce, or maintain interventions.
- Behavioral inertia and public resistance: Policies like congestion pricing or scrappage may be unpopular without alternatives in place.
- Informal sector complexities: Many polluting sources (brick kilns, small-scale industries, open burning) operate informally and evade regulation.
- Data gaps and monitoring deficits: Sparse ambient monitoring capacities and understanding of intra-city exposure gradients.[32]
- Equity risks: Policies should be designed such that they don't impose burdens on low-income populations (e.g., costs of switching vehicles, paying tolls).

Enablers and Equity Strategies

- Link air-quality interventions with climate action to attract climate finance and broader support.
- Subsidize clean alternatives for low-income groups (e.g., low-cost filters, EV purchase support).
- Use participatory planning to engage vulnerable communities in policy design, taking into account all sectors of the community.
- Phase-in reforms gradually and accompany them with acceptable alternatives (e.g., improve bus/public transport systems before imposing congestion fees).
- Mandate that a portion of revenues (e.g., from pollution taxes) fund health mitigation, green infrastructure in marginalized neighborhoods, and fleet electrification incentives for disadvantaged communities.
- Build intersectoral coordination—between health, transport, energy, urban planning, environment—to overcome siloed implementation.

Monitoring, Research, and Data Priorities

To support evidence-informed action:

- High-resolution monitoring networks: Increase density of reference monitors and integrate low-cost sensors; map intra-city exposure gradients and pollution "hot spots."[33]
- Source apportionment at the city scale: Use receptor models, emission inventories, and tracer studies to attribute pollutant loads to sectors, guiding prioritized interventions.
- Intervention evaluation and causal analysis: Use before–after, difference-in-differences, regression discontinuity, or causal inference methods to rigorously assess the impact of policies and programs.
- Health-environment linkage and surveillance: Link pollution data with health outcomes, morbidity and mortality time series, birth registries, and sentinel surveillance to measure intervention benefits.
- Equity and spatial analyses: Monitor exposures and health outcomes by socioeconomic strata, neighborhoods, and vulnerable groups to ensure policies reduce inequities.
- Digital tool development and validation: Advance AI/ML forecasting, digital twins, satellite-geospatial compliance, and crowdsourcing platforms. Validate predictive tools in Indian metro cities.[26,27,30,34]
- Modeling co-benefits and climate integration: Quantify the co-benefits of air-quality interventions in reducing greenhouse gas emissions, healthcare costs, and economic productivity loss.

Conclusion

Air pollution in India's metropolitan cities remains a devastating, yet preventable, driver of disease, disability, and lost life expectancy. The evidence base—especially from India in 2024–2025—is robust and continues to fortify the imperative for action. While individuals can adopt cleaner behaviors and organizations can mitigate local emissions and exposures, the greatest gains require bold policy, regulatory, technological, and financial leadership at the city and national levels.

The strategies laid out here—spanning mobility reform, clean energy transition, digital monitoring, regulatory enforcement, market mechanisms, urban planning, and health protection—offer a comprehensive roadmap. There are unique challenges in India, including informal sectors, resource constraints, and equity vulnerabilities; but it also offers scope for innovation potential in digital air-quality tools, participatory governance, and linking air quality with climate goals.

To succeed, stakeholders must adopt a systems mindset, integrate cross-sectoral policies, engage communities, monitor progress rigorously, and implement prompt action. With commitment and smart design, Indian metropolitan regions can reclaim breathable air, protect health, and advance sustainable urban futures.

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References

1. World Health Organization. Ambient (outdoor) Air Quality and Health, WHO Fact Sheet. Geneva: WHO; 2024.
2. Harvard School of Public Health Commentary. Air Pollution in India Linked to Millions of Deaths; 2024.
3. Jaganathan S, Stafoggia M, Rajiva A, et al. Estimating effect of annual $PM_{2.5}$ exposure on mortality in India (2009–2019). Lancet Planet Health 2024;8(12):e987–e996. DOI: 10.1016/S2542-5196(24)00248-1.
4. de Bont J, Krishna B, Stafoggia M, et al. Ambient air pollution and daily mortality in ten Indian cities. Lancet Planet Health 2024;8:e114. DOI: 10.1016/S2542-5196(24)00114-1.
5. Bhuyan A, Bordoloi T, Debnath R, et al. Assessing AQI of air pollution crisis 2024 in Delhi: Its health risks and nationwide impact. Environ Health Insights 2025 (in press).
6. The Guardian. Pollution in Delhi Hits a Record High; 2024.
7. 2024 India–Pakistan Smog Event. Wikipedia; 2025.
8. Singh V, Singh S, Biswal A. Exceedances and trends of particulate matter (PM2.5) in five Indian megacities. Sci Total Environ 2021;750:141461. DOI: 10.1016/j.scitotenv.2020.141461.
9. Vohra K, Madhumitha S, Chakraborty A, et al. Urgent issues regarding real-time air quality monitoring. Sci Total Environ 2025;25:100308. DOI: 10.1016/j.aeaoa.2024.100308.
10. Tracing the Hazy Air 2025: Progress Report on NCAP; 2025.
11. Patel ZB, Mondal R, Dubey S, et al. Space to policy: Scalable brick kiln detection via geospatial data. arXiv; 2024.
12. D'Evelyn SM, Jung J, Alvarado E, et al. Wildfire, smoke exposure, human health, and environmental justice need to be integrated into forest restoration and management. Curr Environ Health Rep 2022;9(3):366–385. DOI: 10.1007/s40572-022-00355-7.
13. Yadav R, Deora S, Yadav G. Air pollution and its impact on cardiovascular health - It's time to act fast! Indian Heart J 2021;73(1):1–6. DOI: 10.1016/j.ihj.2021.01.021.

