Dissertation Report

On

"Innovate or Stagnate: A Critical Analysis of Emerging Technologies in the Modern Healthcare System"

carried out at

National Medical Commission

(15 March 2026, 15 June 2026)

by

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Enrolment No. PG/24/050

Under the guidance of

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PGDM (Hospital and Health Management)

2024-26



International Institute of Health Management Research (IIHMR)

Delhi

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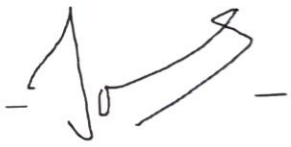
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The dissertation titled "Innovate or Stagnate: A Critical Analysis of Emerging Technologies in the Modern Healthcare System" at the National Medical Commission is hereby approved as a certified study in management carried out and presented in a manner satisfactory to warrant its acceptance as a prerequisite for the award of PGDM (Hospital & Health Management) for which it has been submitted.

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Dr. Mahima Yadav

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About the Organization

The work reported here was undertaken with the National Medical Commission (NMC) as the host organisation. The NMC is the country's principal statutory authority for regulating how doctors are educated and how the medical profession is practised. It was created by an Act of Parliament passed in 2019 and began operating in late 2020, taking over the functions previously held by the body that regulated medical education before it. Its headquarters are in New Delhi.

Instead of functioning as an integrated body, the Commission performs its functions by means of several specialized boards. In general, these boards supervise the teaching of undergraduate medicine, the training of postgraduate students, the assessment and evaluation of medical institutions, and the registration of practitioners along with the matters of professional ethics. As a whole, therefore, the Commission influences the standards of teaching, quality of institutions, the roster of qualified practitioners in the country, and professional behavior.

It is no wonder then that the Commission provided a suitable platform for conducting such a research. Questions like whether the new technology enjoys people's trust, whether it is safe enough, what kind of skills are necessary to implement the technology, and the regulation of technology usage were all the types of questions that regulators had to consider. However, the nature of the research – an analysis based on secondary data – makes its implications more pertinent to the field of evaluation, education, and regulation.

Academic supervision for the dissertation was provided by the International Institute of Health Management Research (IIHMR), New Delhi, as part of the PGDM (Hospital & Health Management) programme.

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List of Abbreviations

Abbreviation	Full Form
ABDM	Ayushman Bharat Digital Mission
ABHA	Ayushman Bharat Health Account
AI	Artificial Intelligence
CAGR	Compound Annual Growth Rate
CDSS	Clinical Decision Support System
DFD	Data Flow Diagram
EHR	Electronic Health Record
ER	Entity-Relationship
FDA	Food and Drug Administration
GIDH	Global Initiative on Digital Health
IoMT	Internet of Medical Things
IoT	Internet of Things
LLM	Large Language Model
MCI	Medical Council of India
ML	Machine Learning
NMC	National Medical Commission
RAS	Robot-Assisted Surgery
RCA	Root Cause Analysis
RCT	Randomised Controlled Trial
ROI	Return on Investment
RPM	Remote Patient Monitoring
UHC	Universal Health Coverage
WHO	World Health Organization

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1. Problem Statement

Healthcare is undergoing unprecedented levels of change. Telemedicine, artificial intelligence, surgical robots, wearables, and blockchain records have been taken from their laboratories and integrated into mainstream healthcare, and they all offer something desperately needed in the industry: quick diagnosis, safer surgeries, constant monitoring beyond hospital walls, and reaching patients who were unreachable before. According to the WHO, the integration of technology into healthcare is essential for universal health coverage and resilience of healthcare systems (1). Nonetheless, despite all the potential offered by technology, it is extremely difficult to overcome the gap between technology's capacity and its application. This distance is what this report attempts to investigate, The justification for acting quickly certainly holds up. With some of these technologies, the evidence base has come together very quickly, markets are growing double digits, and government-led initiatives like India’s Ayushman Bharat Digital Mission have laid the necessary digital plumbing that is crucial for systemic change (2). But there is another side to this equation as well. The adoption rate is uneven at best. There are countless pilots that stay pilots and when there is adoption, it goes to those who need it the least. This is a two-way risk. If the hospital shies away from the technologies that it should adopt, it may fall behind, providing slower, more expensive and less safe services compared to other hospitals and becoming out of sync with contemporary expectations of regulators and payers. But adopting technology thoughtlessly could be equally damaging; investing scarce resources in technology with limited added value, creating new vulnerabilities in safety and social justice, and wasting the goodwill of clinicians and consumers. Blanket caution or blanked approval is not a good policy. Instead, judgement is needed in terms of what technology is valuable, and in what priority.

India makes the issue all the more relevant. Its huge diverse population, fragmented healthcare system, lack of sufficient number of specialists that are grossly inadequate in number and distribution, and governance

The risk runs in both directions. A hospital that holds back from technologies it ought to be using can fall behind, offering slower, costlier and less safe care than its peers and drifting out of step with what regulators and payers now expect. A hospital that buys in without thinking can do just as much damage: scarce capital sunk into equipment that adds little, fresh gaps opened in safety and equity, and the goodwill of clinicians and patients quietly spent. Neither blanket enthusiasm nor blanket caution works as a policy. What helps is judgement, which technologies are worth the money, in what order, and with what safeguards.

India sharpens the question further. It has a vast and varied population, a health system that mixes public and private provision, far too few specialists spread far too unevenly, and a governance environment digitising at speed. Every one of those features raises both the reward and the cost of a new technology. A body like the National Medical Commission, which sets the standards for how doctors are trained and how the profession conducts itself, has a direct stake in how these tools are judged, taught and governed.

The term “emerging technology” gets used loosely. Here it means technology that is already in clinical or operational use, or close to it, but whose proper role, evidence base and rules of governance are still being settled. Five fit that description and form the backbone of this report: artificial intelligence and machine learning; telemedicine and telehealth; robotics and robot-assisted surgery; the Internet of Medical Things, with wearables and remote monitoring; and blockchain and the health-data infrastructure around it. They were chosen for three plain reasons. Each already matters to real health systems. Each has drawn a large recent literature. And between them they cover the main jobs a health system does, from diagnosis and treatment through monitoring and service delivery to the handling of data, which allows for a broad view rather than a narrow technical one. Technologies that are still mostly experimental, or that sit outside direct clinical use, are left aside.

The report therefore asks something narrower, and more useful, than “does this technology work?”. It asks under what conditions a technology turns into measurable value, and why adoption stalls so often

when those conditions are absent. To answer that, it draws together peer-reviewed evidence from roughly a decade of work, 2015 to 2025, and shapes it into a structured critical analysis written for the people who actually have to decide: hospital and health managers, educators and regulators. The aim is to get past the hype cycle and towards a way of telling worthwhile innovation apart from expensive, and sometimes hazardous, novelty.

1.1 Aim

To analyse the major emerging technologies in modern healthcare, weighing what they have actually been shown to do, where they fall short, and what decides whether they are taken up, and from that to build a decision-oriented synthesis that separates innovation worth its cost from adoption that is premature or imprudent.

1.2 Objectives

- To survey and appraise the 2015-2025 literature on AI and machine learning, telemedicine, robotics, IoMT and wearables, and blockchain in healthcare.
- To establish, for each technology, how strong the evidence is and what the main benefits and limitations are.
- To analyse the determinants of adoption that cut across technologies: technical, organisational, financial, regulatory, workforce and ethical.
- To set the analysis within the global and Indian policy and governance context.
- To build conceptual models, process maps, a root-cause analysis, a decision framework and a data-flow view, that turn the evidence into something a manager can act on.

1.3 Outline of the research approach

The study is a literature-based critical analysis, in effect a structured narrative review. It begins from a focused question, applies a transparent way of searching and choosing both recent and landmark sources, appraises and synthesises the evidence technology by technology, and then pulls the findings together into management-oriented models and recommendations. Chapters 2 and 5 set out the method in detail.

2. Scope of the Project

This report is a literature-based critical analysis. No primary patient or organisational data were collected. Instead it appraises and synthesises evidence that has already been published, mostly between 2015 and 2025, while keeping older landmark work where it still anchors the field.

2.1 In scope

- Five families of emerging technology: AI and machine learning; telemedicine and telehealth; robotics and robot-assisted surgery; IoMT, wearables and remote patient monitoring; and blockchain and health-data systems.
- The clinical, operational, economic, ethical and equity sides of each technology.
- The determinants of adoption that cut across all of them, technical, organisational, financial, regulatory, workforce and data-governance factors.
- The policy and governance backdrop, with particular attention to the WHO digital health strategy and India's Ayushman Bharat Digital Mission.

2.2 Out of scope

- Collecting primary data through surveys, interviews or trials.
- Exhaustive engineering detail of individual devices and algorithms.
- Cost-effectiveness modelling for any one institution, which would need organisation-level data.

2.3 Information sources and search approach

This is not a full systematic review but rather a narrative review. Nevertheless, the search process was conducted in an open and unbiased way to prevent selection bias. Search in academic journals, reliable websites, and databases was performed using the keywords mentioned above; systematic reviews and meta-analysis, randomized trials, initial studies and recent narrative reviews; the list of references was used for identifying additional materials; and policy documents were analyzed directly. The timeframe 2015-2025 was selected intentionally in order to consider breakthroughs from the middle of the 2010s and recent developments. See Table 2.1.

Table 2.1: Search strategy and information sources

Element	Detail
Databases / sources	PubMed/MEDLINE, Cochrane Library, ScienceDirect/Elsevier, Frontiers, JMIR, PLOS, IEEE, ACM, and high-quality journals (Nature, NEJM, JAMA, Lancet titles, JAMIA); WHO, OECD and government reports
Time frame	2015-2025 (foundational and recent), with seminal earlier work retained for context
Document types	Systematic reviews, meta-analyses, randomised controlled trials, foundational primary studies, narrative reviews, policy and market reports
Key search terms	“artificial intelligence”, “telemedicine / telehealth”, “robot-assisted surgery”, “wearables / IoMT”, “blockchain”, each combined with “healthcare”, “adoption” and “barriers”
Inclusion	English-language; relevance to clinical or health-system application; emphasis on higher-level and seminal evidence across 2015-2025
Exclusion	Non-health applications; opinion pieces without an evidentiary basis; non-credible or predatory sources

3. Review of Literature

3.1 Introduction

This chapter works through the evidence on each of the five technologies across the 2015-2025 decade. For each one it tracks where the field began, how solid the evidence has since become, what the technology demonstrably delivers and where it falls short, and what tends to drive or block its uptake. The sources run to more than forty in all: systematic reviews, meta-analyses, randomised trials, the foundational primary studies and the main policy documents. From these the chapter draws out the themes the five technologies have in common, sets them in the global and Indian policy context, and pins down the gap that the rest of the report goes on to fill.

