SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

Reimagining Patient Care in the Digital Health Era: A Systematic Literature Review and Analytical Synthesis

Parhlad Singh Ahluwalia[1]
[1] *Dr. Bhim Rao Ambedkar Law University, Rajasthan, India*
Correspondence: ahluwalia002@zohomail.in

Abstract

Background. *Telemedicine, electronic health records (EHRs), mobile and wearable devices, and artificial intelligence (AI) are widely presented as instruments for transforming patient care. The evidence for them is fragmented across technologies, disciplines and settings.*

Objective. *To synthesise evidence on how digital health reshapes access, clinical decision-making, clinician workload, patient engagement, governance and equity, and to derive an integrative framework for reimagining patient care.*

Methods. *A systematic literature review reported in line with PRISMA 2020, combined with an analytical synthesis. Two evidence streams were screened. The first was an author-supplied corpus of 117 records, of which 27 were retained. The second was a purposively assembled external stream of 47 sources. Data were extracted, tabulated and analysed thematically across seven themes and six stakeholder perspectives.*

Results. *Seventy-four sources were synthesised. In a direct-observation study of US ambulatory practice, physicians spent 49.2% of the office day on EHR and desk work against 27.0% on face-to-face care. In same-sample imaging comparisons, deep-learning tools reached a pooled sensitivity of 87.0% against 86.4% for clinicians. A widely deployed sepsis-prediction model, however, achieved an external-validation AUC of only 0.63 and missed 67% of sepsis cases. Globally, 81% of urban residents but only 50% of rural residents used the Internet in 2023, and internet use was 93% in high-income countries against 27% in low-income countries. India's national digital mission had created 79.71 crore health accounts by July 2025.*

Conclusions. *Digital tools improve care when they are embedded in redesigned workflows, validated locally, governed transparently and deployed with equity safeguards. Otherwise they shift burden or reproduce disparities. We propose a five-layer Reimagined Care Framework (Access, Intelligence, Workflow, Trust, Learning) aligned with the Quintuple Aim.*

Keywords: *digital health; patient-centred care; telemedicine; artificial intelligence; electronic health records; health equity; health governance; systematic review*

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

1. Introduction

Health systems everywhere are being asked to do more, for more people, with fewer resources than their inherited care models were designed to use. Ageing populations, the growth of chronic and non-communicable disease, persistent workforce shortages and entrenched inequities in access have exposed the limits of care organised around episodic, hospital-centred and clinician-directed encounters. Digital health is an umbrella term for telemedicine, EHRs, mobile applications, wearable sensors, data analytics and AI. It has been advanced as a structural response to these pressures. The World Health Organization's global strategy on digital health envisages the accelerated adoption of appropriate, accessible and person-centred digital solutions as part of stronger health systems [1]. Influential commentators have gone further, arguing that the convergence of human and machine intelligence could restore time, precision and empathy to medicine [2].

The COVID-19 pandemic turned this aspiration into operational reality almost overnight. Health systems that had treated virtual care as peripheral adopted it at scale within weeks. Contemporary accounts described a "digital revolution" in which regulatory, reimbursement and cultural barriers were temporarily suspended [3–5]. That experience is instructive precisely because it was involuntary. It showed what digital channels can achieve under pressure, and it showed how quickly their weaknesses surface when adoption outpaces design.

The word "reimagining" in the title is deliberate. Digitisation, the replacement of paper with screens, is not the same as reimagining care. The Institute of Medicine defined care quality through six aims: safe, effective, patient-centred, timely, efficient and equitable [6]. Patient-centred care is not a single construct. It is a cluster of practices concerning communication, shared decision-making and responsiveness to patient values [7]. The "quadruple aim" added the wellbeing of the care team to the goals of better experience, better population health and lower cost [8]. The "quintuple aim" has since added health equity as an explicit fifth objective [9]. Measured against these aims, a technology is transformative only if it changes relationships, workflows and the distribution of benefit. A technology that leaves the encounter unchanged, or that shifts burden from institutions to patients or clinicians, is merely digitised inefficiency.

These questions are sharpest in resource-diverse settings. India exemplifies the tension. Its epidemiological transition and public-health challenges have been the subject of recent comprehensive analyses [10,11]. Global connectivity statistics show that roughly one-third of humanity was still offline in 2023, and that rural residents and low-income countries were disproportionately excluded [12]. Digital health strategies that presume universal connectivity, literacy and trust therefore risk deepening the inequities they are meant to reduce.

Despite an expanding literature, the evidence remains fragmented. Studies typically address one technology (telemedicine, AI or EHRs), one stakeholder (patient or clinician) and one outcome (diagnostic accuracy, satisfaction or cost). Syntheses that integrate clinical, organisational, legal and equity perspectives are rarer. Hospital-management perspectives on digital transformation have been synthesised in a recent systematic review [13]. Decision-makers, however, must judge digital investments across all these dimensions simultaneously.

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

This paper reports a systematic literature review with an analytical synthesis to answer four research questions:

- **RQ1.** What does the evidence show about the effects of digital technologies on access, quality, safety, experience and workload?
- **RQ2.** Which organisational, workforce, governance and equity conditions determine whether digital tools improve or degrade care?
- **RQ3.** How do the perspectives of patients, clinicians, managers, regulators, developers and equity advocates converge and diverge?
- **RQ4.** What integrative framework can guide the reimagining of patient care in diverse contexts, including India?

The paper makes four contributions. It presents a transparent, two-stream evidence map. It provides quantitative evidence tables that place efficacy, real-world performance, workload and access data side by side. It offers a structured multi-perspective analysis. It proposes a five-layer framework and six analytical propositions that future studies can test.

2. Conceptual Background and Related Research

2.1 Concepts and theoretical lenses

Digital health is not only a set of tools. Critical scholarship treats it as a socio-cultural formation in which the "digitised patient" is simultaneously an empowered self-manager, a source of monetisable data and an object of surveillance [14]. This view matters because it directs attention to power, meaning and unintended consequence as well as to efficacy. A complementary pragmatic literature stresses that digital interventions must be evaluated on effectiveness, implementation, engagement and context together, rather than on technical performance alone [15].

Three lenses structure the present analysis. The first is the Quintuple Aim, which supplies the normative objectives against which digital tools are judged [8,9]. The second is the NASSS framework (non-adoption, abandonment, scale-up, spread and sustainability), which explains technology failure through seven interacting domains: the condition, the technology, the value proposition, the adopter system, the organisation, the wider context and embedding over time [16]. The third is the sociotechnical model of health information technology, which identifies eight dimensions (hardware and software, clinical content, human-computer interface, people, workflow and communication, organisational features, external rules and regulations, and measurement) and insists that they be studied as an interacting whole [17]. Together they justify a review design that looks beyond effect sizes to the conditions under which effects occur.

2.2 Related research reviews

Prior reviews have illuminated individual components of the digital health landscape. A review of the empirical foundations of telemedicine in primary care found a body of evidence that is generally supportive but uneven in quality and scope [18]. A systematic review of telehealth and patient satisfaction reported generally favourable satisfaction across studies [19]. In medical imaging, a systematic review and meta-analysis compared deep-learning performance

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

with that of health-care professionals. It found comparable accuracy in the small subset of studies that tested both on the same samples, and it cautioned that few studies were externally validated [20].

Equity-oriented work has shown that informatics interventions can create "intervention-generated inequalities" even when they improve average outcomes [21]. Pandemic-era reviews mapped the applications of digital technology in planning and response [22]. Ethical analyses of machine learning in medicine identified recurring challenges of safety, transparency, fairness and privacy [23]. A major commission examined how digital transformation should be governed so that it serves health [24]. Overviews of machine learning in medicine described both its promise and its dependence on data quality and validation [25]. The WHO has issued dedicated guidance on the ethics and governance of AI for health [26].

