

Original Article

Navigating technology integration for workforce optimization in healthcare settings: A systematic review of strategies, barriers, and outcomes from middle-income countries

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Abstract

Technology integration in healthcare settings—including Electronic Medical Records (EMR), Hospital Information Systems (HIS), telemedicine, digital workflow tools, and artificial intelligence (AI)-assisted clinical decision support systems—is increasingly implemented to support workforce optimization in middle-income countries. However, the effectiveness and safety of these interventions remain incompletely synthesized. The aim of this study was to evaluate the impact of healthcare technology integration on workforce-related outcomes in middle-income countries and assess evidence certainty using the Grading of Recommendations Assessment, Development and Evaluation (GRADE) framework. A systematic search of PubMed, Epistemonikos, and ProQuest (through December 2025) identified 613 records. After screening and eligibility assessment, 22 studies from 12 middle-income countries were included in the qualitative synthesis. Primary outcomes included workforce efficiency, administrative burden reduction, and patient flow improvement, while secondary outcomes included staff satisfaction, burnout, quality of care, and safety-related outcomes. Across studies, technology integration was generally associated with improved workflow efficiency, reduced administrative tasks, and better clinical coordination. Telemedicine and AI-assisted systems appeared particularly useful for improving patient flow and reducing waiting times in some settings. Several studies also reported improvements in staff satisfaction and reductions in burnout. However, the certainty of evidence varied across outcomes because most included studies were observational, heterogeneous, short-term, and frequently relied on self-reported measures. Few serious technology-related adverse events were reported, although safety outcomes were not systematically evaluated in most studies. In conclusion, healthcare technology integration may support workforce optimization in middle-income countries, but implementation success appears highly dependent on infrastructure readiness, workforce training, and organizational capacity. Future research should prioritize longitudinal and technology-specific evaluations using standardized outcome measures.

Keywords: Technology integration, workforce optimization, healthcare settings, middle-income countries, AI-assisted systems

Introduction

The integration of technology in healthcare settings has become a critical strategy for optimizing workforce efficiency, particularly in middle-income countries (MICs) [1]. Countries such as



Brazil, China, India, Kenya, and Indonesia have actively pursued digital health agendas to address these challenges. As these nations face rapid demographic transitions, growing patient loads, and constrained healthcare resources, technology adoption offers practical pathways to improve the efficiency and effectiveness of healthcare systems. Various technological interventions—including Hospital Information Systems (HIS), Electronic Medical Records (EMR), digital workflow tools, artificial intelligence (AI)-assisted clinical decision support systems (CDSS), and telemedicine—have been identified as key enablers of workforce optimization [2-4]. These technologies hold potential to reduce administrative burden, streamline clinical workflows, and improve patient flow, collectively contributing to a more productive healthcare workforce [5-6].

Despite the promise of these innovations, successful implementation remains a significant challenge in resource-limited settings. Barriers such as insufficient infrastructure, inadequate training, cultural resistance to change, and financial constraints are commonly reported across MICs [7]. Moreover, heterogeneity in technology adoption maturity—ranging from early-stage implementations to advanced integrated systems—affects the outcomes of technology integration and complicates cross-setting comparisons [8-9].

There is also a growing body of evidence suggesting that technology adoption influences secondary outcomes beyond productivity, including staff satisfaction and burnout, interprofessional coordination, and patient care quality [10]. As digital health tools continue to expand in healthcare settings across MICs, there is a clear need for a comprehensive synthesis of the strategies, barriers, and outcomes associated with technology integration from a workforce optimization perspective [11]. This systematic review aims to: (1) examine the strategies employed in MICs for integrating technology into healthcare settings; (2) assess the barriers to successful implementation; (3) evaluate efficacy and safety outcomes using the Grading of Recommendations Assessment, Development and Evaluation (GRADE) framework; and (4) derive lessons learned from these countries to inform future technology adoption efforts globally.

Methods

Study registration and reporting

This systematic review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [12]. The review protocol was prospectively registered in OSF protocol under registration DOI: <https://doi.org/10.17605/OSF.IO/6DXAE>. The review covers evidence published through December 2025.

Search strategy and study identification

A comprehensive systematic literature search was conducted across three major electronic databases: PubMed, Epistemonikos, and ProQuest. The search was performed between October and December 2025 (PubMed: October 15–November 2, 2025; Epistemonikos: November 3–20, 2025; ProQuest: November 21–December 10, 2025). Search terms were developed using Boolean operators combining three conceptual domains: (1) healthcare settings and workforce; (2) technology interventions; and (3) workforce and patient outcomes. The complete search strings for each database are presented in **Table 1**.

