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Review Research

Technology and Innovation in Healthcare: Adoption of AI and Predictive Analytics in Hospital Management

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Abstract: This review investigates how artificial intelligence (AI) and predictive analytics are reshaping hospital management by enhancing clinical decision-making, operational efficiency, and equitable healthcare delivery. People are increasingly applying AI-driven models to forecast patient demand, optimize workforce planning, improve diagnostic accuracy, and expand telemedicine, especially in the post-pandemic era. When implemented responsibly, predictive tools across healthcare systems can reduce readmissions, strengthen patient outcomes, and support resource utilization. Successful adoption is enabled by robust digital infrastructure, committed leadership, and cross-disciplinary collaboration, yet barriers persist, including fragmented IT systems, interoperability gaps, algorithmic bias, and workforce skill shortages. Ethical and governance challenges centered on transparency, data protection, and accountability remain pivotal to sustainable clinical integration. Comparative insights reveal divergent adoption pathways: high-income countries leverage mature digital ecosystems, while low- and middle-income contexts are innovating with resource-sensitive applications to address workforce constraints and expand access. By synthesizing theoretical frameworks and global case studies, this review underscores that responsible AI adoption can accelerate hospital transformation. Policy recommendations emphasize that it is time for standardized validation, strengthened data ecosystems, inclusive telehealth expansion, and institutional capacity-building to advance efficiency, resilience, and equity in healthcare systems.

Keywords: Artificial Intelligence; Predictive Analytics; Hospital Management; Telemedicine; Digital Health Equity; Healthcare Policy

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1. Introduction

The Global healthcare systems are undergoing unprecedented transformation as they respond to escalating demands in patient care, resource management, and institutional resilience. Rising patient volumes, demographic transitions toward aging populations, and the growing prevalence of chronic illnesses have placed extraordinary strain on hospital operations **(Samal et al., 2021; Akhter et al., 2025)**. Systemic workforce shortages, escalating treatment costs, and the need for more sustainable care delivery models further compound these challenges. The COVID-19 pandemic magnified these vulnerabilities by disrupting global supply chains, overwhelming intensive care units, and accelerating digital health adoption. In this environment, traditional approaches to hospital management often reliant on retrospective reporting, paper-based documentation, or siloed information systems are proving inadequate for contemporary healthcare challenges. Consequently, artificial intelligence (AI) and predictive analytics have gained momentum as transformative tools that can enhance the resilience, efficiency, and adaptability of hospitals **(Chowdhury et al., 2020a; Sheikh et al., 2021).**

AI in hospital management encompasses an expansive spectrum of technologies, including machine learning algorithms, natural language processing (NLP), robotic process automation, and advanced computer vision. Collectively, these innovations enable hospitals to improve operational efficiency, enhance diagnostic accuracy, and optimize limited resources **(Alves et al., 2024; Riaz et al., 2024).** Within this broad ecosystem, predictive analytics has emerged as a particularly impactful subset. By integrating diverse data sources such as electronic health records (EHRs), imaging outputs, laboratory results, and patient-generated data predictive models can anticipate critical events such as hospital readmissions, staff shortages, or emergency department overcrowding **(Chigboh et al., 2024)**. Unlike conventional health information systems that emphasize retrospective reporting, predictive analytics provides forward-looking insights that empower healthcare leaders to proactively design interventions. Hospital systems increasingly recognize this shift from reactive to anticipatory management as fundamental to their sustainability **(Sazzad et al., 2024).**

The transformative potential of AI is already evident across diverse healthcare settings. Predictive models for patient demand forecasting allow administrators to anticipate inpatient volumes, refine bed allocation, and prepare staffing plans more **effectively (Wei & Xiaoyu, 2023)**. Smart scheduling algorithms dynamically align staff availability with fluctuating patient needs, reducing burnout and improving workforce productivity **(Chowdhury et al., 2020b).** Clinical decision-support systems powered by AI assist clinicians in detecting high-risk patients, offering early interventions, and reducing diagnostic inconsistencies across departments **(Hassan & Omenogor, 2025).** These applications illustrate the dual role of AI: empowering clinicians to provide safer, more precise care while simultaneously enabling administrators to optimize hospital resources.

The rapid digitalization of healthcare has created fertile ground for predictive technologies. The widespread adoption of EHRs, advances in diagnostic imaging, and the proliferation of wearable devices generating real-time physiological data provide unprecedented opportunities for data-driven insights **(Khatiwada et al., 2024**). Predictive analytics can synthesize these diverse information streams into integrated dashboards for hospital-wide planning and epidemic preparedness **(Hossain et al., 2024; Olaniyan et al., 2024).** During the COVID-19 crisis, AI models proved indispensable in forecasting infection surges, estimating intensive care demand, and guiding allocation of scarce resources such as ventilators and personal protective equipment. These experiences demonstrated the practical value of AI during global emergencies while also emphasizing the necessity of systemic preparedness, robust data ecosystems, and institutional integration for sustaining long-term benefits.

Despite its promise, the widespread integration of AI in hospitals faces persistent obstacles. Fragmented IT architectures, heterogeneous data formats, and limited interoperability between clinical and administrative systems constrain the seamless deployment of predictive tools. Moreover, a shortage of professionals trained in digital health, data science, and AI system governance further impedes adoption **(Alam et al., 2023; Sunny et al., 2025a)**. The reliability of predictive models is also heavily dependent on data quality. Incomplete datasets, biased variables, or insufficiently representative training populations can generate unreliable outputs, potentially leading to adverse clinical consequences **(Bhati et al., 2023; Ashakin et al., 2024).** These limitations point out the urgent need for rigorous data governance, standardized interoperability frameworks, and robust model validation protocols to ensure safety, accuracy, and equity in predictive healthcare applications.

Equally pressing are the ethical, legal, and governance considerations surrounding AI integration in clinical environments. Concerns related to patient privacy, data ownership, algorithmic accountability, and informed consent have become central to scholarly and policy debates. Black-box algorithms that generate predictions without transparent reasoning undermine trust among both clinicians and patients **(Sazzad et al., 2025)**. In high-stakes environments such as intensive care units or oncology wards, opaque decision-making poses significant risks. Addressing these issues requires regulatory frameworks that enforce explainability, mandate regular bias auditing, and encourage the development of interpretable AI systems. Hospitals must also establish governance mechanisms, such as interdisciplinary oversight committees, to ensure algorithmic decision-making aligns with ethical norms and safeguards patient safety.

Institutional readiness and leadership engagement are additional determinants of successful adoption. Hospitals guided by digitally literate executives and supported by engaged clinical teams are more likely to incorporate AI into strategic objectives such as cost control, quality improvement, and patient-centered care. Enhancing digital literacy through targeted workforce training is essential to overcome resistance and build confidence in AI-driven tools **(Sunny et al., 2025b).** Economic evaluation also plays a crucial role: healthcare leaders require robust cost-effectiveness evidence demonstrating measurable improvements in patient outcomes, staff satisfaction, and workflow efficiency to justify substantial investments in AI systems.

Global adoption patterns reveal striking disparities between high-income and low- and middle-income countries (LMICs). High-income countries, benefiting from mature digital infrastructures and advanced regulatory frameworks, have accelerated AI implementation across hospital systems. In contrast, LMICs face infrastructure deficits, workforce limitations, and inconsistent policy support. Nevertheless, innovative uses of AI are emerging in LMIC contexts, including AI-assisted triage tools for under-resourced emergency departments and predictive models addressing maternal and child health needs **(Chowdhury et al., 2021; Tiva et al., 2025a).** These examples demonstrate both the universal applicability of AI in hospital settings and the importance of contextual adaptation for successful adoption.

Despite widespread acknowledgement of AI's promise in hospital management, the existing literature remains fragmented. Many studies focus narrowly on clinical applications, such as diagnostic support or patient risk stratification. Others emphasize operational benefits like scheduling optimization or logistics management. A smaller body of research addresses ethical, legal, and governance considerations. However, few reviews integrate these diverse perspectives into a unified synthesis that bridges clinical, organizational, and systemic dimensions. This fragmentation limits the ability of healthcare leaders and policymakers to design holistic adoption strategies that are both effective and equitable **(Tiva et al., 2025b)**.