On a methodological point – the hierarchy that is applied when weighting evidence. The most important studies are systematic reviews, meta-analyses and randomised controlled trials, as they provide a definite indication of efficacy. Next are large prospective studies and validations. Lastly are single centre papers, market research and opinion. This is relevant because the discussion in the public sphere regarding technology in healthcare is conducted on such low-hanging fruit, such as the promise of a positive pilot, a favourable forecast for the market, as opposed to a rational and dispassionate assessment, which requires strong evidence. Where available evidence is only of weak quality or an industry report, it has been indicated as indicative only.

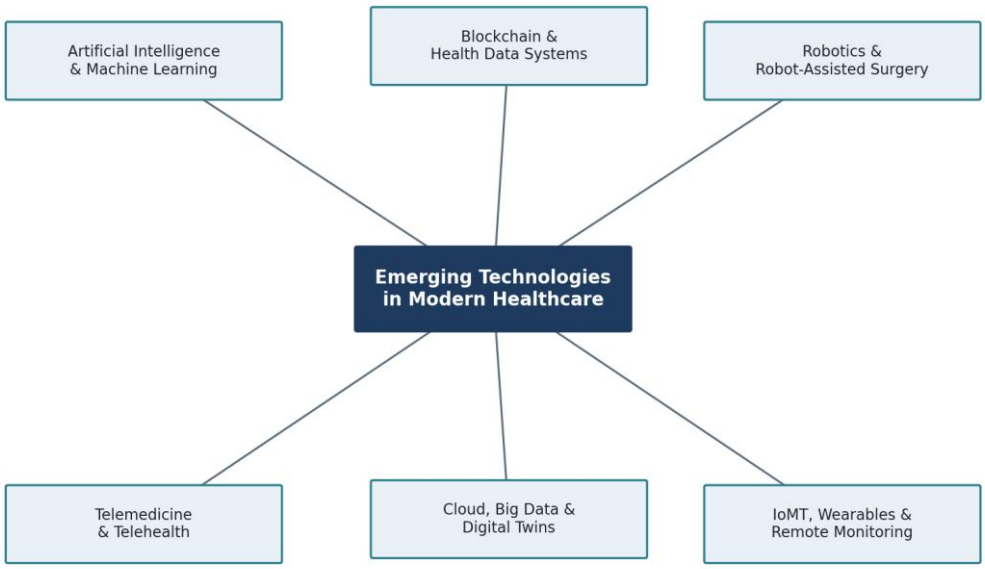


Figure 4.1: Landscape of emerging technologies in modern healthcare

3.2 Artificial Intelligence and Machine Learning

3.2.1 Foundational developments (2015-2020)

The reality is that healthcare applications of AI started with several important papers published around 2015. Gulshan et al. developed and validated a deep learning model capable of identifying diabetic retinopathy from retinal photographs with accuracy comparable to ophthalmologists' (5), and Esteva et al. demonstrated that one convolutional neural network was capable of detecting skin cancer similarly to dermatologists (4). At roughly the same time, Obermeyer and Emanuel claimed that large-scale data and machine learning would move prognosis and diagnosis towards greater quantitization (6), and Jha and Topol predicted the role of radiologists and pathologists to turn into that of an "information specialist" along with the algorithms (12).

All of this was put into perspective by Topol’s well-cited article. He outlined AI operating at three levels: clinician level with quick and accurate imaging interpretation; organizational level by improving work efficiency and minimizing mistakes; and patient level by helping them manage their condition. At the same time, he clearly spelled out the problems with AI, such as bias, lack of privacy, security and opacity (3). Yu, Beam and Kohane reviewed the methodologies and their use cases (7), while Rajkomar, Dean and Kohane published a landmark review of machine learning in

medicine (8). Finally, by the end of the decade, a number of large validation studies, including the worldwide study comparing AI breast-screening system with radiologists, came up with comparable performance results (9).

Pathology was not spared either. Coudray et al. developed deep learning algorithms for whole slide images of non-small-cell lung cancer, which had the ability to classify tumour types, and extract information about specific gene mutations from the pathology images (10), whereas Campanella et al. took the field to its clinical applications, by employing weakly supervised machine learning in tens of thousands of whole slide images, a system designed to scale up without manual labelling (11). Such papers, together with their counterparts in medical imaging, form a pattern in health care applications of AI technologies, which has been consistently repeated: a clear-cut problem, a massive labelled data set, outstanding performance, and an unanswered question regarding the fate of the tool after deployment.

3.2.2 Recent applications and the rise of large language models (2021-2025)

The more recent reviews describe a field that has grown up. It has shifted from building models towards validating them outside their training data and getting them into use. One reading of the 2024 literature counts more than a thousand AI- and ML-enabled medical devices cleared by the US Food and Drug Administration, in a market expected to climb from around USD 26.6 billion in 2024 to roughly USD 187.7 billion by 2030 (14,15). The biggest change, though, is the arrival of large language models. Research has moved off images and onto text, with LLMs put to work on clinical notes, summarising, talking to patients, teaching and routine administration (14).

Evidence on how to deploy these tools is starting to build as well. A review of LLM rollouts in hospitals finds that the programmes that work share a few habits: a multidisciplinary AI committee, fast cycles of piloting, and bias and safety checks that never quite stop. Run that way, they improved workflow and clinician satisfaction with no drop in quality (15). An umbrella review takes us to the same conclusion by way of a different route: The optimal use of the technology

is not an independent exercise of AI but a combination of clinical judgement and algorithms, with the algorithm detecting the pattern and the doctor maintaining the responsibility and liability (16).

General-purpose LLMs mark a departure from the past rather than simply a progression of it. Imaging and pathology applications in the decade after 2010 each had their specific application, while modern LLMs are general-purpose applications utilized for documentation, triage, and communicating/patient education. What makes the applications useful is the very thing that makes them difficult to validate. The failure modes of a classifier are very different from those of a tool that drafts discharge notes, answers patients' questions and summarizes guidelines in one go, as is not always the case – such a model may invent, contradict itself and be highly dependent on the exact phrasing of the prompt. Consequently, the discussion in the literature shifts away from standalone validation towards governance of the entire model lifecycle with ongoing monitoring and responsibility maintained (15,16).

3.2.3 Benefits, limitations and critique

It is clear, however, that these advantages are accompanied by caveats, and the literature recognizes the constraints. Many models which fare well in internal validation turn out to fail when confronted with external data; many algorithms have not yet been tested in prospective trials; and there is always a risk of introducing bias, which could only worsen pre-existing structural inequities. The most striking example is the work done by Obermeyer et al., who found that a widely used proprietary algorithm had been consistently underestimating the healthcare needs of Black people simply because it used previous expenditure on healthcare as a measure of severity (13). A highly advanced system had, seemingly without much fuss, institutionalized a structural bias. The takeaway for the overall discussion is unambiguous: AI is indeed capable of enhancing standards of care, yet mismanaged, it will create risks of inequity and compromised patient safety.

Another distinction worth noting is the one that exists between being cleared and being proven. It is true that so many AI and ML devices currently have approval from the regulator (14), but that does

not automatically mean that their use improves outcomes because getting clearance involves demonstrating equivalence with another marketed medical device, not conducting a prospective study that demonstrates value. For a professional body concerned with setting standards for training and clinical practice, this means that an approved device does not necessarily make a good candidate for use. A better measure of value would be validation from third parties, evidence from a prospective study, transparency regarding the training data and performance across different populations, and a clear post-implementation surveillance plan. This contrast between being allowed and being proven applies to each of the technologies described here, and it is the central theme of Chapter 12 (8,13).

Table 3.1: Selected clinical and operational applications of AI

Domain	Representative application	Reported value
Diagnostics / imaging	Detection of diabetic retinopathy, skin cancer, breast cancer on imaging	Expert-level accuracy on defined tasks (5,4,9)
Risk prediction	Early-warning and deterioration models from EHR data	Earlier intervention; quantitative prognosis (6)
Documentation	LLM-assisted clinical notes and summaries	Reduced clinician documentation burden (15)
Administration	Coding, scheduling, triage and patient messaging	Operational efficiency gains (14)
Decision support	Treatment-option generation reviewed by clinicians	Improved accuracy via human-AI collaboration (16)

3.3 Telemedicine and Telehealth

3.3.1 Early evidence (2015-2019)

There is a strong evidence base for telemedicine even before the coronavirus pandemic, particularly regarding the management of chronic diseases. A meta-analysis of the literature revealed that home telemonitoring among heart-failure patients correlated with decreased mortality and fewer hospitalizations; however, there was high heterogeneity across studies (17). The Cochrane review of structured telephone support and non-invasive telemonitoring among patients with heart failure concluded that fewer patients were admitted for heart failure as well as dying (18), which was reiterated again in another literature review, which also emphasized the inconsistency of the quality

of studies (19). These pre-pandemic trends make it clear that the effectiveness of telemedicine cannot be considered an artifact of the current COVID-19 crisis. In addition, they help distinguish between the aspects that fall under the general concept of telemedicine, as different aspects have a different evidence base.