Table 1. Selected related research reviews and their relevance to the present review

Ref.	Type of work	Principal focus	Principal contribution	Gap addressed here
[13]	Systematic review	Digital transformation in hospital management	Synthesis from a hospital-management standpoint	Extends to clinical, equity and legal perspectives
[18]	Narrative/empirical review	Telemedicine in primary care	Mapped empirical foundations	Limited attention to equity and workload
[19]	Systematic review	Telehealth and patient satisfaction	Consolidated satisfaction evidence	Satisfaction is a process, not outcome, measure
[20]	Systematic review and meta-analysis	Deep learning vs clinicians in imaging	Pooled diagnostic accuracy	Little on real-world deployment
[21]	Conceptual analysis	Informatics and inequality	Intervention-generated inequalities	Not linked to national platforms
[22]	Review	Digital technology in COVID-19 response	Mapped pandemic applications	Time-bound scope
[23,26]	Ethics analysis; WHO guidance	ML and AI governance	Ethical principles and governance	Not tied to workflow evidence
[24]	Commission report	Governing digital health futures	Governance agenda	Limited empirical quantification

2.3 Positioning of the present review

Three gaps follow from this literature. First, technology-specific reviews rarely relate their findings to one another, so cross-cutting phenomena such as alert fatigue, documentation burden and data governance are studied in isolation. Second, reviews from high-income settings dominate, while the interaction between national digital public infrastructure and local capability receives less attention. Third, legal, organisational-leadership and equity

perspectives are seldom integrated with clinical evidence. The present review addresses these gaps through a two-stream design, an explicit multi-perspective analysis and a framework tied to the Quintuple Aim.

3. Methodology

3.1 Design and rationale

We conducted a systematic literature review with an analytical synthesis. Reporting followed the PRISMA 2020 statement [27], adapted for a two-stream design. The scoping-review tradition [28] and its PRISMA extension [29] informed the emphasis on transparent mapping of a heterogeneous field. Two methodological guides on PRISMA-ScR in the supplied corpus were used as procedural references for structuring screening and transparency [30,31]. In Snyder's typology of review methods, the design lies between a systematic and an integrative review. It applies explicit selection and extraction rules, but it also synthesises heterogeneous designs to build a conceptual framework [32].

3.2 Evidence streams

Stream A: author-supplied corpus. The corpus comprised 117 bibliographic records provided by the author in a reference file. Every record was screened for relevance to health systems, digital technology or patient-care delivery.

Stream B: external evidence. Stream B was purposively assembled between August and September 2026 through targeted searching of indexed literature and official sources, together with backward and forward citation chaining from landmark studies. It is not an exhaustive database search. Sources were selected because they were peer-reviewed or issued by authoritative institutions, were directly relevant to a review question, and reported verifiable methods and results. Where possible, key quantitative statements were cross-checked against abstract-level or primary institutional records.

3.3 Eligibility criteria

Table 2. Eligibility criteria

Element	Inclusion	Exclusion
Topic	Digital or data-driven technologies in health care; health-system conditions that shape their use (workforce, leadership, law, equity, epidemiological context)	Records with no link to health, digital technology or care delivery
Evidence type	Systematic reviews, trials, cohort/validation studies, audits, observational studies, official statistics, authoritative guidance, and analytical or conceptual works	Opinion without evidence or argument; duplicates
Language	English (Stream B); English or Hindi records were screened in Stream A	Records not interpretable from bibliographic information

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

Period	No lower bound (to capture foundational studies); searching closed 20 September 2026	Not applicable

3.4 Data extraction and appraisal

For Stream B, we extracted design, setting, sample or scale, principal quantitative results, stated limitations and relevance to each review question. Appraisal was structured by design hierarchy and by the limitations that the original authors reported. It was not a formal risk-of-bias tool, because the designs were too heterogeneous.

For Stream A, the full texts of the records were not available to the review team. Eligibility assessment and coding were therefore conducted at the bibliographic level, using title, outlet, year and declared scope. Accordingly, Stream A records are used in this paper only to document that a topic has been examined in the supplied literature and to position the present work relative to it. No effect estimates or empirical findings are attributed to them. All quantitative claims derive from Stream B sources.

3.5 Synthesis

We used thematic synthesis, proceeding from free coding of extracted material to descriptive themes and then to analytical themes [33]. The procedure followed the phases of reflexive thematic analysis [34]. Quantitative results were tabulated and, where informative, plotted. Any values computed by the reviewers, such as ratios and remainders, are labelled as computed. Themes were then analysed through six stakeholder perspectives (patient, clinician, hospital leader, regulator or legislator, technology developer, and public-health or equity advocate). Finally, the themes were integrated into a framework aligned with the Quintuple Aim [9].

3.6 Research integrity

The study used secondary data only and involved no human participants. It followed accepted principles of transparency, accurate attribution and avoidance of misrepresentation in social and health research [35]. All text is original, sources are attributed by number, and no passage is reproduced from any source.

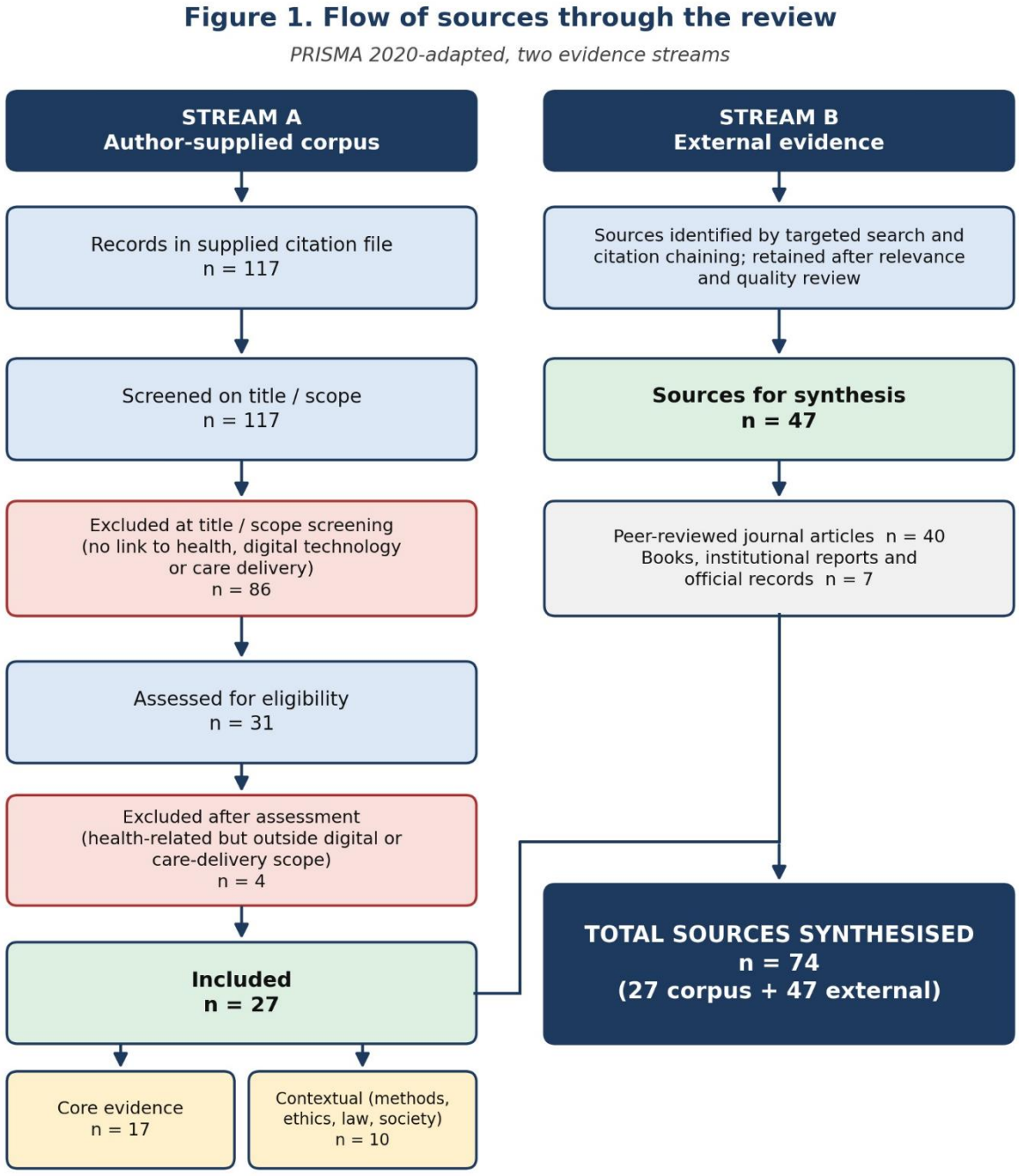
4. Results

4.1 Study selection

The selection process is summarised in Figure 1.

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

Figure 1. Flow of sources through the review (PRISMA 2020-adapted, two streams)



Of the 117 corpus records, 86 were excluded at title or scope screening because their subjects lay outside health, digital technology or care delivery. Thirty-one were assessed for eligibility, and four were excluded because they were health-related but concerned issues other than digital or care-delivery systems. Twenty-seven were retained. Seventeen of these were classed as core records: health-system, digital-health or health-context works [10,11,13,36–49]. Ten were

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

classed as contextual records, covering review methods, research ethics, law and the wider digital society [30,31,35,50–56]. Adding the 47 external sources gave a synthesis base of 74 sources.