This review addresses that gap by offering an interdisciplinary synthesis of AI and predictive analytics adoption in hospital management. Drawing from healthcare informatics, computer science, organizational studies, and public policy, it consolidates empirical findings, theoretical frameworks, and international case studies into a multidimensional analysis of hospital digital transformation **(Chowdhury et al., 2022; Ema et al., 2025).** By critically examining enablers, barriers, and governance mechanisms, the study contributes to the development of evidence-based strategies for responsible and scalable AI integration. Unlike earlier reviews that emphasize either clinical utility or organizational efficiency in isolation, this work provides a comprehensive framework that situates AI within broader institutional, ethical, and global policy contexts. The novelty of this review lies in its holistic scope: it not only synthesizes technological applications but also evaluates institutional readiness, equity challenges, and policy pathways for sustainable hospital transformation. Ultimately, the review contributes to the global understanding of how AI and predictive analytics can boost efficiency, resilience, and equity in healthcare systems.

2. Methodology

2.1 Objectives and Scope

The purpose of this review is to critically evaluate the adoption, integration, and systemic implications of artificial intelligence (AI) and predictive analytics in hospital management. The overarching objective is to consolidate empirical findings, theoretical frameworks, and global case studies to provide a multidimensional understanding of how these technologies are reshaping both clinical care and hospital operations. Four specific aims guided the review. The first was to identify hospital functions where AI and predictive analytics demonstrate the greatest utility, such as patient triage, readmission risk prediction, diagnostic support, and workforce optimization. The second was to examine organizational determinants including digital infrastructure, leadership engagement, regulatory alignment, and workforce readiness that influence adoption success. The third was to assess persistent barriers, such as data fragmentation, interoperability issues, privacy risks, and algorithmic bias, which continue to constrain integration. The final aim was to compare the effectiveness of diverse AI and predictive tools across clinical and operational domains. By addressing these objectives, the review seeks to provide a holistic synthesis of adoption dynamics, outcomes, and challenges.

2.2 Literature Search Strategy

A systematic literature search was conducted to identify peer-reviewed studies that examined AI and predictive analytics in hospital contexts. Google Scholar was chosen as the primary database given its comprehensive coverage of healthcare, computer science, informatics, and policy research. Boolean operators and carefully constructed search terms were applied to capture relevant studies. Keywords included artificial intelligence in hospital management, predictive analytics in clinical settings, machine learning in healthcare operations, AI-driven clinical decision-making, and "predictive tools for patient outcomes."

The initial search yielded a broad pool of publications. After removing duplicates, titles and abstracts were screened for relevance to the objectives of this review. Full texts of potentially relevant studies were retrieved and assessed against predefined inclusion and exclusion criteria. Eligible studies were required to explicitly address AI or predictive analytics in hospital management, present empirical evidence or validated frameworks, and demonstrate methodological transparency. Studies focused exclusively on primary care, non-clinical contexts, or unrelated digital technologies were excluded. To ensure transparency, the process of study identification, screening, and selection followed the principles of systematic review rigor.

2.3 Data Extraction and Thematic Synthesis

Once eligible studies were identified, a structured protocol was used for data extraction. Each article was examined for the following attributes: author(s), year of publication, study objectives, healthcare setting, AI or predictive tool used, reported outcomes, and key challenges. To minimize bias, data extraction was conducted independently by two researchers, with discrepancies resolved through discussion or referral to a third reviewer when necessary.

The extracted information was analyzed through thematic synthesis, which allowed for integration of both qualitative and quantitative findings. Patterns were identified across four analytical domains: clinical versus operational applications of AI, the level of technological maturity of the tools, the depth of integration within hospital systems, and the range of performance outcomes and barriers reported. This approach facilitated a comprehensive understanding of the ways AI and predictive analytics are being implemented across different healthcare contexts.

2.4 Comparative Summary of Selected Studies

Table 1 summarizes the findings from representative studies. These examples highlight both the benefits and challenges of AI applications in hospital management. For instance, patient risk stratification models using gradient boosting demonstrated reductions in readmission rates, though data heterogeneity remained a limitation **(Ko et al., 2021).** Predictive queue management systems improved patient flow in multi-site hospital networks but faced interoperability challenges **(Almadani et al., 2025).** Similarly, convolutional neural networks enhanced diagnostic accuracy in tertiary hospitals, yet integration delays hindered widespread implementation **(Chen et al., 2025).** Nurse scheduling algorithms optimized workforce planning in academic hospitals, though staff resistance persisted **(Wattanapanit, 2025).** Natural language processing classifiers accelerated emergency triage but raised ethical concerns regarding decision-making **(Pandian et al., 2025).**

Table 1. Comparative Summary of Selected Studies on AI and Predictive Analytics in Hospital Management

Study Focus Area	AI Tool / Model Used	Setting Type	Reported Outcome	Key Challenges
Patient Risk Stratification	Gradient Boosting Model	Urban Hospital	Reduced readmission rates	Data heterogeneity **(Ko et al., 2021)**
Operational Efficiency	Predictive Queue Management	Multi-site System	Improved patient flow	System interoperability **(Almadani et al., 2025)**
Diagnostic Support	Convolutional Neural Networks	Tertiary Hospital	Enhanced diagnostic accuracy	Integration lag **(Chen et al., 2025)**
Workforce Planning	Scheduling Optimization Algorithm	Academic Hospital	Optimized nurse staffing levels	Staff resistance to automation **(Wattanapanit, 2025)**
Emergency Triage	NLP-based Real-Time Classifier	Emergency Department	Faster triage and risk flagging	Ethical concerns in decision-making **(Pandian et al., 2025)**

2.5 Screening and Quality Assessment

To ensure rigor, all selected studies underwent multi-stage appraisal. After duplicate removal, titles and abstracts were screened, followed by full-text evaluation against inclusion criteria. Only studies with demonstrable empirical validation, transparent methodology, and relevance to hospital management were retained.

Quality assessment was conducted using a modified version of the Mixed Methods Appraisal Tool (MMAT), suitable for evaluating diverse study designs. The tool considered the robustness of study design, the reliability of data collection, the rigor of analysis, and the clarity of outcome reporting. Each study underwent independent assessment by two reviewers, with a third reviewer resolving discrepancies through either consensus or adjudication. This rigorous process ensured that only high-quality evidence was included in the final synthesis.

2.6 Analytical Framework

The analysis was guided by an integrative framework that accounted for both technical and organizational dynamics of AI adoption. Three dimensions structured the synthesis. The first categorized applications into clinical, operational, or hybrid domains, clarifying the breadth of AI's role. The second examined institutional and contextual readiness, emphasizing leadership support, digital infrastructure, and staff engagement. The third focused on clinical and operational impacts, including outcomes related to efficiency, patient safety, and equity.

The framework drew on established technology adoption models, healthcare readiness indices, and clinical benchmarks. Figure 1 illustrates the conceptual pipeline, highlighting how barriers such as data fragmentation, bias, and workforce shortages interact with enabling factors including leadership, training, and regulation to produce outcomes such as reduced readmissions, improved diagnostics, optimized resources, expanded telehealth, and greater system resilience.

2.7 Comparative Theoretical Frameworks

To enrich interpretation, several theoretical models were applied to contextualize adoption dynamics. At the individual level, the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) emphasize perceived usefulness and ease of use, which are critical for clinician adoption of decision-support tools **(Hennrich, 2024;).** At the organizational level, the Technology-Organization-Environment (TOE) framework assesses readiness in terms of technological infrastructure, organizational structure, and leadership vision **(Kruszyńska-Fischbach et al., 2022)**. At the systemic level, the Consolidated Framework for Implementation Research (CFIR) highlights contextual attributes and intervention design for workflow integration **(Rangachari et al., 2022).**

Theories like Diffusion of Innovations capture broader perspectives by examining how innovation attributes and social networks shape adoption trajectories **(Scrivner Jr., 2024).** Strategic perspectives are provided by the Three-Horizon Innovation model, which distinguishes incremental from radical innovation, offering insights into long-term AI adoption strategies **(Roman-Belmonte et al., 2022).** Together, these frameworks illuminate adoption dynamics across different decision-making levels.