3.3.2 Pandemic acceleration and post-pandemic sustainability

COVID-19 turned telemedicine from a fringe service into ordinary practice almost overnight. A systematic review and meta-analysis of telehealth chronic-disease programmes spanning 2015-2022 found gains in quality of life, self-management and psychological well-being across a long list of randomised trials (20). A review of telehealth's effect on patient outcomes concluded that, in many settings, remote care can hold its own against in-person care for a range of conditions while widening access, the size of the effect depending on the clinical context and on how well the service is run (21). A global post-pandemic analysis recorded that the uptake has largely stuck, and that more advanced uses such as telesurgery are starting to appear in the mature markets (22).

There is a strong evidence base for telemedicine even before the coronavirus pandemic, particularly regarding the management of chronic diseases.

The eSanjeevani platform became one of many millions of teleconsultations and connected the distant and disadvantaged rural populations with healthcare providers showing how government-run telemedicine can be scaled successfully for the population (50). The eSanjeevani platform is integrated into the larger Ayushman Bharat Digital Mission, which provides an identification and registration layer required for interoperability in teleconsultation services (2). In the Indian example, just like in the rest of the telemedicine literature, technology is advanced and efficacious enough; what makes the difference here is the policy design, readiness of clinicians and patients to use the technology, and connectivity (25,24).

The adoption figures show where the value has settled. Industry analysis suggests that by early 2024 roughly four in five US hospitals had a telemedicine system in place, and mental-health care in

particular has kept much of its remote volume, with a large share of visits and antidepressant prescriptions still handled at a distance (26).

India's experience is worth dwelling on for a domestic reader. The eSanjeevani platform grew to many millions of teleconsultations, linking remote and underserved communities to clinicians and proving that publicly run telemedicine can work at population scale (50). It sits inside the wider Ayushman Bharat Digital Mission, which supplies the identity and registry layer that interoperable teleconsultation relies on (2). The Indian case makes the same point as the rest of the telemedicine literature: the technology itself is mature and effective, and what really decides the outcome is policy design, connectivity and how ready clinicians and patients are to use it, not the clinical modality (25,24).

3.3.3 Benefits, barriers and equity

Over and over, the reviews highlight that the actual barriers are not technical at all, but structural and regulatory: reimbursement, jurisdictional licensing of providers, broadband infrastructure, and even patient ability to access the technology (23,25). Both the systematic review on China's experience and the OECD analysis of their member nations highlight that infrastructure, training, and financial sustainability determine whether gains from the pandemic persist (24,25).

There is an irony in terms of those who would benefit most from the use of telemedicine technology. The exact digital divide that would be bridged through the implementation of telemedicine services is what prevents its reach in the rural and disadvantaged areas, especially in India.

Table 3.2: Selected evidence on telemedicine effectiveness

Study / source	Focus	Principal finding
Kitsiou et al. 2015 (17)	Heart-failure telemonitoring	Reduced mortality / hospitalisation in many reviews; heterogeneous
Inglis et al. 2015 (Cochrane) (18)	Telephone support / telemonitoring	Lower HF-related hospitalisation and mortality
Telehealth CDMS review 2023 (20)	Chronic-disease management 2015-22	Improved quality of life, self-management, well-being
Telehealth outcomes review 2025 (21)	Patient outcomes post-pandemic	Often non-inferior to in-person; context-dependent

Study / source	Focus	Principal finding
OECD 2025 (25)	Policy across OECD	Financing and infrastructure decide sustainability

3.4 Robotics and Robot-Assisted Surgery

3.4.1 Evolution, platforms and the evidence question

The technology discussed in the present review is robot-assisted surgery (RAS), which represents the most costly technology in the discussion. It provides an outstanding example of the distinction between the scale of diffusion of something and the level of its effectiveness proven. The da Vinci platform has ruled out the others for years, and it has been used to conduct numerous surgeries with estimates showing that there will be around 2.68 million da Vinci procedures in 2024 with a year-over-year growth of 18 percent against a background of USD 11.2 billion medical service-robotics market in 2024 projected to hit USD 21 billion in 2028 (33). The literature discusses fast-evolving technology facing competition from a large number of platforms.

3.4.2 Randomized and pooled evidence

The trial evidence is more tangled than the market momentum suggests. The landmark ROLARR trial found that, for rectal-cancer resection, robotic surgery did not significantly cut the rate of conversion to open surgery against conventional laparoscopy, and it cost more (27), a result the sceptics of headlong adoption return to often. Later randomised and prospective work has been kinder in particular settings. A phase II randomised trial reported acceptable outcomes for robotic rectal surgery (28), and the multicentre REAL trial found that for middle and low rectal cancer the robotic approach gave better short-term outcomes than laparoscopy, with fewer conversions and quicker recovery in selected patients (29). A meta-analysis of 30-day outcomes across seven oncological procedures came down in favour of robotics on several counts, fewer conversions, less blood loss, fewer transfusions, shorter stays (32), and a review setting real-world evidence against the trials found the two broadly agreed: shorter length of stay and fewer conversions, but longer time in theatre (30).

3.4.3 Cost, adoption and critique

Adoption, though, is very uneven, and that is the key issue. Industry data show large teaching hospitals taking up robotics far faster than smaller facilities, with cost, training and the surgeon's learning curve the barriers that keep recurring (33). The signal that runs through the trials, outcomes that are comparable or a little better, but at higher cost and longer operating time, means the value of robotics depends heavily on context. This is where the innovate-or-stagnate problem shows its most expensive face. Robotics can improve outcomes for the right indications in high-volume centres, yet its price risks pulling well-resourced and under-resourced institutions further apart, which is precisely the kind of equity concern that matters in India (27,30).

Two things sharpen the appraisal further. First, the learning curve means reported outcomes reflect the experience of the surgeon and the centre as much as the machine; an early adopter or a low-volume unit may simply not reproduce what the high-volume reference centres report (30). Second, the economics rarely stand on clinical superiority alone, because theatre time and the capital and maintenance costs run higher; where robotic surgery is worth it, the case is usually a mix of modest clinical gains with strategic, recruitment and patient-preference considerations (29,32). For a system short of resources, the sensible course is selective adoption, putting robotic capacity where the case mix and throughput can turn capability into value, rather than scattering it about for prestige or marketing.

Table 3.3: Selected randomised evidence on robot-assisted surgery

Trial / review	Comparison	Principal finding
ROLARR 2017 (27)	Robotic vs laparoscopic rectal resection	No significant reduction in conversion; higher cost
Kim et al. 2018 (28)	Robotic vs laparoscopic rectal cancer	Acceptable, comparable short-term outcomes
REAL trial 2022 (29)	Robotic vs laparoscopic rectal cancer	Better short-term outcomes in selected patients
Annals meta-analysis 2024 (32)	Robotic vs lap/open, 7 procedures	Fewer conversions, less blood loss, shorter stay
RWE vs RCT review 2025 (30)	Real-world vs trial evidence	Concordant: shorter stay, longer operative time

3.5 Internet of Medical Things, Wearables and Remote Patient Monitoring

3.5.1 Foundations and remote-monitoring evidence

The IoMT links sensors, wearables and home devices into clinical systems, so monitoring can be continuous and grounded in real life rather than in the occasional clinic visit. The early overviews of remote patient monitoring (RPM), in heart failure for instance, generally found favourable effects on outcomes like hospitalisation, while warning that the results varied and that the benefit hung on what was actually done with the data (19). That early work cast RPM as a way of shifting care from episodic and reactive towards continuous and preventive.

3.5.2 Recent advances

The recent systematic and scoping reviews chart a field expanding fast. A systematic review of IoT and wearable health monitoring catalogues a sprawl of sensors and architectures, all streaming physiological data up to cloud platforms for analysis (36). A scoping review of wearables for continuous monitoring reports a steady rise in research activity, with wrist-worn devices the most common form and chronic disease the most common target (35), and a systematic review of wearables in chronic disease confirms benefits for engagement and early detection (37). Co-design studies add a practical note: bring clinicians and patients into the design of these tools and both adoption and the usefulness of the data improve (34).

3.5.3 Limitations

Nevertheless, there should be certain factors that need to be considered in relation to such excitement. Despite the large amount of research, wearable technologies have not yet become a part of daily activities, due to bad usability, low data quality, and lack of interoperability (35).

There are two other issues that should be considered during the critical analysis of wearables. The first issue is the aspect of privacy and security. Any connected device becomes a weak spot, thus an attack on any source of data is dangerous enough (36). Therefore, the topic of IoMT turns out to be directly related to the previous discussion in Section 3.6. Another question is the one of interoperability. Data becomes valuable only if it is properly structured and easy to compare (34). It

means that it is implied that certain standards of data structure exist, and this creates relevance for the programs like Ayushman Bharat Digital Mission (2).

3.6 Blockchain and Health Data Systems

3.6.1 Origins and rationale (2016-2019)

Blockchain is the least mature technology here, and the odd one out, since it is aimed at the trust, security and interoperability of health data rather than at diagnosis or treatment. The field grew out of a few proof-of-concept projects in the mid-2010s. Azaria and colleagues' MedRec prototype used a blockchain to handle access and permissions for medical data, letting patients control who could see their records and leaving a tamper-evident audit trail behind (38). Mettler surveyed the early use cases and argued the technology could remake healthcare data management (40), and Kuo, Kim and Ohno-Machado set out a foundational account of distributed-ledger technologies for biomedical work, mapping their promise for security, provenance and interoperability (39).

3.6.2 Applications and recent evidence

Later reviews tidied the field up. A comparison of blockchain platforms with healthcare examples drew out the trade-offs between permissioned and permissionless designs (41); a systematic review found the technology is used mostly for electronic health records, where an immutable, decentralised ledger can shore up data integrity, auditability and a patient's control over consent (42); and a comprehensive review catalogued the architectures proposed for EHR management and what they offer on security (43). More recent work shows Ethereum- and smart-contract-based prototypes for securing and streamlining EHR management (45). And the problem it is reaching for is real and measurable: reviews count hundreds of healthcare data breaches affecting well over a hundred million records in a single recent year, with major incidents running into the billions in cost, all of which exposes how brittle centralised health-data systems are. The blockchain-in-healthcare market is still small, but reportedly growing very fast (46).

