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Organizational Factors Influencing the Adoption of AI Technologies in Preventive Healthcare

Ezgi Akar

University of Wisconsin-Eau Claire, Department of Business Communication and Information Systems, Wisconsin, USA

akare@uwec.edu

Aysun Bozanta

Bogazici Universitesi, Department of Management Information Systems, Istanbul, Turkey

aysun.bozanta@bogazici.edu.tr

Tugrul Cabir Hakyemez

Istanbul Bilgi Universitesi, Department of Management, Istanbul, Turkey

tugrul.hakyemez@bilgi.edu.tr

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Abstract

Purpose

Artificial intelligence (AI) has the potential to revolutionize preventive healthcare by enabling early risk detection, patient stratification, and support for clinical decision making. However, its implementation in real-world settings remains inconsistent, primarily due to ongoing organizational challenges. Guided by the population, intervention, comparison, outcome (PICO) and preferred reporting items for systematic reviews and meta-analyses (PRISMA) frameworks, this study aims to identify the organizational factors that influence the successful adoption of AI technologies in preventive care.

Design/methodology/approach

This study adopts the PRISMA flow and reviews 536 peer-reviewed articles that met the PICO-defined criteria: healthcare organizations (population), adoption or use of AI technologies (intervention), no comparator required (comparison), and organizational adoption factors (outcomes). Using an AI-assisted screening process combined with thematic analysis, we categorized organizational influences into 12 key topics. These were analyzed through the lens of the organizational readiness for change (ORC) framework.

Findings

The findings highlight that adoption success hinges on strategic leadership, workforce preparedness, effective data governance, seamless workflow integration, and robust ethical oversight. Persistent challenges include fragmented infrastructures, limited trust, and regulatory uncertainty.

Originality

This study advances the field in three respects: it focuses specifically on preventive healthcare as an organizational context; it applies the ORC framework as an integrating theoretical lens across a large, synthesized corpus; and it employs a transparent human–AI-assisted screening process that supports large-scale evidence synthesis while preserving author oversight.

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Keywords: Artificial intelligence; preventive healthcare; organizational factors; organizational readiness

1. Introduction

Preventive healthcare aims to reduce future morbidity, improve long-term patient outcomes, and ease healthcare burdens by emphasizing early risk detection and proactive interventions, such as screening, lifestyle counseling, predictive monitoring, and chronic disease management. In this study, preventive healthcare is broadly defined as prevention-oriented activities that support risk prediction, early detection, screening, monitoring, and disease management. Reflecting growing interest in prevention-focused healthcare services, industry reports estimate the global preventive healthcare market at approximately $251.2 billion in 2023 and project it may exceed $600 billion USD by 2032 (WHX Insights, 2024).

Digital technologies have accelerated the expansion of preventive healthcare by enabling large-scale data collection, continuous monitoring, and data-driven decision-making. Mobile health applications, wearable devices, remote monitoring technologies, and electronic health systems generate substantial amounts of patient data that can support preventive interventions. Central to these developments is artificial intelligence (AI), which encompasses techniques such as machine learning and natural language processing that can identify patterns in complex datasets and support predictive analytics, risk stratification, and personalized healthcare decision-making (Ashok *et al.*, 2022; Canhoto and Clear, 2020; Subbhuraam, 2021). As a result, AI has increasingly been explored to support earlier intervention, improve decision support, and enhance preventive care delivery.

Despite these opportunities, adopting AI in preventive healthcare remains challenging. Successful implementation depends not only on technological capabilities but also on organizational conditions that enable adoption and sustained use. Factors such as leadership support, alignment with organizational objectives, workforce preparedness, interoperability, and infrastructure capacity may influence implementation outcomes. At the same time, industry and academic discussions have identified barriers, including fragmented infrastructure, workforce skill shortages, algorithmic bias, clinician skepticism, and regulatory uncertainty, that may

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impede AI adoption efforts (Kwo, 2021; Sadiku *et al.*, 2020). These observations suggest that technological innovation alone may be insufficient to ensure successful implementation.

The adoption of AI in healthcare has been examined through several complementary theoretical perspectives. Technology acceptance research explains individual-level adoption through constructs such as perceived usefulness, perceived ease of use, and behavioral intention (Davis, 1989; Venkatesh *et al.*, 2003). Sociotechnical systems theory emphasizes the interdependence of technology, workflows, people, organizational structures, and culture in shaping health information technology outcomes (Sittig and Singh, 2010). Implementation science frameworks identify multilevel contextual factors that influence implementation success (Damschroder *et al.*, 2009), while the nonadoption, abandonment, scale-up, spread, and sustainability framework highlights the complexity of adopting, scaling up, spreading, and sustaining health technologies (Greenhalgh *et al.*, 2017). Digital maturity models provide additional perspectives on organizational capabilities for the effective use of digital technologies (Flott *et al.*, 2016). Although these perspectives contribute valuable insights, each focuses on a particular aspect of technology implementation. Technology acceptance models primarily emphasize individual users; sociotechnical frameworks focus on interactions among technological and organizational elements; and implementation frameworks examine contextual determinants and implementation processes. The organizational readiness for change (ORC) framework addresses a related but distinct question: whether organizational members are collectively prepared, motivated, and capable of implementing change (Weiner, 2009).

Despite the growing body of literature on AI in healthcare, several opportunities for further research remain. First, much of the literature has focused on AI adoption across healthcare settings broadly, while comparatively less attention has been devoted to understanding the organizational conditions associated with AI adoption in preventive healthcare contexts specifically (Kwo, 2021; Sadiku *et al.*, 2020). Second, although previous studies and reviews have identified numerous barriers and facilitators of AI adoption, these factors are often examined individually rather than through an organizational-theoretical lens that explains how they collectively influence organizational readiness. Frameworks such as technology acceptance models and implementation science approaches have been widely applied (Damschroder *et al.*,

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2009; Davis, 1989; Venkatesh *et al.*, 2003), whereas the organizational readiness for change framework has received comparatively limited explicit attention as a unifying perspective for understanding AI adoption in preventive healthcare. Third, the rapid growth of the AI-healthcare literature presents challenges for traditional evidence synthesis approaches. As publication volumes continue to expand, AI-assisted screening and classification methods may offer opportunities to improve the efficiency and scalability of review processes while maintaining human oversight and methodological rigor (Chew *et al.*, 2023; Rowe, 2014).

Against this backdrop, the present study addresses the following research question: *Which organizational factors enable or hinder the adoption of AI technologies in preventive healthcare?* To answer this question, we apply the organizational readiness for change (ORC) framework (Weiner, 2009), which conceptualizes readiness as a shared organizational state shaped by factors such as change efficacy, change valence, leadership commitment, and resource availability. Through a large-scale, AI-assisted review of the literature, this study develops a theoretically grounded understanding of the organizational conditions that may facilitate or constrain AI adoption in preventive healthcare settings.

2. Review Methodology

This study employs a systematic literature review (SLR) as its primary research design. An SLR is a method of evidence synthesis that uses an explicit, predefined, and reproducible protocol to locate, appraise, and integrate all available studies relevant to a clearly specified research question (Kitchenham and Charters, 2007; Tranfield et al., 2003). It is distinguished from a traditional narrative review by its methodological transparency: where a narrative review reflects the selective and often implicit judgments of its authors, an SLR documents each decision so that the review can be scrutinized, evaluated, and replicated by others (Rowe, 2014). This emphasis on a transparent and auditable procedure is intended to reduce selection and reporting bias and to strengthen the trustworthiness of the resulting synthesis. The approach is widely used in information systems and organizational research, where the objective is to consolidate fragmented and methodologically diverse bodies of evidence into a coherent understanding of a phenomenon rather than to estimate a pooled quantitative effect (Rowe, 2014; Tranfield et al., 2003). Methodologically, an SLR proceeds through a sequence of structured stages: formulating a focused review question, specifying a search strategy and explicit inclusion and exclusion criteria, screening the retrieved records against those criteria, assessing the eligibility and adequacy of the remaining studies, and synthesizing the included evidence into an organized account of the field (Kitchenham and Charters, 2007; Tranfield et al., 2003). Within this design, two complementary tools support different stages of the process. The population, intervention, comparison, outcome (PICO) framework is used to structure the review question and the search and eligibility criteria, whereas the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines govern the transparent reporting of how records move through the identification, screening, and inclusion stages. The two therefore operate at different points in the SLR: PICO frames what is sought, while PRISMA documents how the corpus was assembled.

SLRs follow a structured, replicable process for identifying, screening, and synthesizing evidence from the existing literature and are particularly well suited to mapping organizational- and implementation-focused research domains where primary data collection is neither feasible nor appropriate (Rowe, 2014). Unlike narrative reviews, an SLR applies explicit eligibility criteria, a transparent search protocol, and systematic synthesis procedures to minimize selection bias and ensure reproducibility. The review was conducted in accordance with the preferred PRISMA guidelines, with Figure 1 presenting the PRISMA flow diagram depicting the article identification, screening, and inclusion and exclusion processes.

2.1. Literature search

To ensure methodological rigor, we apply an adapted population, intervention, comparison, outcome (PICO) framework to structure the search strategy. While PICO was originally developed for clinical effectiveness reviews, its adapted use here follows established practice in organizational and implementation-focused systematic reviews, where it serves as a search-structuring device rather than a causal inference framework. The population (P) included healthcare organizations engaged in preventive care or early disease detection. The intervention

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(I) was defined as the adoption or use of AI-related technologies/tools, the phenomenon of interest. No comparison (C) was required, as organizational studies rarely employ control groups. The outcomes (O) focused on identifying organizational factors that enable or hinder AI adoption, such as leadership, workforce readiness, technological infrastructure, workflow integration, data governance, and ethical considerations; this PICO structure guided keyword selection, database searching, and inclusion and exclusion criteria.

Keyword searches were conducted across major databases, including PubMed, IEEE Xplore, ScienceDirect, ACM Digital Library, and Web of Science, using titles and abstracts (see supplemental file: Full Search Strategy). According to Figure 1, the initial search retrieved 11,897 records. During the first screening, we excluded articles that were not published in peer-reviewed journals, were not in English, were not published between January 2020 and April 2025, or were non-journal formats, such as reviews, meta-analyses, letters, book chapters, reports, and conference papers. We also removed retracted journal articles. After this step, 9,109 records remained. Duplicate removal reduced the dataset to 9,035 unique articles.