Table 2. Comparative Adoption Frameworks for AI in Hospital Management

Framework	Level of Analysis	Principal Constructs	Illustrative Applications
TAM / UTAUT	Individual	Perceived utility, ease of use	Clinician adoption of decision-support tools **(Hennrich, 2024)**
TOE Framework	Organizational	Technology readiness, structure	Hospital digital transformation readiness **(Kruszyńska-Fischbach et al., 2022)**
CFIR	Systemic	Contextual attributes, intervention design	Workflow integration of AI **(Rangachari et al., 2022)**

Framework	Level of Analysis	Principal Constructs	Illustrative Applications
Diffusion of Innovations	Social / Systemic	Innovation attributes, adoption paths	Gradual rollout of predictive analytics **(Scrivner Jr, 2024)**
Three-Horizon Innovation	Strategic	Incremental vs. radical innovation	Long-term AI adoption strategy **(Roman-Belmonte et al., 2022)**

Table 3. Alignment of Frameworks Across Hospital Decision-Making Levels

Framework	Hospital Decision-Making Level
TAM / UTAUT	Individual (clinician, staff adoption)
TOE Framework	Organizational (infrastructure, leadership)
CFIR	Systemic (workflow and policy integration)
Diffusion of Innovations	Social/Systemic (community, networks)
Three-Horizon Innovation	Strategic (long-term planning, scalability)

2.8 Ensuring Rigor and Acknowledging Limitations

Several measures were employed to maintain rigor. The systematic search process with clear inclusion and exclusion criteria enhanced transparency. Independent double-screening and consensus-based resolution reduced selection bias. Thematic synthesis allowed integration of diverse methodologies, while the application of multiple theoretical frameworks provided triangulation and interpretive depth.

However, limitations must be acknowledged. Relying on Google Scholar as the primary database may have introduced bias toward English-language and highly cited publications. The diversity of methodologies across studies limited the feasibility of conducting a meta-analysis, necessitating reliance on narrative synthesis. Despite these constraints, the review's methodological rigor ensures that the findings provide a robust and transferable synthesis of current knowledge on AI adoption in hospital management.

3. Results and Discussion

3.1 Telehealth Trends and Demographic Patterns

The COVID-19 pandemic catalysed an extraordinary inflection in telehealth adoption, with utilization increasing by more than 700% in early 2020 relative to the prior year **(Iacopetta et al., 2024).** Although the surge moderated as in-person services resumed, telehealth use has stabilized well above pre-pandemic baselines, signaling a structural shift rather than a temporary spike. By 2021, more than one-third of U.S. adults reported at least one virtual visit, formalizing telemedicine's transition from emergency substitute to routine mode of care delivery **(Alsaif et al., 2022).** Similar directional trends are reported in other health systems, suggesting a durable reconfiguration of access pathways, patient expectations, and health system workflows.

However, aggregate growth conceals pronounced heterogeneity in adoption patterns. Demographically, women, older adults, and individuals with higher education, income, and digital literacy exhibit consistently higher uptake **(Islam et al., 2018; Burrows, 2024; Alam et al., 2024).** The link between digital capital and telehealth use underscores a central equity challenge: access depends not only on clinical need but also on infrastructural and socio-technical readiness. The rural-urban divide is particularly salient. In metropolitan areas, reported telehealth use regularly surpasses 40%, whereas many rural regions remain below 25% **(Fischer et al., 2020).** Network constraints limited broadband coverage, unstable connectivity, and device scarcity amplify existing disparities in service availability, specialist reach, and travel burdens. These patterns reinforce that telehealth's inclusiveness is conditional on infrastructural investment and digitally inclusive policy.

Clinical profile also shapes utilization. Patients managing chronic diseases most notably diabetes, hypertension, COPD, and heart failure engage more frequently with telehealth due to the fit between remote monitoring and ongoing condition management **(Bingham et al., 2021).** In these contexts, telehealth functions not merely as a visit replacement but as an extension of care: asynchronous messaging, algorithm-triggered alerts, and structured remote assessments allow earlier intervention and adherence support. In parallel, patient-reported experience consistently highlights reduced travel time, lower indirect costs, and shorter wait times as key advantages of telehealth **(Gray et al., 2023)**. These gains are meaningful for mobility-limited patients, caregivers with competing responsibilities, and workers with rigid schedules.

Yet, not all patient groups benefit equally. Video fatigue, discomfort with technology, and privacy concerns in home environments remain barriers, especially for older adults and individuals with lower digital literacy **(Islam et al., 2025).** Accessibility accommodations audio-only options, simplified user interfaces, multilingual prompts, and navigation support mitigate, but do not fully eliminate, these hurdles. Consequently, many hospitals are converging on hybrid care models that combine virtual and in-person encounters. Hybridity is not simply a compromise; it is a deliberate design that allocates the right modality for the right task, e.g., using telehealth for medication titration and lifestyle counselling while preserving in-person assessments for physical exams, procedures, and complex diagnostics.

In terms of system performance, telehealth has rebalanced capacity across time and place. Same-day virtual slots absorb demand spikes, while asynchronous channels smooth contact outside peak clinic hours. This elasticity enhances surge responsiveness, as observed during seasonal influenza waves and COVID-19 resurgences. Nonetheless, unmanaged growth can generate unintended consequences e.g., supply-induced demand (more contacts without commensurate outcome gains) or fragmented documentation when telehealth platforms do not fully interoperate with EHRs. In short, the telehealth uptake story is a story about fit: fit with patient resources and preferences, fit with clinical pathways, and fit with digital infrastructure. Where fit is strong, sustained adoption follows; where it is weak, the modality plateaus, and inequities persist.

3.2 Clinical Applications Across Specialties

Evidence across multiple specialties indicates that telehealth is not merely convenient it can be clinically effective when integrated into coherent care pathways. In **endocrinology**, remote diabetes programs combining continuous glucose monitoring, structured virtual check-ins, and algorithmic alerts have reduced HbA1c and improved adherence **(Ezeamii et al., 2024).** Key mechanisms include more frequent dose adjustments, faster troubleshooting of side effects, and real-time lifestyle reinforcement. These programs exemplify synergy between telemedicine (modality) and predictive analytics (intelligence), where data-driven risk flags focus clinician attention on patients who most need it.

In cardiology and pulmonology, home monitoring for heart failure and COPD has reduced exacerbation-related admissions through early detection of physiologic deterioration. Remote weight, oxygen saturation, symptom indices, and sometimes device telemetry allow risk-stratified outreach. Importantly, telemonitoring's impact hinges on the response protocol: without timely clinical action, data do not translate into outcomes. Workflow matters dedicated nurse navigators and escalation trees close the loop from detection to intervention.

Psychiatry stands out for scale and equity implications. Telepsychiatry has lowered no-show rates by ~30% and improved adherence for depression, anxiety, and PTSD **(Gude et al., 2021).** Beyond convenience, reduced stigma for certain patients, the possibility of sessions from private familiar settings, and expanded appointment windows increase engagement. Nevertheless, privacy constraints (e.g., crowded living conditions) and device sharing within households can exclude the same groups telehealth aims to serve. Again, hybrid design e.g., initial rapport-building in person followed by virtual maintenance often optimizes both participation and therapeutic alliance.

In pediatrics, telehealth has accelerated the pathway to diagnosis for developmental disorders, particularly in rural settings with limited specialist access **(Jones, 2023).** Care pathways that blend caregiver-submitted videos, standardized virtual assessments, and targeted in-person exams shorten time-to-diagnosis and initiate early interventions sooner. In maternal health, remote fatal monitoring when combined with clear thresholds and escalation protocols has reduced emergency caesarean sections among high-risk pregnancies by 22% **(Li et al., 2023).** These use cases underscore that clinical benefit is context-sensitive: structured protocols, clear data thresholds, and defined escalation routes are the difference between information and impact.

Other domains show similar patterns. Telerehabilitation supports adherence by removing travel barriers and embedding therapy into daily routines. Tele-dermatology, using store-and-forward imaging, has cut specialist waitlists by >40% where implemented, with consult triage enabling dermatologists to prioritize in-person slots for lesions warranting biopsy (**Mashoudy et al., 2024**). Multidisciplinary virtual boards in oncology and complex chronic disease streamline cross-specialty coordination, reducing opaque handoffs and decision latency.