3.6.3 Barriers

On the obstacles the reviews are unanimous: limited scalability, worries about energy and cost, immature standards, regulatory uncertainty, and very little real-world adoption (42,44). A systematic review of the challenges of blockchain in digital health concluded that, after a decade of prototypes, almost nothing has moved into sustained clinical use, and that this is precisely because the organisational, legal and standards-based scaffolding around it is still underdeveloped (44). So blockchain shows a different face of stagnation: a technology with a genuinely compelling rationale that has, for the most part, never made it past the pilot.

The proposed mechanisms still deserve attention, because they address real system needs. Smart contracts, self-executing code that lives on the ledger, could automate consent, claims adjudication and access control without anyone having to trust an intermediary (39,45), and hybrid designs that keep the bulky records off-chain while anchoring only an index on-chain get round the scalability and privacy objections that tripped up earlier prototypes like MedRec (38,43). The open questions are less about cryptography than about governance: who runs the network, how identities and permissions are managed, how the whole thing squares with data-protection law, and how it talks to the record systems already in place. Those are the same enabler questions that surface everywhere in this review, which is why the most defensible stance on blockchain today is to watch it closely and help shape the standards, rather than to buy in at scale (41,44).

3.7 Cross-Cutting Themes: Adoption, Equity and the Digital Divide

Compared side by side, the five bodies of literature all tend to converge on the same shortlist of factors. First, there is always a necessity for evidence that proves technology works, but the proof will not be sufficient for implementation because that will depend entirely on organizational readiness and management of change (15,21). Second, there will usually not be any technological constraints on implementation, and the factors that constrain each technology are reimbursement, regulation, staffing and data governance across the five technologies (25,44). Third, it is possible that the application of each technology might contribute to widening or closing health inequalities,

as telemedicine might increase reach but depends on connectivity; robotics increases quality but concentrates among wealthier hospitals; while artificial intelligence might improve access to expertise but also increase health disparities through biases (13,24,30). Another important theme is the difference between the available evidence and the needed evidence. Most of the literature discusses what technologies are able to accomplish in controlled situations, in selected sites, with trained users and controlled subjects. The evidence required by the decision-maker, on the other hand, describes the performance of the technologies in real-world scenarios. This explains why even the most promising technologies have under-delivered, and this is the reason why this report makes the distinction between what a technology can do and what it can reliably do. As the data-flow analysis in Chapter 10 makes plain, these technologies are worth most in combination, so the things that decide adoption for one of them, interoperability and data governance among them, are frequently the same things that decide it for the others (36,39).

3.8 Policy and Governance Context

The governance setting increasingly shapes what gets adopted. The WHO digital health strategy presses for investment in workforce, institutions and governance (1), and the Global Initiative on Digital Health, launched in 2023 during India's G20 presidency, puts that strategy to work through shared standards and country support (47).

Data governance deserves particular weight in India. A maturing data-protection regime, together with the sectoral guidance on telemedicine and the registries built under ABDM, sets the rules every one of The Indian government's own initiative, the Ayushman Bharat Digital Mission, which started in 2021, has developed a backbone to integrate the ecosystem, in the form of the ABHA health identifier, a Health Facility Registry, and a Healthcare Professionals Registry, and in just a couple of years reported

beneficiary registrations and linkages in the hundreds of millions (2). Along with that, examples such as eSanjeevani teleconsultation platform, and the CoWIN vaccination system, illustrate what can be done with digital services when taken to scale.

Discussion of ABDM is quite critical, highlighting true success and achievements, however, noting also significant differences between states and low levels of actual registrations of facilities and healthcare professionals (2). In addition, research into adoption on the ground illustrates insufficient digital health literacy among those who need it most (49). Commentaries repeatedly stress the same point, namely, infrastructure alone does not guarantee success and there is a need for legal frameworks, institutionalized support, and consistent funding to make digital backbone result in tangible health benefits (48). It means, in other words, that the policy literature mirrors the clinical literature.

In particular, data governance matters greatly in India. The development of the data protection regime, alongside the telemedicine guidelines, and the creation of registers in ABDM, define the rules that all five innovations have to follow, since each of them deals with sensitive health information (2,1). It means that strict data governance policies become a prerequisite for further development rather than an obstacle for it. If no rules regarding consent, security, and accountability are established, then neither doctors nor patients will have reasons to trust an outcome of a machine learning algorithm, a flow of monitoring data or a shared electronic medical record, which makes implementation impossible. Therefore, the policy aspect becomes directly connected to the security rationale for using blockchain technology and the interoperability issue of IoT mentioned above, and it shows that both agendas should be considered at once.

3.9 Research Gap

There is no lack of research on individual technologies, while there is a remarkable paucity when it comes to comparisons between technologies. Reviews that go deeply into a particular technology are quite common, but reviews that compare them by focusing on their advantages, drawbacks, and

relative adoptability are few. Even rarer are the studies that have transformed knowledge into practice.

Table 3.4: Comparative summary of major emerging technologies

Technology	Evidence maturity	Principal benefit	Principal barrier
AI / ML	High and rising	Diagnostic accuracy, efficiency	Bias, weak external validation
Telemedicine	Mainstream	Access, non-inferior outcomes	Reimbursement, connectivity
Robotics / RAS	Established, stratified	Precision, selected outcome gains	High cost, longer operative time
IoMT / wearables	Emerging	Continuous, preventive monitoring	Usability, interoperability
Blockchain	Early / pilot	Data security, consent	Scalability, standards, regulation

3.10 Summary of the Literature

Pulling the decade together, the chapter leaves four observations that carry into the rest of the report. The technologies sit at very different stages of evidence: telemedicine and AI rest on large and growing bodies of work, robotics on a rich trial literature that keeps running into cost, and wearables and blockchain on promising findings that mostly predate real adoption (20,3,27,35,44). Benefit, second, is almost always conditional on something other than the technology itself. Third, the same barriers, cost, interoperability, regulation, workforce, data governance, recur across all five, which suggests the things that make adoption succeed are largely shared rather than specific to any one technology. And fourth, equity is a risk that cuts across the lot: unless connectivity, literacy and access are tackled head-on, any of these technologies can widen disparities rather than close them (24,13). Those four points frame the background, the models and the recommendations that follow.

4. Background of Project Implementation

Innovate or stagnate is more than a catchy phrase – it captures the very real strategic dilemma that faces many health system leaders today. The technologies described in Chapter 3 have left the drawing board and entered the world of commerce, regulation and, in many cases, evidence. That raises an entirely new management challenge. No longer can one assume that the relevant technology doesn't exist – rather, the issue is which technologies to pursue, and in what sequence and with what controls. This is a pressing question for three reasons. First, demographics and the demand for healthcare have put immense pressure on traditional episodic models, which are becoming increasingly less effective, thus driving the need for more sustainable, data-driven, and automated healthcare (17,37).

Second, the dynamics in the market itself provide both opportunity and challenge. Figure 4.2 below shows that the market for AI, robotics and blockchain in health are on a rapid upwards trajectory, which is good news – and bad (15,33,46). Third, national and global policies increasingly assume digital are that is interoperable.

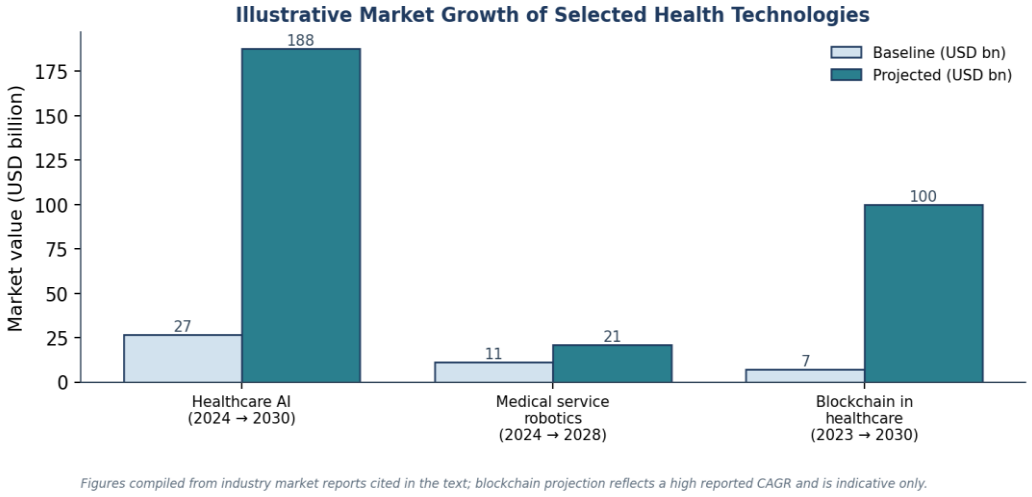


Figure 4.2: Illustrative market growth of selected health technologies

Set against those pressures are the hard facts of implementation. Tight capital, fragmented information systems, regulatory uncertainty, exposure to cyber-attack, and a workforce with uneven digital skills together mean that adoption is neither automatic nor reliably worthwhile (44,25). For a regulator like

the National Medical Commission, those facts turn into pointed questions. How much evidence should be demanded before a technology enters routine practice, or the medical curriculum? How should competence with these tools be assessed? How is equity to be protected as adoption spreads? Emerging technologies are both a strategic necessity and a strategic risk, and disciplined analysis is needed to avoid both rushing in and standing still. The chapters that follow treat the dissertation as a small project of this kind, with a plan, a change-management lens, models of how the technologies fit together, and lessons for those who have to decide.

Finally, the standpoint of the host organisation shapes this study. Because the National Medical Commission's remit covers medical education, assessment and professional standards, its interest in these technologies is less about procurement than about competence, evidence and governance. A study written with that standpoint in mind dwells not on which device a hospital should purchase but on what a system should demand of any technology before it is taught, trusted and put to use, and that emphasis runs through the analysis and recommendations later on.