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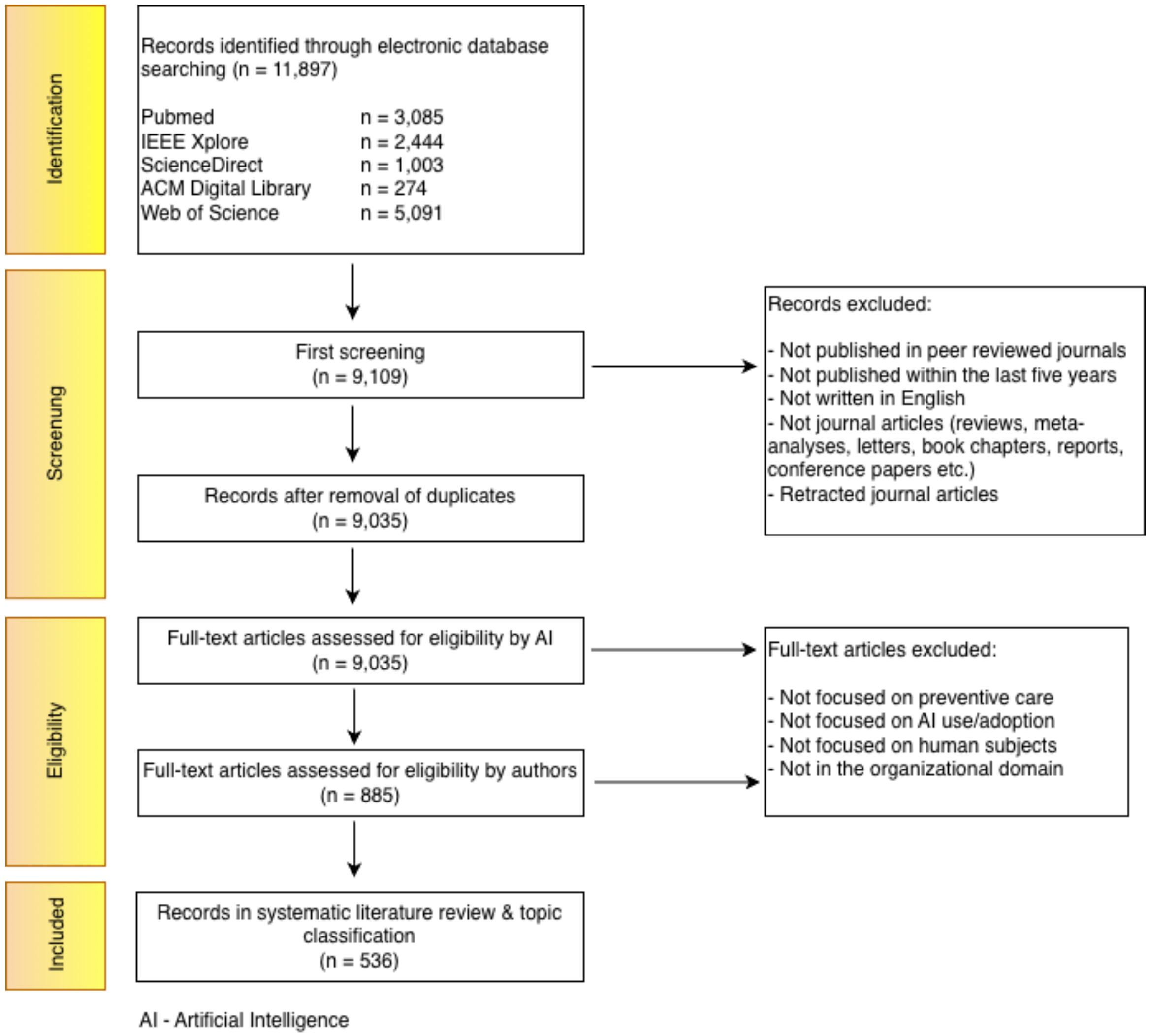

Figure 1. PRISMA flow diagram (Source: Authors' own work)

2.2. Eligibility assessment

After removing duplicates, titles and abstracts were screened to determine whether the articles met the PICO framework criteria. We assessed all 9,035 unique articles for eligibility using predefined criteria aligned with the research objectives.

To manage this large dataset efficiently, we employed Grok, a generative AI chatbot by xAI, to assist with the first round of title and abstract screening. Recent studies have increasingly used AI to enhance qualitative analysis by making it more efficient and reducing the manual effort required with traditional methods. AI tools support essential tasks, including pattern recognition, coding, thematic analysis, and content extraction (Chew *et al.*, 2023; Christou, 2024; Gao *et al*., 2023). Like a human coder, an AI chatbot requires clear and well-structured instructions, known as prompts. Therefore, following Chew *et al*. (2023), we co-developed and refined the AI prompt using a pilot sample of 123 randomly selected journal articles from five databases. Each author independently reviewed and manually coded these articles to establish consistency in coding practices (Rowe, 2014). We then compared coding decisions among authors and between human coders and AI outputs. Agreement was measured using Cohen's kappa (Cohen, 1960).

- Human–human agreement: Authors A and B showed near-perfect agreement (κ = 0.85), while agreement with Author C was substantial (A–C: κ = 0.69; B–C: κ = 0.62) (Landis and Koch, 1977).
- AI–human agreement (initial prompt): moderate with A (κ = 0.51) and B (κ = 0.54), substantial with C (κ = 0.72).

Disagreements mainly concerned the interpretation of preventive healthcare and were resolved through discussion. Iterative prompt refinements improved the average κ from 0.66 to 0.85, exceeding the 0.80 threshold for high reliability. Using the validated prompt (see Appendix A), AI screened all 9,035 articles and identified 885 articles that met the inclusion criteria. These AI-selected articles were then manually reviewed by the authors individually to ensure accuracy and adherence to the criteria. During this manual review, articles were excluded for the same reasons as before: not focused on preventive care, not focused on AI use or adoption, not involving human subjects, or outside the organizational domain.

To mitigate reproducibility risks associated with AI-assisted screening, we took four concrete steps. First, the validated prompt (Appendix A) was fully documented to allow future replication under comparable model conditions. Second, all AI screening decisions were subjected to full manual review by the authors, meaning that no article was included or excluded solely based on Grok's output; human judgment constituted the final decision at every stage.

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Third, kappa-based agreement measurement was conducted iteratively across prompt refinement cycles, providing an empirical record of how screening stability evolved and confirming that the final prompt exceeded the 0.80 reliability threshold before large-scale deployment. Together, these steps do not eliminate reproducibility risk inherent to AI-assisted methods, but they establish a transparent, human-verified audit trail that substantially reduces the dependence of the review's conclusions on any single AI output. After the final review, 536 articles remained for inclusion in the systematic literature review.

2.3. Quality eligibility

Given the methodological heterogeneity of the included studies spanning qualitative interviews, case studies, surveys, technical validation studies, implementation reports, and mixed-methods research, no single standardized appraisal instrument, such as the mixed methods appraisal tool or the critical appraisal skills programme checklist, could be applied uniformly across the full corpus without introducing systematic bias against particular study designs. A formal meta-analytic quality-scoring approach was therefore not pursued, consistent with methodological guidance for conceptual and organizational systematic reviews, where the goal is thematic synthesis rather than effect estimation (Rowe, 2014).

However, to ensure a minimum standard of methodological adequacy across included studies, we applied a tiered quality threshold during the manual review stage. Studies were retained only if they met three criteria: (1) sufficient conceptual clarity to allow reliable topic assignment—the organizational argument or finding was clearly articulated rather than incidental; (2) demonstrable organizational relevance—the study addressed internal organizational factors rather than purely technical or clinical outcomes; and (3) adequate methodological transparency—sufficient procedural information was reported to support meaningful interpretation of the findings. Studies failing any of these criteria were excluded during the manual verification phase described in Section 2.2. While this approach does not constitute a formal quality-scoring protocol, it establishes a defensible, design-neutral minimum threshold appropriate for an organizationally focused synthesis, and it was applied consistently across all 536 included articles.

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2.4. Topic classification

After confirming the final set of 536 articles through manual review, we conducted a structured topic classification procedure to organize the literature into meaningful, non-overlapping categories relevant to the organizational adoption of AI in preventive healthcare. To make the derivation of the topics transparent and auditable, the procedure followed a hierarchical coding logic consistent with the Gioia methodology (Gioia et al., 2013), progressing from a large pool of granular, article-level raw labels, to a smaller set of first-order concepts that grouped synonymous or closely related labels, and finally to second-order themes that constituted the 12 organizational topics carried forward into the analysis. This three-level chain (raw labels → first-order concepts → second-order themes) is described stage by stage below and is intended to allow readers to trace how the final topics were derived from the underlying corpus. This step involved four sequential stages: AI-assisted initial coding, author-led consolidation, validation of the thematic structure, and final labeling.

In the first stage, we used Grok to perform an initial inductive coding of all 536 articles based on their titles and abstracts. Using a co-developed and piloted prompt (see Appendix B), Grok assigned one or more short, descriptive organizational topic labels to each article, such as "leadership support," "staff training," "workflow integration," or "data privacy." Because a single article could address multiple organizational dimensions, multi-label assignment was permitted and expected throughout the classification process. This produced a large pool of granular, article-level labels that reflect the full diversity of organizational themes in the corpus; these article-level labels constitute the raw codes (the first level of the coding chain).

In the second stage, the authors independently reviewed the full list of AI-generated labels and grouped semantically related labels into candidate topics. This consolidation proceeded in two steps. First, synonymous or closely related raw labels were collapsed into first-order concepts that preserved the informants' language while removing redundancy. Second, conceptually adjacent first-order concepts were aggregated into second-order themes, each representing a coherent organizational domain; these second-order themes became the 12 final topics. For instance, labels such as "leadership support," "strategic alignment," and "executive sponsorship" were consolidated under the topic *Leadership and Strategic Planning*, while labels such as "data privacy," "algorithmic bias," and "regulatory compliance" were grouped under *Governance, Ethics, and Trust*. Where label boundaries were ambiguous, the authors discussed and resolved the overlap by examining the substantive focus of the underlying articles. This process was iterative: candidate topics were tested against the full set of articles and refined until each topic represented a coherent, internally consistent organizational domain.

To make this progression fully traceable, Table 1 summarizes the complete chain for each of the 12 topics, showing how representative raw labels were consolidated into first-order concepts and then aggregated into the second-order theme that became the final topic. For Workforce Development and Expertise, raw labels such as "staff training," "digital self-efficacy," "clinician upskilling," and "role change" formed first-order concepts of workforce training and competence, as well as evolving professional roles. For Data Management and Analytics, labels such as "data quality," "data integration," "model generalizability," and "privacy-preserving analytics" formed first-order concepts of data quality, representativeness, and analytics capability. For Technological Infrastructure, labels such as "cloud and edge computing," "interoperability," "wearables and sensors," and "system scalability" formed first-order concepts of computing and hardware infrastructure, interoperability, and standardization. For Clinical Workflow Integration, labels such as "EHR integration," "workflow compatibility," "usability," and "administrative burden" formed first-order concepts of workflow alignment and system usability. For Financial Management and Investment, labels such as "cost reduction," "resource allocation," "implementation cost," and "economic sustainability" formed first-order concepts of cost and efficiency outcomes, as well as of investment and sustainability. For Governance, Ethics, and Trust, labels such as "data privacy," "algorithmic bias," "regulatory compliance," and "explainability" formed first-order concepts of fairness and accountability, transparency, and trust. For Collaboration and Partnerships, labels such as "developer–clinician collaboration," "multidisciplinary teams," and "cross-institutional partnership" formed first-order concepts of intra-organizational collaboration, external partnerships, and data sharing. For Leadership and Strategic Planning, labels such as "leadership support," "strategic alignment,"

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"executive sponsorship," and "change management" formed first-order concepts of leadership commitment and strategic alignment and planning. For Patient-Centered Approaches, labels such as "patient engagement," "social determinants of health," "cultural responsiveness," and "co-design" served as first-order concepts for patient needs and preferences, equity, and community engagement. For Quality Assurance and Validation, labels such as "clinical validation," "diagnostic accuracy," "external generalization," and "quality control" served as first-order concepts for performance validation, reliability, and monitoring. For Research and Innovation, labels such as "novel architectures," "proof-of-concept," and "translational applicability" formed first-order concepts of methodological innovation and translational maturity. Finally, for Implementation and Change Management, labels such as "implementation readiness," "scale-up," "organizational support," and "sustained adoption" formed first-order concepts of implementation readiness, process and sustainability, and scale-up. In each case, the second-order theme is the topic name, and the first-order concepts it subsumes provide the intermediate link back to the raw, article-level labels, rendering the full derivation chain explicit.