Despite these gains, three caveats recur. First, interoperability: telehealth data that sit outside the EHR reduce continuity and foreshorten longitudinal analytics. Second, equity: benefits accrue where broadband and devices exist without compensatory policies, telehealth can widen gaps it seeks to close. Third, policy drift: many programs scaled under temporary reimbursement/licensure flexibilities; durability requires codifying these flexibilities into stable frameworks. In sum, telehealth's clinical promise is real, but it is contingent on system integration, equity scaffolding, and policy stability.

3.3 Barriers, Equity Challenges, and Policy Developments

Barriers to telehealth and predictive analytics cluster into human, operational, technical, and policy domains and these domains interlock. The human layer centers on digital literacy, trust, and clinician workflow adaptation. Older adults and digitally novice users face interface navigation challenges and privacy concerns that suppress utilization **(Rea et al., 2023)**. Clinicians encounter cognitive load when toggling between platforms, inconsistent documentation fields, and uncertainty about medico-legal risk, all of which can dampen enthusiasm for new tools **(Islam et al., 2025).** Trust is also a function of explainability: both patients and clinicians prefer systems that provide understandable rationales for recommendations.

Operationally, training and change management are frequently under-resourced. Without protected time to learn systems and refine protocols, new modalities simply overlay existing work creating duplication (e.g., double documentation), rather than substitution. Role clarity matters: who reviews remote monitoring alerts? At what thresholds? With what response windows? The absence of such designs leads to alarm fatigue and missed opportunities.

Technical barriers revolve around bandwidth, device access, and interoperability. Integration gaps between telehealth platforms, predictive tools, and EHRs impede closed-loop workflows and hamper analytics that depend on unified, longitudinal data. Data quality the lifeblood of predictive accuracy can be compromised by missingness, inconsistent coding, and sampling bias. When models are trained on unrepresentative populations, predictions degrade for those already underserved.

Policy frameworks are evolving but remain fragmented. Reimbursement parity across payers is inconsistent; licensing restrictions complicate cross-jurisdictional care; and data governance rules are variably interpreted, especially for cross-state or cross-border services **(Rana et al., 2023).** For hospitals, uncertainty is itself a barrier: capital investments are difficult to justify when revenue models may shift.

Table 4. Barriers to Telehealth Implementation in Hospital Management

Category	Description	Examples / Implications
Human	Digital literacy gaps; technology anxiety; trust concerns	Older adults struggle with video tools; patient privacy at home; clinician skepticism of black-box AI

Category	Description	Examples / Implications
Operational	Workflow misalignment; insufficient training and role clarity	Duplicate documentation; unclear triage/escalation protocols; staff burnout
Technical	Bandwidth and device access; poor interoperability; data quality issues	Rural drop-offs in video stability; siloed platforms; biased/incomplete datasets degrading model outputs
Policy/Regulatory	Reimbursement variability; licensure constraints; data governance gaps	Uneven parity across payers; barriers to cross-state practice; inconsistent privacy interpretations

Addressing these barriers requires a portfolio approach: device and connectivity subsidies; multilingual, low-literacy interfaces; workforce training with protected time; standardized integration profiles; and harmonized reimbursement/licensure rules. Critically, equity must be designed in, not audited after: co-create workflows with communities, fund community digital navigators, and adopt outreach strategies that meet patients where they are **(Mithun et al., 2024; Rea et al., 2023).**

3.4 Adoption of AI and Predictive Analytics in U.S. Hospitals

The U.S. landscape illustrates both the ambition and fragmentation of AI adoption. Approximately 73% of hospitals report some use of predictive analytics, yet fewer than 19% self-identify as "formal AI adopters," reflecting a persistent gulf between pilots and institution-wide integration **(Callahan et al., 2023; Rahman et al., 2024).** In practice, risk prediction dominates: 93% of AI-using hospitals apply models to inpatient risk, and 82% extend risk stratification to outpatient populations **(Saati, 2022).** Common foci include readmissions, sepsis, and perioperative risk. These models have clear clinical logic and fit within existing quality imperatives.

By contrast, operational AI for scheduling, capacity management, and logistics remains underused. Only 12.9% report AI in surgical scheduling and less than 10% in staff management **(Saati, 2022),** despite evidence that operational optimization reduces burnout and improves throughput. Thus, hospitals underutilize operational AI by focusing on clinically visible endpoints, neglecting the back-office engines that influence patient experience and financial sustainability.

Adoption is stratified by institutional characteristics. Large nonprofit teaching hospitals and integrated systems outpace smaller independent facilities, leveraging research partnerships, capital reserves, and centralized governance **(Al Amin et al., 2025).** Geographically, the Northeast and West Coast lead, buoyed by proximity to technology hubs and more mature innovation ecosystems **(Kalpanapriya & Bhavana, 2025**). Early pilots in smaller hospitals still show promise e.g., 15% improvements in bed turnover forecasting and 10% reductions in ED congestion suggesting that even modest deployments can yield measurable gains when tied to clear workflows **(Kalpanapriya & Bhavana, 2025).**

Three impediments explain the pilot trap. First, economics: total cost of ownership includes integration, change management, governance, and model maintenance investments harder to sustain on thin margins. Second, trust and explainability: clinicians resist opaque models, especially for high-stakes decisions **(Trivedi & Patel, 2021).** Third, governance complexity: liability, validation standards, and reimbursement pathways for AI-augmented decisions remain unsettled. The FDA's digital health initiatives signal progress, but many hospitals still perceive regulatory risk.

A pragmatic path forward involves (1) use-case portfolios that blend clinical and operational AI; (2) explainable models for frontline adoption and black-box models guarded by robust oversight; (3) lifecycle governance that funds post-deployment monitoring, drift detection, and retraining; and (4) return-on-value frameworks that account for safety, equity, goodwill, and staff retention not just immediate revenue. Absent these elements, the U.S. will continue to exhibit islands of excellence amid a sea of pilots.

3.5 Advanced Technologies and Global Implementations

AI adoption is broadening beyond traditional supervised models to include natural language processing (NLP), large language models (LLMs), computer vision, predictive maintenance, and conversational AI. Each addresses distinct friction points in hospital care.

NLP unlocks value from unstructured clinical text progress notes, discharge summaries, and consult letters supporting risk extraction, cohort identification, and documentation efficiency. In emergency departments, NLP-enabled triage accelerates risk flagging for high-acuity presentations. On the administrative side, coding assistance improves accuracy and reduces denials. The clinical return stems from fewer missed signals; the operational return stems from recaptured clinician time **(Happy et al., 2024; Ifty et al., 2024)**.

LLMs extend NLP by generating coherent summaries, drafting discharge instructions, and collating guideline-based recommendations. Their current role is **assistive**, not autonomous: hallucination risk mandates clinician verification. Early adopters report time savings in documentation and patient communication benefits that, if combined with clear guardrails, can mitigate cognitive load for overextended clinicians.

Computer vision advances safety and diagnostics. Bed-exit detection reduces falls; sterile-field monitoring in the OR flags contamination risks; and pathology image recognition achieves >95% sensitivity for certain cell morphologies **(Alsulimani et al., 2024)**. The productivity play is twofold: reduce adverse events upstream and triage specialist attention to the most suspicious images.

Predictive maintenance algorithms, powered by device sensors, preempt downtimes for ventilators, dialysis machines, and imaging equipment critical for ICU resilience. Meanwhile, chatbots and voice assistants streamline scheduling, symptom screening, and documentation, with reports of up to 30% reductions in clinician documentation time **(Elhadad et al., 2024).** These tools expand service windows beyond clinic hours, improving patient access and smoothing call center loads.

Global implementation pathways diverge depending on system design and policy culture. The U.K. NHS scaled predictive bed management and capacity planning at speed facilitated by centralized governance and unified procurement **(Krishnan et al., 2023)**. India leveraged AI for population-scale TB screening and triage in high-volume urban hospitals, prioritizing technologies that amplify scarce specialist capacity. Kenya employed mobile AI platforms for prenatal monitoring, meeting patients where smartphones outnumber clinics **(Bajpai & Wadhwa, 2021; Ifty et al., 2023b)**. Australia emphasizes rigorous validation before clinical integration slower at the front end, potentially smoother at scale. Japan's public-private consortia model accelerates code development and pilots, distributing risk across sectors. The U.S., as noted, innovates rapidly but standardizes slowly.