4.2 Characteristics of the included evidence

Table 3. Core corpus records: declared focus, theme and role in this review

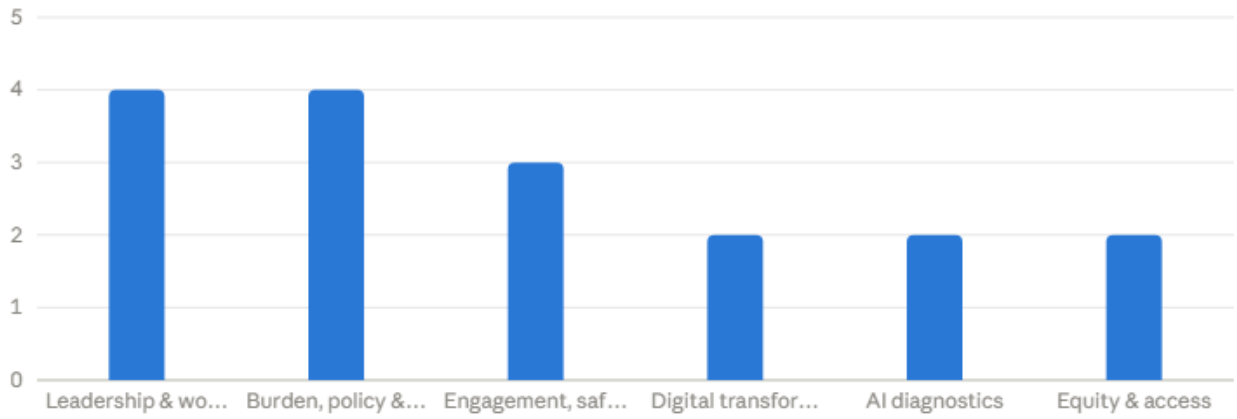
Ref.	Year	Declared focus (from bibliographic record)	Theme	Role in this review
[13]	2025	Digital transformation and hospital management (systematic review)	Digital transformation	Positions prior synthesis
[49]	2025	Machine learning for smart facility management in hospitals	Digital transformation	Scope: operational analytics
[36]	2025	AI in diagnostic medicine	AI diagnostics	Scope: AI-enabled diagnosis
[37]	2025	ML with genomic epidemiology for antimicrobial-resistance prediction	AI diagnostics	Scope: predictive stewardship
[38]	2025	Patient engagement in AI-driven healthcare systems	Engagement, safety, environment	Scope: engagement redesign
[39]	2025	Evidence-based environmental design and educational interventions	Engagement, safety, environment	Scope: care environment
[40]	2024	Reducing hospital-acquired infections	Engagement, safety, environment	Scope: patient safety
[41]	2025	Telemedicine access and outcomes across socioeconomic groups	Equity and access	Scope: digital health equity
[42]	2026	Socio-legal study of health disparities in Punjab	Equity and access	Scope: structural inequity, legislation
[43]	2025	Leadership styles in hospital administration	Leadership and workforce	Scope: management
[44]	2025	Crisis leadership and organisational learning after the pandemic	Leadership and workforce	Scope: organisational learning
[45]	2025	Trauma-informed care in healthcare leadership	Leadership and workforce	Scope: culture and outcomes
[46]	n.d.	Burnout and bureaucracy in healthcare professionals	Leadership and workforce	Scope: workforce strain
[10]	2025	Disease burden in India	Burden, policy, resilience	Epidemiological context
[11]	2025	Disease patterns and trends in India, 2020–2025	Burden, policy, resilience	Epidemiological context
[47]	2025	Floods and health-system vulnerability in Asian countries	Burden, policy, resilience	Scope: infrastructure resilience

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

[48]	2025	Health legislation and national health systems	Burden, policy, resilience	Scope: legal framework

Among the core corpus records, 14 of 17 were published in 2025, one in 2024, one in 2026 and one is undated. Among the ten contextual records, nine were published in 2025 and one in 2024. The external sources span 2001 to 2025. Two date from 2001, four from 2005–2010, three from 2011–2015, 29 from 2016–2020 and nine from 2021–2025, which reflects the concentration of digital-health scholarship in the past decade. Figure 2 shows the thematic distribution of the core corpus records.

Figure 2. Core corpus records by primary theme (n = 17)



Primary theme	Number of records
Leadership & workforce	4
Burden, policy & resilience	4
Engagement, safety & environment	3
Digital transformation	2
AI diagnostics	2
Equity & access	2

Leadership and workforce, and burden, policy and resilience, are the two largest clusters in the supplied corpus (four records each). Equity and access and AI diagnostics are the smallest (two each), so the corpus is stronger on the organisational and contextual side than on direct technology evaluation. This is why Stream B supplies the effect-size evidence.

4.3 Thematic findings

Synthesis produced seven analytical themes: virtual access and continuity; equity and the digital divide; clinical intelligence; workflow, records and workforce; patient engagement,

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

safety and the care environment; leadership, learning and resilience; and law, ethics and governance.

Theme 1: Virtual access and continuity of care

The evidence on telemedicine is broadly supportive but uneven. Reviews of primary-care telemedicine report a favourable but heterogeneous evidence base [18]. Patient satisfaction with telehealth is generally high across published studies, and this is commonly attributed to convenience and reduced travel [19]. Satisfaction is a process indicator, however. It cannot by itself establish clinical effectiveness, safety or fairness of access. The pandemic experience showed that virtual care could be scaled rapidly, but it also showed that rapid scaling exposes gaps in workflow design and inclusion [3–5].

India provides the largest publicly funded demonstration of virtual care embedded in national digital infrastructure. The Ayushman Bharat Digital Mission (ABDM) was launched in September 2021 to create an interoperable online platform for health data [57]. Its eSanjeevani service operates on a hub-and-spoke model. Doctors, including specialists, at hubs serve patients at rural Ayushman Arogya Mandirs, and patients can also use an outpatient module directly [57]. By 30 January 2024, 20.41 crore (204.1 million) teleconsultations had been completed through the platform [57]. By 28 July 2025, the government reported over 39 crore patients served through 1,34,029 spoke facilities supported by 17,568 hubs, together with 79.71 crore ABHA accounts and 65.09 crore linked health records [58].

Table 4. Indicators of India's national digital health infrastructure

Indicator	Value	Source date	Ref.
ABDM launch	September 2021	n/a	[57]
Cumulative eSanjeevani teleconsultations	20.41 crore (≈204.1 million)	30 Jan 2024	[57]
Patients served by eSanjeevani	>39 crore (>390 million)	28 Jul 2025	[58]
Ayushman Arogya Mandirs operating as spokes	1,34,029	28 Jul 2025	[58]
Hubs	17,568	28 Jul 2025	[58]
ABHA accounts created	79.71 crore (≈797.1 million)	28 Jul 2025	[58]
Health records linked to ABHA	65.09 crore (≈650.9 million)	28 Jul 2025	[58]
Health facilities in the facility registry	4.17 lakh (≈417,000)	28 Jul 2025	[58]
Health professionals registered	6.76 lakh (≈676,000)	28 Jul 2025	[58]
Linked records per account (computed)	≈0.82	28 Jul 2025	Computed from [58]

Three analytical observations follow. First, the unit of count changed between reports, from consultations to patients served, so the two eSanjeevani figures should not be plotted as a continuous trend. Second, accounts created is an enrolment metric, not a usage metric. The computed ratio of about 0.82 linked records per account indicates that record linkage lags enrolment, and that the number of records is not the number of persons. Third, the doctor-to-doctor spoke model relocates the digital interface from the patient to a local facility [57]. This

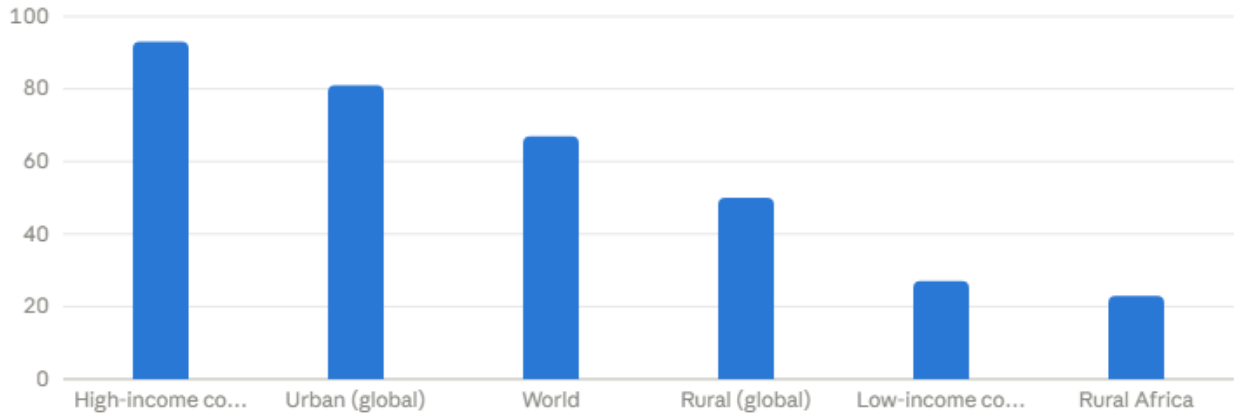
SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

is a design response to variable patient digital literacy and connectivity, and it deserves evaluation as a distinct model of "assisted telemedicine".