Table 1. Data structure: derivation of the 12 organizational topics from raw labels to second-order themes (Source: Authors' own work)

Representative raw labels (article-level codes)	First-order concepts	Second-order theme (final topic)
"staff training," "digital self-efficacy," "clinician upskilling," "role change"	Workforce training and competence; evolving professional roles	*Workforce Development and Expertise*
"data quality," "data integration," "model generalizability," "privacy-preserving analytics"	Data quality and representativeness; analytics capability	*Data Management and Analytics*
"cloud and edge computing," "interoperability," "wearables and sensors," "system scalability"	Computing and hardware infrastructure; interoperability and standardization	*Technological Infrastructure*
"EHR integration," "workflow compatibility," "usability," "administrative burden"	Workflow alignment; system usability	*Clinical Workflow Integration*
"cost reduction," "resource allocation," "implementation cost," "economic sustainability"	Cost and efficiency outcomes; investment and sustainability	*Financial Management and Investment*
"data privacy," "algorithmic bias," "regulatory compliance," "explainability"	Fairness and accountability; transparency and trust	*Governance, Ethics, and Trust*
"developer–clinician collaboration," "multidisciplinary teams," "cross-institutional partnership"	Intra-organizational collaboration; external partnership and data sharing	*Collaboration and Partnerships*

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"leadership support," "strategic alignment," "executive sponsorship," "change management"	Leadership commitment; strategic alignment and planning	*Leadership and Strategic Planning*
"patient engagement," "social determinants of health," "cultural responsiveness," "co-design"	Patient needs and preferences; equity and community engagement	*Patient-Centered Approaches*
"clinical validation," "diagnostic accuracy," "external generalization," "quality control"	Performance validation; reliability and monitoring	*Quality Assurance and Validation*
"novel architectures," "proof-of-concept," "translational applicability"	Methodological innovation; translational maturity	*Research and Innovation*
"implementation readiness," "scale-up," "organizational support," "sustained adoption"	Implementation readiness and process; sustainability and scale-up	*Implementation and Change Management*

In the third stage, the thematic structure was validated through two checks. First, each of the 536 articles was re-examined against the final topic set to confirm assignment accuracy; articles addressing multiple organizational dimensions were assigned to all relevant topics, reflecting the inherently cross-cutting nature of organizational factors in AI adoption. Consequently, topic frequencies reported in Figure 2 reflect the total number of article-topic assignments rather than unique article counts, and their sum therefore exceeds 536. Second, the authors assessed the conceptual distinctiveness of the 12 topics by comparing their definitions, ensuring that no two topics were redundant or substantially overlapping. This iterative validation process confirmed the thematic structure and resulted in 12 final organizational topics.

In the fourth stage, final topic labels were assigned by consensus among the authors, prioritizing terminology that was both conceptually precise and consistent with established organizational and implementation science vocabulary. The resulting 12 topics formed the analytical structure for the synthesis reported in Section 3.

3. Results

3.1 Descriptives

The final set of 536 articles was classified into 12 organizational topics. According to Figure 2, the most frequently mentioned areas were leadership and strategic planning, data management and analytics, technological infrastructure, and workforce development and expertise, highlighting the practical focus of implementation research. In contrast, quality

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assurance and validation, implementation and change management, and clinical workflow integration were less common, indicating essential but overlooked areas of study.

Figure 3 shows that data management and analytics, and technological infrastructure consistently ranked among the most studied topics. Similarly, workforce development and expertise grew strongly from 2020 to 2024, reflecting the emphasis on human capital and training as critical enablers of AI integration. Governance, ethics, and trust also accelerated sharply between 2020 and 2024, signaling heightened attention to ethical and regulatory frameworks; this acceleration likely reflects the broader regulatory momentum of this period, including the development of the European Union AI Act, updated U.S. Food and Drug Administration guidance on AI-based medical devices, and the World Health Organization's global framework on AI ethics in health, all of which prompted institutional attention to accountability and transparency.

Implementation and change management, and quality assurance and validation remained very low across all years, highlighting a gap in research on operational integration and quality control. This underrepresentation is consistent with the field's dominant technical orientation, in which algorithmic development continues to receive disproportionate scholarly attention relative to the organizational processes through which algorithms are embedded into practice. Similarly, patient-centered approaches, research, and innovation were underrepresented. Across the synthesized literature, enabling factors were more frequently and thoroughly documented than hindering factors, reflecting a publication tendency toward reporting successful or promising implementations. This asymmetry should be borne in mind when interpreting the findings: the review maps the organizational landscape as represented in the published literature, which may underrepresent failure cases and implementation barriers relative to their actual prevalence.

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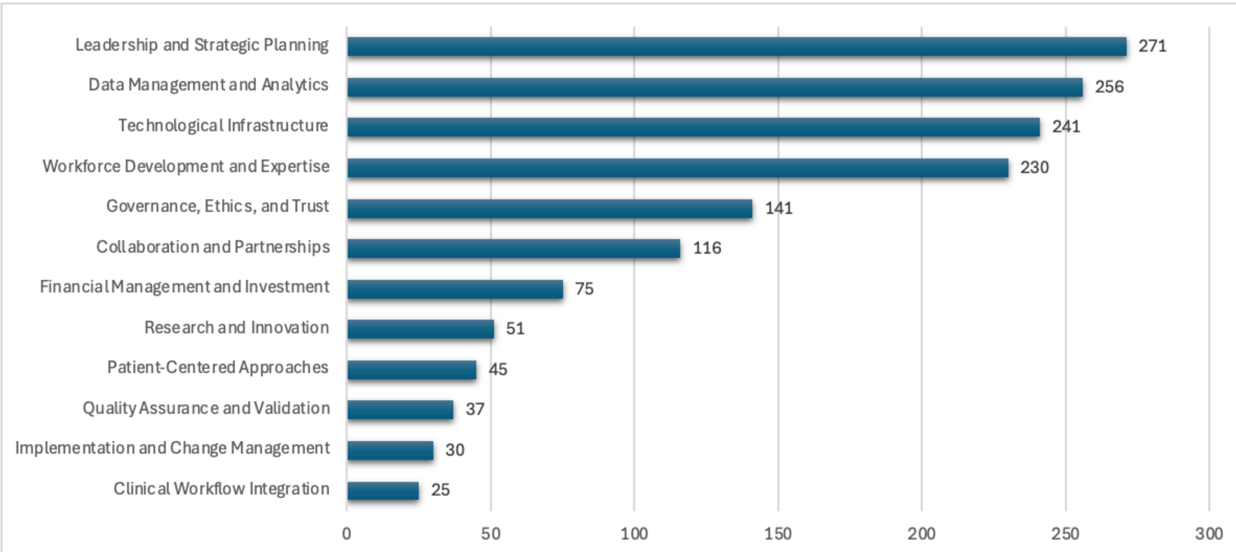

Figure 2. Papers per topic (Source: Authors' own work)

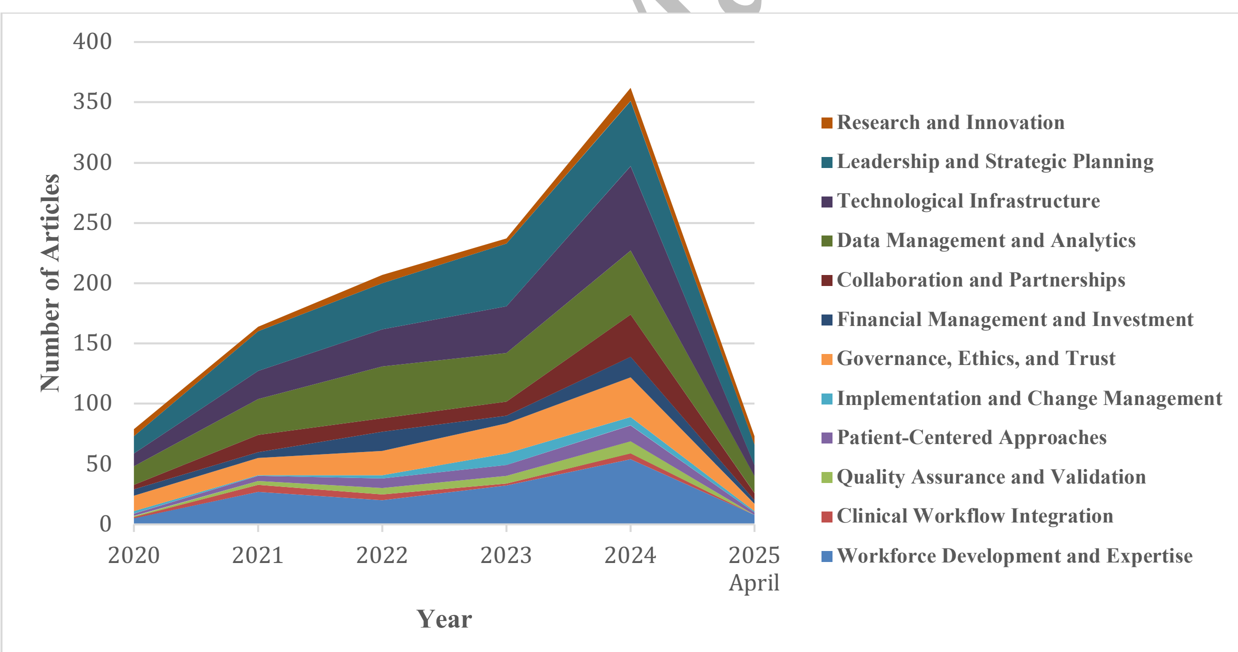

Figure 3. Topic trends over time (Source: Authors' own work)

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3.2 Theoretical mapping

This study applied the organizational readiness for change (ORC) framework to examine the organizational factors influencing the use of AI-driven predictive analytics in preventive healthcare (Weiner, 2009). The ORC framework highlights internal conditions that affect an organization's ability to implement change. It includes four primary constructs: *Change valence* refers to the shared belief that the proposed innovation is valuable and beneficial. *Change efficacy* reflects the collective confidence that the organization possesses the necessary skills, knowledge, and capacity to successfully adopt technology. *Resource availability* assesses whether the technical, financial, and human resources needed to support the change are in place. Finally, *leadership commitment* indicates how actively organizational leaders support, prioritize, and advocate for innovation.

It is important to note that the 12 organizational topics were derived inductively through the classification procedure described in Section 2.4, prior to and independently of the ORC mapping. The application of ORC, therefore, represents a post hoc interpretive step — mapping empirically derived topics onto a theoretical framework to provide explanatory coherence — rather than a prospective deductive coding scheme. This sequencing reflects a hybrid inductive-deductive approach consistent with framework synthesis methodology. The mapping of the 12 organizational topics to ORC constructs was conducted through a structured interpretive procedure. In the first step, each author independently reviewed the operational definitions of the four ORC constructs as specified by Weiner (2009) and assigned each of the 12 topics to the construct or constructs it most directly implicated based on the synthesized evidence within that topic. Because organizational topics are inherently multidimensional, topics were permitted to map onto more than one ORC construct where the evidence clearly supported multiple alignments. In the second step, the authors compared their independent mappings and discussed all instances of disagreement until consensus was reached. The decision rule governing disagreements was that a topic-construct link was retained only when the synthesized evidence within that topic contained explicit, recurring references to the construct's defining mechanism. The resulting mapping is presented in Figure 4 and should be understood as a theoretically grounded interpretive synthesis rather than a mechanical coding exercise; as such, it represents the authors' collective scholarly judgment.

3.3 Workforce development and expertise

AI is increasingly discussed as a tool that may augment clinical work and improve efficiency, potentially allowing healthcare professionals to focus more on complex, patient-centered tasks (Khodabandehloo *et al.*, 2021). In radiology, AI-assisted systems have been used to support early cancer detection and reduce repetitive image-analysis workloads, potentially enabling radiologists to devote greater attention to complex interpretive and clinical responsibilities (Ha *et al.*, 2024). In oncology, clinicians have described AI as a supplementary second opinion that may validate prognostic intuition and support earlier conversations about goals of care (Parikh *et al.*, 2022). Similarly, AI-assisted triage systems may reshape the responsibilities of primary care and allied health professionals by broadening access to services such as skin lesion screening (Jones *et al.*, 2025). Collectively, these developments suggest that AI implementation may alter professional roles and workflows, requiring not only technical upskilling but also broader workforce development and implementation support strategies.