Three lessons emerge. First, structure matters: centralized systems can scale faster, while fragmented systems excel at experimentation but struggle with uniformity. Second, resource constraints do not preclude innovation: LMICs often deploy high-leverage, focused AI that directly addresses the binding constraint (e.g., specialist scarcity), yielding large marginal gains. Third, culture and regulation shape the slope of diffusion: stringent validation builds trust at the cost of speed; permissive environments enable rapid learning but demand strong post-market surveillance to maintain safety.

Across contexts, the winning strategies share DNA: align AI with a real, felt operational or clinical bottleneck; codify workflows before scaling; use explainability where it matters most (frontline adoption); and build feedback loops that measure outcomes and equity impacts not just utilization or algorithmic accuracy **(Mahjabin et al., 2024).**

3.6 Systemic Challenges, Ethical Concerns, and Future Directions

Beyond individual tools, hospitals face systemic questions about trustworthiness, accountability, sustainability, and equity. The black-box nature of many models undermines clinician confidence and complicates liability when errors occur. Explainability is not a generic solution; instead, it is role-specific. Frontline users benefit from concise rationales (e.g., sepsis risk elevated due to lactate trend, hypotension, and prior ICU stay), whereas oversight committees require calibration plots, subgroup performance, and drift analytics **(Trivedi & Patel, 2021).** The regulatory trajectory e.g., interpretability expectations for high-risk use reinforces this tiered approach.

Data quality and representativeness remain structural issues. Biased or incomplete datasets impair model performance for minority, rural, or low-income populations, risking algorithmic unfairness. Technical mitigations federated learning for privacy-preserving diversity and synthetic data augmentation to bolster rare phenotypes are promising **(Pickard et al., 2023; Mahin et al., 2021; Tiva et al., 2025**). But socio-technical mitigations equitable data governance, community engagement in dataset curation, and routine bias audits are equally necessary. The sobering reality that only ~3.8% of U.S. hospitals qualify as advanced adopters, with over half reporting no AI use, reflects not just cost but readiness gaps in data pipelines, workforce, and governance **(Trivedi & Patel, 2021).**

Economically, AI's value case must move beyond pilot-era anecdotes to transparent return-on-value frameworks capturing safety events averted, capacity reclaimed, staff turnover reduced, and equity improvements achieved. Capital planning should treat AI like any other durable asset: with depreciation, maintenance schedules, and refresh cycles. Otherwise, promising deployments decay as models drift, champions depart, and integration debt accrues.

Workforce readiness is pivotal. Clinicians need AI literacy to calibrate trust appropriately; administrators need change leadership to realign roles and incentives; IT teams need MLOps capability for monitoring and retraining. New roles clinical informaticians and AI stewards bridge technical and clinical realms, translating between model telemetry and bedside reality **(Petretto et al., 2024; Ifty et al., 2023a; Hossain et al., 2024).** Without these roles, AI programs become orphaned after initial fanfare.

Ethically, patient privacy, consent, and data ownership remain contested. Telehealth intensifies these debates as intimate clinical interactions shift onto consumer-grade networks and devices. Hospitals should institute multidisciplinary oversight boards (clinical, ethical, legal, and patient representatives) to evaluate use cases, monitor harms, and sanction course corrections **(Fahad & Chowdhury, 2022; Gupta et al., 2025)**. Consent models should be intelligible and revocable; audit trails should be routine; and patients should have meaningful visibility into how their data fuel algorithmic tools.

Fragmented IT ecosystems continue to obstruct scale **(Rahman et al., 2024)**. Interoperability is not purely a standards problem; it is a priority problem. When leadership makes one patient, one record, one source of truth a strategic objective, integration follows: vendor selection reflects it, timelines enforce it, and budgets protect it. On the other hand, the proliferation of bolt-on pilots leads to their eventual failure in isolated environments.

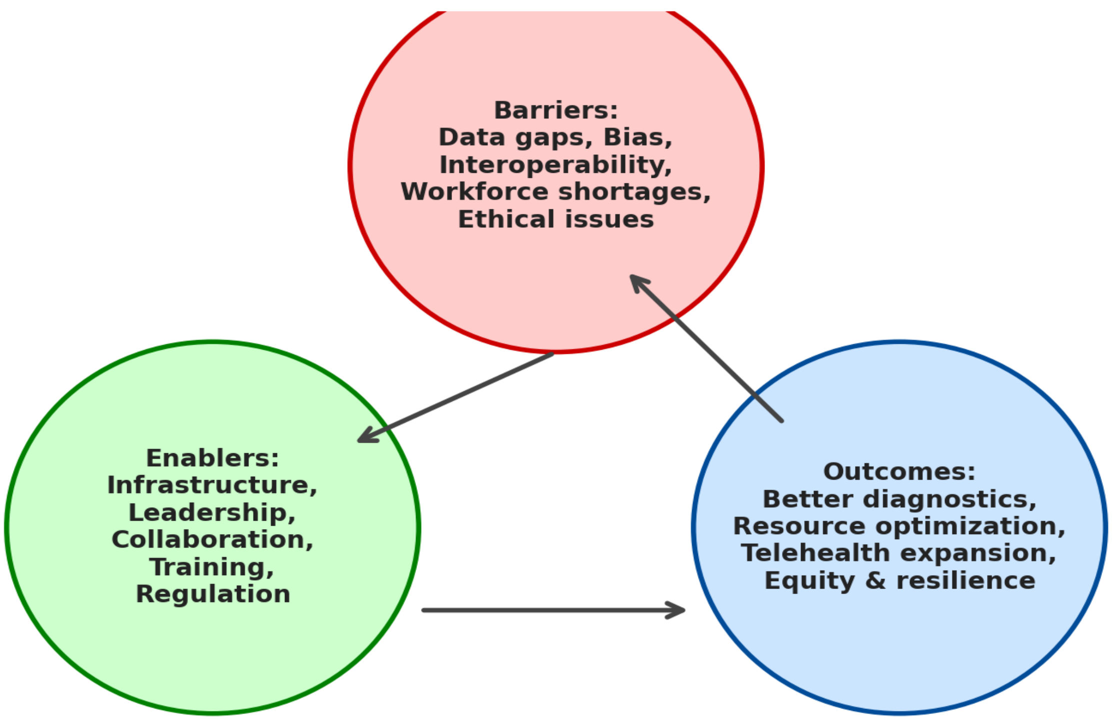

Figure 1. Conceptual pipeline for AI and predictive analytics adoption in hospital management.

The framework illustrates how systemic barriers such as fragmented data infrastructures, algorithmic bias, workforce shortages, interoperability challenges, and ethical concerns interact with enabling factors, including robust infrastructure, leadership commitment, cross-disciplinary collaboration, clinician training, and supportive regulatory frameworks. When these enablers offset barriers, hospitals can achieve improved diagnostics, reduced readmissions, optimized resource allocation, expanded telehealth capacity, and enhanced equity and resilience. The figure positions adoption not as a linear technological process but as a socio-technical system requiring alignment between technical design, organizational readiness, and policy support.

Looking ahead, sustainable AI requires post-deployment vigilance: drift detection, recalibration, and retirement criteria. Safety cases should evolve from one-time validations to living dossiers updated as populations, pathogens, and practice patterns change. Internationally, convergence of standards on validation, transparency, and fairness will accelerate safe diffusion. Comparative cross-country research can illuminate which governance models (e.g., the NHS's centralization, Japan's consortia, Australia's validation gatekeeping) best balance speed and safety for differing contexts **(Krishnan et al., 2023; Bajpai & Wadhwa, 2021; Chowdhury et al., 2025).**

The throughline across this Results & Discussion is straight forward: AI, predictive analytics, and telehealth can materially improve clinical outcomes and operational resilience, but only when embedded in trustworthy infrastructures, equitable policies, and well-designed workflows. Hospitals that treat these tools as add-ons will see partial, fragile gains. Hospitals that treat them as systems changes with governance, training, evaluation, and equity at the center will convert pilots into durable performance.

