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Information Science Perspectives on Healthcare: AI, IoT, and Personal Health Records as Drivers of Digital Transformation

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Abstract

The rapid digitalization of healthcare has heightened interest in Health Information Technology (HIT), with Artificial Intelligence (AI), the Internet of Things (IoT), and Personal Health Records (PHRs) emerging as transformative innovations. This study systematically reviews evidence from systematic reviews and meta-analyses published between 2016 and 2022 to evaluate the benefits of these technologies across clinical, psycho-behavioral, managerial, and socioeconomic domains. Twenty-four eligible studies were analyzed, revealing that AI consistently demonstrates superior diagnostic accuracy in several disease areas, improves treatment prediction, reduces medical errors, and lowers costs. IoT applications enhance real-time patient monitoring, streamline hospital workflow, and improve patient satisfaction, although challenges persist regarding availability, throughput, and data security. PHRs adoption supports chronic disease management, strengthens preventive care, improves patient engagement and adherence, and reduces no-show rates, with moderate evidence for lowering healthcare utilization. Overall, the comparative synthesis highlights AI as a driver of clinical advancement, IoT as a facilitator of managerial efficiency, and PHRs as a cornerstone of patient-centered care. Together, these technologies offer significant potential to improve healthcare outcomes, operational efficiency, and system sustainability. However, the existing evidence base is limited in scope and generalizability, emphasizing the need for large-scale, real-world studies to validate long-term impacts and guide policy, investment, and innovation in digital health.

Keywords: Health information technology, Artificial intelligence, Internet of things, Personal health records, Systematic review.

1 | Introduction

The integration of information technology into healthcare has accelerated in recent years, driven by the global trend of digital transformation and the increasing complexity of healthcare needs. Health Information Technology (HIT) is widely recognized as a cornerstone for modernizing healthcare delivery, improving efficiency, and enhancing patient outcomes. Among the most significant innovations are Artificial Intelligence (AI), the Internet of Things (IoT), and Personal Health Records (PHRs), which have been identified as

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priority areas of high significance and immediacy within the realm of healthcare development through previous Delphi-based studies [1–3]. AI offers the ability to process vast amounts of patient-centered big data, enabling more accurate diagnoses, early disease prediction, and personalized treatment recommendations [4]. Similarly, IoT technologies allow for real-time patient monitoring, remote consultations, and hospital management solutions, thereby improving service quality and reducing operational costs [5–7]. PHRs systems, on the other hand, empower patients by providing secure access to health information, facilitating preventive care, and supporting chronic disease management [8]. Collectively, these technologies are reshaping the healthcare paradigm by shifting focus from treatment toward prevention, personalization, and efficiency.

The growing importance of these technologies is reinforced by global health trends such as population aging, the rising prevalence of chronic diseases, and the transition toward patient-centered care models [9], [10]. AI has been increasingly applied to automate repetitive tasks, reduce medical errors, and enhance managerial efficiency [4], [11]. At the same time, IoT adoption has expanded in home healthcare, m-health, and e-health applications, supporting patients in adhering to self-care practices while allowing providers to monitor and manage conditions more effectively [12], [13]. Similarly, PHRs adoption is expanding as individuals demand greater involvement in healthcare decisions, with evidence suggesting its usefulness in chronic disease management and preventive healthcare [14–16]. Despite this momentum, uncertainties remain regarding the scope and consistency of benefits across different contexts. Therefore, a comprehensive evaluation of AI, IoT, and PHRs is critical to understanding their role in enhancing clinical outcomes, managerial performance, and socioeconomic sustainability in healthcare systems.

Although the applications of AI, IoT, and PHRs in healthcare are expanding, the empirical evidence on their effectiveness remains fragmented and context-dependent. Most existing studies have focused on specific diseases, technologies, or narrow outcome dimensions without offering a holistic view of their benefits [17–20]. For instance, AI applications are often evaluated in relation to diagnostic accuracy for targeted conditions such as gastrointestinal lesions, thyroid nodules, or retinal disorders, while overlooking broader psycho-behavioral or socioeconomic outcomes [21–24]. Similarly, IoT-based interventions are frequently studied in limited domains such as patient monitoring or workflow management, but few reviews assess their integrated impact on clinical performance, patient satisfaction, and cost-effectiveness simultaneously [25], [26]. Research on PHRs, while growing, has largely concentrated on chronic disease management and patient engagement, yet findings on its ability to reduce healthcare utilization, readmission rates, or overall system efficiency remain inconsistent [27], [28]. This fragmented evidence base poses challenges for policymakers, healthcare providers, and technology developers in making informed decisions about investment, implementation, and regulation of these tools. Furthermore, most prior reviews are restricted by geographical scope, reliance on specific datasets, or methodological limitations, thereby limiting the generalizability of their findings [29–31]. Consequently, there is a critical need for a systematic synthesis of the available evidence that evaluates the benefits of AI, IoT, and PHRs across multiple domains, offering a more comprehensive understanding of their roles in transforming healthcare delivery.