From the ORC perspective, these workforce and workflow changes may affect both change efficacy and resource availability. Change efficacy may be strengthened when healthcare professionals believe they have the knowledge, technical competence, and organizational support needed to integrate AI into routine practice. Educational and workforce development initiatives may build this confidence by helping clinicians become familiar with AI-supported systems and implementation processes. For example, AI-assisted simulation training in nursing education has been explored to support skill development and enhance engagement with technology-enabled learning environments (Simsek-Cetinkaya and Cakir, 2023). Similarly, clinicians' perceptions of the usefulness and reliability of AI-supported decision tools may influence their confidence in applying these technologies within clinical workflows (Parikh *et al.*, 2022). However, evidence also suggests that strong intentions to use digital tools do not necessarily translate into sustained adoption when perceived behavioral control and digital self-efficacy remain insufficiently developed (Olofsson *et al.*, 2024). These findings suggest that implementation confidence depends not only on technical exposure but also on broader organizational support structures that reinforce clinicians' ability to use AI systems effectively.

Resource availability also appears central to successful AI adoption. Implementing AI-enabled healthcare systems often requires substantial organizational investment in training materials, technical infrastructure, interoperability mechanisms, Information Technology support, and protected time for implementation. In radiology and AI-assisted screening environments, workflow integration and sustained operational support may be necessary to ensure that AI systems function reliably within existing clinical processes (Ha *et al.*, 2024; Jones *et al.*, 2025). In addition, workforce adaptation may require ongoing organizational support as professional roles evolve alongside AI integration. Limited infrastructure, insufficient training support, and competing clinical demands may hinder clinicians' ability to incorporate AI tools into already complex workflows. Concerns about automation bias, workflow disruption, workload changes, and the potential erosion of professional judgment further suggest that organizational readiness is influenced not only by technological capability but also by the availability of sufficient operational, educational, and infrastructural resources to support sustainable implementation.

3.4 Data management and analytics

Advances in digital health technologies have enabled the collection of large volumes of heterogeneous data from sources such as wearable devices, electronic health records, medical imaging, and administrative claims databases, creating new opportunities for early disease detection and risk stratification (Hyde *et al.*, 2023; Naseri *et al.*, 2023). In parallel, AI and machine learning techniques have shown promise across a range of healthcare applications, including disease classification, personalized treatment recommendations, and multimorbidity management (Ismail *et al.*, 2020; Zheng *et al.*, 2021). These developments suggest that data-driven approaches may support more proactive and individualized preventive healthcare strategies.

Despite these advances, substantial implementation challenges remain. Preventive healthcare systems must manage increasingly heterogeneous, high-volume datasets, straining existing technological infrastructure and complicating large-scale data integration and processing. Cloud- and edge-based computing architectures have been proposed to improve scalability, efficiency, and real-time data processing (Jayaram and Prabakaran, 2021). However, implementing and maintaining these technologies may be difficult for organizations with limited technical and financial resources. In addition, adopting advanced analytics often requires specialized AI and data science competencies that many healthcare professionals and institutions are still developing (Till *et al.*, 2024). These limitations may reduce organizational confidence in their ability to successfully implement and sustain AI-driven preventive healthcare initiatives over time.

Data quality and representativeness remain important concerns. Imbalanced, sparse, or heterogeneous datasets may reduce predictive reliability and limit the portability of AI models across healthcare settings (Mariscal-Harana *et al.*, 2023; Tran *et al.*, 2021). To address these issues, researchers have proposed techniques such as the synthetic minority oversampling technique and meta-learning to improve model performance in the presence of data imbalance (Lee *et al.*, 2024). Nevertheless, external validation across diverse populations and clinical settings remains limited, raising concerns about the model's generalizability and real-world applicability (Birkenbihl *et al.*, 2020). Privacy and trust issues further complicate implementation. Federated learning and encryption-based approaches have been introduced to support privacy-preserving analytics and secure data sharing across institutions (Jayaram and Prabakaran, 2021; Qiu *et al.*, 2024). At the same time, explainable AI approaches, including SHapley Additive exPlanations-based explanations, have been developed to improve transparency by identifying the factors influencing model predictions (El-Sappagh *et al.*, 2021). However, empirical evidence on the extent to which these approaches improve clinician trust, patient acceptance, and routine clinical adoption remains limited.

From the ORC perspective, these technological and operational challenges may affect both the effectiveness of change and the availability of resources. Persistent concerns about infrastructure limitations, data quality, interoperability, model generalizability, and workforce preparedness may erode confidence in organizations' ability to manage AI-driven preventive healthcare systems effectively. At the same time, resource availability, including access to

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technical expertise, financial support, computational infrastructure, and training opportunities, plays a critical role in shaping implementation capacity. Healthcare organizations with insufficient technological and human resources may face greater difficulty integrating advanced analytics into routine preventive care practices. Consequently, the successful adoption of AI-driven preventive healthcare systems may depend not only on technological advancement but also on organizations' perceptions of their readiness, capabilities, and resources to support sustained implementation.

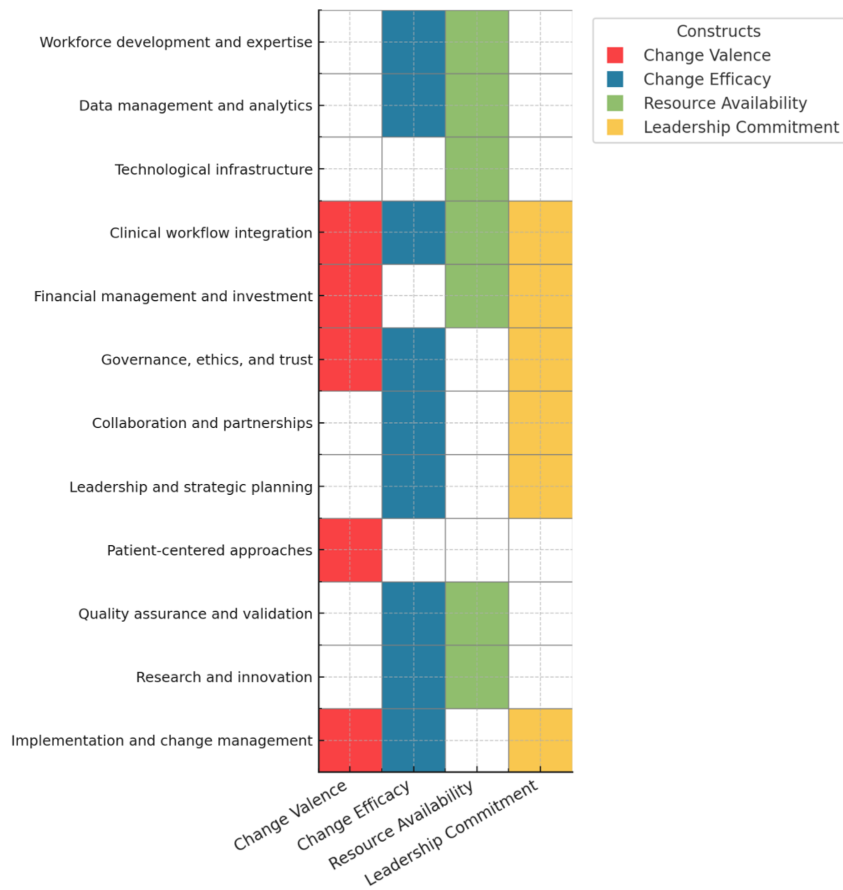

Figure 4. Mapping of 12 organizational topics to ORC constructs* (Source: Authors' own work)

*Topics may align with more than one construct, where synthesized evidence supports multiple associations.

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3.5 Technological infrastructure

The shift from reactive healthcare toward preventive and precision-oriented care increasingly depends on technological infrastructures capable of managing large, heterogeneous datasets, enabling advanced analytics, and integrating effectively with clinical workflows (Almenara *et al.*, 2022; Ennis-O'Connor and O'Connor, 2024). The growing adoption of AI, wearable technologies, and digital health systems has expanded opportunities for early disease detection, continuous monitoring, and personalized interventions across healthcare settings. However, successful implementation depends not only on developing advanced algorithms but also on the availability of scalable, secure, interoperable, and clinically adaptable digital infrastructures that can support long-term integration into healthcare delivery systems (Jacobs *et al.*, 2025).

Core technological components include hardware systems, software frameworks, and integrated data management platforms. Wearable devices, portable biosensors, and mobile health technologies increasingly enable continuous monitoring of physiological indicators, including electrocardiogram signals, blood pressure, pulmonary function, and blood oxygen saturation (Borah *et al.*, 2024; Zhao *et al.*, 2023). At the infrastructure level, cloud and high-performance computing platforms support the storage and training requirements of large-scale AI models, while edge computing architectures enable real-time analysis in resource-constrained environments (Zhao *et al.*, 2023). On the software side, deep learning architectures such as convolutional neural networks and convolutional neural network–long short-term memory models are increasingly used for medical image and physiological signal analysis (Ahmed *et al.*, 2024; Zhao *et al.*, 2023). Federated learning approaches have also been proposed to support distributed disease prediction while preserving institutional data privacy (Chen *et al.*, 2024). In parallel, blockchain-enabled frameworks have been explored as mechanisms for secure, decentralized healthcare data sharing across institutions (Kumar *et al.*, 2021). Emerging data management systems for precision medicine further underscore the importance of interoperability, privacy-compliant data stewardship, and real-time analytics in supporting integrated healthcare and research environments (Jacobs *et al.*, 2025).

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Despite these advances, significant organizational and operational challenges remain. Data quality, interoperability, and standardization continue to vary across healthcare institutions, limiting the effective integration and reuse of clinical data for predictive analytics and decision support (Jacobs *et al.*, 2025; Morgenstern *et al.*, 2021). Workflow integration also presents a substantial challenge. AI-enabled systems that are poorly aligned with clinical routines may increase administrative burden and complicate care delivery processes rather than improve efficiency (Jonnalagedda-Cattin *et al.*, 2025). In addition, the implementation and maintenance of AI infrastructures often require considerable financial investment, long-term planning, and institutional leadership support, particularly in resource-constrained healthcare environments (Ennis-O'Connor and O'Connor, 2024). Although federated learning, blockchain-enabled systems, and edge-computing architectures demonstrate technical promise for secure and distributed analytics, evidence regarding their large-scale routine clinical implementation remains limited (Borah *et al.*, 2024; Chen *et al.*, 2024).

Concerns about bias, equity, and workforce preparedness further complicate implementation. AI systems trained on incomplete or nonrepresentative datasets may reinforce existing healthcare disparities and reduce predictive reliability across diverse patient populations (Morgenstern *et al.*, 2021). Healthcare organizations continue to report barriers, including limited technical expertise, interoperability challenges, cost constraints, and insufficient trust in AI-enabled tools (Schepart *et al.*, 2023).

From the ORC perspective, these challenges may shape perceptions of resource availability. Resource availability is the extent to which organizations perceive they have sufficient financial resources, technological infrastructure, technical expertise, staffing, training opportunities, and implementation support to successfully adopt and sustain organizational change initiatives. In preventive healthcare settings, limited access to interoperable systems, specialized personnel, computational resources, and long-term financial support may reduce organizations' capacity to integrate AI-driven technologies into routine practice. Consequently, the successful implementation of AI-enabled preventive healthcare systems may depend not only on technological innovation but also on whether healthcare organizations perceive adequate resources to support sustainable adoption and ongoing operational use.

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3.6 Clinical workflow integration

Integrating AI into clinical workflows remains a significant challenge in preventive healthcare. Technical incompatibilities, particularly limited interoperability between AI applications and electronic health record (EHR) systems, continue to constrain implementation. Reeves *et al.* (2021) emphasized that large-scale data sharing, effective health information exchange, and EHR interoperability remained major informatics challenges during the Coronavirus Disease 2019 response, despite the rapid expansion of digital health infrastructure. Similarly, Schepart *et al.* (2023) identified poor EHR interoperability, usability limitations, cost constraints, limited AI knowledge, and lack of trust as major barriers to adopting AI-enabled tools in cardiovascular medicine. These findings suggest that successful AI implementation depends not only on technical capabilities but also on how effectively AI systems are integrated into existing clinical workflows and organizational infrastructures.