This becomes even more relevant in light of India's specific healthcare system landscape,

since that dictates not only what innovations are possible, but also which are likely to be profitable and which aren't. Indeed, with its extensive public sector, large, fragmented private sector, high out-of-pocket

expenditures, and significant discrepancies between the urban and rural and inter-state distributions of physicians and medical equipment, any technology which extends the reach of a limited resource, from telemedicine to AI-enabled triage and remote monitoring, is a no-brainer, whereas capital-intensive technologies like surgical robots raise issues of equity and cost-effectiveness. On top of that, India's significant investments in digital infrastructure, outlined in Chapter 3, make some challenges – e.g., identity and interoperability – less pressing, while drawing other challenges into sharp focus – digital

literacy, connectivity. All in all, it makes India an intriguing case study when it comes to innovating or stagnating.

5. Project Management Plan

This dissertation is a structured review, not a software build, so the project plan really governs the research process: settling the question, searching and selecting the literature, pulling out and appraising the evidence, synthesising it, and writing the report. The whole thing was planned across the three-month dissertation window, from 15 March 2026 to 15 June 2026.

5.1 Gantt chart

Figure 5.1 lays the schedule out as a Gantt chart. The activities overlap on purpose, screening starts before the searching is quite finished, and drafting begins while the synthesis is still under way, which compresses the timeline without breaking the logical order of the work.

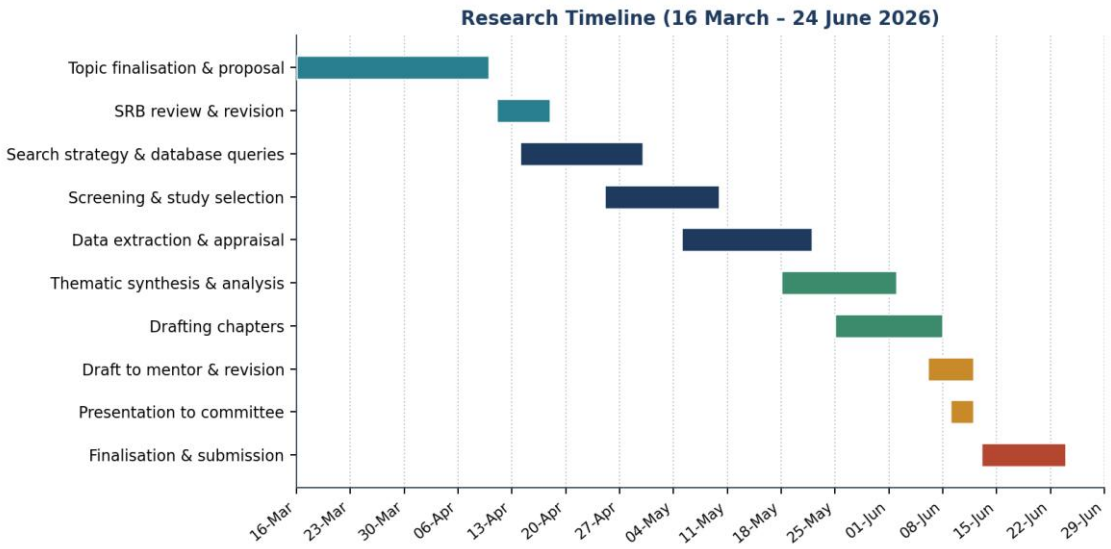


Figure 5.1: Research timeline (Gantt chart)

5.2 Network (PERT) diagram

Figure 5.2 shows those same activities as a network (PERT) diagram, which brings the dependencies and the critical path into the open. The critical path runs from proposal through searching, screening, data extraction and synthesis to writing; quality appraisal sits in parallel with screening and so carries

some float. Anything that slips on the critical path threatens the submission date directly, so those were the activities watched most closely.

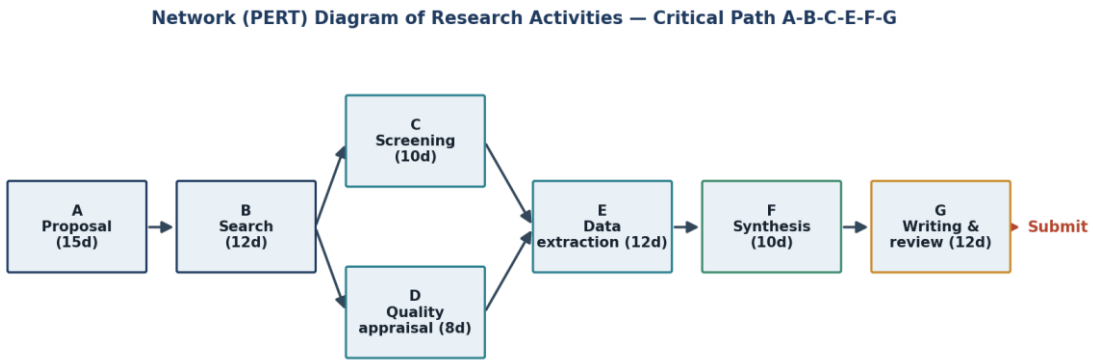


Figure 5.2: Network (PERT) diagram of research activities

5.3 Risk Management

Even a desk review can go wrong, and naming the risks early is part of running one properly. The main ones here were ordinary enough: more literature than the time allowed, fields moving fast enough, generative AI above all, to date the sources, trouble getting at full texts, and scope quietly creeping as new sub-topics appeared. Table 5.1 lists them with a rough likelihood and impact and the steps taken to keep them in check. The same habit of spotting and heading off risk is, in miniature, exactly what the report argues organisations need when they adopt these technologies for real.

Table 5.1: Risk register for the dissertation

Risk	Likelihood	Impact	Mitigation
Literature volume exceeds time	High	Medium	Bounded scope; prioritise reviews and trials
Fast-moving fields outdate sources	Medium	Medium	Widen window to 2015-25; flag recency limits
Limited full-text access	Medium	Low	Use open-access and abstracts; cite reviews
Scope creep	Medium	Medium	Fixed five-technology scope; mentor review
Synthesis bias (single author)	Medium	Medium	Explicit evidence hierarchy; balanced appraisal

6. Change Management with Plan

Adopting an emerging technology is, at bottom, a change-management problem, not a purchase. The thing the literature keeps showing is that the technology rarely fails on its own terms; adoption stalls because the organisation underestimated how much human and process change it would take (15,21). This chapter borrows an established change framework and applies it both to health-technology adoption and, by extension, to how this study was run.

6.1 A change framework for technology adoption

Figure 6.1 lays the ADKAR model, Awareness, Desire, Knowledge, Ability and Reinforcement, over the stages an organisation has to pass through to adopt a technology well. Awareness makes the clinical and financial case; desire builds a coalition of clinicians and leaders who actually want it; knowledge trains people to use it; ability is tested in piloting, where barriers get found and removed one by one; and reinforcement locks the change in through audit, governance and plain habit. The same arc shaped this dissertation: becoming aware of the evidence, building the skill to appraise it, piloting a way of synthesising it, then reinforcing the conclusions against the literature.

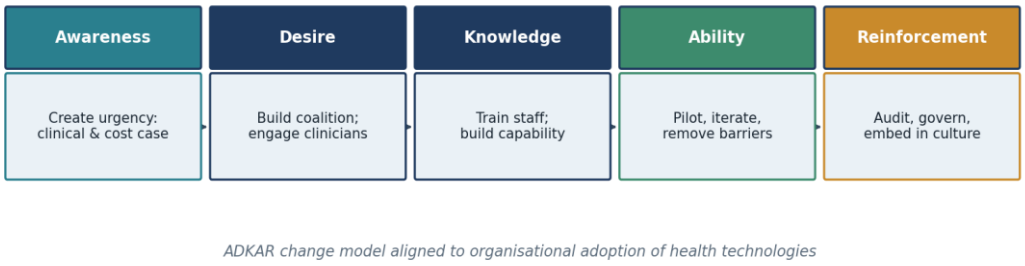


Figure 6.1: Change-management framework for technology adoption

Table 6.1: ADKAR applied to health-technology adoption

Stage	What it requires	Practical action in a health organisation
Awareness	Understanding why change is needed	Share the clinical and financial case and the evidence
Desire	Willingness to participate	Engage clinician champions; address fears about workload and roles
Knowledge	Knowing how to change	Train staff on the tool and on revised workflows
Ability	Being able to perform	Pilot, support super-users, remove technical barriers

Stage	What it requires	Practical action in a health organisation
Reinforcement	Sustaining the change	Audit use and outcomes; embed in governance and culture

Laying the barriers from the literature over these stages shows why adoption stalls where it does. Trouble with awareness and desire shows up as sceptical clinicians and half-hearted leadership; trouble with knowledge and ability shows up as poor training and clumsy tools; trouble with reinforcement shows up as pilots that are never embedded and simply fade out. Since most of the failure the evidence describes lives in the human and organisational stages rather than the technology, change management is not a bolt-on to adoption. It is the thing that decides it (15,34).

6.2 Managing change in this study

For the research itself, change management mostly meant keeping scope under control and acting on mentor feedback. The scope was deliberately bounded (Chapter 2) so the workload stayed feasible; the search and synthesis methods were tried out on one technology before being rolled out across all five; and interim drafts were read and corrected early rather than late. In a small way, these are the same disciplines the literature says decide technology adoption in organisations.

7. Activity Allocation

As a single-author dissertation, activity allocation is about how effort was split across the phases of work, not across a team. Most of it went into searching, screening and synthesis, which is what a critical review of this kind demands.

- Conceptualisation and proposal, framing the question, scope and objectives (approx. 10% of effort).
- Searching and study selection, database queries, screening and selection of sources across 2015-2025 (approx. 25%).
- Data extraction and critical appraisal, reading, note-taking and quality assessment (approx. 25%).
- Synthesis and analysis, thematic integration, modelling and figure creation (approx. 20%).

- Writing, revision and finalisation, drafting chapters, incorporating feedback and formatting (approx. 20%).

Run instead as a team or organisational project, the same activities would be shared out: dual independent screening to cut bias, a subject expert for the appraisal, and a coordinator pulling the synthesis and the writing together.

8. Time Allocation

The time allocation follows the schedule in Figure 5.1. The three-month window (15 March 2026 to 15 June 2026) was split so that the first half leaned on searching and selection, the middle on extraction and synthesis, and the closing weeks on writing, mentor review, the committee presentation and finalisation. A buffer was kept before submission to take in feedback from the dissertation evaluation committee, in line with the institute's timelines.