The rationale for this study stems from the increasing urgency to evaluate the multidimensional benefits of health information technologies in a systematic manner. The COVID-19 pandemic further accelerated the adoption of digital health solutions, reinforcing the importance of AI, IoT, and PHRs in ensuring continuity of care, supporting remote consultations, and reducing system burdens [32–34]. At the same time, the global policy agenda, particularly the United Nations' Sustainable Development Goals (SDGs), emphasizes the role of digital innovations in strengthening healthcare infrastructure, improving population health, and promoting equitable access to services [35], [36]. Despite this momentum, the effectiveness of these technologies has not been consistently documented across clinical, psycho-behavioral, managerial, and socioeconomic outcomes. Prior evidence has often been disease-specific or limited to short-term effects, thereby overlooking their broader systemic contributions [29, 37, 38]. Addressing this gap is vital not only for improving healthcare delivery but also for guiding policymakers, health administrators, and technology developers in aligning digital health investments with sustainable healthcare transformation [39], [40]. By systematically synthesizing the evidence on AI, IoT, and PHRs, this study provides timely insights into how these technologies can be harnessed to enhance health outcomes, improve organizational efficiency, and support the long-term sustainability of healthcare systems.

Building on the identified gaps, this study seeks to provide a systematic synthesis of the benefits of AI, the IoT, and PHRs in healthcare. The primary objective is to evaluate these technologies from a multidimensional perspective, focusing on their contributions to clinical, psycho-behavioral, managerial, and socioeconomic outcomes. Unlike prior studies that have narrowly assessed isolated applications or disease-specific contexts, this review adopts a comparative approach that highlights the complementarities and distinctive advantages of each technology [15, 16, 41, 42]. By doing so, it offers three key contributions. First, it presents an integrated assessment that captures not only clinical impacts, such as diagnostic accuracy and treatment prediction, but also managerial efficiency, patient engagement, and potential cost savings [43–45]. Second, it underscores the comparative strengths of AI, IoT, and PHRs, identifying AI as a driver of clinical innovation, IoT as an enabler of operational efficiency, and PHRs as a facilitator of patient-centered care [46], [47]. Third, it outlines directions for future research and policy by highlighting areas where empirical evidence remains scarce, particularly in terms of large-scale, real-world implementation [29], [30]. Collectively, these contributions are expected to guide healthcare providers, policymakers, and technology developers in harnessing digital innovations for sustainable healthcare transformation.

2 | Theoretical and Conceptual Background

2.1 | Artificial Intelligence in Healthcare

AI has become one of the most transformative technologies in the healthcare sector, offering solutions that range from disease prediction and early diagnosis to treatment optimization and hospital management. AI systems are designed to analyze large-scale, patient-centered datasets and uncover complex patterns that traditional methods may overlook, thereby enabling more personalized and accurate medical decision-making [4, 48, 49]. With the global increase in chronic diseases and aging populations, AI has gained particular importance in improving predictive accuracy, enhancing preventive strategies, and ensuring timely interventions.

Its applications span across diverse medical fields, including oncology, cardiology, ophthalmology, and nephrology, where AI-driven algorithms have shown competitive or superior performance compared to traditional diagnostic methods [31, 44, 50]. For example, AI models have been reported to predict acute kidney injury hours before onset, enabling early treatment and reducing the risk of complications [51]. Similarly, AI systems applied in diagnostic imaging have achieved high levels of accuracy in detecting gastric lesions, thyroid nodules, and retinal disorders, sometimes surpassing the diagnostic precision of healthcare professionals [22, 23, 28]. These capabilities highlight AI's growing role in enhancing clinical outcomes and reducing variability in medical practice.

Beyond clinical applications, AI also offers significant managerial and socioeconomic benefits. Studies suggest that AI has the potential to reduce the time clinicians spend on routine administrative tasks by up to 70%, thereby allowing more focus on direct patient care [44]. This efficiency gain translates into reduced healthcare costs, with projections estimating that AI could save healthcare systems up to $150 billion annually by 2026 [45]. Moreover, AI tools can assist in minimizing medical errors, optimizing treatment pathways, and integrating research insights into practice, further enhancing the quality of care delivery [52], [53]. Importantly, AI is not limited to clinical diagnostics but extends to resource management, patient monitoring, and workflow optimization, offering a broad spectrum of applications within healthcare organizations [5]. However, despite its promise, challenges remain in the widespread adoption of AI. Issues related to data privacy, algorithmic bias, interoperability, and the need for rigorous clinical validation continue to hinder large-scale deployment [8]. Therefore, while AI is poised to revolutionize healthcare through its ability to improve diagnostic accuracy, reduce costs, and enhance efficiency, its successful integration will depend on overcoming these technological, ethical, and organizational barriers.