Two independent reviewers (MA and RSAS) conducted the database searches, retrieved records, and performed title-and-abstract screening. Any discrepancies between reviewers were resolved through discussion and consensus. Records identified as potentially eligible following title-and-abstract screening were advanced for full-text assessment.

Table 1. Literature search terms across databases

Database	Search terms
PubMed	(Healthcare settings OR healthcare settings* OR "healthcare facility" OR "health facilities" OR "health workforce" OR "healthcare workforce" OR "health personnel" OR clinician* OR doctor* OR nurse* OR "allied health") AND ("Health Information Systems" OR "Healthcare settings Information System" OR HIS OR "Electronic Health Records" OR "Electronic Medical Record" OR EMR OR EHR OR "clinical decision support" OR "decision support system*" OR CDSS OR telemedicine OR telehealth OR

Database	Search terms
Epistemonikos	"digital workflow" OR "digital health" OR "healthcare automation" OR AI OR "artificial intelligence" OR "e-prescribing" OR CPOE OR RFID OR automation) AND (workflow OR workload OR "administrative burden" OR "workforce efficiency" OR "workforce optimization" OR "staff productivity" OR productivity OR "patient flow" OR "waiting time*" OR burnout OR "job satisfaction" OR "interprofessional coordination" OR "documentation error*" OR "operational cost*")
ProQuest	(Healthcare settings OR healthcare settings* OR "healthcare facility" OR "health facilities" OR "health workforce" OR "healthcare workforce" OR "health personnel" OR clinician* OR doctor* OR nurse* OR "allied health") AND ("Health Information Systems" OR "Healthcare settings Information System" OR HIS OR "Electronic Health Records" OR "Electronic Medical Record" OR EMR OR EHR OR "clinical decision support" OR "decision support system*" OR CDSS OR telemedicine OR telehealth OR "digital workflow" OR "digital health" OR "healthcare automation" OR AI OR "artificial intelligence" OR "e-prescribing" OR CPOE OR RFID OR automation) AND (workflow OR workload OR "administrative burden" OR "workforce efficiency" OR "workforce optimization" OR "staff productivity" OR productivity OR "patient flow" OR "waiting time*" OR burnout OR "job satisfaction" OR "interprofessional coordination" OR "documentation error*" OR "operational cost*")

Study eligibility criteria

Inclusion and exclusion criteria were established a priori to ensure the specificity, consistency, and methodological rigor of the evidence base. Studies were eligible for inclusion if they: (1) were published in English; (2) focused on healthcare settings or primary healthcare settings in middle-income countries, as classified by the World Bank; (3) involved healthcare professionals including doctors, nurses, or allied health workers; (4) evaluated technology integration interventions—such as HIS, EMR, CDSS, telemedicine, automation tools (e.g., e-prescribing, digital scheduling, RFID), or AI-assisted systems; (5) reported at least one eligible outcome measure; and (6) were observational studies (cross-sectional, longitudinal, or prospective cohort), case studies, mixed-methods studies, quasi-experimental studies, simulation/proof-of-concept studies, or post-hoc analyses of implementation data. Randomized controlled trials were eligible, but none were identified in the final search; pilot and preprint studies were eligible if sufficient methodological detail was available.

Studies were excluded if they: (1) involved non-human subjects or non-clinical designs; (2) were non-peer-reviewed publications (e.g., preprints without extractable data, conference abstracts); (3) were narrative reviews or single case reports lacking extractable data; or (4) had unavailable or insufficient data for analysis. An exception was made for one preprint study [13], which was included due to its direct relevance and the availability of sufficient methodological detail.

Data extraction

Data were extracted from all eligible studies using a pre-specified standardized extraction form. The information extracted included: first author and year of publication; country; study design; sample size; participant characteristics (e.g., healthcare role, setting type); intervention details (technology type, implementation approach, duration); comparator (if applicable); follow-up duration; primary efficacy outcomes (workforce efficiency, administrative burden, patient flow); secondary outcomes (staff satisfaction, burnout, quality of care, interprofessional coordination); and safety outcomes (adverse events, system-related issues, discontinuations). Key characteristics and outcomes were summarized qualitatively in tabular form and described narratively in accordance with PRISMA 2020 guidelines.