Human and organizational factors further complicate AI integration. Kotp *et al.* (2025) found that leadership readiness, staff engagement, technical preparedness, and perceived organizational support were positively associated with nurse leaders' perceptions of AI benefits and readiness to implement AI. The study also emphasized the importance of training, governance, and ethical awareness in facilitating AI adoption. Rudolph *et al.* (2024) showed that a Picture Archiving and Communication System-integrated AI-based brain volumetry system substantially improved diagnostic performance while reducing processing time, illustrating the practical value of workflow-compatible AI tools that align with routine clinical processes. However, the authors also acknowledged the need for further research to evaluate long-term clinical impact and broader implementation outcomes. Together, these studies indicate that technical performance alone is insufficient to ensure successful AI adoption.

From the ORC perspective, these implementation barriers and facilitators reflect several interrelated organizational conditions. Change valence becomes evident when clinicians and organizational leaders perceive AI as beneficial for improving patient care, operational efficiency, or clinical decision making. Studies such as Kotp *et al.* (2025) and Schepart *et al.* (2023) suggest that positive perceptions of AI's usefulness can strengthen organizational motivation to adopt these technologies. Change efficacy is reflected in the extent to which

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healthcare professionals and institutions believe they possess the knowledge, technical competence, and operational capability necessary for implementation. Concerns about usability, interoperability, insufficient training, and limited familiarity with AI may weaken confidence in organizational capabilities. Resource availability also plays a central role, particularly in technical infrastructure, integration capacity, financial investment, and workforce training. Finally, leadership commitment emerges as a critical enabling condition, as organizational leaders influence strategic prioritization, policy development, resource allocation, and the cultivation of supportive implementation climates. Collectively, these findings suggest that AI adoption in preventive healthcare is shaped not only by technological sophistication but also by organizational readiness conditions that determine whether AI initiatives can be sustainably integrated into clinical practice.

3.7 Financial management and investment

Rising healthcare costs and resource constraints have heightened interest in preventive healthcare strategies that may improve efficiency, enable earlier intervention, and reduce avoidable healthcare utilization. AI and predictive analytics have been explored as tools to support healthcare decision-making, improve risk stratification, and inform resource allocation in preventive care settings. In some cases, AI-enabled approaches have shown potential to reduce unnecessary testing while maintaining acceptable clinical screening performance. For example, a decision-tree-based Bayesian approach to hypertension screening substantially reduced electrocardiogram use while maintaining a low rate of missed high-risk cases (Herazo-Padilla *et al.*, 2022). Similar data-driven profiling approaches have also been explored in chronic disease prevention contexts, where predictive analytics may help align preventive interventions with population health priorities and healthcare resource constraints.

Predictive and forecasting approaches have also been examined for their potential to support healthcare planning and utilization management. Outreach and care-management programs targeting high-risk heart failure patients have been linked to lower hospitalization rates and reduced healthcare expenditures (Ukert *et al.*, 2020). In addition, transformer-based models using electronic health records have been developed to estimate healthcare visit costs and to forecast healthcare utilization and support resource planning (Chen *et al.*, 2023). Digital health platforms and AI-supported monitoring systems have also been explored to improve remote patient monitoring, care coordination, and early identification of high-risk patients in resource-constrained settings (Berquedich *et al.*, 2020; Esposito *et al.*, 2022). These technologies may offer opportunities to support preventive healthcare delivery and operational planning, particularly in settings facing growing service demands and workforce limitations.

Despite these potential benefits, the economic evidence on AI-enabled preventive healthcare systems remains fragmented. Many studies rely on pilot programs, simulation models, controlled environments, or disease-specific implementations, which may limit the generalizability of findings across healthcare systems with different reimbursement structures, organizational capacities, and patient populations. In addition, cost savings observed in controlled or short-term settings may not translate into sustainable long-term outcomes at larger scales of implementation. Although some studies report reductions in healthcare utilization or operational costs, fewer comprehensively evaluate implementation-related expenses, such as infrastructure investment, workforce training, system maintenance, interoperability integration, and long-term governance requirements. Emerging technologies such as blockchain-enabled healthcare systems and data augmentation approaches have also been explored to improve healthcare data management, predictive modeling, and data security (Ahmed *et al.*, 2024; Chen *et al.*, 2023). However, many of these technologies remain in relatively early stages of implementation, with limited evidence on their long-term economic sustainability and routine large-scale clinical deployment.

From the ORC perspective, financial and operational considerations may influence the valence of change, resource availability, and leadership commitment associated with AI-enabled preventive healthcare initiatives. Healthcare organizations may be more likely to support AI-enabled preventive healthcare systems when these technologies are perceived as capable of improving efficiency, reducing avoidable utilization, and supporting value-based care objectives. However, uncertainty regarding long-term financial sustainability, implementation complexity, and scalability may reduce perceived value and weaken organizational enthusiasm for adoption. Resource availability also plays an important role in shaping implementation capacity. The

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adoption and maintenance of AI-enabled systems often require substantial financial investment, technical infrastructure, interoperability support, workforce training, and specialized expertise, all of which may be difficult to secure in resource-constrained healthcare environments. Leadership commitment may therefore be critical to sustaining implementation efforts by supporting long-term investment decisions, allocating organizational resources, promoting cross-functional collaboration, and reinforcing strategic priorities for preventive and data-driven healthcare transformation.

3.8 Governance, ethics, and trust

Across preventive healthcare applications, ethical risks and implementation uncertainties remain significant organizational concerns that may affect confidence in AI adoption. Algorithmic bias stemming from non-representative datasets can raise concerns about fairness, equity, and reliability, particularly when AI systems are applied across diverse patient populations (Jones *et al.*, 2025; Morgenstern *et al.*, 2021; Pelly *et al.*, 2023). Jones *et al.* (2025), for example, reported stakeholder concerns about demographic representativeness, generalizability, and the risk of inaccurate clinical predictions in AI-assisted skin cancer detection systems. Similarly, Morgenstern *et al.* (2021) identified poor data quality, inequity, inadequate regulation, and limited implementation capacity as major barriers to AI adoption in public health settings. Pelly *et al.* (2023) further emphasized that trust, usability, and perceived reliability strongly shape stakeholder acceptance of AI-enabled health management systems. Privacy and data governance concerns may also persist even in systems using technical safeguards such as de-identification and multisource data integration (Artemova *et al.*, 2023). Collectively, these concerns suggest that uncertainty surrounding fairness, trustworthiness, and governance may complicate organizational confidence in AI implementation.

The perceived organizational value of AI adoption may also be shaped by perceptions of transparency, interpretability, and clinical usefulness. Stakeholders are less likely to support implementation when AI systems are viewed as opaque, unreliable, or inconsistent across patient subgroups. Explainable AI has therefore been proposed as a key mechanism for improving interpretability and supporting clinicians' understanding of AI-generated predictions (Bopche *et*

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al., 2024; Moreno-Sánchez, 2023; Parikh *et al.*, 2022). Bopche *et al.* (2024) demonstrated that explainable predictive analytics frameworks can improve interpretability in hospital risk prediction models, while Moreno-Sánchez (2023) emphasized that explainable AI can support clinicians' understanding by identifying the specific clinical features that contribute to predictions of chronic kidney disease. Parikh *et al.* (2022) further highlighted clinicians' concerns about prognostic accuracy, automation bias, and the ethical implications of AI-assisted prognostic disclosure in oncology settings. These findings suggest that clinicians may perceive AI systems as more valuable when predictions are interpretable, clinically contextualized, and aligned with patient care priorities, whereas concerns about usability, ethical implications, or workflow disruption may reduce perceived implementation benefit.

From the ORC perspective, governance structures and organizational oversight may influence the valence of change, change efficacy, and leadership commitment during AI implementation. Change valence may strengthen when healthcare professionals and organizational leaders perceive AI systems as trustworthy, interpretable, equitable, and capable of improving patient outcomes or operational efficiency. In contrast, concerns about bias, transparency, regulation, and accountability may diminish perceptions of AI adoption as organizationally worthwhile. Change efficacy may also be affected by the extent to which organizations believe they possess the technical infrastructure, governance capacity, implementation processes, and operational expertise required to deploy AI systems safely and effectively. Jones *et al.* (2025) and Penzkofer *et al.* (2021) suggest that uncertainty surrounding regulation, workflow integration, validation standards, and long-term monitoring may undermine organizational confidence in implementation capability. Leadership commitment likewise appears important in sustaining organizational readiness, particularly through strategic governance development, investment in validation and monitoring systems, infrastructure coordination, and the establishment of clear accountability structures. Strengthening governance through rigorous validation procedures, transparent operational standards, explicit workflow integration strategies, and ongoing performance monitoring may therefore help reduce perceived implementation risk while reinforcing organizational confidence in the strategic value of AI-enabled preventive healthcare systems.

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3.9 Collaboration and partnerships

Collaboration among AI developers, clinicians, healthcare organizations, and institutional stakeholders has been identified as a key factor in integrating AI into preventive healthcare settings. Winter and Carusi (2023) emphasized that successful AI implementation depends not only on technical model performance but also on close collaboration between AI developers and clinical professionals during system design, validation, and deployment. Their findings suggest that collaborative development processes help integrate clinical reasoning and domain expertise into AI systems, thereby improving transparency, interpretability, and acceptance within healthcare environments. Similarly, Guenoun *et al.* (2024) highlighted the importance of multidisciplinary radiology initiatives and expert consensus frameworks for evaluating AI solutions, particularly regarding clinical workflow integration, scientific validation, cybersecurity, and implementation readiness. These findings suggest that collaboration helps align AI systems with clinical realities and institutional expectations, thereby facilitating more sustainable implementation.

Large-scale collaborations and cross-institutional partnerships are increasingly important for advancing AI implementation in healthcare. Justice *et al.* (2024) described how the Million Veteran Program–CHAMPION collaboration integrated expertise from healthcare organizations, data scientists, and computational research institutions to support large-scale AI development, genomic analysis, and predictive modeling. The study emphasized that extensive multidisciplinary coordination, shared infrastructure, and sustained institutional collaboration were essential to long-term AI research and implementation. Similarly, Birkenbihl *et al.* (2020) demonstrated the importance of external validation across independent cohorts, showing that differences in cohort structure, recruitment criteria, and data characteristics can substantially affect AI model generalizability and predictive performance. These findings suggest that successful AI implementation requires collaboration not only within organizations but also across institutions to support data sharing, model validation, and scalable deployment strategies.

From the ORC perspective, collaborative implementation processes may strengthen change efficacy by increasing organizational confidence in the successful adoption and operationalization of AI systems. Interdisciplinary partnerships can enhance technical

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understanding, facilitate knowledge exchange, and build implementation capabilities across clinical and administrative teams. Leadership commitment also appears central to sustaining collaborative AI initiatives, particularly through strategic coordination, infrastructure investment, governance development, and the allocation of organizational resources for implementation and validation. Studies such as Justice *et al.* (2024) illustrate how sustained institutional leadership and coordinated partnerships support complex AI initiatives that require long-term collaboration across multiple organizational and technical domains. Collectively, these findings suggest that collaborative structures, organizational coordination, and leadership support play important roles in strengthening organizational readiness for AI adoption in preventive healthcare.

3.10 Leadership and strategic planning

Leadership and strategic planning are key to implementing AI-enabled healthcare systems and preventive healthcare initiatives. Successful implementation depends not only on technical model performance but also on organizational alignment, governance structures, infrastructure readiness, and coordinated implementation processes. Ng and Tan (2021), in their nationwide AI-supported discharge management initiative across Singapore public hospitals, emphasized that successful implementation required alignment among organizational processes, culture, human capital, and senior management sponsorship. The authors further highlighted that change management was critical to moving predictive analytics systems beyond proof-of-concept development toward operational implementation.