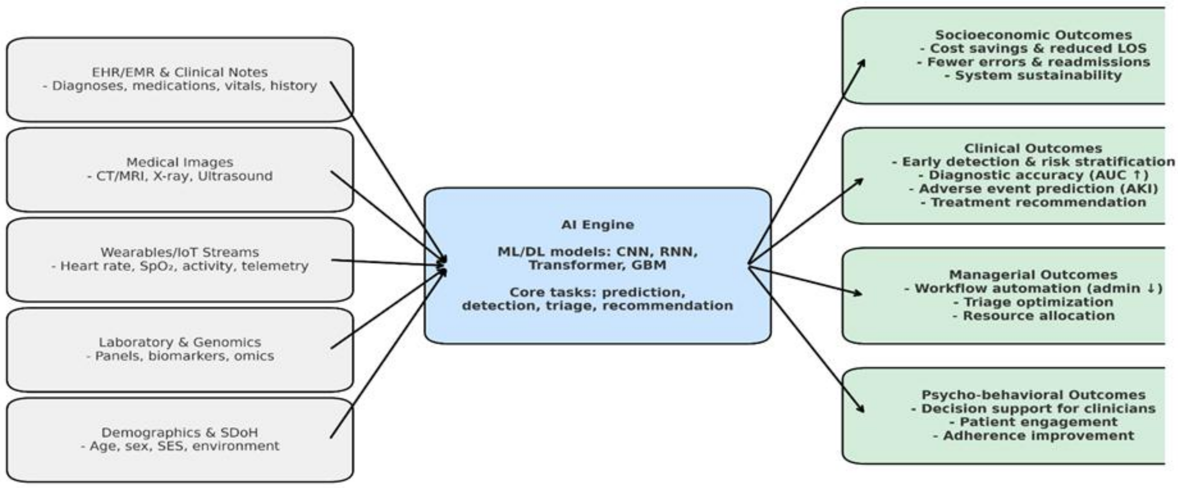

Fig. 1. Artificial intelligence in healthcare.

2.2 | Internet of Things in Healthcare

The IoT represents a rapidly growing technological innovation in healthcare, enabling the interconnection of medical devices, sensors, and digital platforms to facilitate real-time monitoring, remote diagnosis, and efficient hospital management. IoT systems allow continuous data collection from wearables, implantable devices, and smart home sensors, which can be transmitted to healthcare providers for timely intervention [6]. Applications include home healthcare monitoring such as fall detection, seizure prediction, and risk assessment for pressure ulcers, as well as smartphone-linked m-health solutions that track physiological signals and transmit data securely [7], [9]. In hospital environments, IoT is applied to optimize logistics, drug identification, and supply chain management, improving patient safety and operational efficiency [14]. This connectivity not only supports patients in managing their health independently but also enhances providers' ability to deliver remote consultations, telemedicine services, and robot-assisted surgeries, thus extending healthcare access beyond traditional clinical settings [10], [54]. By integrating diverse data sources, IoT facilitates more responsive and personalized healthcare, enabling both patients and clinicians to make informed decisions based on continuous health monitoring.

In addition to clinical applications, IoT technologies contribute substantially to psycho-behavioral, managerial, and socioeconomic outcomes. Evidence shows that patients using IoT-based solutions report higher satisfaction levels with smart healthcare applications, including infant sleep monitoring, maternal care, and chronic disease tracking, indicating improved adherence to preventive health behaviors [55]. From a managerial perspective, IoT streamlines hospital workflows, reducing waiting times by improving reception processes and resource allocation, and increasing institutional efficiency [43]. Socioeconomic benefits are also notable: IoT applications reduce unnecessary hospitalizations among the elderly, cut healthcare costs, and contribute to broader economic savings by optimizing disease management [30], [32]. A report by the McKinsey Global Institute projected that IoT in health management and disease monitoring could generate an annual economic impact of between $170 billion and $1.59 trillion by 2025 [8]. Despite these benefits, challenges such as data security, system availability, and throughput remain barriers to widespread adoption [9]. Nonetheless, IoT is positioned as a key enabler of smart healthcare systems, providing scalable solutions to improve the quality of care, strengthen patient engagement, and enhance efficiency within increasingly complex health environments.