4. Conclusions and Policy Recommendations

This review highlights the transformative potential of artificial intelligence, predictive analytics, and telemedicine in reshaping hospital management and patient care. These technologies improve forecasting of patient risk, optimize resource allocation, enhance diagnostic accuracy, and expand access to care. The COVID-19 pandemic accelerated their adoption, with telemedicine shifting from an emergency measure to a mainstream modality and predictive models strengthening preparedness through reduced readmissions and more efficient workflows. Such outcomes demonstrate that digital transformation is not aspirational but already producing tangible benefits for patients and hospitals.

At the same time, adoption remains uneven. High-income countries have advanced rapidly, supported by strong infrastructure and policy frameworks, while many low- and middle-income countries rely on targeted, context-specific solutions to overcome constraints. Examples such as mobile-based maternal monitoring and AI-assisted tuberculosis screening show that focused applications can deliver high impact even in resource-limited settings. However, persistent challenges restrict scale, including fragmented IT ecosystems, lack of interoperability, high implementation costs, algorithmic opacity, and shortages of digitally skilled professionals. Ethical concerns around transparency, consent, and accountability further complicate integration, particularly in high-stakes clinical contexts where trust is critical.

To move forward, hospitals and policymakers must pursue strategies that address infrastructure, financing, workforce, and governance simultaneously. Digital infrastructure is foundational: reliable broadband, device subsidies, and multilingual design are necessary to close access gaps. Community-based literacy programs have the potential to benefit disadvantaged groups, preventing them from falling behind. Interoperability must be treated as a policy priority, since without unified data-sharing frameworks predictive analytics cannot deliver accurate or equitable insights.

Financial sustainability is also essential. Reimbursement parity between virtual and in-person services should be maintained, and outcome-based incentives can encourage investment in predictive tools. Smaller hospitals will require innovation grants, cooperative purchasing, and partnerships to overcome cost barriers. Beyond revenue, cost-effectiveness evaluations should capture wider returns such as workforce efficiency, reduced admissions, and greater resilience.

Human capital remains central to digital transformation. Clinicians must be equipped with AI literacy, data interpretation skills, and digital ethics training. New roles like AI stewards and clinical informaticians can bridge technical and clinical expertise, while cultural change is needed so staff view digital tools as supportive rather than threatening. Patient trust must also be secured through transparent communication and safeguards for privacy and security.

Governance and accountability mechanisms will be essential to embed trustworthiness. Explainability should be mandated for high-stakes AI models, and hospitals should establish oversight structures to monitor equity impacts and recalibrate tools as needed. Bias audits, transparency in procurement, and routine post-deployment monitoring should become standard practice. These measures will ensure that digital innovations remain safe, equitable, and aligned with patient interests.

Finally, global collaboration is vital. High-income countries can provide validation protocols and governance expertise, while low- and middle-income countries offer lessons in lean, impactful innovation. Shared platforms for cross-country learning will help harmonize standards, accelerate safe adoption, and reduce duplication of effort. Future research should focus on large-scale validation studies, economic evaluations, and equity assessments to strengthen the evidence base for responsible adoption.

In conclusion, telehealth, AI, and predictive analytics have already demonstrated their ability to improve efficiency, resilience, and equity in hospital management. Their promise lies not only in technological capability but also in the ecosystems that sustain them. Hospitals that approach digital transformation as a system-wide reform investing in infrastructure, financing, workforce, and governance will secure lasting gains. The challenge is not whether to adopt these innovations but how to ensure that adoption is inclusive, sustainable, and patient-centered.

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Author Contribution

The authors were involved in the creation of the study design, data analysis, and execution stages. Every writer gave their consent after seeing the final work.

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The authors declare that none of the work reported in this study could have been impacted by any known competing financial interests or personal relationships.

5. References

Akhter, S., Ansari, M. A. S., Tiva, M. G., & Bhuyian, M. S. (2025). Improving treatments for oral diseases, head and neck cancers, as well as developing new technologies. *Pathfinder of Research, 3*(1), 1–25.

Al Amin, M., Baldacci, R., & Kayvanfar, V. (2025). A comprehensive review on operating room scheduling and optimization. *Operational Research, 25*(1), 1–30. https://doi.org/10.1007/s12351-023-00850-4

Alam, K., Chowdhury, M. Z. A., Jahan, N., Rahman, K., Chowdhury, R., Mia, M. T., & Mithun, M. H. (2023). Relationship between brand awareness and customer loyalty in Bangladesh: A Case study of fish feed company. *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)*, *2*(3), 212-222.

Alam, M. R., Ansari, M. A. S., Chowdhury, M. E., Urbi, S. R. C., Rahman, K., Siddika, B. A., ... & Sazzad, S. A. (2024). Integrating Health Analytics tools to Enhance Pharmacological Management and Patient Outcomes in Hospital Settings. *Integrative Biomedical Research (Former Journal of Angiotherapy)*, *8*(12), 1-9.

Almadani, B., Kaisar, H., Thoker, I. R., & Aliyu, F. (2025). A systematic survey of distributed decision support systems in healthcare. *Systems, 13*(3), 157. https://doi.org/10.3390/systems13030157

Alsaif, S. S., Kelly, J. L., Little, S., Pinnock, H., Morrell, M. J., Polkey, M. I., & Murphie, P. (2022). Virtual consultations for patients with obstructive sleep apnoea: A systematic review and meta-analysis. *European Respiratory Review, 31*(166), 220037. https://doi.org/10.1183/16000617.0037-2022

Alsulimani, A., Akhter, N., Jameela, F., Ashgar, R. I., Jawed, A., Hassani, M. A., & Dar, S. A. (2024). The impact of artificial intelligence on microbial diagnosis. *Microorganisms, 12*(6), 1051. https://doi.org/10.3390/microorganisms12061051

Alves, M., Seringa, J., Silvestre, T., & Magalhães, T. (2024). Use of artificial intelligence tools in supporting decision-making in hospital management. *BMC Health Services Research, 24*(1), 1–13. https://doi.org/10.1186/s12913-024-10835-1

Ashakin, M. R., Bhuyian, M. S., Hosain, M. R., Deya, R. S., & Hasan, S. E. (2024). Transforming to smart healthcare: AI innovations for improving affordability, efficiency, and accessibility. *Pathfinder of Research*, *2*(2), 1-12.

Bajpai, N., & Wadhwa, M. (2021). India's experience with ICT in the health sector: Lessons for sub-Saharan Africa (No. 51). ICT India Working Paper. Columbia University.

Bhati, D., Deogade, M. S., & Kanyal, D. (2023). Improving patient outcomes through effective hospital administration: A comprehensive review. *Cureus, 15*(10), e40211. https://doi.org/10.7759/cureus.40211

Bingham, J. M., Black, M., Anderson, E. J., Li, Y., Toselli, N., Fox, S., … & Silva-Almodóvar, A. (2021). Impact of telehealth interventions on medication adherence for patients with type 2 diabetes, hypertension, and/or dyslipidemia: A systematic review. *Annals of Pharmacotherapy, 55*(5), 637–649. https://doi.org/10.1177/1060028020953849

Burrows, J. G. (2024). The accessibility and use of telehealth in rural areas (Doctoral dissertation, Aspen University). ProQuest Dissertations Publishing.

Callahan, A., Ashley, E., Datta, S., Desai, P., Ferris, T. A., Fries, J. A., … & Shah, N. H. (2023). The Stanford medicine data science ecosystem for clinical and translational research. *JAMIA Open, 6*(3), ooad054. https://doi.org/10.1093/jamiaopen/ooad054

Chen, D., Zhang, W., & Ding, Z. (2025). Embedding dynamic graph attention mechanism into clinical knowledge graph for enhanced diagnostic accuracy. *Expert Systems with Applications, 267,* 126215. https://doi.org/10.1016/j.eswa.2024.126215

Chigboh, V. M., Zouo, S. J. C., & Olamijuwon, J. (2024). Predictive analytics in emergency healthcare systems: A conceptual framework for reducing response times and improving patient care. *World, 7*(2), 119–127. https://doi.org/10.3390/world7020009

Chowdhury, T. E., Chowdhury, R., & Urbi, S. R. C. (2025). Integrating Artificial Intelligence into Business Analytics: Sectoral Adoption Patterns and Strategic Implications in the United States. *Pathfinder of Research*, *3*(1), 72-97.