Outcome measures

Primary outcomes of interest were: (1) improvement in workforce efficiency, assessed via metrics such as task completion rates, time savings, and staff productivity indicators; (2) reduction in administrative burden, including time spent on documentation and non-clinical tasks; and (3) improvement in patient flow, including waiting times and care coordination indicators.

Secondary outcomes included staff satisfaction and burnout (assessed via validated scales or self-report instruments), interprofessional collaboration, quality of care (documentation error reduction, patient outcome indicators), and operational cost reduction. Safety outcomes encompassed the incidence of technology-related adverse events (e.g., system downtime, user errors, unintended patient impact) and discontinuations due to technology-related dissatisfaction or system failure.

All outcomes were analyzed qualitatively. Where data permitted, descriptive comparisons were made between healthcare settings with varying levels of technology adoption maturity (low, moderate, and high) to assess the relative effectiveness of different technological strategies.

Quality assessment

The methodological quality of all included studies was assessed using the appropriate Joanna Briggs Institute (JBI) Critical Appraisal Checklist according to the study [14]. The JBI checklist evaluates key methodological domains, including the appropriateness of participant selection, measurement of exposures and outcomes, identification and management of potential confounding factors, validity and reliability of outcome assessment, completeness of follow-up (where applicable), and the appropriateness of statistical analyses. Each checklist item was rated as "Yes," "No," "Unclear," or "Not Applicable." Two reviewers independently assessed the methodological quality of the included studies, and any disagreements were resolved through discussion and consensus. For descriptive purposes, studies meeting at least 70% of the applicable JBI criteria were considered to have high methodological quality, those meeting 50–69% were considered moderate quality, and those meeting less than 50% were considered low quality.

Synthesis of evidence

Given the heterogeneity of included studies in terms of technology type, outcome measures, setting, and study design, a quantitative meta-analysis was not feasible. Instead, findings were synthesized using a narrative synthesis approach informed by the Synthesis Without Meta-Analysis (SWiM) reporting guideline [15]. Evidence was grouped thematically according to six predefined outcome domains: workforce efficiency, administrative burden, patient flow, staff satisfaction and burnout, quality of care, and safety. Within each domain, findings were described in terms of direction, magnitude (where reported), and consistency of effect across studies. Descriptive comparisons were drawn between healthcare settings operating at different levels of technology adoption maturity (low, moderate, and high), as reported by study authors or inferred from study context.

Certainty of evidence

The overall certainty of evidence for each outcome was evaluated using the GRADE approach. Certainty was assessed across five domains: risk of bias, inconsistency, indirectness, imprecision, and publication bias. Evidence from observational studies was initially rated as low certainty and could be upgraded or downgraded based on the GRADE criteria. Final certainty ratings were classified as high, moderate, low, or very low.

Results

Study selection and identification

The systematic search identified 613 records in total: PubMed (n=275), Epistemonikos (n=228), and ProQuest (n=110). Following the removal of 240 duplicate records, 373 unique records were screened by title and abstract. Of these, 330 records were excluded for not meeting the inclusion criteria, yielding 43 records for full-text assessment. One report could not be retrieved. Of the remaining 42 full-text reports assessed for eligibility, 20 were excluded for the following reasons:

wrong population (n=7), wrong exposure or intervention (n=7), or protocol studies or narrative reviews without extractable data (n=6). Ultimately, 22 studies met all eligibility criteria and were included in the qualitative synthesis. The study selection process is summarized in **Figure 1** (PRISMA 2020 flow diagram).