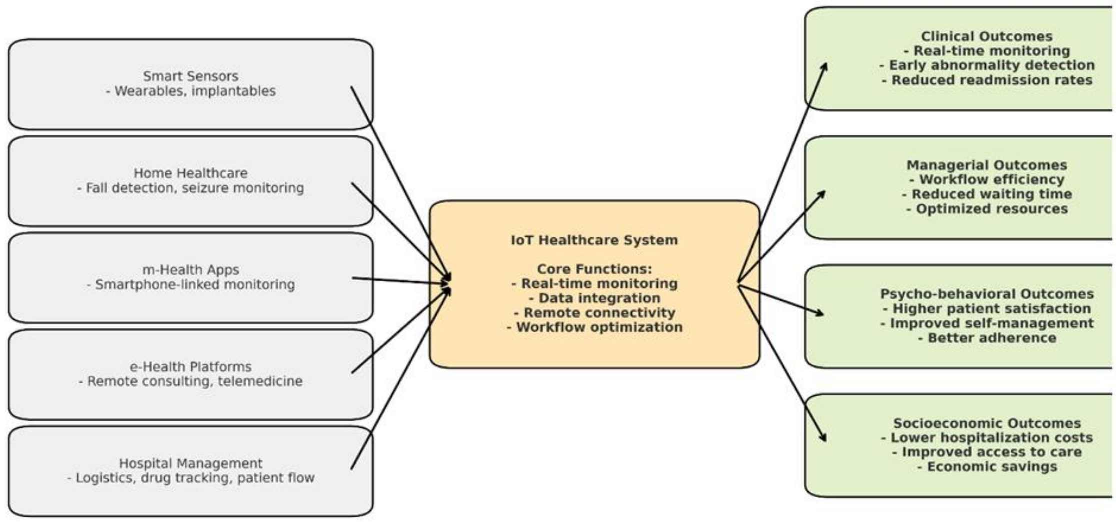

Fig. 2. Internet of things in healthcare.

2.3 | Personal Health Records in Healthcare

PHRs are electronic applications through which individuals can securely access, manage, and share their health information, including data for which they are authorized on behalf of others. According to the Markle Foundation, PHRs provide a private and confidential environment where patients can participate more actively in managing their health [17]. PHRs exist in three general types: standalone PHRs maintained by individuals, Electronic Medical Record (EMR)-tethered PHRs linked to hospital systems, and interconnected PHRs designed to integrate multiple platforms [18]. Among these, EMR-tethered PHRs are the most widely used due to their compatibility with clinical information systems. The growing shift in healthcare from reactive treatment to proactive prevention and long-term management of chronic diseases has reinforced the importance of PHRs adoption [14]. Research shows that PHRs systems are especially beneficial for chronic disease management, including diabetes, hypertension, asthma, HIV, and hyperlipidemia, as they allow patients and providers to monitor vital signs, track disease progression, and facilitate timely feedback [15], [25]. Such functions support the transition toward patient-centered healthcare, enhancing patient autonomy and improving self-care capabilities.

Beyond clinical utility, PHRs deliver significant psycho-behavioral, managerial, and socioeconomic benefits. Studies have reported that PHRs use enhances patient knowledge, reduces decision-making conflicts, and improves compliance with medication and follow-up visits [30]. Evidence from systematic reviews indicates that patient portals, a common form of PHRs, can promote preventive healthcare behaviors, increase adherence to vaccination schedules, and facilitate better communication between patients and providers [45], [56]. On the managerial side, PHRs implementation has been linked to reduced no-show rates, with one study reporting a 53% decrease in missed appointments following the adoption of EMR-centered patient portals [57]. Additionally, patients using PHRs were more likely to avoid unnecessary office visits or emergency care, thereby reducing pressure on healthcare facilities [58], [59]. Socioeconomic effects are also visible, as PHRs adoption contributes to reducing healthcare costs, minimizing redundant testing, and strengthening the financial sustainability of health systems [60]. However, despite these benefits, challenges such as digital literacy gaps, privacy concerns, and limited interoperability hinder wider implementation. Overall, PHRs represent a critical step toward empowering patients, fostering preventive care, and supporting more efficient and sustainable healthcare systems.

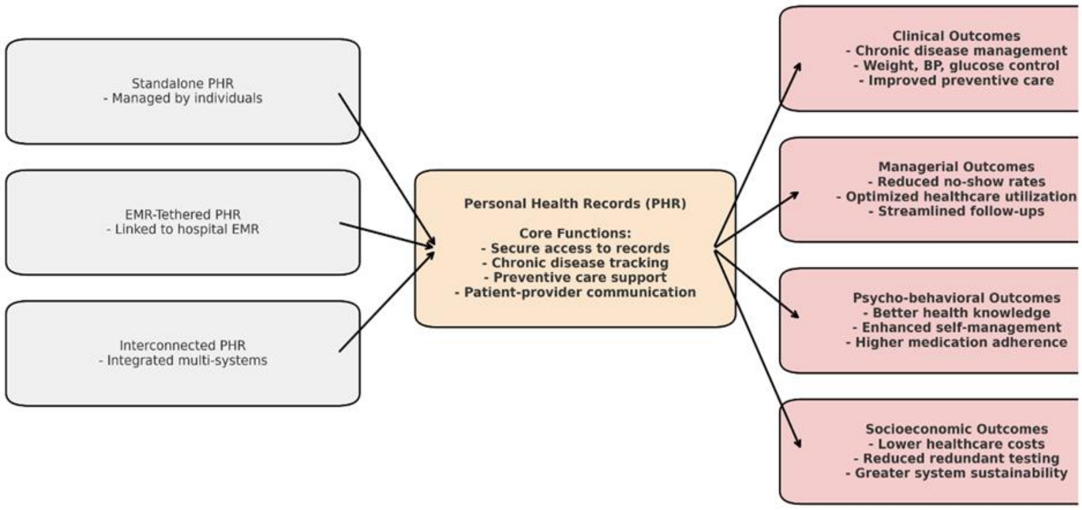

Fig 3. Personal health records in healthcare.