Elhadad, A., Hamad, S., Elfiky, N., Alanazi, F., Taloba, A. I., & El-Aziz, R. M. A. (2024). Advancing healthcare: Intelligent speech technology for transcription, disease diagnosis, and interactive control of medical equipment in smart hospitals. *AI, 5*(4), 2497–2517. https://doi.org/10.3390/ai5040150

Ema, S. J., Das, A. R., & Sazzad, S. A. (2025). Coastal livelihoods under pressure: Vulnerability and adaptation among Bangladesh's small-scale fishers. *Pathfinder of Research*, *3*(1), 42-71.

Ezeamii, V. C., Okobi, O. E., Wambai-Sani, H., Perera, G. S., Zaynieva, S., Okonkwo, C. C., … & Obiefuna, N. G. (2024). Revolutionizing healthcare: How telemedicine is improving patient outcomes and expanding access to care. *Cureus, 16*(7), e59812. https://doi.org/10.7759/cureus.59812

Fahad, M. A. H., & Chowdhury, R. (2022). Evolution and future trends in web development: A comprehensive review. *Pathfinder of Research, 3*(1), 13–13.

Fischer, S. H., Ray, K. N., Mehrotra, A., Bloom, E. L., & Uscher-Pines, L. (2020). Prevalence and characteristics of telehealth utilization in the United States. *JAMA Network Open, 3*(10), e2022302. https://doi.org/10.1001/jamanetworkopen.2020.22302

Gray, C., Ambady, L., Chao, S., Smith, W., & Yoon, J. (2023). Virtual management of chronic conditions during the COVID-19 pandemic: Insights from primary care providers and clinical pharmacists. *Military Medicine, 188*(7–8), e2615–e2620. https://doi.org/10.1093/milmed/usad139

Gude, J., Subhedar, R. V., Zhang, M. H., Jain, P., Bhela, J., Bangash, F., … & Subhedar, R. (2021). Emerging needs and viability of telepsychiatry during and post COVID-19 era: A literature review. *Cureus, 13*(8), e16818. https://doi.org/10.7759/cureus.16818

Gupta, H., Dixit, P., & Parmar, B. J. (2025). Data-driven decision-making approach on healthcare services. In *Geometrical enhancements based on data-driven design decisions* (pp. 155–172). Springer. https://doi.org/10.1007/978-981-99-4742-6_9

Happy, A. T., Hossain, M. I., Islam, R., Shohel, M. S. H., Jasem, M. M. H., Faysal, S. A., ... & Sunny, A. R. (2024). Enhancing Pharmacological Access and Health Outcomes in Rural Communities through Renewable Energy Integration: Implications for chronic inflammatory Disease Management. *Integrative Biomedical Research*, *8*(12), 1-12.

Hassan, E., & Omenogor, C. E. (2025). AI-powered predictive healthcare: Deep learning for early diagnosis, personalized treatment, and disease prevention. *[Preprint]*.

Hennrich, J. (2024). *From potential to practice: Promoting the adoption of artificial intelligence in medical diagnosis* [Doctoral dissertation, Universität Bayreuth]. Universität Bayreuth Repository.

Hossain, B., Sunny, A. R., Gazi, M. M. R. N., Das, A. R., Mohajon, R., Miah, A. T. H., & Rana, M. N. U. (2024). Advancing fish farming through deep learning: Applications, opportunities, challenges, and future directions. *Pathfinder of Research*, *2*(3), 58-80.

Hossain, B., Chowdhury, T. E., Fahad, M. A. H., Hossen, M. E., Ahmed, R., Nesa, A., ... & Sunny, A. R. (2024). Machine Learning for Cardiovascular Healthcare: Opportunities, Challenges, and the Path Forward. *Integrative Biomedical Research (Former Journal of Angiotherapy)*, *8*(12), 1-11.

Iacopetta, D., Catalano, A., Ceramella, J., Pellegrino, M., Marra, M., Scali, E., … & Aquaro, S. (2024). The ongoing impact of COVID-19 on pediatric obesity. *Pediatric Reports, 16*(1), 135–150. https://doi.org/10.3390/pediatric16010015

Ifty, S. M. H., Ashakin, M. R., Hossain, B., Afrin, S., Sattar, A., Chowdhury, R., Tusher, M. I., Bhowmik, P. K., Mia, M. T., Islam, T., Tufael, M., & Sunny, A. R. (2023a). IoT-based smart agriculture in Bangladesh: An overview. *Applied Agriculture Sciences, 1*(1), 1–6. https://doi.org/10.25163/agriculture.119563

Ifty, S. M. H., Bayazid, H., Ashakin, M. R., Tusher, M. I., Shadhin, R. H., Hoque, J., Chowdhury, R., & Sunny, A. R. (2023b). Adoption of IoT in agriculture: A systematic review. *Applied Agriculture Sciences, 1*(1), 1–10. https://doi.org/10.25163/agriculture.9676

Ifty, S. M. H., Irin, F., Shovon, M. S. S., Amjad, M. H. H., Bhowmik, P. K., Ahmed, R., Ashakin, M. R., Hossain, B., Mushfiq, M., Sattar, A., Chowdhury, R., & Sunny, A. R. (2024). Advancements, applications, and future directions of artificial intelligence in healthcare. *Journal of Angiotherapy, 8*(8), 1–18. https://doi.org/10.25163/angiotherapy.889843

Islam, M. A., Kunda, M., Harun-Al-Rashid, A., Sunny, A. R., Mithun, M. H., Sazzad, S. A., & Bhuiyan, M. K. A. (2025). Can climate-resilient tilapia cage culture support sustainable livelihoods in flood-prone Bangladesh? *Water, 17*(4), 585. https://doi.org/10.3390/w17040585

Islam, M. M., Sunny, A. R., Hossain, M. M., & Friess, D. A. (2018). Drivers of mangrove ecosystem service change in the Sundarbans of Bangladesh. *Singapore Journal of Tropical Geography, 39*(2), 244–263. https://doi.org/10.1111/sjtg.12241

Jones, J. M. (2023). Use of nirsevimab for the prevention of respiratory syncytial virus disease among infants and young children: Recommendations of the Advisory Committee on Immunization Practices-United States, 2023. *MMWR. Morbidity and Mortality Weekly Report, 72*(34), 905–911. https://doi.org/10.15585/mmwr.mm7234a4

Kalpanapriya, D., & Bhavana, P. (2025). Optimizing hospital length of stay and bed allocation using a fuzzy stochastic transportation problem framework with Lomax distribution. *MethodsX, 14,* 103208. https://doi.org/10.1016/j.mex.2025.103208

Khatiwada, P., Yang, B., Lin, J. C., & Blobel, B. (2024). Patient-generated health data (PGHD): Understanding, requirements, challenges, and existing techniques for data security and privacy. *Journal of Personalized Medicine, 14*(3), 282. https://doi.org/10.3390/jpm14030282

Ko, M., Chen, E., Agrawal, A., Rajpurkar, P., Avati, A., Ng, A., … & Shah, N. H. (2021). Improving hospital readmission prediction using individualized utility analysis. *Journal of Biomedical Informatics, 119,* 103826. https://doi.org/10.1016/j.jbi.2021.103826

Krishnan, G., Singh, S., Pathania, M., Gosavi, S., Abhishek, S., Parchani, A., & Dhar, M. (2023). Artificial intelligence in clinical medicine: Catalyzing a sustainable global healthcare paradigm. *Frontiers in Artificial Intelligence, 6,* 1227091. https://doi.org/10.3389/frai.2023.1227091

Kruszyńska-Fischbach, A., Sysko-Romańczuk, S., Napiórkowski, T. M., Napiórkowska, A., & Kozakiewicz, D. (2022). Organizational e-health readiness: How to prepare the primary healthcare providers' services for digital transformation. *International Journal of Environmental Research and Public Health, 19*(7), 3973. https://doi.org/10.3390/ijerph19073973

Li, S., Yang, Q., Niu, S., & Liu, Y. (2023). Effectiveness of remote fetal monitoring on maternal-fetal outcomes: Systematic review and meta-analysis. *JMIR mHealth and uHealth, 11*(1), e41508. https://doi.org/10.2196/41508

Mahin, M. R. H., Ahmed, E., Akhi, S. S., Fahad, M. A. H., Tusher, M. I., Chowdhury, R., & Rana, M. N. U. (2021). Advancements and challenges in software engineering and project management: A 2021 perspective. *Pathfinder of Research*, *2*(1), 15–15.