Case studies further underscore the importance of organizational coordination and implementation readiness in AI-enabled healthcare systems. Jones *et al.* (2025), examining stakeholder perspectives on AI-assisted skin cancer detection, identified concerns about workflow integration, usability, trust, regulation, workload, and long-term implementation sustainability. The findings suggest that implementation challenges extend beyond algorithmic accuracy and involve broader organizational coordination that can influence successful adoption. Similarly, Wang *et al.* (2021) demonstrated the importance of coordinated care structures, clearly defined professional responsibilities, infrastructure support, and integrated telehealth pathways for managing chronic diseases within multidisciplinary healthcare teams. In addition, Xie *et al.*

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(2021) emphasized that integrating AI, blockchain, and wearable technologies into patient-centered chronic disease management requires secure data-sharing frameworks, coordinated infrastructure, and sustained organizational support. Large-scale predictive modeling initiatives also demonstrate the importance of multisource data systems, structured governance processes, and cross-disciplinary coordination in supporting AI-enabled healthcare implementation (Artemova *et al.*, 2023). Collectively, these studies indicate that organizational readiness, governance capacity, and implementation coordination remain central considerations in scaling AI-enabled preventive healthcare systems.

From the ORC perspective, these findings suggest that leadership commitment and change efficacy are particularly important for AI implementation in preventive healthcare. Leadership commitment is reflected in how organizational leaders prioritize AI initiatives through strategic planning, governance development, infrastructure investment, workforce coordination, and sustained implementation support. Studies such as Ng and Tan (2021) demonstrate that senior management sponsorship and organizational alignment can facilitate large-scale implementation, while Jones *et al.* (2025) illustrate that uncertainty surrounding workflow integration, regulation, and implementation processes may complicate organizational coordination. Change efficacy is the shared organizational belief that healthcare teams have the technical capability, operational knowledge, and institutional capacity to successfully implement AI systems. Coordinated telehealth systems, integrated care structures, and multidisciplinary implementation pathways described by Wang *et al.* (2021) suggest that organizational confidence may be strengthened when institutions establish clear responsibilities, communication structures, and operational support mechanisms. Overall, these studies indicate that successful AI adoption in preventive healthcare depends not only on technological sophistication but also on organizational leadership, implementation confidence, and coordinated institutional readiness.

3.11 Patient-centered approaches

Patient-centered approaches are increasingly recognized as essential to the development and implementation of AI-enabled preventive healthcare systems. These approaches emphasize aligning healthcare technologies with patients' needs, preferences, social contexts, and lived experiences, while acknowledging the influence of social determinants of health (SDOH) on healthcare access and outcomes (Harmon *et al.*, 2022). In preventive healthcare settings, patient-centered design may improve the acceptability and relevance of AI-enabled tools by incorporating community perspectives, supporting culturally responsive implementation strategies, and fostering greater responsiveness to population-specific health challenges.

Several studies highlight the value of participatory and equity-oriented approaches in AI-enabled healthcare initiatives. The FAITH! ancillary study used a community-based participatory research framework to engage underserved African American communities in evaluating an AI-enhanced electrocardiogram for cardiovascular disease screening, underscoring the importance of community engagement and culturally informed implementation strategies in AI-supported healthcare initiatives (Harmon *et al.*, 2022). Similarly, integrating SDOH variables into machine learning models improved predictions of cardiovascular outcomes among breast cancer patients, particularly non-Hispanic Black women, suggesting that incorporating social context into predictive analytics may improve risk stratification for historically underserved populations (Stabellini *et al.*, 2023). Other studies have explored adaptive and personalized approaches to digital health design. Reinforcement learning applications for diabetes management have demonstrated the potential of AI systems to support adaptive treatment strategies (Zheng *et al.*, 2021), while conceptual proposals for culturally tailored digital platforms for farmworkers emphasize the importance of designing technologies that account for users' literacy levels, occupational conditions, and access barriers (Sikalidis *et al.*, 2022).

Despite these opportunities, several implementation challenges remain. Pre-implementation studies indicate that although patients may be receptive to AI-supported healthcare tools, they often continue to view clinicians as the primary interpreters of medical information and decision-making guidance (Ho *et al.*, 2023). Concerns about privacy, depersonalization, data misuse, and reduced human interaction may undermine trust and long-term engagement with AI-enabled systems. In addition, sustaining patient engagement in digital health interventions remains a persistent challenge, particularly when technologies are not sufficiently aligned with users' preferences, motivations, or daily routines. Participatory co-design approaches, such as those used in the MiSmartHeart study, highlight the value of involving patients and healthcare professionals in the iterative development of digital health tools to better align system features with user expectations and engagement needs (Pelly *et al.*, 2023).

From the ORC perspective, patient-centered approaches may influence the valence of change by shaping organizational members' perceptions of the value, relevance, and benefits of AI-enabled preventive healthcare initiatives. AI systems perceived as culturally responsive, patient-informed, and capable of addressing health disparities may generate stronger support among clinicians, administrators, and community stakeholders. Conversely, concerns about privacy, limited patient trust, weak engagement, or insufficient attention to patient experiences may reduce perceptions of the value and desirability of implementation efforts. Leadership support may therefore play an important role in reinforcing change valence by prioritizing equity-focused strategies, supporting culturally responsive implementation practices, and encouraging the inclusion of patient perspectives in organizational decision making.

3.12 Quality assurance and validation

In AI-enabled diagnostic and screening applications in preventive healthcare, systems are generally expected to demonstrate reliable, clinically meaningful performance through validation against expert-level diagnostic standards (Ahmed *et al.*, 2024; Zhu *et al.*, 2021). Such validation evidence may strengthen organizational confidence in AI systems' ability to operate safely and effectively in clinical settings. For instance, a deep learning model for lung cancer detection achieved high diagnostic accuracy with processing times under 10 seconds, while the AI-assisted thinprep-based system for cervical screening achieved higher sensitivity than senior cytologists while maintaining comparable specificity and processing slides within 180 seconds (Ahmed *et al.*, 2024; Zhu *et al.*, 2021). These validated performance outcomes suggest that AI systems may improve workflow efficiency and support perceptions that implementation is both feasible and organizationally valuable.

Validation pathways also vary by application type, closely reflecting resource availability. In diagnostic pathology, quality assurance emphasizes empirical generalization across smear preparation methods, staining protocols, and imaging conditions. Zhu *et al.* (2021) further incorporated automated safeguards, including a digital pathology image quality-control module that verified image usability before analysis. These controls illustrate the organizational resources, data quality processes, computing infrastructure, and interoperability mechanisms likely required to support dependable AI performance. In contrast, continuous monitoring and IoT-enabled healthcare systems rely more heavily on architectural quality assurance to meet non-functional requirements such as real-time responsiveness, low latency, reliability, and secure distributed processing (Shumba *et al.*, 2022). These architectures highlight the operational and infrastructural resources required to sustain latency-sensitive healthcare environments.

From the ORC perspective, these findings particularly reflect change efficacy and resource availability. Change efficacy may be strengthened when healthcare organizations believe they have the technical infrastructure, operational capacity, governance processes, and implementation support needed to deploy AI systems successfully. Demonstrated gains in diagnostic accuracy, workflow efficiency, system reliability, and processing speed may reinforce organizational confidence that AI systems can be implemented safely and effectively in clinical settings. Studies such as Zhu *et al.* (2021) and Shumba *et al.* (2022) further illustrate how data quality controls, interoperability mechanisms, distributed computing architectures, and real-time processing capabilities may contribute to greater perceived feasibility of implementation. At the same time, these studies highlight the importance of resource availability, particularly computing infrastructure, quality assurance mechanisms, interoperability support, data management processes, and long-term operational coordination. Sustaining AI-enabled healthcare systems, therefore, appears to depend not only on validated technical performance but also on the availability of sufficient organizational and infrastructural resources required for reliable implementation and ongoing system support.

3.13 Research and innovation

The rapid evolution of AI is expanding opportunities for preventive healthcare through advances in early disease detection, continuous monitoring, predictive analytics, and diagnostic support systems. Recent developments include novel machine learning architectures, the integration of heterogeneous health data streams, greater attention to model interpretability, and efforts to improve clinical validation and translational applicability. Several studies illustrate the technical potential of these approaches. The ME-TIME study proposed a framework that combines self-supervised and multiple-instance learning to detect atrial fibrillation and heart failure from wearable device data, highlighting the potential of smartwatch-based monitoring for continuous cardiovascular assessment (Naseri *et al.*, 2023). Similarly, a Gated recurrent unit and multitask Gaussian process, temporal convolutional network architectures, have been developed to support early sepsis prediction in intensive care settings by addressing challenges associated with missing and irregular electronic medical record data (Lee *et al.*, 2024).

Advances are also evident in diagnostic imaging and predictive phenotyping. In oncology, deep convolutional neural network–based systems have shown strong performance in prostate cancer detection, grading, and quantification, while reducing interobserver variability among pathologists (Huang *et al.*, 2021). Interpretable machine learning and computational phenotyping approaches have also been used to identify outpatient clinical phenotypes associated with the risk of future acute myocardial infarction using longitudinal electronic health records (Hodgman *et al.*, 2024). Other innovations extend monitoring beyond traditional hospital settings. For example, simulation-based IoT edge computing architectures have been proposed to support real-time clinical decision support systems, reducing latency and improving responsiveness in healthcare monitoring settings (Kumar and Rajaram, 2024). AI-enabled retinal screening systems have similarly shown potential to support automated disease detection in resource-constrained environments and large-scale screening initiatives (Acharyya *et al.*, 2024). Collectively, these developments illustrate the growing technical sophistication and expanding scope of AI-enabled preventive healthcare applications.

Despite these advancements, much of the current literature remains focused on predictive performance, diagnostic accuracy, and proof-of-concept validation rather than long-term organizational implementation and sustainable clinical integration. Many studies continue to rely on retrospective datasets, simulation environments, or institution-specific workflows, which may limit the generalizability and transferability of findings across healthcare settings. In addition, ongoing challenges related to reproducibility, interoperability, workflow integration, and scalability complicate the transition from experimental systems to routine clinical implementation (Ahn and Lee, 2022). The absence of widely accepted validation standards and implementation frameworks may further hinder broader adoption and contribute to fragmented AI deployment across healthcare institutions. Although explainability approaches such as SHapley Additive exPlanations values, Local Interpretable Model-Agnostic Explanations, and interpretable machine learning models are increasingly incorporated into predictive systems, empirical evidence on their effectiveness in improving clinician trust, decision confidence, and sustained adoption remains limited (Hodgman *et al.*, 2024). Furthermore, while several AI-enabled systems demonstrate strong technical or diagnostic performance, fewer studies evaluate long-term workflow integration, operational sustainability, or patient outcomes in real-world healthcare environments (Huang *et al.*, 2021).

From the ORC perspective, these implementation challenges may affect both change efficacy and resource availability in AI-enabled preventive healthcare initiatives. Change efficacy is the shared confidence among organizational members in their collective ability to implement and sustain organizational change. Persistent concerns about interoperability limitations, workflow disruption, scalability, validation reliability, and uncertainty about long-term integration may reduce confidence in organizations' ability to effectively operationalize AI-enabled systems in routine preventive healthcare settings. Resource availability also plays a critical role in shaping implementation capacity. The successful adoption of AI-driven technologies often requires substantial investments in technical infrastructure, interoperability support, workforce training, data governance, and ongoing system maintenance. Healthcare organizations with limited financial, technological, or human resources may therefore face greater difficulty integrating AI innovations into existing clinical workflows. Consequently, the long-term success of AI-enabled preventive healthcare systems may depend not only on technical advancement but also on organizations' perceptions of their readiness, capabilities, and available resources to support sustainable implementation and operational integration.