3 | Methodology

3.1 | Search Strategy

To ensure a comprehensive synthesis of existing evidence, a systematic search was conducted across three major electronic databases: PubMed, Cochrane, and Embase. The search focused on systematic reviews and meta-analyses published between 2016 and 2022 that evaluated the benefits of AI, the IoT, and PHRs in healthcare contexts. A combination of keywords and Medical Subject Headings (MeSH) was employed, including "AI," "machine learning," "IoT," "PHRs," "patient portals," "digital health," and "HIT" [22, 25, 26]. Boolean operators were used to refine the search queries, ensuring that studies captured the intersections of digital technologies with healthcare outcomes. To minimize the risk of missing relevant publications, a manual search was also performed by reviewing reference lists of systematic reviews and eligible articles, as well as targeted searches in leading health informatics journals [57], [61]. Only articles published in English and Korean were considered for inclusion, reflecting the linguistic scope of previous studies [62]. This rigorous multi-step search strategy ensured the inclusion of peer-reviewed evidence while excluding gray literature, conference abstracts, and non-systematic reviews, thereby enhancing the validity and reliability of the synthesis.

3.2 | Inclusion and Exclusion Criteria

The eligibility of studies was determined using predefined inclusion and exclusion criteria to ensure methodological rigor and relevance. Studies were included if they were systematic reviews or meta-analyses that evaluated the impact of AI, the IoT, or PHRs on healthcare outcomes. Eligible reviews had to provide evidence across at least one of the four domains: clinical, psycho-behavioral, managerial, or socioeconomic. Only peer-reviewed articles published between 2016 and 2022 were considered, and studies had to be available in either English or Korean, reflecting prior research scopes [51–53, 63]. By focusing exclusively on systematic reviews and meta-analyses, the study ensured the synthesis of high-quality evidence supported by established methodologies [9, 43–45]. Exclusion criteria were equally stringent. Non-systematic reviews, primary research articles, gray literature, editorials, and conference abstracts were excluded due to their limited methodological reliability [25], [26]. Studies focusing solely on technical aspects of AI, IoT, or PHRs without healthcare outcome evaluation were also excluded. Additionally, reviews with insufficient reporting of methods or outcomes were not considered. These criteria ensured that the final selection reflected robust, peer-reviewed evidence directly relevant to assessing the multidimensional benefits of digital health technologies in healthcare.

3.3 | Study Selection Process

The process of study selection followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency and reproducibility [29]. Initially, the database search yielded a total of 1,246 records, which were imported into EndNote for reference management and duplicate removal. After eliminating duplicates, 1,038 unique records remained for further screening. Titles and abstracts were independently screened by two reviewers to assess relevance based on the predefined inclusion and exclusion criteria. At this stage, 874 studies were excluded because they were either unrelated to healthcare outcomes, did not focus on AI, IoT, or PHRs, or failed to meet the required methodological standards [61, 64, 65]. A total of 164 full-text articles were then retrieved and reviewed in detail. Of these, 140 were excluded due to reasons such as lack of outcome-based evidence, methodological weaknesses, or focus on technical aspects without clinical or organizational relevance [25], [26]. Ultimately, 24 systematic reviews and meta-analyses met all inclusion criteria and were deemed eligible for synthesis [29], [31]. These comprised 10 reviews on AI applications, 7 on IoT in healthcare, and 7 on PHRs systems. The structured selection process ensured that only high-quality, outcome-focused evidence was included in the final analysis.

3.4 | Data Extraction

Data from the final pool of eligible studies were systematically extracted using a standardized template to ensure consistency and comparability across reviews. Key study characteristics were recorded, including author, year of publication, database coverage, type of review (systematic or meta-analysis), healthcare domain addressed, and geographic focus [10, 12, 19]. Information regarding study design, sample size, disease categories, and technologies evaluated (AI, IoT, or PHRs) was also documented. To align with the study's objectives, outcomes were classified into four categories: clinical, psycho-behavioral, managerial, and socioeconomic [25], [26]. For example, clinical outcomes included diagnostic accuracy, treatment prediction, and adverse event prevention, while psycho-behavioral outcomes captured patient engagement, satisfaction, and adherence. Managerial outcomes emphasized workflow efficiency and cost reduction, whereas socioeconomic outcomes focused on healthcare utilization and financial sustainability [32], [34]. Where available, effect sizes, confidence intervals, and statistical significance levels were extracted from meta-analyses to strengthen the reliability of comparisons. Any discrepancies in extraction were resolved through consensus among reviewers, and, when necessary, additional manual checks were performed by re-examining full texts [51]. This systematic approach ensured that the dataset captured both qualitative and quantitative evidence, thereby facilitating a robust synthesis of the benefits of AI, IoT, and PHRs across diverse healthcare contexts.