Table 8.1: Indicative time allocation across phases

Phase	Indicative duration	Key deliverable
Proposal & approval	~3.5 weeks	Approved proposal
Search & selection (2015-25)	~3 weeks	Final set of included sources
Extraction & appraisal	~2.5 weeks	Evidence tables and notes
Synthesis & analysis	~2 weeks	Themes, models and figures
Writing & review	~2 weeks	Draft report
Finalisation	~1.5 weeks	Final submitted report

9. Process Maps, Root-Cause Analysis and Decision Models

This chapter sets out the conceptual models that came out of the synthesis. Where a software project would produce use-case, activity and entity-relationship artefacts, the models here do something different: they show how an emerging technology slots into clinical work, why adoption stalls, how a manager might decide whether to adopt, and how health data are organised across an integrated ecosystem.

9.1 Process map of an AI-augmented clinical workflow

Figure 9.1 maps a typical clinical workflow with AI added. Data from a patient encounter go to AI/ML models that produce decision support or triage alerts; a clinician reads those outputs, brings judgement to bear and makes the call; and the outcomes loop back to sharpen the models. The human-in-the-loop shape is deliberate, and it reflects the central lesson of the literature, that AI is there to support clinical judgement, not stand in for it (16,3).

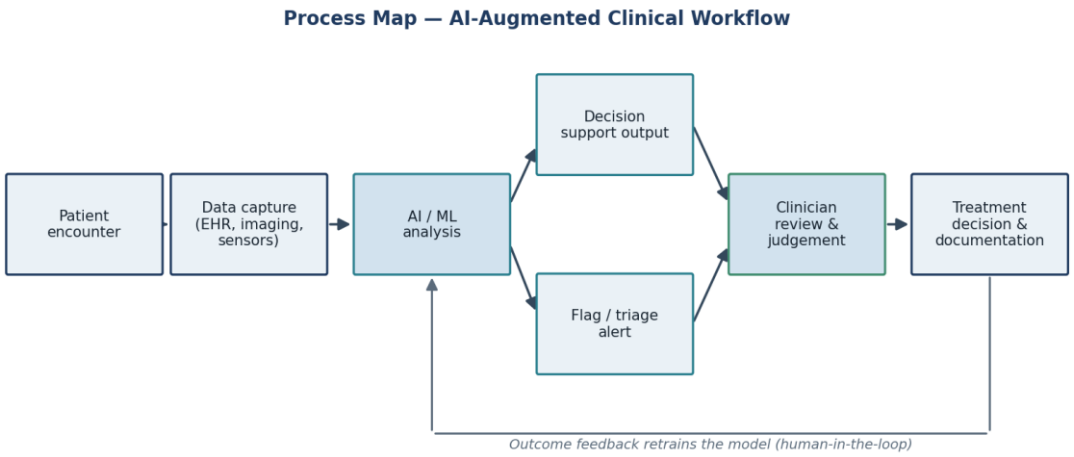


Figure 9.1: Process map, AI-augmented clinical workflow

9.2 Root-cause analysis of adoption stagnation

Figure 9.2 uses an Ishikawa (fishbone) diagram to sort the causes of stagnation found across the literature into six families: technology, organisation, finance, people, regulation and data/ethics. The point it makes visually is that no single cause explains a failed adoption. The causes interact, a high capital cost together with weak change management and murky reimbursement, say, and it is the

combination that produces the stall (27,44,25). Framed this way, a manager's attention is pulled to the whole system of barriers rather than to the technology by itself.

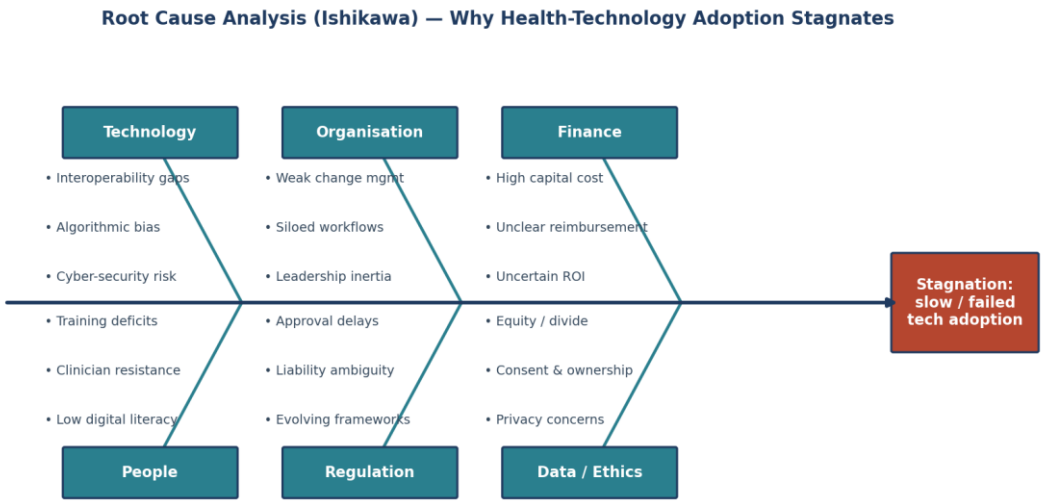


Figure 9.2: Root cause analysis (Ishikawa) of adoption stagnation

9.3 Decision flowchart for adopting an emerging technology

Figure 9.3 turns the analysis into a working decision aid. An organisation should adopt a technology only when there is a clear clinical or operational need, credible evidence that it is safe and effective, and a tool that is affordable, interoperable and governable. Fail any of those tests and the rational move is to wait and watch, not to jump. Pass them all and adoption can go ahead, through a human-in-the-loop pilot, then evaluation, then scaling and reinforcement. In effect this is the innovate-or-stagnate judgement brought down to the level of a single decision.

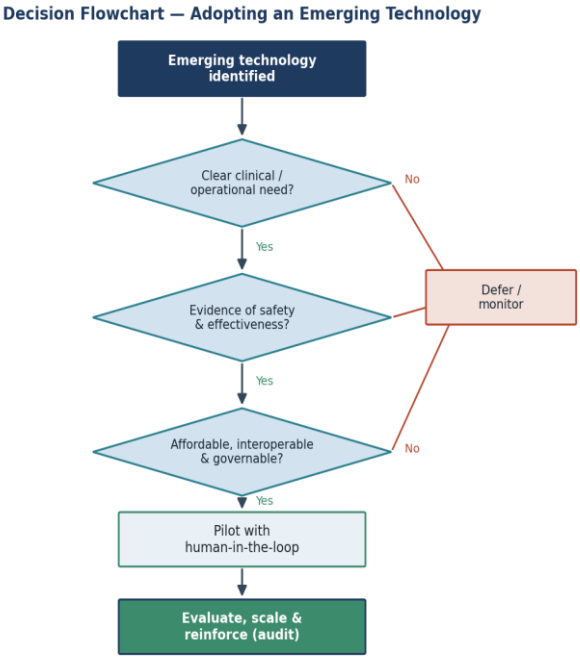


Figure 9.3: Decision flowchart for adopting an emerging technology

9.4 Conceptual entity-relationship model of digital health data

Figure 9.4 sets out a conceptual entity-relationship model for the data an integrated digital health ecosystem has to hold: patients keyed to an ABHA number, encounters, providers, devices, health records, and a consent log anchored to a ledger. It shows how interoperability and consent, the very things the blockchain literature worries about, can be captured in one coherent data architecture (39,45,2).

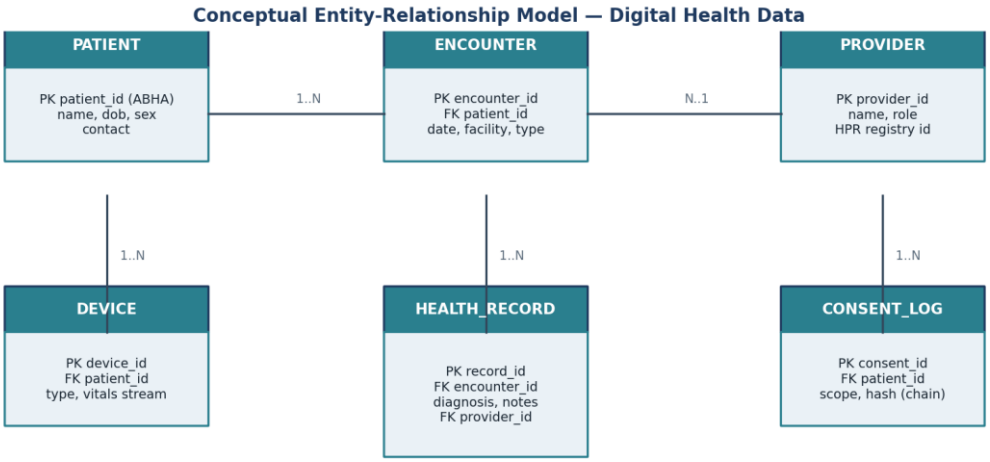


Figure 9.4: Conceptual entity-relationship model of digital health data

Put together, the four models are really one picture, not four. The process map shows how a technology enters clinical work; the fishbone shows why that entry so often fails; the decision flowchart shows how a manager ought to choose; and the entity-relationship model shows the data foundation underneath it all. The common thread is the report's central claim, that value comes from disciplined integration, of the technology into the workflow, the decision into the evidence, and the data into a governed, interoperable whole, rather than from the technology on its own. The data-flow diagram in the next chapter finishes the picture by showing all five technologies working as a single system.

10. Data Flow Diagram

The integration of the five technologies is shown in Figure 10.1. Data from wearable devices or IoMT devices worn by patients are fed to the cloud platform via an IoT gateway, after which analysis takes place on the data through AI. Subsequently, results obtained are sent to the electronic health record system and to the clinician dashboard; meanwhile, the use of the blockchain technology provides transparency in terms of consent obtained from users and an unalterable audit trail. This figure brings home the idea that the technologies are complementary but not competing, whereby wearable devices provide the data, AI analyzes it, telemedicine and dashboards transfer the insight gained, and blockchain creates the necessary trust and interoperability (36,39).