Theme 2: Equity and the digital divide

Digital access is a precondition of digital care. The International Telecommunication Union estimated that 5.4 billion people (67% of the world) used the Internet in 2023, leaving about 2.6 billion (33%) offline [12]. Internet use was 93% in high-income countries and 27% in low-income countries, a gap of 66 percentage points [12]. Worldwide, 81% of urban residents used the Internet against 50% of rural residents, an urban-rural ratio of about 1.6 [12]. In Africa, the corresponding figures were 57% and 23% [12].

Figure 3. Internet use by population group, 2023 (% of population) [12]



Category	Share using the Internet (%)
High-income countries	93
Urban (global)	81
World	67
Rural (global)	50
Low-income countries	27
Rural Africa	23

The gradient is steep. A rural resident of Africa is about four times less likely to be online than a resident of a high-income country (23% against 93%). Any care model that depends on patient-side connectivity therefore inherits this gradient.

Connectivity is only the first of several gradients. A conceptual analysis of informatics and inequality argues that even well-intentioned interventions generate inequalities when they reach advantaged groups first, or when they demand skills and resources that disadvantaged

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

groups lack [21]. The Lancet and Financial Times Commission likewise treats digital access and design as determinants of health that require governance [24]. Within the supplied corpus, recent analyses have examined telemedicine access and outcomes across socioeconomic groups [41], and the socio-legal dimensions of health disparities in Punjab, including structural inequities and legislative gaps [42]. Related analyses have examined algorithmic bias and social stratification [53] and spatial justice in technology-enabled urban settings [55].

Synthesising these strands yields four gradients of exclusion, which we treat as an analytical construct.

1. **Connectivity:** whether a signal and a device exist.
2. **Capability:** whether the user has the digital, health and language literacy to use them.
3. **Content and design:** whether the service is built for the user's language, disability and context.
4. **Consequence:** whether algorithmic outputs treat the user fairly.

The fourth gradient is illustrated by an audit of a commercial risk-prediction algorithm, discussed under Theme 3.

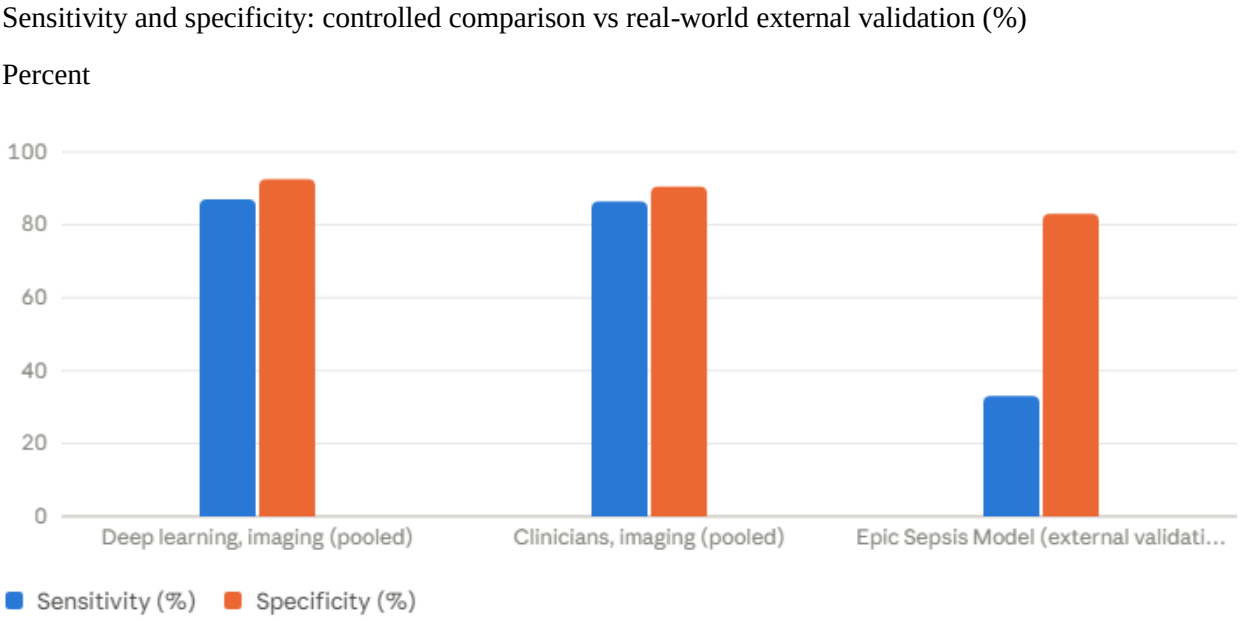
Theme 3: Clinical intelligence

AI has produced some of the most striking diagnostic results in medicine. A deep neural network trained on 129,450 clinical images covering 2,032 diseases matched the performance of 21 board-certified dermatologists in classifying skin lesions [59]. A deep-learning algorithm for diabetic retinopathy, developed on 128,175 retinal images, achieved sensitivities of 97.5% and 96.1% with specificities of 93.4% and 93.9% on two validation sets at its high-sensitivity operating point [60]. In breast-cancer screening, an AI system reduced false positives by 5.7% (US) and 1.2% (UK) and false negatives by 9.4% (US) and 2.7% (UK) in absolute terms [61].

Pooled evidence tempers enthusiasm. In the 14 studies that compared deep learning with health-care professionals on the same samples, pooled sensitivity was 87.0% for deep learning and 86.4% for clinicians, and pooled specificity was 92.5% and 90.5% respectively. The review also found that few studies were externally validated [20]. Performance under real-world deployment can be markedly worse. An external validation of a proprietary sepsis-prediction model widely implemented in US hospitals examined 38,455 hospitalisations. Sepsis occurred in 2,552 (about 7%). The model's area under the curve was 0.63, its sensitivity 33%, specificity 83%, positive predictive value 12% and negative predictive value 95%. It failed to identify 67% of patients with sepsis while generating alerts for 18% of all hospitalised patients [62].

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

Figure 4. Reported performance of AI tools under different evaluation conditions (%) [20,62]



Category	Sensitivity (%)	Specificity (%)
Deep learning, imaging (pooled)	87	92.5
Clinicians, imaging (pooled)	86.4	90.5
Epic Sepsis Model (external validation)	33	83

Figure 4 must be read with care. The three bars come from different tasks, populations and designs, so they are not a like-for-like comparison. Their value lies in a contrast of evidence types. Curated retrospective imaging comparisons show sensitivity near 87%, whereas a deployed predictive model evaluated externally showed 33%. The lesson is not that AI fails. The lesson is that performance reported by developers does not transfer automatically to new settings, and that local validation and post-deployment monitoring are part of the intervention.

Equity compounds the problem. An audit of an algorithm used to manage the health of populations found that it used health costs as a proxy for health needs. Black patients at the same risk score were therefore sicker than White patients. Correcting the bias would have raised the share of Black patients flagged for additional care from 17.7% to 46.5% [63]. The finding shows how the "consequence" gradient of exclusion operates even where no patient ever touches a device. Two further points arise from the wider literature. Federated learning offers a technical route to multi-institutional model development without centralising patient data [64], but privacy protection in the era of medical big data remains a legal and organisational challenge, not only a technical one [65].