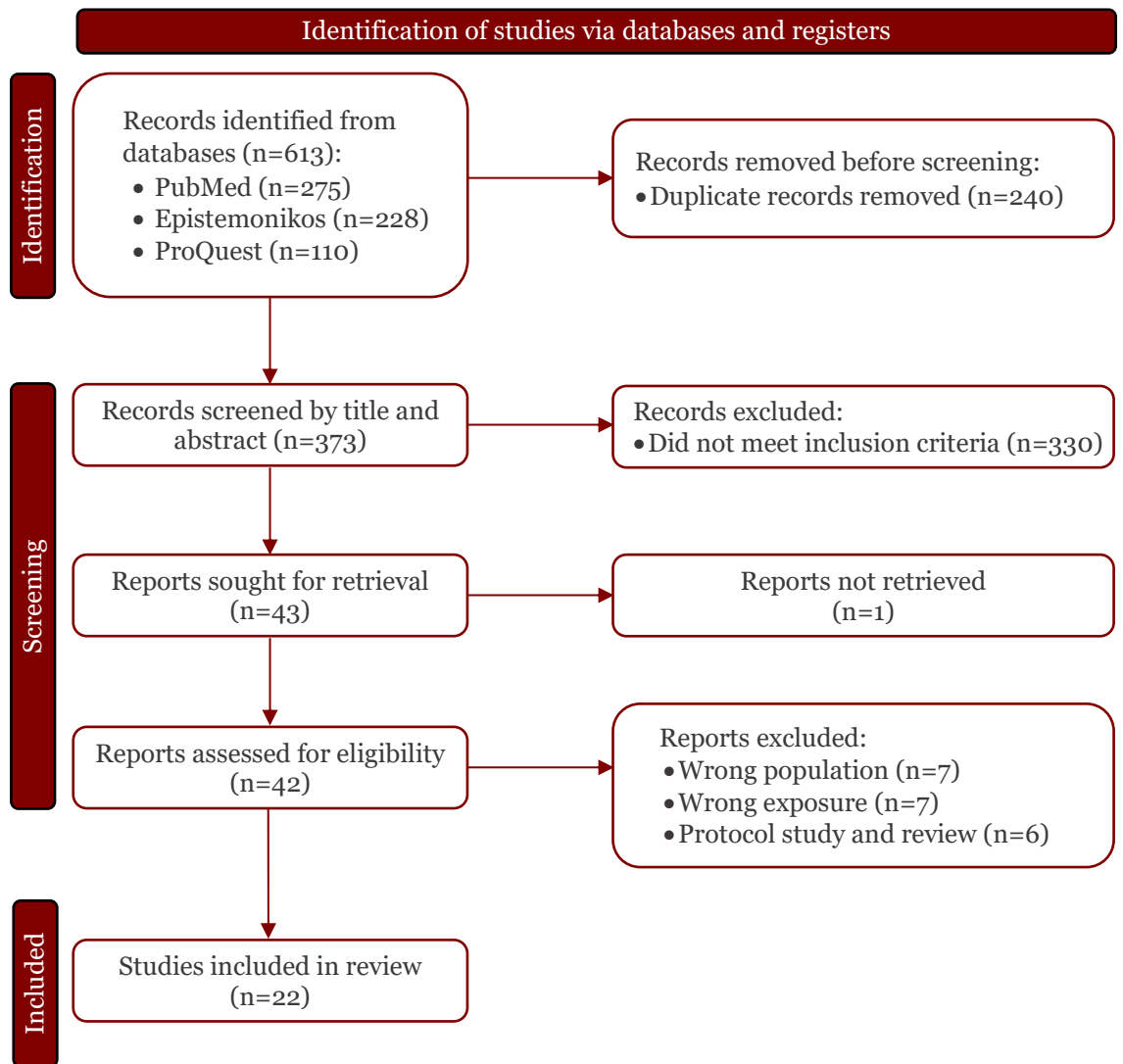


Figure 1. PRISMA 2020 flow diagram summarizing the study selection process.

Study characteristics

The 22 included studies were published between 2020 and 2025 and encompassed a range of study designs, including cross-sectional, case study, mixed-methods, and quasi-experimental studies [13,16-36]. Studies were conducted across 12 countries spanning four continents, with representation from Sub-Saharan Africa (Kenya, Nigeria, Ghana, South Africa, Tanzania), Asia (China, Indonesia, India, Philippines), South America (Brazil, Colombia), and the Middle East (Lebanon). Interventions evaluated included EMR and EHR systems (n=9), telemedicine (n=5), AI-assisted decision support (n=4), digital workflow tools and HIS (n=3), and multimodal digital health systems (n=1) [13,16-36]. A summary of study characteristics is presented in **Table 2**.

Quality assessment

The methodological quality of the 22 included studies (**Table 3**) was assessed using the JBI Critical Appraisal Checklist [14]. Overall, the included studies demonstrated high methodological quality. Most studies clearly defined their inclusion criteria, adequately described the study setting and participants, employed valid and reliable methods for measuring exposures and outcomes, and applied appropriate statistical analyses [13,16-36].