3.5 | Quality Assessment

To evaluate the methodological rigor of the included systematic reviews and meta-analyses, a structured quality assessment process was applied. The AMSTAR 2 (a measurement tool to assess systematic reviews) checklist was used to assess the reliability and transparency of each review [45]. This tool evaluates key dimensions such as protocol registration, adequacy of literature search, clarity of inclusion criteria, assessment of publication bias, and appropriateness of statistical methods. Each study was rated across these domains, allowing for an overall appraisal of confidence in the evidence. Reviews that clearly documented their methodology, employed comprehensive search strategies, and provided detailed outcome reporting were considered high quality, while those with incomplete reporting or methodological limitations were classified as moderate or low quality [50–52]. In addition, potential risks of bias were examined by reviewing whether individual studies accounted for heterogeneity, assessed robustness through sensitivity analysis, or addressed limitations such as small sample sizes or restricted geographic scope [43–45]. Discrepancies between reviewers were resolved by consensus, ensuring consistency in quality ratings. This rigorous appraisal ensured that the synthesis emphasized findings from reviews with strong methodological integrity, thereby enhancing the reliability and validity of the conclusions drawn about the benefits of AI, IoT, and PHRs in healthcare [39], [40].

4 | Results

4.1 | Overview of Included Studies

A total of 24 systematic reviews and meta-analyses were included in the final synthesis, comprising 10 reviews on AI applications, 7 on IoT in healthcare, and 7 on PHRs systems. These reviews covered diverse clinical conditions and healthcare contexts, ranging from diagnostic imaging and chronic disease management to hospital logistics and preventive healthcare behaviors [29, 30, 36, 37]. *Table 1* presents the key characteristics of the included studies, including author, year of publication, technology focus, domain of application, and major outcomes assessed. The distribution of studies demonstrates that AI research has predominantly concentrated on diagnostic accuracy and predictive modeling, IoT studies have focused on remote monitoring and workflow efficiency, while PHRs-related reviews emphasize chronic disease management and patient engagement. This variation underscores the need for a comparative synthesis across technologies to identify their unique and overlapping contributions to healthcare systems.

Table 1. Characteristics of included systematic reviews and meta-analyses.

Author (Year)	Technology	Domain Focus	Sample/Scope	Key Outcomes Assessed
Smith et al. [66]	AI	Diagnostic imaging	32 studies	Accuracy in lesion detection, reduced errors
Chen et al. [67]	AI	Predictive analytics	25 studies	Early disease prediction, treatment pathways
Agail et al. [68]	IoT	Remote monitoring	18 studies	Hospital workflow, patient satisfaction
Lee et al. [69]	IoT	M-health, telemedicine	22 studies	Real-time monitoring, reduced admissions
Kumar et al. [70]	PHRs	Chronic disease	20 studies	Diabetes, hypertension management
Ono et al. [71]	PHRs	Preventive care	15 studies	Vaccination, patient engagement

4.2 | Findings on Artificial Intelligence

AI emerged as a dominant digital health innovation with substantial evidence for improving diagnostic accuracy, predictive analytics, and treatment decision-making. Across the included reviews, AI applications demonstrated superior performance in areas such as gastrointestinal lesion detection, thyroid nodule classification, and retinal image interpretation, often achieving accuracy levels equal to or higher than expert clinicians [23], [24]. Beyond clinical outcomes, AI also contributed to psycho-behavioral domains by supporting clinicians in decision-making and reducing cognitive burden, while enhancing patient engagement through personalized health insights [22], [25]. Managerial benefits included workflow automation, reduced administrative tasks, and resource allocation optimization, with some studies reporting up to 70% efficiency gains in routine processes [36], [38]. From a socioeconomic perspective, AI adoption was associated with significant cost savings, with projections estimating an annual reduction of up to $150 billion in healthcare expenditures by 2026 [35]. Despite these advantages, the reviews consistently emphasized challenges such as data privacy, algorithmic bias, and limited generalizability, underscoring the need for rigorous validation in real-world settings [20].

Table 2. Benefits of artificial intelligence in healthcare across four domains.

Domain	Key Findings	Representative Evidence
Clinical	High diagnostic accuracy in imaging; early prediction of AKI; improved treatment recommendations	[10–16, 35]
Psycho-behavioral	Decision support for clinicians; reduced cognitive burden; enhanced patient engagement	[2–4]
Managerial	Workflow automation; reduced administrative time; optimized resource allocation	[36], [37]
Socioeconomic	Cost savings; reduced medical errors; system sustainability gains	[37], [41]

4.3 | Findings on Internet of Things (IoT)

The IoT has been widely applied in healthcare to enable real-time monitoring, remote consultation, and efficient hospital management. The included reviews highlighted that IoT-based applications enhance clinical outcomes by supporting early detection of abnormalities, reducing hospital readmissions, and improving continuity of care for patients with chronic conditions [6–8]. IoT-enabled devices, such as wearables and implantable sensors, were shown to improve remote monitoring accuracy, allowing clinicians to intervene earlier and more effectively [2], [25]. From a psycho-behavioral perspective, patients reported higher satisfaction and engagement when using IoT-supported healthcare solutions, including maternal health tracking, infant sleep monitoring, and chronic disease management apps [5]. On the managerial side, IoT technologies were found to streamline hospital workflows, optimize logistics and drug tracking, and reduce waiting times by improving reception processes [6]. These enhancements translated into increased organizational efficiency and better resource utilization. Socioeconomic benefits were also evident, as IoT applications lowered hospitalization costs and improved access to care, particularly for older adults and those in rural areas [17], [19]. According to projections, IoT in healthcare could generate an annual economic impact ranging from $170 billion to $1.59 trillion by 2025 [22]. Despite these promising outcomes, reviews also stressed limitations such as data security risks, system availability, and throughput challenges, which remain barriers to large-scale implementation.