Mahjabin, Z., Dey, D., Islam, M. M., Mahamud, S., & Sunny, A. R. (2024). Anthropogenic and Environmental Factors Affecting Biodiversityand Human Well-being in an Ecologically Sensitive Wetland. *Pathfinder of Research*, *2*(3), 18-18.

Mithun, M. H., Shaikat, M. F. B., Sazzad, S. A., Billah, M., Al Salehin, S., Foysal, M., … & Sunny, A. R. (2024). Microplastics in aquatic ecosystems: Sources, impacts, and challenges for biodiversity, food security, and human health-A meta-analysis. *Journal of Angiotherapy, 8*(11), 1–12. https://doi.org/10.25163/angiotherapy.119843

Olaniyan, O., Yusuf, A., Igbin, L. A., & Oluwakemi, A. K. H. (2024). Data-driven decision-making in healthcare: The impact of business analytics on hospital management. *[Preprint]*.

Pandian, A., Mohankumar, K. P., Padmini, S., Amaran, S., & Sreekumar, K. (2025). Enhancing trust and collaboration using explainability in natural language processing for AI-driven healthcare. In *Explainable artificial intelligence in the healthcare industry* (pp. 619–650). Springer. https://doi.org/10.1007/978-981-97-1228-9_26

Petretto, D. R., Carrogu, G. P., Gaviano, L., Berti, R., Pinna, M., Petretto, A. D., & Pili, R. (2024). Telemedicine, e-health, and digital health equity: A scoping review. *Clinical Practice and Epidemiology in Mental Health, 20,* e17450179279732. https://doi.org/10.2174/17450179202020240103125052

Pickard Strange, M., Booth, A., Akiki, M., Wieringa, S., & Shaw, S. E. (2023). The role of virtual consulting in developing environmentally sustainable health care: Systematic literature review. *Journal of Medical Internet Research, 25,* e44823. https://doi.org/10.2196/44823

Rahman, S., Islam, M., Hossain, I., & Ahmed, A. (2024). Utilizing AI and data analytics for optimizing resource allocation in smart cities: A US-based study. *International Journal of Artificial Intelligence, 4*(7), 70–95.

Rahman, K., Alam, M. R., Chowdhury, R., & Urbi, S. R. C. (2024). The Evolution of Business Analytics: Frameworks, Tools, and Real-World Impact on Strategic Decision-Making in the Digital Age. *Pathfinder of Research*, *2*(2), 37-58.

Rana, M. N. U., Akhi, S. S., Tusher, M. I., Mahin, M. R. H., Ahmed, E., Chowdhury, T. E., … & Bashir, M. (2023). The role of AI and generative AI in US business innovations, applications, challenges, and future trends. *Pathfinder of Research, 1*(3), 17–33.

Rangachari, P., Mushiana, S. S., & Herbert, K. (2022). A scoping review of applications of the Consolidated Framework for Implementation Research (CFIR) to telehealth service implementation initiatives. *BMC Health Services Research, 22*(1), 1450. https://doi.org/10.1186/s12913-022-08779-1

Rea, S., Mikesell, L., Cuddihy, C., Perry, M., & Allison, B. (2023). Exploring the complexity of telehealth privacy through a lens of adolescent development. *Qualitative Health Research, 33*(3), 220–235. https://doi.org/10.1177/10497323221149774

Riaz, M. S., Shaukat, M., Saeed, T., Ijaz, A., Qureshi, H. N., Posokhova, I., … & Imran, A. (2024). iPREDICT: AI-enabled proactive pandemic prediction using biosensing wearable devices. *Informatics in Medicine Unlocked, 46,* 101478. https://doi.org/10.1016/j.imu.2024.101478

Roman-Belmonte, J. M., De la Corte-Rodriguez, H., Rodriguez-Merchan, E. C., Vazquez-Sasot, A., Rodriguez-Damiani, B. A., Resino-Luís, C., & Sanchez-Laguna, F. (2022). The three horizons model applied to medical science. *Postgraduate Medicine, 134*(8), 776–783. https://doi.org/10.1080/00325481.2022.2083489

Saati, A. (2022). An analysis of the effectiveness of a commercial hospital artificial intelligence system in reducing readmissions in high-risk Medicare patients (Doctoral dissertation, Rutgers University–School of Health Professions). ProQuest Dissertations Publishing.

Samal, L., Fu, H. N., Camara, D. S., Wang, J., Bierman, A. S., & Dorr, D. A. (2021). Health information technology to improve care for people with multiple chronic conditions. *Health Services Research, 56*(Suppl 1), 1006–1036. https://doi.org/10.1111/1475-6773.13627

Sazzad, S. A., Ana, R. A., Shawon, R., Moniruzzaman, M., Hussain, M. H., & Zaman, F. Z. (2024). Climate change and socioeconomic challenges of fishing communities in the coastal district of Shariatpur in Bangladesh. *Pathfinder of Research, 2*(1), 1–10.

Sazzad, S. A., Chowdhury, R., Hasan, M. R., Tiva, M. G., Rahman, K., Ansari, M. A. S., & Sunny, A. R. (2025). Public health, risk perception, and governance challenges in the 2025 Los Angeles wildfires: Evidence from a community-based survey. *Pathfinder of Research, 3*(1), 26–41.

Scrivner, J. H., Jr. (2024). The adoption of AI technological innovation in hospital systems: The case of computer-assisted diagnosis adoption and diffusion (Doctoral dissertation, Sullivan University). ProQuest Dissertations Publishing.

Sheikh, A., Anderson, M., Albala, S., Casadei, B., Franklin, B. D., Richards, M., … & Mossialos, E. (2021). Health information technology and digital innovation for national learning health and care systems. *The Lancet Digital Health, 3*(6), e383–e396. https://doi.org/10.1016/S2589-7500(21)00005-4

Sunny, A. R., Rahman, M. A., Hasan, M. N., Bhuyian, M. S., Miah, M. F., Ashrafuzzaman, M., Pervin, A., Rahman, J. F., & Prodhan, S. H. (2025a). Hilsa (*Tenualosa ilisha*) genetic diversity and conservation strategies for sustainable wetland management in northeastern Bangladesh. *Egyptian Journal of Aquatic Biology & Fisheries, 29*(1), 1089–1105. https://doi.org/10.21608/ejabf.2025.259581

Sunny, A. R., Sazzad, S. A., Bhuyian, M. S., Hasan, M. N., Miah, M. F., Ashrafuzzaman, M., & Prodhan, S. H. (2025b). Fish genetic resources and wetland conservation in Bangladesh: Comparative insights on biodiversity, sustainable management, and sustainable development goals. *Limnological Review, 25*(2), 20–34. https://doi.org/10.3390/limnolrev25020020

Tiva, M. G., Tarin, N. N., Hasan, M. R. K., Urbi, S. R. C., & Sazzad, S. A. (2025a). Post-COVID-19 Workforce Management in US Healthcare: Burnout, Retention, and Strategies for Enhancing Cultural Competency. *Pathfinder of Research*, *3*(1), 98-119.

Tiva, M. G., Urbi, S. R. C. & Hasan, M. R. K. (2025b). Preventable Readmissions and Financial Management in Healthcare: A Comparative Study of Cost Containment in Non-Profit and For-Profit Hospitals. *Pathfinder of Research*, *3*(2), 1-21

Trivedi, S., & Patel, N. (2021). The determinants of AI adoption in healthcare: Evidence from voting and stacking classifiers. *ResearchBerg Review of Science and Technology, 1*(1), 69–83.

Wattanapanit, S. (2025). Reinforcement learning for adaptive scheduling and optimization of healthcare staff and resources in multi-departmental hospitals. *Open Journal of Robotics, Autonomous Decision-Making, and Human-Machine Interaction, 10*(5), 1–15.

Wei, L., & Xiaoyu, C. (2023). A strategic framework for enhancing hospital management efficiency through predictive analytics and AI-driven resource planning. *Applied Journal of Computational Thinking, Modeling, and Simulation, 7*(10), 1–10.