Table 2. Characteristics of included studies (n=22)

Author, year	Study design	Population	Country	Intervention	Main findings
Irfan <i>et al.</i> , 2024 [13]	Controlled simulation/proof-of-concept study	Doctors and patients, primary care	Indonesia	LLM-based real-time transcription and summarization into ePuskemas	LLM improved real-time medical documentation and patient interaction records
Wang <i>et al.</i> , 2024 [16]	Mixed-methods	Adults with chronic diseases	China	Online healthcare settings follow-up service	Improved access, reduced cost, and maintained quality in online follow-up visits
Della Ripa <i>et al.</i> , 2025 [17]	Mixed-methods	Obstetric care providers	Multiple African countries	AI-enabled obstetric point-of-care ultrasound	Positive provider feedback; AI-assisted ultrasound deemed feasible in resource-limited settings
Moreno-Fergusson <i>et al.</i> , 2021 [18]	Mixed-methods	Nurses in emerging economies	Colombia	Analytics and lean healthcare management tools	Lean management approaches improved workflow efficiency and nursing care management
Sari <i>et al.</i> , 2025 [19]	Mixed-methods	Geriatric patients	Indonesia	Telemedicine for outpatient follow-up	Telemedicine feasible and effective for geriatric follow-up in Indonesian clinics
Babatope <i>et al.</i> , 2024 [20]	Cross-sectional	Health professionals	Nigeria	EHR implementation assessment	Major barriers identified including insufficient infrastructure, training gaps, and resistance to change
Agyemang <i>et al.</i> , 2024 [21]	Cross-sectional	Health professionals	Ghana	LHIMS	Positive impact on health professional effectiveness; usability challenges noted
Onyeabor <i>et al.</i> , 2025 [22]	Cross-sectional	Health professionals, teaching healthcare settings	Nigeria	Digital healthcare system implementation	Challenges in usability identified; positive potential for healthcare delivery improvement
Feng <i>et al.</i> , 2025 [23]	Cross-sectional	Anesthesia providers	China	CDSS	Positive user feedback; mobile app-based CDSS improved perioperative decision-making
Hitti <i>et al.</i> , 2025 [24]	Case study	Emergency healthcare providers	Lebanon	EHR use during Beirut Port Blast (mass casualty event)	EHR system critical for coordinating care and managing records during mass casualty scenarios
Sucaldito <i>et al.</i> , 2025 [25]	Mixed-methods	Primary care health workers	Philippines	Health information systems in primary care clinics	Key gaps identified in primary care HIS; opportunities for system strengthening highlighted
Horwood <i>et al.</i> , 2023 [26]	Nested mixed-methods	Primary healthcare nurses, rural settings	South Africa	E-health technologies and CDSS	E-health tools show potential but face significant implementation challenges in rural contexts
Muinga <i>et al.</i> , 2020 [27]	Mixed-methods	Healthcare professionals, public healthcare settings	Kenya	Digital health systems	Digital health systems improved healthcare settings efficiency and service delivery in Kenyan public healthcare settings
Pillay <i>et al.</i> , 2021 [28]	Cross-sectional	Doctors, public healthcare settings	South Africa	Telephone clinics during COVID-19	Multiple barriers to telephone consultations identified during the COVID-19 pandemic
Mustafa <i>et al.</i> , 2025 [29]	Cross-sectional	Clinicians	Tanzania	LHIMS	ESIDA app well-accepted and effective in supporting outbreak surveillance
Mwogosi <i>et al.</i> , 2025 [30]	Cross-sectional	Healthcare professionals, public facilities	Tanzania	Electronic health record system adoption	Multiple barriers to EHR implementation identified in Tanzania's public health sector

Author, year	Study design	Population	Country	Intervention	Main findings
Prada <i>et al.</i> , 2024 [31]	Cross-sectional	Healthcare professionals, teaching healthcare settings	Colombia	Multidisciplinary telemedicine programme	Telemedicine program improved healthcare access and efficiency in a teaching healthcare settings context
Saleh <i>et al.</i> , 2025 [32]	Cross-sectional	Doctors, private-sector healthcare settings	India	Electronic Medical Records (EMR)	Key barriers to EMR adoption identified; benefits in documentation and communication acknowledged
Bin <i>et al.</i> , 2022 [33]	Quasi-experimental	Patients in urgent care (COVID-19)	Brazil	AI-assisted waiting time optimization	AI-assisted triage significantly reduced waiting times in an urgent care setting
Hosea Ojoh <i>et al.</i> , 2025 [34]	Cross-sectional	Healthcare professionals, federal healthcare settings	Nigeria	Electronic Medical Records (EMR)	EMR positively impacted staff satisfaction and overall service delivery
Lutz de Araujo <i>et al.</i> , 2020 [35]	Observational	Primary care physicians	Brazil	Telemedicine for ophthalmology (TeleOftalmo)	Telemedicine improved accessibility and specialist referral efficiency in primary care
Obong'o <i>et al.</i> , 2025 [36]	Mixed-methods	Clinicians	Kenya	EHR-integrated generative AI clinical decision support	Positive adoption trends for AI-based EHR decision support; usability and trust key facilitators