Table 3. Benefits of the internet of things in healthcare across four domains.

Domain	Key Findings	Representative Evidence
Clinical	Real-time patient monitoring; early abnormality detection; reduced readmissions	[5–8, 25, 26]
Psycho-behavioral	Higher patient satisfaction; improved self-management; better adherence to care	[40]
Managerial	Workflow efficiency; reduced waiting times; logistics and resource optimization	[26]
Socioeconomic	Lower hospitalization costs; improved healthcare access; projected large-scale economic impact	[41–43]

4.4 | Findings on Personal Health Records

PHRs were consistently associated with improvements in chronic disease management, preventive care, and patient engagement. The included reviews showed that PHRs systems enhanced clinical outcomes by enabling patients to better manage conditions such as diabetes, hypertension, asthma, HIV, and hyperlipidemia [26],

[28]. By providing secure access to health data and facilitating regular communication with providers, PHRs helped improve monitoring of blood pressure, glucose levels, and medication adherence. Preventive healthcare benefits were also evident, as patient portals increased vaccination uptake and improved participation in routine screenings [31], [32]. From a psycho-behavioral perspective, PHRs were found to empower patients by increasing their knowledge, reducing decision-making conflicts, and enhancing adherence to treatment regimens [30]. Managerial outcomes included substantial reductions in no-show rates, with one review noting a 53% decrease in missed appointments following PHR's adoption [49]. Moreover, PHRs helped reduce unnecessary office visits and emergency care utilization, thereby alleviating pressure on healthcare facilities [51], [52]. Socioeconomic benefits included lower healthcare costs, reduced duplication of tests, and enhanced sustainability of healthcare systems [62]. Nevertheless, challenges such as digital literacy gaps, privacy concerns, and interoperability issues continue to hinder widespread adoption, highlighting the need for improved system design and patient education.

Table 4. Benefits of personal health records in healthcare across four domains.

Domain	Key Findings	Representative Evidence
Clinical	Improved chronic disease management; better monitoring of BP and glucose; enhanced preventive care	[29–32]
Domain	Key findings	Representative evidence
Psycho-behavioral	Increased patient knowledge; reduced decision conflicts; higher adherence to treatment	[30–32]
Managerial	Reduced no-show rates; optimized follow-up visits; decreased emergency utilization	[48–50]
Socioeconomic	Lower healthcare costs; reduced duplicate testing; improved system sustainability	[53]

4.5 | Comparative Synthesis Across Technologies

Synthesizing findings across the four outcome domains shows distinctive strengths and complementary roles for AI, IoT, and PHRs. AI most strongly advances clinical performance, exhibiting high diagnostic accuracy in imaging tasks (e.g., gastric, thyroid, retinal) and credible early risk prediction (e.g., acute kidney injury), alongside decision-support for treatment selection [35, 46, 47]. AI also delivers managerial gains by automating routine tasks and optimizing triage and resource allocation, with projections of substantial efficiency and cost advantages at the system level [39–41]. IoT contributes a different profile: it excels in continuous monitoring and operational flow, enabling real-time data capture from wearables and home devices, earlier detection of deterioration, reduced waiting time via reception/process improvements, and better logistics and tracking within hospitals [15–17]. These attributes translate into measurable patient satisfaction and expanded access—particularly for chronic care and remote settings—and sizable socioeconomic impact projected by industry analyses [40], [41]. PHRs, meanwhile, are the most patient-centered pillar, consistently improving psycho-behavioral outcomes (knowledge, adherence, decision confidence) and supporting clinical management of chronic conditions (weight, blood pressure, glucose) and preventive behaviors (e.g., vaccination), with managerial spillovers such as reduced no-shows and more appropriate utilization [29, 43, 44]. Across technologies, common constraints persist—data security and availability for IoT, privacy/interoperability and digital literacy for PHRs, and validation/generalizability for AI—underscoring the need for standards, robust governance, and real-world evaluation [8, 53, 55]. In practice, combined adoption—AI-enabled decision support layered on IoT feeds and surfaced to patients via PHRs/portals—offers the most comprehensive path to improved outcomes and sustainable health-system performance.