Within the supplied corpus, AI has been examined in diagnostic medicine [36] and in the prediction of antimicrobial-resistance patterns for antibiotic stewardship [37]. Machine-

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

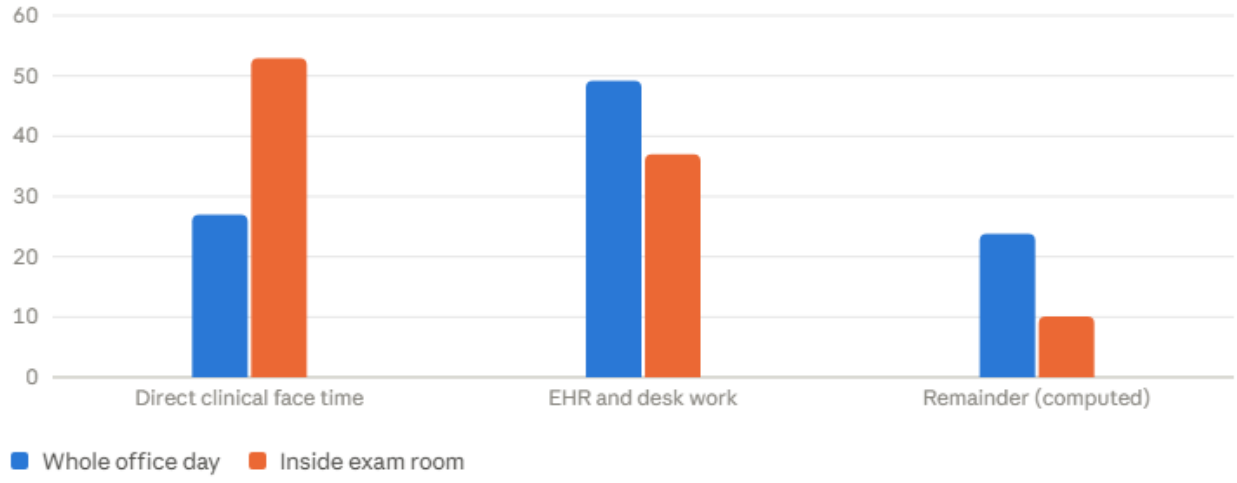
learning-based facility management has also been examined [49]. These works indicate that clinical intelligence extends beyond image classification to stewardship and operations. A further conceptual point follows. Machine learning in medicine is a family of methods whose usefulness depends on data quality, problem framing and validation [25], and the effects of these methods are therefore inseparable from the organisational system into which they are placed.

Theme 4: Workflow, records and workforce

EHR adoption has been transformative in scale. In the United States, adoption of at least a basic EHR among hospitals rose from 9.4% in 2008 to 83.8% in 2015 following the HITECH Act [66]. Information technology can reduce errors in medicine, particularly through order entry and decision support [67]. The workflow consequences, however, have been costly.

A direct-observation study of 57 physicians in four specialties, observed for 430 hours, found that during the office day physicians spent 27.0% of their time on direct clinical face time and 49.2% on EHR and desk work. Inside the examination room, they spent 52.9% of their time on face-to-face care and 37.0% on EHR and desk work. Those who kept diaries reported one to two hours of after-hours EHR work each night. The authors cautioned that the practices were self-selected, high-performing sites and that findings might not generalise [68].

Figure 5. Allocation of physician time in US ambulatory practice (% of time) [68]



Category	Whole office day	Inside exam room
Direct clinical face time	27	52.9
EHR and desk work	49.2	37
Remainder (computed)	23.8	10.1

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

The remainder values are computed as 100 minus the two reported percentages. They combine administrative and other tasks. The ratio of EHR and desk work to face time over the office day is 49.2 / 27.0 ≈ 1.8 (computed), consistent with the original authors' summary that each hour of face-to-face care is accompanied by nearly two hours of EHR and desk work [68].

The workforce implications are documented. A national survey of US physicians linked clerical burden and features of the electronic environment to burnout and lower professional satisfaction [69]. Alert design compounds the burden. Repeated alerts in a clinical decision-support system were associated with lower alert acceptance, a pattern known as alert fatigue [70]. The sepsis-model finding, in which alerts fired for 18% of all hospitalised patients, is a large-scale illustration [62]. Within the supplied corpus, a systems-level analysis of burnout and bureaucracy in healthcare professionals examines the organisational side of the same problem [46].

The Theme 4 evidence supports a clear analytical conclusion. Digitisation that adds documentation and alert burden without removing other work does not free time for patients. It consumes the clinical attention that patient-centred care depends on. Given the quadruple-aim principle that care of the patient requires care of the provider [8], workload is a design outcome to be measured, not a side effect to be tolerated.

Theme 5: Patient engagement, safety and the care environment

Mobile health and wearables extend care beyond facilities [71,72]. Their evidence base includes large pragmatic studies. In a study of 419,297 smartwatch users, 0.52% received an irregular-pulse notification. Among notified participants who returned an ECG patch, 34% had atrial fibrillation on the patch, and 84% of notifications concurrent with patch recording were concordant with atrial fibrillation [73]. The study demonstrates feasibility at scale. It does not by itself demonstrate improved patient outcomes, and it raises questions about downstream burden on clinicians.

Digital mental-health tools show similar promise. In a randomised trial of 70 young adults, a conversational agent delivering cognitive behavioural therapy reduced depressive symptoms over two weeks compared with an information control, while the difference in anxiety was not significant [74]. The trial was small and short, and it illustrates both the potential and the evidentiary limits of automated engagement.

The supplied corpus addresses engagement, safety and environment from a health-system perspective. It includes analyses of patient engagement in AI-driven healthcare systems [38], evidence-based environmental design and educational interventions for healthcare outcomes [39], and strategies to reduce hospital-acquired infections [40]. Such works remind us that digital care is embedded in physical and organisational settings. Smart-facility analytics [49] and digital transformation in hospital management [13] connect the digital layer to the built environment.

An additional consideration concerns attention. The corpus contains analyses of social-media addiction among adolescents [50], doomscrolling and cognitive overload [51], and digital

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

minimalism as a form of resistance [52]. Together they signal a societal backlash against engagement-maximising design. For digital health, the implication is a design principle: patient-facing tools should aim at health outcomes and informed use, not at time-on-app. Notification volumes, streak mechanics and constant tracking can become sources of anxiety if applied uncritically.

Table 5. Quantitative evidence extracted from external sources

Ref.	Design and setting	Sample or scale	Key quantitative result	Implication for reimagined care
[68]	Time-and-motion observation and diaries; US ambulatory care	57 physicians; 430 h	Face time 27.0% vs EHR/desk work 49.2% (office day); 52.9% vs 37.0% (exam room); 1–2 h nightly after-hours work (21 diaries)	Documentation competes with presence
[62]	Retrospective external validation; US academic centre	38,455 hospitalisations; 2,552 sepsis cases (≈7%)	AUC 0.63; sensitivity 33%; specificity 83%; PPV 12%; NPV 95%; 67% of cases missed; alerts for 18%	Local validation and alert governance are essential
[63]	Algorithm audit; US health system	≈50,000 patients	Black patients flagged for extra care would rise from 17.7% to 46.5% if bias corrected	Proxy-label choice can embed inequity
[20]	Systematic review and meta-analysis; imaging	14 same-sample comparison studies	DL sensitivity 87.0% vs clinicians 86.4%; specificity 92.5% vs 90.5%	AI can match clinicians in curated tasks
[60]	Diagnostic validation; retinal images	128,175 development images; two validation sets	Sensitivity 97.5% and 96.1%; specificity 93.4% and 93.9% (high-sensitivity point)	Screening at scale is feasible
[61]	Retrospective diagnostic study; mammography	UK and US test sets	False-positive reduction 1.2% (UK), 5.7% (US); false-negative reduction 2.7% (UK), 9.4% (US)	AI may support double-reading workflows
[73]	Prospective single-arm study; smartwatch	419,297 participants	0.52% notified; 34% AF among notified with patch data; 84% concordance	Consumer sensing scales but creates follow-up demand
[74]	Randomised controlled trial; conversational agent	70 young adults	Depressive symptoms reduced vs control; anxiety difference not significant	Promising but small and short-term
[12]	Global statistics	World population	Internet use 93% (high-income) vs 27% (low-income); 81% urban vs 50% rural	Access infrastructure conditions equity

Theme 6: Leadership, learning and resilience

Technology adoption is an adaptive organisational challenge. The NASSS framework predicts that complexity across domains lowers the probability that technologies will be adopted, scaled

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

and sustained [16], and the sociotechnical model locates many failures in workflow, people and organisational features rather than in hardware or software [17]. The supplied corpus contains four works within this theme. They address leadership styles in hospital administration [43], crisis leadership and organisational learning from pandemic failures [44], trauma-informed care in healthcare leadership [45] and burnout in healthcare bureaucracies [46].