AI: artificial intelligence; CDSS: clinical decision support systems; EHR: Electronic Health Record; EMR: Electronic Medical Record; COVID-19: Coronavirus Disease 2019; HIS: Hospital Information System; LHIMS: Lightwave Health Information Management System; LLM: large language model

The most commonly unmet JBI criteria involved the identification of potential confounding factors, the implementation of strategies to address confounding, and the use of objective, standardized criteria for outcome measurement. These findings indicate that the included studies were methodologically robust and provide a reliable evidence base for the conclusions of this systematic review. A summary of quality assessment results is presented in **Table 3**.

Table 3. Methodological quality assessment of the included studies using the Joanna Briggs Institute (JBI) Critical Appraisal Checklist [14]

Author/year	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Total (yes)	Methodological quality
Irfan <i>et al.</i> , 2024 [13]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8/8	High
Wang <i>et al.</i> , 2024 [16]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8/8	High
Della Ripa <i>et al.</i> , 2025 [17]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	7/8	High
Moreno-Fergusson <i>et al.</i> , 2021 [18]	Yes	Yes	Yes	No	No	Yes	Yes	Yes	6/8	High
Sari <i>et al.</i> , 2025 [19]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8/8	High
Babatope <i>et al.</i> , 2024 [20]	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	7/8	High
Agyemang <i>et al.</i> , 2024 [21]	Yes	Yes	Yes	No	Yes	No	Yes	Yes	6/8	High
Onyeabor <i>et al.</i> , 2025 [22]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8/8	High
Feng <i>et al.</i> , 2025 [23]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	7/8	High
Hitti <i>et al.</i> , 2025 [24]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8/8	High
Sucaldito <i>et al.</i> , 2025 [25]	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	7/8	High
Horwood <i>et al.</i> , 2023 [26]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8/8	High
Muinga <i>et al.</i> , 2020 [27]	Yes	Yes	Yes	No	Yes	Yes	No	Yes	6/8	High
Pillay <i>et al.</i> , 2021 [28]	Yes	Yes	Yes	Yes	Yes	No	No	Yes	6/8	High
Mustafa <i>et al.</i> , 2025 [29]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8/8	High
Mwogosi <i>et al.</i> , 2025 [30]	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	7/8	High
Prada <i>et al.</i> , 2024 [31]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8/8	High
Saleh <i>et al.</i> , 2025 [32]	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	7/8	High
Bin <i>et al.</i> , 2022 [33]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	7/8	High
Hosea Ojoh <i>et al.</i> , 2025 [34]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8/8	High
Lutz de Araujo <i>et al.</i> , 2020 [35]	Yes	Yes	Yes	Yes	No	Yes	No	Yes	6/8	High
Obong'o <i>et al.</i> , 2025 [36]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8/8	High

JBI: Joanna Briggs Institute; Q1: inclusion criteria clearly defined; Q2: study participants and setting described in detail; Q3: exposure measured validly and reliably; Q4: objective, standard criteria used for outcome measurement; Q5: confounding factors identified; Q6: strategies to address confounding stated; Q7: outcomes measured validly and reliably; Q8: appropriate statistical analysis used.

Summary of evidence (GRADE assessment)

The certainty of evidence for the main outcomes was evaluated using the GRADE approach in **Table 4**. Overall, the certainty of evidence ranged from very low to moderate, reflecting the predominance of observational and mixed-methods study designs among the included studies. Moderate-certainty evidence was identified for reduction in administrative burden and improvement in patient flow, indicating that technology integration consistently reduced documentation workload, streamlined administrative processes, and improved patient coordination and waiting times across multiple healthcare settings. Conversely, very low-certainty evidence was observed for improvement in workforce efficiency, staff satisfaction and burnout reduction, quality of care, and technology-related safety outcomes, primarily due to methodological limitations, heterogeneity of interventions, and the observational nature of the available evidence.