3.14 Implementation and change management

Implementing AI in preventive healthcare requires overcoming not only technical challenges but also organizational, cultural, and operational barriers. A commonly discussed challenge is epistemic opacity, in which clinicians and healthcare professionals perceive AI systems as difficult to interpret or insufficiently transparent in their decision-making processes (Gjødsbøl *et al.*, 2024; Winter and Carusi, 2023). Concerns about explainability, accountability, and trust may contribute to uncertainty about the clinical value and reliability of AI-enabled systems. In addition, healthcare professionals may express concerns about professional autonomy, workflow disruption, and the evolving role of clinical expertise in AI-supported environments (Gjødsbøl *et al.*, 2024). These challenges may complicate organizational efforts to integrate AI technologies into routine preventive healthcare practices.

Data and infrastructure limitations may further intensify implementation challenges. Many healthcare organizations continue to face challenges related to fragmented data systems, insufficient interoperability, limited technical infrastructure, and shortages of personnel with specialized expertise in data management and analytics (Mazumdar *et al.*, 2021). Large-scale healthcare innovation initiatives have also highlighted the complexity of implementing system-wide transformation efforts in highly fragmented healthcare environments, where organizational coordination, stakeholder alignment, and operational integration remain difficult to achieve (Bedoya Reina *et al.*, 2021). Similarly, although digital health and AI-enabled monitoring systems show promise for improving remote care and preventive interventions, evidence on their long-term sustainability, scalability, and routine integration into healthcare workflows remains limited (Berquedich *et al.*, 2020; Hurvitz *et al.*, 2021). These findings suggest that technological feasibility alone may be insufficient to ensure sustained organizational adoption and successful implementation.

Addressing these barriers may require viewing AI not solely as a technical tool but as a socio-technical innovation that must be integrated into existing clinical practices, organizational routines, and collaborative decision-making processes (Winter and Carusi, 2023). Positioning AI systems as supportive technologies that augment rather than replace professional judgment may improve clinician acceptance and encourage more collaborative implementation (Gjødsbøl *et al.*, 2024). In addition, involving clinicians, informatics specialists, and operational stakeholders early in system development and implementation may support greater alignment between AI initiatives and institutional priorities, workflows, and user expectations (Mazumdar *et al.*, 2021).

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Pilot implementations, iterative feedback, and cross-functional collaboration may also help organizations identify operational barriers before broader deployment.

From the ORC perspective, the successful implementation of AI-enabled preventive healthcare systems may depend on change valence, change efficacy, and leadership commitment. Change valence is the extent to which organizational stakeholders perceive a proposed innovation as beneficial, worthwhile, and aligned with organizational and clinical goals. AI initiatives perceived as improving diagnostic support, preventive monitoring, workflow efficiency, or patient outcomes may generate stronger organizational support and greater motivation to adopt. However, concerns about transparency, workflow disruption, limited evidence of sustainability, or uncertain clinical value may reduce perceived benefits and weaken support for implementation efforts. Change efficacy is the shared confidence among organizational members in their collective ability to implement and sustain organizational change. Persistent concerns about interoperability, data quality, workforce preparedness, technical complexity, and integration with existing workflows may undermine confidence in organizations' ability to operationalize AI systems effectively. Leadership commitment may therefore play an important role in sustaining implementation efforts by supporting strategic alignment, encouraging stakeholder collaboration, allocating organizational resources, and reinforcing long-term organizational priorities related to preventive and data-driven healthcare transformation. Although emerging adaptive and personalized AI systems show promise for supporting preventive healthcare delivery, additional longitudinal and implementation-focused research may be necessary to better understand their sustainability, scalability, and long-term organizational impact.

4. Discussion

This study applied Weiner's (2009) organizational readiness for change (ORC) framework to examine the organizational factors influencing the adoption of AI-driven predictive analytics in preventive healthcare. Successful implementation is not merely a technical challenge but a deeply organizational one, shaped by four interdependent ORC constructs: change efficacy, change valence, resource availability, and leadership commitment. This lens

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departs from the field's dominant emphasis on diagnostic accuracy and technical validation (Acharyya *et al.*, 2024; Huang *et al.*, 2021; Rudolph *et al.*, 2024; Zhu *et al.*, 2021), where implementation has often been assumed to follow from algorithmic performance. Yet even high-performing tools stall at the institutional threshold (Morgenstern *et al.*, 2021; Schepart *et al.*, 2023); this study maps the high interdependence among the four constructs. Change efficacy, the belief that an organization can successfully implement AI, rests on leadership support and resource allocation as much as on technical training, with strategic leadership serving as the connective tissue between AI capability and organizational uptake (Ennis-O'Connor and O'Connor, 2024; Kotp *et al.*, 2025). Change valence, in turn, is shaped by cultural alignment, clinician trust, and ethical governance, with trust functioning as a precondition for adoption rather than a downstream outcome (Ashok *et al.*, 2022; Olofsson *et al.*, 2024). Persistent competency gaps across professional groups further reinforce the idea that weakness in any one construct undermines overall readiness (Elchaghaby and Wahby, 2025; Till *et al.*, 2024). The recurrence of these patterns across varied settings, professional groups, and methodological approaches places them among the highest-confidence conclusions in the synthesized literature.

Readiness must also be understood at multiple levels: individual, team, and institutional. Clinicians may be technically prepared yet resist adoption due to concerns about autonomy or workflow, a pattern that recurs across diverse clinical contexts (Ho *et al.*, 2023; Jonnalagedda-Cattin *et al.*, 2025; Parikh *et al.*, 2022; Pelly *et al.*, 2023). Conversely, enthusiastic leadership may fail to engage frontline staff, stalling implementation (Jones *et al.*, 2025). These individual-level dynamics are the analytical terrain of health technology acceptance models, such as a technology acceptance model and unified theory of acceptance and use of technology (Davis, 1989; Venkatesh *et al.*, 2003), which explain adoption intention through perceived usefulness, ease of use, and facilitating conditions, while sociotechnical perspectives further situate such decisions within the mutual constitution of technology, workflow, and organizational culture (Sittig and Singh, 2010). ORC complements these traditions by identifying the organizational conditions under which collective adoption is even feasible. Readiness assessments must therefore go beyond surface indicators to capture organizational culture, communication patterns, and decision-making structures, aligning with broader calls for interpretive, transparency-oriented engagement with clinical AI (Gjødsbøl *et al.*, 2024; Winter and Carusi, 2023).

Several themes, implementation and change management, quality assurance, and research-to-practice translation, were underrepresented despite their importance, leaving conclusions in these emerging areas necessarily more tentative and revealing a gap between innovation and operationalization. Many institutions remain stuck in pilots due to fragmented strategies, unclear evaluation metrics, and insufficient stakeholder engagement, a value-destruction dynamic in which the very conditions enabling AI to generate value go unaddressed (Canhoto and Clear, 2020). Translation from research to practice requires deliberate organizational scaffolding rather than ad hoc adoption (Mazumdar *et al.*, 2021), and highly publicized disruptive initiatives illustrate how scale-up can falter when organizational dimensions are underestimated (Bedoya Reina *et al.*, 2021). This pilot-to-scale gap is precisely the phenomenon theorized by the non-adoption, abandonment, scale-up, spread, and sustainability (NASSS) framework (Greenhalgh *et al.*, 2017), which attributes non-adoption and abandonment of health technologies to unmanaged complexity across condition, technology, value proposition, adopter system, organization, wider context, and embedding-over-time domains.

Addressing these gaps requires a shift from technology-centric to change-centric approaches, and the field's three most pertinent organizational frameworks operate at complementary levels of abstraction: ORC (Weiner, 2009) specifies the antecedent psychological and structural conditions for collective action; consolidated framework for implementation research (Damschroder *et al.*, 2009) catalogues the multilevel determinants that translate readiness into implementation; and non-adoption, abandonment, scale-up, spread and sustainability (Greenhalgh *et al.*, 2017) models the dynamic complexity through which implemented technologies either embed or fail over time. ORC alone explains why organizations are prepared to act. Together, these frameworks explain why preparedness so often fails to convert into sustained use.

For healthcare leaders, the findings offer a roadmap: investing in workforce development (Simsek-Cetinkaya and Cakir, 2023; Till *et al.*, 2024), aligning AI initiatives with strategic goals

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(Ennis-O'Connor and O'Connor, 2024), and fostering cross-disciplinary collaboration. Equally important is cultivating trust through transparent governance, inclusive design, and ethical oversight (Ashok *et al.*, 2022; Winter and Carusi, 2023). These priorities reflect a broader pattern in which organizational and governance factors are rated as more constraining than technical limitations (Schepart *et al.*, 2023). Echoed across the workforce, leadership, and trust literatures cited above (Ennis-O'Connor and O'Connor, 2024; Till *et al.*, 2024), this pattern is among the most consistently supported conclusion of the synthesis and grounds the manuscript's central organizational-over-technical claim. Institutions should also develop AI maturity models that benchmark readiness across ORC dimensions. Existing digital health maturity frameworks (Flott *et al.*, 2016) were designed for digitization and interoperability rather than for the organizational demands of algorithmic systems, and empirical guidance for AI-specific maturity assessment in healthcare remains scarce.

This study contributes by operationalizing ORC (Weiner, 2009) in healthcare AI, where organizational theory is underutilized. Mapping twelve organizational themes to ORC constructs provides a structured framework for empirical research and demonstrates the value of combining AI-assisted review with human judgment (Chew *et al.*, 2023; Christou, 2024; Gao *et al.*, 2023), a scalable approach that complements established review traditions (Rowe, 2014). The hybrid methodology employed here, encompassing AI-assisted screening, iterative kappa-based validation, full manual verification, and structured interpretive mapping, represents a transparent and defensible model for large-scale organizational evidence synthesis. At the same time, it should be acknowledged that AI-assisted systematic review methodology is still maturing as a scholarly practice: reproducibility constraints tied to prompt design and model evolution mean that the field has not yet converged on universal standards for this approach. This study's human-AI hybrid design should therefore be understood as a substantive step toward methodological best practice rather than its culmination, and future work should continue to develop and validate reproducibility standards, quality appraisal frameworks, and reporting guidelines suited to AI-assisted evidence synthesis in organizational and implementation research.

Ultimately, AI adoption in preventive healthcare is part of a broader transformation toward a learning health system (Friedman *et al.*, 2010). Infrastructure efforts in large-scale

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clinical data integration and precision medicine supply the technical scaffolding (Jacobs *et al.*, 2025; Justice *et al.*, 2024), but data architecture alone is insufficient without parallel organizational maturation. Organizational readiness is, therefore, a dynamic capability that must be cultivated over time. By embedding ORC principles into strategic planning, training, and evaluation, healthcare institutions can move beyond pilots toward sustainable, equitable innovation.

5. Conclusion

This review synthesized organizational factors influencing AI adoption in preventive healthcare, using the organizational readiness for change (ORC) framework to integrate evidence on leadership, workforce preparedness, infrastructure, ethics, and trust. The findings indicate that AI adoption is shaped not only by the technical capabilities of AI systems but also by the organizational and institutional contexts in which they are implemented. Across the studies included in this review, organizational factors emerged as recurring themes linked to implementation success, underscoring the importance of considering readiness alongside technological development. By applying the ORC lens, this review offers a complementary perspective to existing technology adoption and implementation frameworks, emphasizing the collective organizational conditions that may facilitate or hinder AI adoption.