Read alongside the empirical evidence, these works suggest that leadership shapes three conditions on which digital care depends. First, leaders decide whether digital investment is accompanied by workflow redesign or merely by added tasks, which determines the workload outcomes in Theme 4. Second, leaders determine whether organisations learn from failures, including model failures such as those documented in Theme 3. Third, leaders set the cultural conditions of psychological safety and care of staff that the quadruple and quintuple aims presuppose [8,9]. Pandemic experience reinforces the point. Digital technologies were mobilised widely for planning and response, but their effectiveness varied with organisational readiness [22].

Resilience is a related concern. Health-system vulnerability to flooding and other climate-related disasters has been analysed for Asian countries [47]. Digital care depends on electricity, connectivity and devices, so it is exposed to the same infrastructure shocks. It follows, as an inference from these two literatures, that resilient digital health requires offline-capable design, redundancy and continuity planning.

Theme 7: Law, ethics and governance

Governance determines whether digital health earns trust. Ethical analyses of machine learning in medicine identify safety, transparency, fairness and privacy as recurring challenges [23]. The WHO's guidance on the ethics and governance of AI for health translates these concerns into principles and recommendations for developers, providers and regulators [26]. Privacy protection must address the scale and secondary use of medical data [65], and governance should be designed so that digital transformation serves health rather than commercial or state interests alone [24].

The supplied corpus adds three relevant strands. It examines the role of health legislation in strengthening national health systems from a policy-legal perspective [48]. It includes an analysis of the law of negligence [56]. The general doctrine of negligence, with its concepts of duty, breach and causation, will supply the legal vocabulary through which harms arising from erroneous algorithmic outputs are likely to be adjudicated. Finally, it examines digital surveillance and sovereignty in the Global South [54]. Concerns about surveillance and data sovereignty bear directly on national health-data platforms of the kind described in Table 4. They frame a dual-use question: infrastructure that enables continuity of care can also enable monitoring, and safeguards must be designed from the outset.

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

Table 6. Certainty of evidence by domain (reviewer judgement)

Domain	Principal evidence	Consistency	Directness	Overall certainty
Virtual access	[18,19,57, 58]	Consistent on satisfaction; heterogeneous on outcomes	Mostly process measures	Moderate
Equity and exclusion	[12,21,63]	Consistent direction	Indirect for health outcomes	Moderate for risk; low for effect size
AI in imaging	[20,59–61]	Consistent in retrospective comparisons	Few external validations	Moderate for accuracy; low for patient outcomes
AI in deployed prediction	[62,63]	Consistent concern	Direct for tested tools	Moderate (few, high-quality studies)
EHR workload and burnout	[68–70]	Consistent	Direct	Moderate to high for burden; low for remedial interventions
Mobile and digital mental health	[73,74]	Single studies	Direct but short-term	Low to moderate
Leadership and organisational learning	[16,17,43–46]	Conceptually consistent	Indirect	Low (not appraised for effects)
Governance and law	[23,26,48, 54,56,65]	Conceptually consistent	Normative	Low (normative evidence)

Note: certainty ratings reflect reviewer judgement informed by the domains used in evidence-grading approaches (consistency, directness, precision, risk of bias). They are not a formal GRADE assessment.

5. Analytical Synthesis: Multiple Perspectives

5.1 Stakeholder perspectives

The seven themes look different from different vantage points. Table 7 organises the findings by six perspectives.

Table 7. Multi-perspective analysis of digital health

Perspective	What they seek	Supporting evidence	Principal risk	Success indicator
Patient and carer	Convenient, understandable, safe and respectful care; control over data	Satisfaction with telehealth [19]; engagement tools [73,74]	Exclusion, alert anxiety, loss of human contact, privacy loss [21,65]	Access without extra burden; experience and outcome improvement

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

Frontline clinician	Time with patients; useful, accurate decision support	EHR time burden [68]; alert fatigue [70]	Burnout, documentation overload, opaque algorithms [62,69]	Reduced after-hours work; alert acceptance; well-being
Hospital leader	Efficiency, safety, financial sustainability, workforce retention	Digital transformation in hospital management [13]; smart facility analytics [49]; leadership [43–45]	Implementation failure, sunk cost, unsafe adoption [16,17]	Sustained adoption; safety and workforce indicators
Regulator or legislator	Safety, accountability, privacy, equity	Governance guidance [24,26]; health legislation [48]; negligence doctrine [56]	Lagging regulation; surveillance and sovereignty concerns [54]	Clear liability and standards; post-deployment monitoring
Technology developer	Adoption, scalability, evidence of value	Diagnostic accuracy evidence [20,59–61]	Performance shortfall outside development data [62]; biased labels [63]	External validation; transparent performance reporting
Public-health and equity advocate	Population reach, closing gaps	Connectivity gradients [12]; equity analyses [41,42]; national platforms [57,58]	Intervention-generated inequality [21]; algorithmic bias [53]	Equity-stratified reporting; reduced disparities

5.2 Convergences

Three convergences emerge. All perspectives value usable, trustworthy tools, and each names the same failure modes from a different angle. Clinicians experience alert fatigue [70], managers experience abandoned implementations [16], and developers experience performance shortfalls outside the development setting [62]. All perspectives also depend on data quality and interoperability. The national platform described in Table 4 is an attempt to provide this at population scale [57,58]. Finally, workforce wellbeing is now recognised as a core objective rather than a by-product [8].

5.3 Tensions

Four tensions structure the trade-offs.

Efficiency versus presence. Automation can free time, but documentation and alert burdens can consume it [68,70]. The net effect depends on whether workflows are redesigned or merely digitised.

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

Personalisation versus privacy. Personalised care requires rich data, yet the scale and secondary use of data create privacy risks [65]. Federated approaches reduce, but do not eliminate, the problem [64].

Scale versus equity. Consumer sensing scales rapidly [73], but scale without inclusion widens gaps [21]. Assisted-access designs, such as India's hub-and-spoke telemedicine, illustrate an alternative [57].

Automation versus accountability. Algorithmic outputs diffuse responsibility across developers, deployers and clinicians. Legal doctrine, including the law of negligence [56], and governance frameworks [26] will determine where accountability lands.

5.4 The Reimagined Care Framework

Integrating the themes and perspectives, we propose a five-layer Reimagined Care Framework (RCF). It is a conceptual synthesis derived from the evidence above. It has not been empirically validated.

Table 8. The Reimagined Care Framework (RCF)

Layer	Purpose	Core practices	Indicative measures	Quintuple Aim link
1. Access and inclusion	Ensure people can reach and use care	Assisted telemedicine; multilingual and low-bandwidth design; offline capability	Reach by rural/urban, income, gender; completed visits; digital-exclusion audits	Equity; patient experience
2. Intelligence and decision support	Improve decisions safely	Local validation; calibration; human oversight; bias audits	Sensitivity, PPV and calibration in local data; subgroup performance; override rates	Better outcomes; equity
3. Workflow and workforce	Return time to clinicians and patients	Workflow redesign before deployment; alert governance; documentation support	Minutes of EHR work per visit; after-hours work; alert acceptance; burnout	Clinician well-being; cost
4. Trust, law and governance	Sustain legitimacy	Privacy by design; transparent performance reporting; clear liability; data-sovereignty safeguards	Audit completion; incident reporting; consent quality	All aims (enabling condition)

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

5. Learning and resilience	Improve continuously and withstand shocks	Post-deployment monitoring; learning after failures; continuity planning for power and connectivity	Time to detect and correct model drift; uptime in disasters	Sustainable outcomes and cost

6. Discussion

6.1 Principal findings

This review supports four principal conclusions. First, digital technologies can perform well in controlled conditions, whether that is imaging classification, wearable arrhythmia detection or virtual consultation, but performance and benefit are contingent on context. The contrast between pooled imaging accuracy [20] and the external validation of a deployed sepsis model [62] is the clearest illustration. Second, the burden of digitisation falls disproportionately on the workforce. Documentation and alert demands consume time that patient-centred care requires [68–70]. Third, access infrastructure shapes who benefits. The connectivity gradients in Figure 3 [12] and the audit of algorithmic bias [63] show that inequity can enter through both the front door of access and the back door of algorithm design. Fourth, governance and leadership are not peripheral. They are determinants of whether the same technology improves or degrades care [16,17,24,26].

6.2 Analytical propositions

We offer six propositions, framed as testable hypotheses that follow from the synthesis and are not established findings.

Proposition 1 (Workflow displacement). A digital tool improves clinician time allocation only when its deployment is accompanied by the removal or redesign of at least as much existing work as it adds. Otherwise, documentation and alert burdens displace face-to-face care, consistent with the time allocation observed in ambulatory practice [68].