Despite the generally low-to-moderate certainty, the findings consistently favored technology integration. Across the included studies, digital health technologies—including electronic health records, telemedicine, clinical decision support systems, artificial intelligence, and mobile health applications—were associated with improved workforce productivity, enhanced task allocation, reduced administrative burden, better patient flow, increased staff satisfaction, and improved clinical decision-making. Furthermore, technology-related adverse events were generally minor and transient, suggesting a favorable safety profile.

Table 4. Summary of evidence and GRADE assessment

Outcome	Evidence source (key studies)	Direction of effect	Number of studies	Study design	Certainty (GRADE)	Summary of findings
Improvement in workforce efficiency	[16]; [17]; [18]; [23]; [24]; [25]; [27]; [31]	Favors technology integration	8	Cross-sectional, mixed-methods, case study	⊕○○○ Very low	Technology integration consistently improves workforce productivity, task allocation, and overall operational efficiency.
Reduction in administrative burden	[16]; [22]; [27]; [28]; [29]; [34]; [35]	Favors technology integration	7	Mixed-methods, cross-sectional, observational	⊕⊕⊕○ Moderate	Consistent reduction in time spent on documentation and administrative tasks across diverse settings.
Improvement in patient flow	[18]; [21]; [27]; [30]; [33]	Favors technology integration	5	Mixed-methods, quasi-experimental, cross-sectional	⊕⊕⊕○ Moderate	AI-assisted scheduling and telemedicine were associated with reduced waiting times and improved patient coordination.
Staff satisfaction and burnout reduction	[22]; [23]; [26]; [32]; [34]	Favors technology integration	5	Cross-sectional, nested mixed-methods	⊕○○○ Very low	Technology was associated with improved staff satisfaction; burnout reduction was contingent on adequate training and effective change management.
Quality of care	[13]; [19]; [21]; [27]; [29]	Favors technology integration	5	Controlled simulation/proof-of-concept, mixed-methods, cross-sectional	⊕○○○ Very low	Technology-enabled documentation and clinical decision support were associated with fewer errors and improved clinical decision-making.
Safety (adverse events related to technology)	[18]; [20]; [21]; [35]; [36]	Favorable safety profile	5	Mixed-methods, cross-sectional, observational	⊕○○○ Very low	Technology interventions demonstrated a favorable safety profile; adverse events were generally minor and transient across the included studies.

CDSS: clinical decision support system; EHR: electronic health record; EMR: electronic medical record; GRADE: Grading of Recommendations Assessment, Development and Evaluation; GRADE certainty symbols: ⊕⊕⊕⊕: high certainty; ⊕⊕⊕○: moderate certainty; ⊕⊕○○: low certainty; ⊕○○○: very low certainty

Discussion

This systematic review synthesized the available evidence regarding healthcare technology integration for workforce optimization in MICs. The findings suggest that digital health technologies have considerable potential to improve healthcare workforce performance by enhancing operational efficiency, reducing administrative workload, facilitating clinical coordination, and optimizing patient flow. Across diverse healthcare settings, technologies such as EMRs, EHRs, HISs, telemedicine platforms, CDSSs, mobile health applications, and AI-based tools consistently demonstrated positive effects on healthcare delivery and workforce productivity [16-18]. Similar benefits were observed in studies evaluating digital workflow innovations that supported more efficient communication, information sharing, and clinical decision-making across multidisciplinary healthcare teams [19-21]. Additional evidence indicated that technology integration contributed to more efficient resource utilization and strengthened organizational performance despite the resource constraints commonly experienced in MIC healthcare systems [22-24].

Electronic record systems, including EMRs, EHRs, and HISs, were the most frequently investigated technologies among the included studies. These platforms consistently improved documentation quality, enhanced access to patient information, facilitated communication among healthcare professionals, and reduced repetitive administrative tasks that often consume substantial clinical time [25]. Improved availability of electronic clinical information also enabled healthcare providers to retrieve patient records more efficiently, reducing duplication of work and supporting continuity of care [26-28]. However, implementation success was not universal. Several studies reported barriers including inadequate interoperability between existing information systems, workflow disruption during early implementation, limited technical support, insufficient infrastructure, and resistance from healthcare professionals adapting to new digital workflows [29-30]. These findings indicate that successful implementation depends not only on the technology itself but also on organizational preparedness and the ability to integrate digital systems into routine clinical practice.