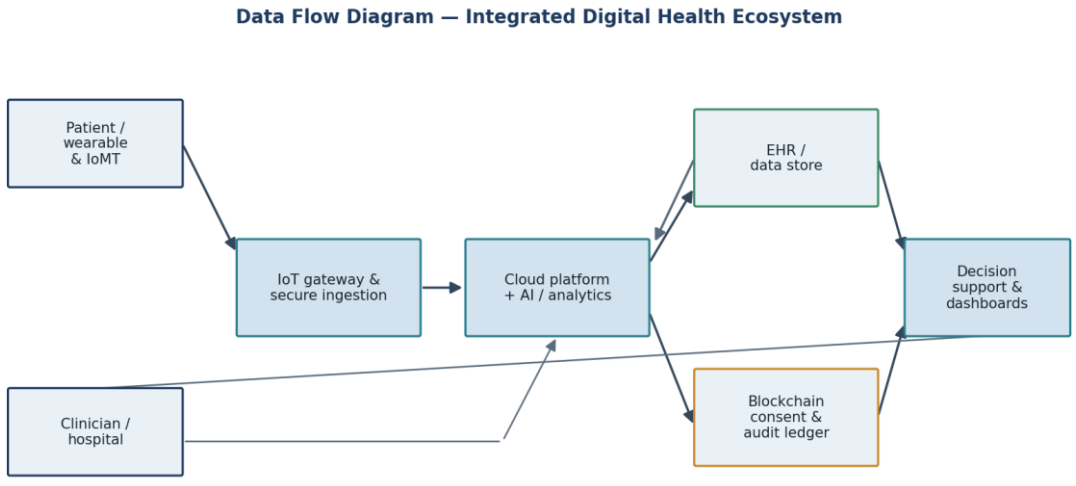


Figure 10.1:Integrated digital health ecosystem

The same theory can explain why incomplete implementation does not work either. A device without the support of analytics creates data that will never be used; an AI without interoperability cannot analyze the entire patient; and all of these without effective consent and governance become vulnerable to breaches, which are the focus of the blockchain literature (46). The value lives in the connected whole, which is the real reason fragmented, single-technology pilots so often stall.

11. Illustrative Interfaces

Because this is a literature-based critical analysis rather than a build, there is no software to screenshot. The conceptual dashboards and decision aids that an integrated system would put in front of clinicians and managers are instead represented by the process map, the decision flowchart and the data-flow diagram in Chapters 9 and 10. In a later implementation project, this is where screenshots of the live analytics dashboard, the clinician decision-support screen and the patient-facing app would go.

12. Findings, Critical Analysis and Lessons Learned

This chapter brings the review together into a critical answer to the report's question, and pulls out what it means for hospital and health managers, educators and regulators.

12.1 The core finding: conditional, not automatic, value

Across all five technologies the evidence points to one conclusion above the rest. These tools do deliver real value, and in several cases well-evidenced value, but the value is conditional, never automatic. AI sharpens diagnosis and lightens the administrative load when it is paired with human oversight and bias auditing (5,15,13). Telemedicine extends reach and competes well enough with face-to-face services in many cases, provided certain technical, financial, and organizational preconditions are met (20,25). The application of robotics yields better results in particular procedures if the quantity and experience warrant the investment but even a large randomized study did not find a difference in its primary endpoint (27,32). Wearables and IoMT facilitate predictive and proactive healthcare if analyzed and utilized properly (19,35). Blockchain technologies are capable of protecting and

integrating healthcare data as soon as the infrastructure matures (39,44). Again, it is always the context, never the technology itself, that determines whether innovation or stagnation occurs in the organization. This context alters the interpretation of the title. While “Innovate or Stagnate” might sound like a battle between those who embrace technology and those who fear it, the research clearly indicates that it is, rather, between those with self-discipline and those without it. One can poorly innovate, waste capital on acquiring a robot that sits idle, use an algorithm that remains untested, distribute wearables that generate data that will never be analyzed, and all the while look very contemporary. Conversely, one can stagnate not through hesitation, but by not paying attention to the enabling factors (like interoperability, training, governance) needed to make any innovation valuable. The key capability here is not an enthusiasm for technology, but rather the discipline to align its adoption to needs, evidence and preparedness, which is precisely what the decision model in Chapter 9 was designed to do.

12.2 Critical appraisal by technology

12.2.1 Artificial intelligence

AI has the richest and most rapidly growing evidence base of the five technologies discussed here, and also the most cautionary tales.

The leap from narrow imaging algorithms (4, 5) to broad-ranging LLMs (14) has outpaced both validation and regulation. Obermeyer et al.'s discovery of bias (13) should be the cautionary tale in question: even excellent performance overall can mask serious problems for certain subgroups.

The prudent approach would be to embrace validated narrow technologies quickly while being highly cautious about autonomous or non validated technologies.

12.2.2 Telemedicine

There is no more apparent example of needing innovation than telemedicine. Decades of research (17,18,20) have shown results at least as effective, if not more so, in many conditions, where the

limiting factors are policy and technology rather than clinical efficacy (25). The threat for India is not whether or not telemedicine works, but whether it will overcome the digital divide (24).

12.2.3 Robotics

Robotics exemplifies the situation most clearly where innovation equates with decline, at the very least in monetary terms. In light of the subsequent trial results and the meta-analysis that showed more promise (29,32,30), one is forced to admit that the advantages are genuine but conditional and dearly paid for. A robotic device purchased by a low-volume institution incapable of utilizing it properly may be considered the ideal prototype of a destructive innovation.

12.2.4 IoMT and wearables

The IoMT devices are very promising; however, the technology itself remains unrefined; there is a lot of academic interest but virtually no clinical application (35,34). The conclusion here is rather direct – any information that isn't used by the workflow is a liability.

12.2.5 Blockchain

Blockchain is a prime example of an innovative concept that has failed to reach its full potential. Ten years since MedRec (38), the underlying concept continues to remain valid (39), yet implementation in practice is extremely limited due to a lack of supporting factors (44).

12.2.6 Implications for India and the National Medical Commission

For India, and specifically for a regulatory organization such as the National Medical Commission,

the synthesis implies certain things. The country's digital infrastructure in the form of ABDM, eSanjeevani, and the ecosystems surrounding them has established enabling factors that many other systems do not have, especially when it comes to telemedicine and the issue of data interoperability (2,50). Thus, there is no question of the lack of technological means, but rather the uneven distribution thereof, the significant digital divide, and the problem of a work force who is insufficiently trained on the emerging technologies (49,48).

This is precisely the direction from which the regulator will have to influence its domain, namely, by

mandating digital literacy and literacy in artificial intelligence within medical programs and medical competencies; by establishing the required standards of evidence before introducing any new technology into the process of learning and actual use; and by setting clear expectations regarding transparency and monitoring equity and post-deployment evaluation. In this sense, the role of the regulator does not include technology selection, but rather improving the conditions for the deployment of available technologies (1,8).

12.3 Promise versus barriers.

Table 12.1 summarizes, for each type of technology, the major promise and major obstacle, concluding with an assessment of maturity level. The trend repeats itself: the higher the demand for capital or the reliance on trust associated with a technology, the less dependent its successful implementation is on technological success per se.

Table 12.1: Synthesis, promise versus barriers across technologies

Technology	Principal promise	Principal barriers	Maturity
AI / ML	Diagnostic accuracy, efficiency, documentation	Bias, weak external validation, governance	High and rising
Telemedicine	Access, convenience, non-inferior outcomes	Reimbursement, connectivity, digital literacy	Mainstream
Robotics / RAS	Precision, selected outcome gains	High cost, longer operative time, concentration	Established, stratified
IoMT / wearables	Continuous, preventive monitoring	Usability, data quality, interoperability	Emerging
Blockchain	Data security, consent, interoperability	Scalability, standards, regulation, low adoption	Early / pilot

12.4 Lessons for hospital and health managers, educators and regulators

- Start by identifying the need and not the technology. Only adopt where there is a clear requirement, following the decision process depicted in Figure 9.3.
- Ensure the proof is relevant to the stakes and focus on external validation and outcomes rather than the marketing claims made by vendors (27,13).
- Focus your attention on the enabling factors, such as interoperability, reimbursement, workforce capability and data governance, and not the technology (25,44).
- Design for human-in-the-loop use, preserving clinical judgement and accountability (16).

- Treat adoption as change management, using a structured model and piloting before scaling.
- Protect equity vigilantly because every innovation has the potential to exacerbate the digital divide if the issues of connectivity, literacy, and access are ignored (24,30).
- •For educators and regulators, develop skills and standards: digital and AI literacy in medical curriculum, and evidence threshold and audit requirements for adoption, directly relevant to organizations like the National Medical Commission (1).
- Think holistically: the integrated flow of data (see Figure 10.1) is far more valuable than stand-alone projects.

12.5 Conclusion

Thus, the question of "innovate or stagnate" is not one where there are two simple options, one being to accept all and the other of accepting none. Innovation must be done through a disciplined approach – by adopting with intent based on what is needed and supported by evidence and where the organization has truly developed the conditions to facilitate this process. Without discipline innovation will be a waste of resources, while delaying endlessly will leave the organization behind in terms of costs, quality, and accessibility. It is up to the healthcare management, as well as the policymakers and healthcare educators who establish the standards, to differentiate between innovation and costly novelty and to develop the organizational, financial, and governance structures necessary to convert the technology into superior, safer, and equitable care.

India's prognosis is cautiously optimistic. The country has established technological infrastructure which several other healthcare organizations lack, has proven its ability to deliver population-scale benefits, and has needs, accessibility issues, and efficiency problems that some of the technologies discussed have a lot to offer. The danger is not that India fails to innovate but that the innovation lands unevenly, piling benefit where infrastructure and skills already exist and passing over the people who are underserved. Realising the promise depends less on buying more technology than on closing the gaps in connectivity, literacy and capability, and on the standard-setting and teaching that a body like the National Medical Commission is well placed to lead. The report's overall conclusion, then, is that

emerging technologies are neither a cure-all nor a threat. They are tools, and their value is made or lost by the discipline, equity and governance with which they are taken up.