Proposition 2 (Validation transferability). The performance of a predictive tool in a new setting is systematically lower than in its development setting unless it is locally recalibrated and monitored. The external validation of a widely deployed model [62] and the limited number of externally validated imaging studies [20] both point in this direction.

Proposition 3 (Proxy-label inequity). When an algorithm optimises a proxy for need, such as cost, it reproduces the inequities embedded in the proxy. The audit reported in [63] provides the paradigmatic case.

Proposition 4 (Assisted access). In settings with variable patient-side digital capability, assisted models that place the digital interface at a local facility can extend specialist reach

more equitably than direct-to-patient models. The hub-and-spoke architecture in [57] is a candidate for evaluation.

Proposition 5 (Enrolment is not use). Enrolment metrics such as accounts created overstate the functional reach of digital health infrastructure unless accompanied by measures of linked records, active use and outcome. The computed ratio of linked records to accounts in Table 4 illustrates the gap between enrolment and use.

Proposition 6 (Attention-neutral design). Patient-facing tools designed to maximise engagement time risk harming users' wellbeing, whereas tools designed around minimum effective use are more likely to sustain trust. This proposition draws on concerns about digital attention and overload in the wider digital-society literature [50–52].

6.3 Implications for practice

For clinicians and managers, the implication is that technology procurement must be preceded by workflow analysis. Measuring EHR minutes per visit, after-hours work and alert acceptance before and after deployment would turn workload from anecdote into evidence [68,70]. For AI, procurement should require external validation, subgroup performance data and a plan for local recalibration and monitoring [20,62,63]. Frameworks such as NASSS can be used prospectively to identify complexity in each domain before investment [16].

6.4 Implications for policy and law

Policymakers should treat digital access as part of health equity policy. The connectivity gradients in Figure 3 imply that rural and low-income populations need alternatives such as assisted access, offline capability and community facilities [12,57]. Regulators should require transparent reporting of algorithm performance and post-deployment surveillance, aligned with international ethical guidance [23,26]. Health legislation can provide the legal foundation for these obligations [48], while liability doctrines will need to clarify allocation of responsibility for algorithmic errors [56]. Data-sovereignty and surveillance concerns [54] should be addressed in the design of national health-data platforms, for example through purpose limitation, consent architecture and independent oversight.

6.5 Implications for research

Five research priorities emerge. The first is pragmatic trials of AI and virtual care that measure patient outcomes, not only accuracy or satisfaction. The second is equity-stratified reporting as a default requirement [21]. The third is the evaluation of assisted-access models. The fourth is the measurement of workload as a primary outcome of digital deployments. The fifth is longitudinal studies of national digital public infrastructure that distinguish enrolment from use.

SHODH PRAKASHAN
An International Open Access, Peer Reviewed, Refereed Journal
ISSN : 2583-9861
VOL. 4, ISSUE 5, NOVEMBER 2026
Available Online : https://shodhprakashan.in/

Table 9. A phased roadmap for reimagining patient care

Horizon	Priority actions	Lead actors	Evidence link
Short term (0–12 months)	Baseline audits of EHR time, alert burden and digital exclusion; require external validation evidence in AI procurement	Hospital leaders; procurement bodies	[62,68,70]
Medium term (1–3 years)	Workflow redesign before deployment; assisted-access pilots with equity-stratified reporting; bias audits of risk algorithms	Health systems; public health agencies	[21,57,63]
Long term (3–7 years)	Interoperable records with usage and outcome metrics; legal clarity on algorithmic accountability; continuity planning for infrastructure shocks	Governments; regulators; professional bodies	[24,47,48,56,58]

7. Limitations

Several limitations qualify these conclusions. First, Stream B was purposive and not an exhaustive database search, so relevant studies may have been missed and selection bias is possible. The review is best read as a structured, PRISMA-guided synthesis with transparent limits and not as a comprehensive census of the field. Second, the full texts of the Stream A corpus records were not available. Their assessment was bibliographic, and they contribute topic-level positioning only, not effect estimates. Third, the certainty ratings in Table 6 are reviewer judgements. Fourth, several key studies come from US settings, and their generalisability to India and other low- and middle-income countries is uncertain. Fifth, official statistics on India's digital platforms are self-reported by government sources. Sixth, the Reimagined Care Framework and the six propositions are conceptual and require empirical testing. Finally, rapid technological change means that the evidence base will date quickly, and the review reflects sources available up to 20 September 2026.

8. Conclusion

Digital health does not reimagine patient care by default. The evidence synthesised here shows that its benefits are real but conditional. Diagnostic AI can match clinicians in curated tasks yet falter when deployed without local validation. Electronic records can reduce errors yet consume nearly two hours of clinician time for every hour of face-to-face care. Telemedicine can extend access, yet its reach follows the connectivity gradients that divide urban from rural and high-income from low-income populations. National platforms can create the infrastructure for continuity, but enrolment is not use, and infrastructure raises governance questions that technology alone cannot answer.

Reimagining care therefore requires a shift in the unit of analysis from the tool to the system in which the tool operates. The proposed Reimagined Care Framework (access and inclusion, intelligence and decision support, workflow and workforce, trust and governance, and learning and resilience) offers a structure for that shift. It aligns digital investment with the Quintuple Aim, so that better outcomes, better experience, lower cost, clinician well-being and equity are

pursued together. The task for the coming decade is not to add more technology to health care. It is to design, govern and evaluate technology so that it gives time back to clinicians, power back to patients and access back to those now excluded.

References

1. World Health Organization. Global strategy on digital health 2020–2025. Geneva: World Health Organization; 2021.
2. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25(1):44-56.
3. Keesara S, Jonas A, Schulman K. Covid-19 and health care's digital revolution. N Engl J Med. 2020;382(23):e82.
4. Hollander JE, Carr BG. Virtually perfect? Telemedicine for Covid-19. N Engl J Med. 2020;382(18):1679-81.
5. Wosik J, Fudim M, Cameron B, Gellad ZF, Cho A, Phinney D, et al. Telehealth transformation: COVID-19 and the rise of virtual care. J Am Med Inform Assoc. 2020;27(6):957-62.
6. Institute of Medicine (US) Committee on Quality of Health Care in America. Crossing the quality chasm: a new health system for the 21st century. Washington (DC): National Academies Press; 2001.
7. Epstein RM, Street RL Jr. The values and value of patient-centered care. Ann Fam Med. 2011;9(2):100-3.
8. Bodenheimer T, Sinsky C. From triple to quadruple aim: care of the patient requires care of the provider. Ann Fam Med. 2014;12(6):573-6.
9. Nundy S, Cooper LA, Mate KS. The quintuple aim for health care improvement: a new imperative to advance health equity. JAMA. 2022;327(6):521-2.
10. Ahluwalia PS. Disease burden in India: a comprehensive analysis. Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:179-235.
11. Ahluwalia PS, John S. Disease pattern/trends in India: a comprehensive analysis of epidemiological transitions and public health challenges (2020-2025). Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:20-51.
12. International Telecommunication Union. Measuring digital development: facts and figures 2023. Geneva: International Telecommunication Union; 2023.
13. Ahluwalia PS. Assessing the impact of digital transformation on hospital management: a systematic review. International Journal of Healthcare and Hospital Management Studies. 2025:1-16.
14. Lupton D. Digital health: critical and cross-disciplinary perspectives. London: Routledge; 2017.
15. Murray E, Hekler EB, Andersson G, Collins LM, Doherty A, Hollis C, et al. Evaluating digital health interventions: key questions and approaches. Am J Prev Med. 2016;51(5):843-51.
16. Greenhalgh T, Wherton J, Papoutsi C, Lynch J, Hughes G, A'Court C, et al. Beyond adoption: a new framework for theorizing and evaluating nonadoption, abandonment, and challenges to the scale-up, spread, and sustainability of health and care technologies. J Med Internet Res. 2017;19(11):e367.
17. Sittig DF, Singh H. A new sociotechnical model for studying health information technology in complex adaptive healthcare systems. Qual Saf Health Care. 2010;19(Suppl 3):i68-74.
18. Bashshur RL, Howell JD, Krupinski EA, Harms KM, Bashshur N, Doarn CR. The empirical foundations of telemedicine interventions in primary care. Telemed J E Health. 2016;22(5):342-75.
19. Kruse CS, Krowski N, Rodriguez B, Tran L, Vela J, Brooks M. Telehealth and patient satisfaction: a systematic review and narrative analysis. BMJ Open. 2017;7(8):e016242.