14. Rajagopalan S, Al-Kindi SG, Brook RD. Air pollution and cardiovascular disease: JACC state-of-the-art review. J Am Coll Cardiol 2018;72(17):2054–2070. DOI: 10.1016/j.jacc.2018.07.099.
15. Aithal SS, Sachdeva I, Kurmi OP. Air quality and respiratory health in children. Breathe (Sheff) 2023;19(2):230040. DOI: 10.1183/20734735.0040-2023.
16. Duan RR, Hao K, Yang T. Air pollution and chronic obstructive pulmonary disease. Chronic Dis Transl Med 2020;6(4):260–269. DOI: 10.1016/j.cdtm.2020.05.004.
17. Wang M, Kim RY, Kohonen-Corish MRJ, et al. Particulate matter air pollution as a cause of lung cancer: Epidemiological and experimental evidence. Br J Cancer 2025;132(11):986–996. DOI: 10.1038/s41416-025-02999-2.
18. Thaichana P, Sripan P, Rerkasam A, et al. Association of maternal PM2.5 exposure with preterm birth and low birth weight: A large-scale cohort study in Northern Thailand (2016–2022). Toxics 2025;13(4):304. DOI: 10.3390/toxics13040304.
19. Morgan ZEM, Bailey MJ, Trifonova DI, et al. Prenatal exposure to ambient air pollution is associated with neurodevelopmental outcomes at 2 years of age. Environ Health 2023;22(1):11. DOI: 10.1186/s12940-022-00951-y.
20. Block ML, Calderón-Garcidueñas L. Air pollution: Mechanisms of neuroinflammation and CNS disease. Trends Neurosci 2009;32(9):506–516. DOI: 10.1016/j.tins.2009.05.009.
21. Olloquequi J, Díaz-Peña R, Verdaguer E, et al. From inhalation to neurodegeneration: Air pollution as a modifiable risk factor for Alzheimer’s disease. Int J Mol Sci 2024;25(13):6928. DOI: 10.3390/ijms25136928.
22. Cacciatore S, Sofia M, Nunez MV, et al. Urban health inequities and healthy longevity: traditional and emerging risk factors across the cities and policy implications. Aging Clin Exp Res 2025;37(1):143. DOI: 10.1007/s40520-025-03052-1.
23. State of Global Air. SOGA Report 2024; 2024.
24. Available from: https://indianexpress.com/article/explained/explained-climate/world-first-particulate-emissions-market-gujarat-9949535/. [Last accessed September, 2025].
25. Available from: https://climate.uchicago.edu/news/worlds-first-particulate-matter-trading-scheme-in-gujarat-cut-pollution-by-up-to-30-finds-study. [Last accessed September, 2025]
26. Rautela KS, Goyal MK. Transforming air pollution management in India with AI and ML. Sci Rep 2024;14:20412. DOI: 10.1038/s41598-024-71269-7.
27. Naveed K, Umer T, Asghar AB, et al. Machine learning assisted predictive urban digital twin for AQI forecasting. Energy Build 2025. DOI: 10.1016/j.envsoft.2025.106559.
28. Jiang W, Wang Y, Tsou M-H, et al. Using social media to detect outdoor air pollution and monitor air quality index (AQI): A geo-targeted spatiotemporal analysis framework with Sina Weibo (Chinese Twitter). PLoS One 2015;10:e0141185. DOI: 10.1371/journal.pone.0141185.
29. Chamberlain RC, Fecht D, Davies B, et al. Health effects of low emission/congestion zones: Systematic review. Lancet Public Health 2023;8:e278–e289. DOI: 10.1016/S2468-2667(23)00120-2.
30. Abdelmalek MM, Mahmoud H, Shokry H, et al. Prognosis of air quality index using ML. Sci Rep 2025;15:25890.
31. Sidhu KK, Balogun H, Oseni KO. Predictive modelling of AQI across Indian cities using ML. arXiv; 2024.
32. Apte JS, Manchanda C. High-resolution urban air pollution mapping. Science 2024;385:380–385. DOI: 10.1126/science.adq3678.
33. Liu X, Jayaratne R, Thai P, et al. Low-cost sensors as an alternative for long-term air quality monitoring. Environ Res 2020;185:109438. DOI: 10.1016/j.envres.2020.109438.
34. Transforming Air Pollution Management in India with AI & ML; 2024.