12.6 Limitations and suggestions for future work

Being a narrative review, this study carries the usual caveats. It is open to selection and interpretation bias, it leans on secondary evidence of uneven quality, and in places it uses market and industry figures that should be read as indicative rather than exact. Some fast-moving areas, generative AI most of all, may well have moved on since the sources were published. There is plenty of room to build on it: a fully systematic review with dual screening on a single technology; primary data on the adoption barriers inside a particular Indian hospital or health system; cost-effectiveness modelling to test the decision framework proposed here; and a closer look at what all this means for the regulatory and educational work of bodies like the National Medical Commission.

12.7 A Phased Roadmap for Adoption

To make the analysis usable, the recommendations can be lined up into a phased roadmap an organisation could follow whatever technology is on the table. It deliberately puts the enabling work, assessing the need, appraising the evidence, getting ready, before any purchase, and treats scaling as something earned by demonstrated value rather than assumed. Table 12.2 sets out the phases. The sequence is the central argument in practice: that disciplined adoption, not a taste for novelty, is what separates innovation that creates value from innovation that destroys it.

Table 12.2: A phased roadmap for adopting an emerging technology

Phase	Focus	Key actions
1. Frame	Need and strategy	Define the clinical / operational problem; set success measures
2. Appraise	Evidence	Assess external validation, prospective outcomes, equity impact
3. Ready	Enablers	Build interoperability, financing, training, governance
4. Pilot	Controlled use	Human-in-the-loop pilot; measure against baseline
5. Evaluate	Decision	Scale, adapt or stop based on evidence of value
6. Reinforce	Sustain	Audit, monitor for drift and bias, embed in culture

Followed consistently, the roadmap turns “innovate or stagnate” from an abstract warning into a repeatable way of working. It lets an organisation say “yes” to the right technologies at the right moment, “not yet” to the ones whose enablers are not ready, and “no” to the ones whose cost or risk outruns their evidence, and to think again as the evidence changes.

Appendix A: Summary of Key Sources

The table below summarises the principal sources appraised in this dissertation, mapped to technology / theme and contribution. Full citations are given in the References.

No.	Source (first author / title)	Theme	Key contribution
1	World Health Organization	Policy	WHO digital health strategy; calls for capacity investment
2	The Ayushman Bharat Digital Mission of India: an assessment	Policy / India	ABDM assessment; progress with inter-state variation
3	Topol EJ	AI	Review of AI across clinicians, systems and patients
4	Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, et	AI	Dermatologist-level skin-cancer classification
5	Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A	AI	Deep learning detects diabetic retinopathy
6	Obermeyer Z, Emanuel EJ	AI	Big data and ML reshaping clinical medicine
7	Yu KH, Beam AL, Kohane IS	AI	Overview of AI techniques and applications
8	Rajkomar A, Dean J, Kohane I	AI	Primer on machine learning in medicine
9	McKinney SM, Sieniek M, Godbole V, Godwin J, Antropova N, As	AI	Evaluation of AI breast-cancer screening
10	Coudray N, Ocampo PS, Sakellaropoulos T, Narula N, Snuderl M	AI / pathology	Lung histology subtype and mutation prediction
11	Campanella G, Hanna MG, Geneslaw L, Miraflor A, Werneck Krau	AI / pathology	Clinical-grade weakly supervised pathology
12	Jha S, Topol EJ	AI	Radiologists / pathologists as information specialists
13	Obermeyer Z, Powers B, Vogeli C, Mullainathan S	AI / ethics	Racial bias in a clinical algorithm
14	Artificial intelligence in healthcare: 2024 year in review [	AI	2024 review; shift towards LLMs and text data

No.	Source (first author / title)	Theme	Key contribution
15	Artificial intelligence in healthcare: a narrative review of	AI	LLM implementation; leadership and governance
16	The application of artificial intelligence in healthcare pra	AI	Umbrella review; human-AI collaboration
17	Kitsiou S, Paré G, Jaana M	Telemedicine	HF telemonitoring; reduced mortality / hospitalisation
18	Inglis SC, Clark RA, Dierckx R, Prieto-Merino D, Cleland JGF	Telemedicine	Cochrane: telemonitoring benefits in heart failure
19	Bashi N, Karunanithi M, Fatehi F, Ding H, Walters D	Telemedicine / RPM	Overview of HF remote-monitoring reviews
20	Evaluation of the effectiveness of telehealth chronic diseas	Telemedicine	Chronic-disease telehealth improves QoL / self-management
21	The impact of telehealth adoption on patient outcomes: a sys	Telemedicine	Outcomes often non-inferior to in-person care
22	Post-pandemic analysis on comprehensive utilization of teleh	Telemedicine	Post-pandemic global utilisation analysis
23	Understanding telemedicine adoption: evidence, gaps, and fut	Telemedicine	Adoption theories; barriers and gaps
24	Ye J, He L, Beestrum M	Telemedicine	China; implementation in developing countries
25	Organisation for Economic Co-operation and Development	Policy	OECD telemedicine policy across countries
26	The future of telemedicine adoption in the United States: ho	Telemedicine	US hospital adoption and utilisation data
27	Jayne D, Pigazzi A, Marshall H, Croft J, Corrigan N, Copelan	Robotics	ROLARR RCT; no conversion benefit, higher cost
28	Kim MJ, Park SC, Park JW, Chang HJ, Kim DY, Nam BH, et al	Robotics	Phase II RCT; comparable rectal-cancer outcomes
29	Feng Q, Yuan W, Li T, Tang B, Jia B, Zhou Y, et al	Robotics	REAL trial; better short-term outcomes in selected patients
30	Patel N, Yankovsky A, Hebert A, Kreaden U	Robotics	Real-world evidence concordant with trials
31	Rivero-Moreno Y, Echevarria S, Vidal-Valderrama C, et al	Robotics	Comprehensive review and current trends
32	Meta-analysis of 30-day surgical outcomes across seven oncol	Robotics	Meta-analysis; benefits across seven procedures
33	Surgical robotics statistics and facts 2025 [industry report	Robotics	Market size and adoption statistics
34	Su J, et al	IoMT / RPM	Co-design improves monitoring adoption
35	Lodewyk K, Wiebe M, Dennett L, Larsson J, Greenshaw A, Haywa	IoMT / wearables	Scoping review; not yet routine in care
36	Driving healthcare monitoring with IoT and wearable devices:	IoMT	Systematic review of IoT / wearable monitoring

No.	Source (first author / title)	Theme	Key contribution
37	Wearable devices for remote monitoring of chronic diseases:	IoMT / wearables	Wearables for chronic-disease monitoring
38	Azaria A, Ekblaw A, Vieira T, Lippman A	Blockchain	MedRec prototype; patient-controlled data access
39	Kuo TT, Kim HE, Ohno-Machado L	Blockchain	Distributed ledgers for biomedical applications
40	Mettler M	Blockchain	Early healthcare blockchain use cases
41	Kuo TT, Zavaleta Rojas H, Ohno-Machado L	Blockchain	Comparison of blockchain platforms
42	Mayer AH, da Costa CA, Righi RDR	Blockchain	Systematic review; EHR-focused applications
43	Hasib KM, et al	Blockchain	Comprehensive review of EHR architectures
44	Kostick-Quenet K, et al	Blockchain	Challenges; low real-world adoption
45	Simi Mole JS, Shaji RS	Blockchain	Ethereum / smart-contract EHR prototype
46	Blockchain applications in electronic health records: market	Blockchain	Breaches, market and adoption data
47	Leveraging digital health initiatives to enhance the effecti	Policy	Global Initiative on Digital Health
48	From infrastructure to impact: why foundations matter in dig	Policy	Foundations needed for digital-health impact
49	Adoption, digital health literacy, and patient satisfaction	Policy / India	ABDM adoption; digital-literacy barriers
50	World Economic Forum	Policy / India	India digital health; eSanjeevani, CoWIN

Appendix B: Glossary of Key Terms

Term	Definition
Artificial intelligence (AI)	Computer systems performing tasks that normally require human intelligence, such as interpretation and prediction.
Machine learning (ML)	A branch of AI in which systems learn patterns from data rather than following hand-coded rules.
Deep learning	ML using multi-layered neural networks, especially effective for images and language.
Large language model (LLM)	A general-purpose model trained on large text corpora, used for documentation, summarisation and dialogue.
Telemedicine / telehealth	Delivery of clinical and related services remotely using information and communication technology.
Remote patient monitoring (RPM)	Continuous or periodic collection of patient data outside conventional clinical settings.
Internet of Medical Things (IoMT)	Networked medical devices and sensors that collect and exchange health data.
Wearable device	A body-worn sensor (for example a watch or patch) that measures physiological signals.
Robot-assisted surgery (RAS)	Surgery performed with a robotic system that extends the surgeon's precision and visualisation.
Blockchain	A decentralised, tamper-evident ledger of records secured by cryptography and distributed consensus.
Smart contract	Self-executing code on a ledger that performs actions when predefined conditions are met.
Electronic health record (EHR)	A digital record of a patient's health information shared across care settings.
Interoperability	The ability of systems to exchange and use data in a consistent, structured form.
ABHA	Ayushman Bharat Health Account, a unique digital health identifier for individuals in India.
ABDM	Ayushman Bharat Digital Mission, India's national digital health ecosystem programme.
Algorithmic bias	Systematic error in a model that produces unfair outcomes for particular groups.
External validation	Testing a model on data from a different setting than that used for development.
Human-in-the-loop	A design in which a clinician reviews and is accountable for an algorithm's output.
Digital divide	Inequality in access to and ability to use digital technologies.
Change management (ADKAR)	A structured approach to organisational change: Awareness, Desire, Knowledge, Ability, Reinforcement.
Clinical decision support	Tools that provide clinicians with knowledge or patient-specific information to aid decisions.
Narrative review	A structured but non-systematic synthesis of literature on a topic.

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