The review also highlights important differences in the maturity of current knowledge. Evidence on workforce capability, leadership commitment, resource availability, and trust is relatively well represented in the literature, whereas AI-specific maturity assessment, team-level implementation dynamics, and the translation of AI innovations from research environments into routine healthcare practice remain less-developed areas of inquiry. Collectively, these findings suggest that successful AI adoption in preventive healthcare should be viewed not solely as a technological challenge but also as an organizational change process. Future research would benefit from greater attention to longitudinal implementation outcomes, multilevel organizational dynamics, and the development of validated measures that operationalize key dimensions of organizational readiness for AI adoption.

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5.1 Limitations

Several limitations of this review should be acknowledged. First, although AI-assisted screening and topic classification enhanced the efficiency and scalability of the review process, these tools introduce methodological challenges related to reproducibility. Grok's outputs depended on prompt design and the model's underlying training characteristics; because generative AI systems evolve over time, future replication attempts may yield different screening or classification outcomes even when using identical prompts. To mitigate these risks, all AI-generated decisions were subjected to full manual verification by the authors, the screening prompt was iteratively validated against a kappa-based reliability, and both prompts are fully documented in Appendices A and B to support transparency and reproducibility. Accordingly, the hybrid human–AI approach adopted in this study should be viewed as one possible approach to AI-assisted evidence synthesis rather than a definitive methodological standard.

Second, this review did not employ a formal quality appraisal scoring protocol. The methodological heterogeneity of the included studies limited the applicability of any single standardized appraisal instrument across the full corpus. Instead, studies were retained based on predefined criteria related to conceptual relevance, organizational focus, and methodological transparency, as described in Section 2.3. While this approach is consistent with guidance for organizationally focused conceptual synthesis (Rowe, 2014), it does not provide the study-level quality ratings associated with formal appraisal frameworks. Consequently, the synthesized findings should be interpreted with appropriate consideration of this limitation. The development of design-sensitive appraisal frameworks may represent a useful direction for future methodological research in organizational AI adoption studies.

Third, inter-rater reliability was formally assessed only during the screening stage. No kappa statistic or equivalent reliability coefficient was calculated for the topic classification or ORC mapping stages, which involved greater interpretive judgment. Although both stages followed structured independent-then-consensus procedures, the absence of quantitative reliability measures limits the ability to assess consistency at these stages of analysis. Future AI-assisted reviews may benefit from extending formal reliability assessment to all major interpretive phases of analysis.

Fourth, the mapping of the 12 organizational topics to ORC constructs, while grounded in a structured independent-then-consensus procedure and guided by explicit decision rules, remains an interpretive exercise. The boundaries between ORC constructs are not always clearly delineated within the underlying literature, and alternative mappings may be equally defensible. The assignments presented in Figure 4, therefore, represent the authors' collective scholarly judgment and should be understood as a theoretically informed synthesis rather than a definitive classification. Although the mapping process was designed to maximize transparency and consistency, some degree of interpretive subjectivity is inherent in theory-based synthesis.

5.2 Prospective Research Agenda

To support the responsible adoption of AI in preventive healthcare, future research should shift from largely descriptive accounts toward empirical, theory-informed investigation. Drawing on the ORC framework, we propose four research directions spanning foundational, process-oriented, and integrative priorities. These are presented as a conceptual progression—readiness assessment provides a basis for studying leadership, change processes, and the cultural and ethical conditions of adoption—but should be understood as complementary and mutually reinforcing rather than strictly sequential.

Priority 1 (Foundational): Readiness and maturity models. The review revealed a lack of validated tools for assessing organizational preparedness for AI adoption. Future work should develop and validate readiness and maturity models grounded in ORC dimensions (e.g., workforce capability, leadership commitment, data governance, and ethical safeguards), using expert consensus methods such as Delphi studies, alongside psychometric and longitudinal validation. Such tools would provide organizations with a systematic basis for identifying strengths, gaps, and intervention priorities.

Priority 2 (Process): Leadership and longitudinal change. Leadership commitment recurred throughout the literature, yet the mechanisms linking it to adoption remain unclear. Multi-site comparative case studies—combining established instruments (e.g., the MLQ-5X) with interviews and organizational records—could clarify how leadership translates into observable actions such as resource allocation and governance decisions. Because most existing studies are cross-sectional, this work should be longitudinal, treating readiness as a dynamic process and tracking how capabilities and organizational responses evolve across adoption phases, including longer-term outcomes such as sustained use and workforce impacts.

Priority 3 (Integrative): Culture, ethics, and trust. Organizational culture, ethical governance, and trust appear central to the long-term sustainability of AI adoption. Mixed-methods research should examine how these factors interact with leadership and readiness and should empirically evaluate participatory governance mechanisms—such as clinician co-design and patient advisory structures—for their influence on implementation outcomes and stakeholder trust. Attention to equity, including AI performance across demographic groups, is a particular priority.

Together, these priorities point to three needs: stronger measurement foundations, a deeper understanding of organizational change, and greater attention to the cultural and ethical conditions shaping implementation. Ultimately, realizing the benefits of AI in preventive healthcare may depend less on algorithmic performance than on organizations' capacity to align technology, people, governance, and values toward sustainable and equitable adoption.

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Appendix A

We used the following prompt for the article selection process.

You are a qualitative coder.

Evaluate the title and abstract of each article carefully and assign codes based on the following inclusion criteria. Mark each criterion clearly as either "Include" or "Exclude." If an article's relevance is unclear based on the title and abstract, flag it for manual review.

Criteria:

1. Preventive Healthcare or Early Disease Detection Focus

   Use the following definition to guide your analysis:

   Preventive healthcare focuses on preventing diseases and maintaining overall health before they become serious. It includes routine check-ups, vaccinations, screenings, and counseling on healthy lifestyles. This proactive approach aims to detect problems early and prevent complications or chronic conditions.

   Include: The articles explicitly focus on preventive/preventative healthcare or early disease detection on human subjects.

2. AI use or AI adoption

   Include: The articles explicitly examine the use of AI or the adoption of AI technologies.

3. Organizational Domain

   Use the following domain definition to guide your analysis:

   Organizational domain: Internal factors within an organization influencing AI adoption, such as organizational structure, resources, culture, leadership support, or employee readiness.

   Include: The articles address the organizational domain.

   Write the results in a tabular format, including the reasoning.

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Appendix B

We used the following prompt for topic classification.

You are a qualitative coder.

Evaluate the title and abstract of each article carefully and assign one or more organizational topics based on the content. Use inductive reasoning to identify and label the core topics addressed within the organizational domain of AI adoption or use in preventive healthcare. If an article does not present an identifiable topic, flag it for manual review.

Instructions:

Use the following domain definition to guide your analysis

Organizational domain: Internal factors within an organization influencing AI adoption or use, such as organizational structure, resources, culture, leadership support, or employee readiness.

Carefully analyze the title and abstract to determine the main organizational themes discussed.

Assign one or more short, descriptive topic labels that reflect the article's focus (e.g., "leadership support," "workflow integration," "staff training").

If the topic(s) are unclear based on the title and abstract, mark the article as "Flag for Manual Review."

Present the results in a tabular format, including the reasoning.

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Full Search Strategy

Databases: PubMed, IEEE Xplore, ScienceDirect, ACM Digital Library, Web of Science

Date of Search: March 1-3, 2025

Language: English

Publication Years: 2020 January –2025 April

Filters: Peer-reviewed journal articles only; exclude reviews, meta-analyses, letters, book chapters, reports, and conference papers.

1. Search Execution Approach

All search terms were applied to the title and abstract fields in each database to ensure high sensitivity to studies that explicitly reference artificial intelligence, machine learning, predictive analytics, preventive/preventative healthcare, early disease detection, or organizational adoption factors.

2. Complete List of Search Strings

2.1. Preventive Healthcare + AI/ML

- "artificial intelligence" AND "predictive analytics" AND "preventative healthcare"
- "machine learning" AND "predictive analytics" AND "preventative healthcare"
- "artificial intelligence" AND "preventative healthcare"
- "machine learning" AND "preventative healthcare"
- "predictive analytics" AND "healthcare"
- "AI" AND "preventative healthcare"
- "artificial intelligence" AND "predictive analytics" AND "preventive healthcare"
- "machine learning" AND "predictive analytics" AND "preventive healthcare"
- "artificial intelligence" AND "preventive healthcare"
- "machine learning" AND "preventive healthcare"
- "predictive analytics" AND "healthcare"

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- "AI" AND "preventive healthcare"

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2.2. Early Detection, Diagnosis, Disease Prediction

- "AI-driven predictive analytics" AND "early disease detection"
- "artificial intelligence-driven predictive analytics" AND "early disease detection"
- "AI" AND "early disease detection"
- "artificial intelligence" AND "early disease detection"
- "artificial intelligence" AND "disease prediction"
- "AI" AND "disease prediction"
- "AI" AND "preventative medicine"
- "artificial intelligence" AND "preventative medicine"
- "AI" AND "preventive medicine"
- "artificial intelligence" AND "preventive medicine"
- "artificial intelligence" AND "early diagnosis"
- "AI" AND "early diagnosis"

2.3.Technology Adoption Models

- "healthcare technology adoption models" AND "artificial intelligence"
- "healthcare technology adoption models" AND "AI"

2.4. Challenges, Barriers, Benefits, Ethics, Risks, Opportunities, Regulations

- "AI" AND "challenges" AND "preventative healthcare"
- "artificial intelligence" AND "challenges" AND "preventative healthcare"
- "AI" AND "barriers" AND "preventative healthcare"
- "artificial intelligence" AND "barriers" AND "preventative healthcare"
- "AI" AND "benefits" AND "preventative healthcare"
- "artificial intelligence" AND "benefits" AND "preventative healthcare"
- "artificial intelligence" AND "ethics" AND "preventative healthcare"
- "AI" AND "ethics" AND "preventative healthcare"
- "artificial intelligence" AND "risks" AND "preventative healthcare"
- "AI" AND "risks" AND "preventative healthcare"
- "artificial intelligence" AND "opportunities" AND "preventative healthcare"

- "AI" AND "opportunities" AND "preventative healthcare"
- "artificial intelligence" AND "regulations" AND "preventative healthcare"
- "AI" AND "regulations" AND "preventative healthcare"
- "AI" AND "challenges" AND "preventive healthcare"
- "artificial intelligence" AND "challenges" AND "preventive healthcare"
- "AI" AND "barriers" AND "preventive healthcare"
- "artificial intelligence" AND "barriers" AND "preventive healthcare"
- "AI" AND "benefits" AND "preventive healthcare"
- "artificial intelligence" AND "benefits" AND "preventive healthcare"
- "artificial intelligence" AND "ethics" AND "preventive healthcare"
- "AI" AND "ethics" AND "preventive healthcare"
- "artificial intelligence" AND "risks" AND "preventive healthcare"
- "AI" AND "risks" AND "preventive healthcare"
- "artificial intelligence" AND "opportunities" AND "preventive healthcare"
- "AI" AND "opportunities" AND "preventive healthcare"
- "artificial intelligence" AND "regulations" AND "preventive healthcare"
- "AI" AND "regulations" AND "preventive healthcare"

2.5. Chronic Disease, Cardiovascular Disease, Cancer, Mental Health

- "artificial intelligence" AND "chronic disease"
- "AI" AND "chronic disease"
- "artificial intelligence" AND "cardiovascular disease"
- "AI" AND "cardiovascular disease"
- "artificial intelligence" AND "early cancer detection"
- "AI" AND "early cancer detection"
- "artificial intelligence" AND "mental health" AND "preventative"
- "AI" AND "mental health" AND "preventative"
- "artificial intelligence" AND "mental health" AND "preventive"
- "AI" AND "mental health" AND "preventive"

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- "artificial intelligence" AND "cancer detection"
- "AI" AND "cancer detection"

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3. Search Execution Notes

- Search strings were executed separately AND then merged into a combined dataset.
- Synonyms (e.g., *preventive* vs. *preventative*) were intentionally included to reduce missed records.
- Title/abstract relevance determined inclusion for full-text review.

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List of Included Studies

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