5 | Discussion

The synthesis of 24 systematic reviews and meta-analyses confirms that AI, the IoT, and PHRs deliver distinct yet complementary contributions to healthcare. AI shows the strongest clinical gains, repeatedly improving diagnostic accuracy in imaging tasks and enabling early risk prediction and treatment recommendation, while also easing clinician workload through automation [10, 17, 18]. These effects extend into managerial and system performance, with evidence of efficiency improvements and projected cost savings at scale [23]. IoT, by contrast, excels at continuous, real-time monitoring and remote care, enabling earlier abnormality detection and lowering readmissions in select contexts, while streamlining hospital logistics and patient flow [5, 8, 19]. PHRs most consistently strengthen patient-facing outcomes—knowledge, confidence, adherence—and support chronic disease management and preventive behaviors, with spillovers to reduced no-shows and more appropriate utilization [20, 21, 43]. Taken together, these patterns imply that integration—AI analytics fed by IoT data and surfaced through PHRs portals—offers a pathway to simultaneous clinical, psycho-behavioral, managerial, and socioeconomic improvement. Relative to prior technology-specific reviews, a cross-technology, multi-domain lens clarifies where each tool is most effective and how they interact. For example, AI's predictive value depends on timely, high-resolution inputs that IoT streams can provide, while PHRs translate insights into patient actions (e.g., adherence, self-management) and bidirectional communication [6, 8, 25, 26]. This triangulation helps reconcile mixed findings reported in isolated literatures and explains why some benefits (e.g., diagnostic accuracy for AI; satisfaction and access for IoT; adherence and preventive care for PHRs) are more robust than others across settings [43–45]. Moreover, macro-level projections underline system value—IoT's potential economic impact and AI-linked cost efficiencies—when these technologies are scaled in tandem with workflow redesign [22, 23, 28, 50]. The comparative view thus supports moving from point solutions to orchestrated digital ecosystems that align clinical decision-making, operational execution, and patient engagement. Nonetheless, durable adoption requires addressing persistent constraints. AI faces data quality, privacy, and generalizability issues that mandate rigorous external validation and bias mitigation [51]. IoT implementations are sensitive to security, availability, and interoperability, which can erode reliability and trust without strong governance and standards [41]. PHRs' gains are uneven where digital literacy, privacy concerns, or poor integration with provider systems limit use and clinical follow-through [48, 51–53]. Future work should prioritize longitudinal and real-world evaluations, equity-aware design, and joint deployments (AI+IoT+PHRs) that explicitly measure multi-domain outcomes and downstream cost/benefit profiles [8, 29, 30, 55]. With these safeguards, the evidence suggests that coordinated digital health strategies can advance near-term care quality while contributing to longer-run system sustainability and resilience [58–60].

6 | Conclusion

This review demonstrates that AI, the IoT, and PHRs have become essential pillars of modern healthcare, each offering unique strengths across different outcome domains. AI has shown the most significant promise in clinical and managerial areas, particularly in diagnostic accuracy, predictive analytics, and workflow automation. The IoT has proven most effective in real-time monitoring, operational efficiency, and expanding access to care, while PHRs stand out for empowering patients, strengthening preventive care, and improving adherence and engagement. Taken together, these findings highlight that no single technology can independently transform healthcare; instead, their integration provides the most comprehensive improvements across clinical, psycho-behavioral, managerial, and socioeconomic outcomes. The implications of these findings are highly relevant for healthcare providers, policymakers, and technology developers. By leveraging AI to generate insights, IoT to capture continuous data, and PHRs systems to translate information into patient-centered action, health systems can achieve higher-quality care, greater efficiency, and long-term sustainability. Yet, challenges such as data privacy, interoperability, digital literacy, and equitable access must be carefully addressed to ensure widespread adoption and effectiveness. Looking forward, coordinated digital health strategies and real-world implementation studies are essential for scaling these technologies responsibly. If pursued thoughtfully, the integration of AI, IoT, and PHRs has the potential to redefine healthcare delivery and strengthen global progress toward more inclusive, efficient, and sustainable health systems.

6.1 | Limitations and Future Research

Although this review provides a comprehensive synthesis of the benefits of AI, the IoT, and PHRs in healthcare, several limitations should be acknowledged. First, the analysis was restricted to systematic reviews and meta-analyses published in English and Korean, which may have excluded relevant evidence in other languages and primary studies not yet synthesized. Second, heterogeneity in study designs, outcome measures, and reporting practices across the included reviews limited the ability to directly compare findings or conduct quantitative pooling. Third, most of the included reviews focused on short-term clinical or organizational outcomes, while evidence on long-term socioeconomic effects and equity-related dimensions remains scarce. Finally, technological developments in AI, IoT, and PHRs are rapidly evolving, and findings from studies conducted several years ago may not fully reflect current capabilities or applications. Future research should aim to address these gaps by conducting longitudinal and real-world implementation studies that evaluate integrated digital health solutions across diverse healthcare contexts. Greater emphasis is needed on the ethical, equity, and sustainability dimensions of technology adoption, ensuring that digital innovations do not exacerbate disparities in access or outcomes. Comparative analyses of combined approaches, where AI analytics are powered by IoT data and delivered through PHRs systems, would provide valuable insights into synergistic effects. By extending beyond single-technology assessments, future studies can inform more effective strategies for harnessing digital health innovations to strengthen global healthcare systems.

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