20. Liu X, Faes L, Kale AU, Wagner SK, Fu DJ, Bruynseels A, et al. A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis. Lancet Digit Health. 2019;1(6):e271-97.
21. Veinot TC, Mitchell H, Ancker JS. Good intentions are not enough: how informatics interventions can worsen inequality. J Am Med Inform Assoc. 2018;25(8):1080-8.
22. Whitelaw S, Mamas MA, Topol E, Van Spall HGC. Applications of digital technology in COVID-19 pandemic planning and response. Lancet Digit Health. 2020;2(8):e435-40.
23. Vayena E, Blasimme A, Cohen IG. Machine learning in medicine: addressing ethical challenges. PLoS Med. 2018;15(11):e1002689.
24. Kickbusch I, Piselli D, Agrawal A, Balicer R, Banner O, Adelhardt M, et al. The Lancet and Financial Times Commission on governing health futures 2030: growing up in a digital world. Lancet. 2021;398(10312):1727-76.
25. Rajkomar A, Dean J, Kohane I. Machine learning in medicine. N Engl J Med. 2019;380(14):1347-58.
26. World Health Organization. Ethics and governance of artificial intelligence for health: WHO guidance. Geneva: World Health Organization; 2021.
27. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ. 2021;372:n71.
28. Arksey H, O'Malley L. Scoping studies: towards a methodological framework. Int J Soc Res Methodol. 2005;8(1):19-32.
29. Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. Ann Intern Med. 2018;169(7):467-73.
30. Ahluwalia PS. Enhancing systematic transparency through PRISMA-ScR: a scoping review approach for emerging researchers. Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:1-27.
31. Ahluwalia PS. Structured exploration through PRISMA-ScR: a transparent method for mapping research landscapes. Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:137-67.
32. Snyder H. Literature review as a research methodology: an overview and guidelines. J Bus Res. 2019;104:333-9.
33. Thomas J, Harden A. Methods for the thematic synthesis of qualitative research in systematic reviews. BMC Med Res Methodol. 2008;8:45.
34. Braun V, Clarke V. Using thematic analysis in psychology. Qual Res Psychol. 2006;3(2):77-101.
35. Ahluwalia PS. Ethical issues in social science research. Shodh Patra: International Journal of Multidisciplinary Studies. 2024:1-8.
36. Ahluwalia PS. Artificial intelligence in healthcare: the role of artificial intelligence in diagnostic medicine. Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:164-75.
37. Ahluwalia PS. Artificial intelligence-driven prediction of antimicrobial resistance patterns: integrating machine learning with genomic epidemiology for precision antibiotic stewardship. Journal of Integrated Research. 2025:97-122.
38. Ahluwalia PS. Redesigning patient engagement in AI-driven healthcare systems: an analysis. Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:203-17.
39. Ahluwalia PS. Transforming healthcare outcomes through evidence-based environmental design and educational interventions. Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:279-318.
40. Ahluwalia PS. Improving patient safety: strategies for reducing hospital-acquired infections. Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2024:126-45.

41. Ahluwalia PS. Digital health equity: evaluating access and outcomes in telemedicine across socioeconomic groups. Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:84-92.
42. Singh D, Ahluwalia PS. A socio-legal study on health disparities in Punjab: structural inequities, legislative gaps, and pathways to equitable healthcare. Shodh Prakashan. 2026:1-14.
43. Ahluwalia PS. Healthcare leadership and management: effective leadership styles in hospital administration. Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:69-82.
44. Ahluwalia PS. Crisis leadership in healthcare: organizational learning from pandemic failures. Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:136-46.
45. Ahluwalia PS, John S, Elliason EK. Embedding trauma-informed care into healthcare leadership: a paradigm shift in organizational culture and patient outcomes. Interdisciplinary Journal of the African Alliance for Research, Advocacy and Innovation. 2025;1(2).
46. Ahluwalia PS. Burnout and bureaucracy: a systems-level analysis of mental health challenges in healthcare professionals. [Publication details and date not available in source record].
47. Ahluwalia PS. Impacts of floods on health and healthcare systems in Asian countries: a comprehensive analysis of direct and indirect health consequences, economic burden, and healthcare infrastructure vulnerability. Shodh Prakashan. 2025:72-102.
48. Ahluwalia PS, John S. The role of health legislation in strengthening national health systems: a policy-legal perspective. Interdisciplinary Journal for Analysis in Education, Science, Commerce, Management & Law. 2025:1-20.
49. Singh P. Integrating machine learning for smart facility management in healthcare hospitality environments. Shodh Patra: International Journal of Multidisciplinary Studies. 2025:82-92.
50. Ahluwalia PS. Digital dopamine: the neuropsychology of social media addiction among adolescents. Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:93-109.
51. Ahluwalia PS. Doomscrolling and mental fatigue: cognitive overload in the era of crisis media. Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:250-70.
52. Ahluwalia PS, Singh D. The rise of digital minimalism: a new form of social resistance? Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:218-39.
53. Ahluwalia PS. Algorithmic bias and social stratification: how AI shapes inequality in digital societies. Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:28-37.
54. Ahluwalia PS. The rise of techno-authoritarianism: digital surveillance and sovereignty in the Global South. Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:34-54.
55. Ahluwalia PS. Smart cities and social divide: spatial justice in the age of urban tech. Siddhanta's International Journal of Advanced Research in Arts & Humanities. 2025:185-202.
56. Ahluwalia PS. Negligence under law of torts. Shodh Prakashan. 2025:1-18.
57. Rajya Sabha. Unstarred question no. 421: expansion of ABDM. Answered 2024 Feb 6. New Delhi: Ministry of Health and Family Welfare, Government of India; 2024 [cited 2026 Sep 20]. Available from: https://rsdebate.nic.in/bitstream/123456789/747563/1/PQ_263_06022024_U421_p414_p417.pdf
58. Press Trust of India. 79.71 crore ABHA accounts created, 65.09 crore health records linked: govt to Lok Sabha. The Week [Internet]. 2025 Aug 1 [cited 2026 Sep 20]. Available from: https://www.theweek.in/wire-updates/national/2025/08/01/del53-lsq-health-record.html
59. Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature. 2017;542(7639):115-8.

60. Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA. 2016;316(22):2402-10.
61. McKinney SM, Sieniek M, Godbole V, Godwin J, Antropova N, Ashrafian H, et al. International evaluation of an AI system for breast cancer screening. Nature. 2020;577(7788):89-94.
62. Wong A, Otles E, Donnelly JP, Krumm A, McCullough J, DeTroyer-Cooley O, et al. External validation of a widely implemented proprietary sepsis prediction model in hospitalized patients. JAMA Intern Med. 2021;181(8):1065-70.
63. Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. Science. 2019;366(6464):447-53.
64. Rieke N, Hancox J, Li W, Milletarì F, Roth HR, Albarqouni S, et al. The future of digital health with federated learning. NPJ Digit Med. 2020;3:119.
65. Price WN 2nd, Cohen IG. Privacy in the age of medical big data. Nat Med. 2019;25(1):37-43.
66. Adler-Milstein J, Jha AK. HITECH Act drove large gains in hospital electronic health record adoption. Health Aff (Millwood). 2017;36(8):1416-22.
67. Bates DW, Cohen M, Leape LL, Overhage JM, Shabot MM, Sheridan T. Reducing the frequency of errors in medicine using information technology. J Am Med Inform Assoc. 2001;8(4):299-308.
68. Sinsky C, Colligan L, Li L, Prgomet M, Reynolds S, Goeders L, et al. Allocation of physician time in ambulatory practice: a time and motion study in 4 specialties. Ann Intern Med. 2016;165(11):753-60.
69. Shanafelt TD, Dyrbye LN, Sinsky C, Hasan O, Satele D, Sloan J, et al. Relationship between clerical burden and characteristics of the electronic environment with physician burnout and professional satisfaction. Mayo Clin Proc. 2016;91(7):836-48.
70. Ancker JS, Edwards A, Nosal S, Hauser D, Mauer E, Kaushal R, et al. Effects of workload, work complexity, and repeated alerts on alert fatigue in a clinical decision support system. BMC Med Inform Decis Mak. 2017;17(1):36.
71. Steinhubl SR, Muse ED, Topol EJ. The emerging field of mobile health. Sci Transl Med. 2015;7(283):283rv3.
72. Sim I. Mobile devices and health. N Engl J Med. 2019;381(10):956-68.
73. Perez MV, Mahaffey KW, Hedlin H, Rumsfeld JS, Garcia A, Ferris T, et al. Large-scale assessment of a smartwatch to identify atrial fibrillation. N Engl J Med. 2019;381(20):1909-17.
74. Fitzpatrick KK, Darcy A, Vierhile M. Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automatic conversational agent (Woebot): a randomized controlled trial. JMIR Ment Health. 2017;4(2):e19.