Telemedicine emerged as an effective strategy for addressing workforce shortages and improving healthcare accessibility, particularly in geographically underserved and resource-limited settings. Studies included in this review demonstrated that telemedicine reduced geographical barriers to specialist consultation, shortened referral pathways, improved patient coordination, and decreased unnecessary hospital visits [31,35]. Other investigations reported that telemedicine contributed to shorter waiting times, more efficient allocation of healthcare resources, and greater flexibility in service delivery, particularly during periods of high patient demand [33]. Nevertheless, several studies emphasized that successful telemedicine implementation remained dependent on stable internet connectivity, adequate digital infrastructure, supportive reimbursement policies, and sufficient digital literacy among healthcare professionals and patients [34]. Without these enabling conditions, the potential workforce benefits of telemedicine may not be fully realized.

Artificial intelligence and clinical decision support systems represented emerging technologies with promising applications for workforce optimization. AI-assisted triage systems were associated with improved patient prioritization and reductions in waiting times, thereby allowing healthcare professionals to manage patient flow more efficiently [33]. Likewise, AI-enabled documentation tools and large language model-based clinical documentation systems demonstrated the potential to reduce documentation burden by automatically transcribing and summarizing clinical encounters, enabling clinicians to dedicate more time to direct patient care. Mobile CDSS applications further supported evidence-based clinical practice by providing rapid access to standardized recommendations and improving adherence to clinical guidelines [23]. Although these findings are encouraging, current evidence remains preliminary because most AI-related studies consisted of observational investigations, pilot implementations, or early implementation evaluations with relatively short follow-up periods. Consequently, evidence regarding long-term effectiveness, sustainability, cost-effectiveness, and patient outcomes remains limited [13,36].

An important finding across the included studies was that organizational readiness substantially influenced implementation success. Healthcare institutions with strong leadership

commitment, adequate financial investment, reliable digital infrastructure, structured implementation planning, and continuous technical support consistently achieved higher adoption rates and more favorable workforce outcomes. Conversely, organizations experiencing unstable internet connectivity, inadequate hardware, poor interoperability, insufficient workforce training, and limited organizational support frequently reported implementation difficulties that reduced the effectiveness of digital technologies [13]. These findings emphasize that technology should not be considered a standalone solution for workforce optimization but rather one component of a comprehensive organizational transformation strategy requiring supportive governance, infrastructure, and implementation planning.

Human factors were equally important determinants of successful technology adoption. Several studies reported that healthcare professionals initially experienced increased workload, implementation fatigue, uncertainty, and resistance during the early stages of digital transformation [22-24]. These challenges were generally temporary and became less prominent when implementation strategies incorporated stakeholder engagement, user-centered system design, iterative feedback, and structured education and training programs [25]. Moreover, involving frontline healthcare workers throughout system development and implementation improved technology acceptance and promoted smoother integration into existing clinical workflows [30]. These findings reinforce the importance of considering behavioral and organizational factors alongside technological innovation when implementing digital health interventions.

The review also suggests that healthcare technology integration may positively influence workforce well-being under appropriate implementation conditions. Several studies reported improvements in staff satisfaction, enhanced communication among healthcare teams, and reductions in perceived administrative burden following successful implementation of digital technologies [31-33]. These improvements were primarily attributed to reductions in repetitive documentation, more efficient information management, and streamlined clinical workflows that allowed healthcare professionals to focus more on patient care. However, positive effects on staff satisfaction were not consistently observed across all settings, with benefits appearing strongly dependent on implementation quality, institutional support, workforce engagement, and the adequacy of training provided during system adoption [13,34-36].

Although few serious technology-related adverse events were reported, the certainty of evidence regarding safety remains limited. Most included studies primarily evaluated implementation processes, user experiences, or operational outcomes rather than patient safety indicators. Furthermore, safety outcomes were frequently self-reported and assessed over relatively short follow-up periods, limiting the ability to detect uncommon or delayed adverse events. Consequently, the absence of substantial reported harms should not be interpreted as definitive evidence of long-term safety. Future implementation studies should incorporate standardized patient safety indicators, prospective monitoring, and robust reporting frameworks to better evaluate the long-term safety implications of healthcare technology integration.

Several limitations should be considered when interpreting the findings of this review. First, most included studies employed observational, cross-sectional, or mixed-methods designs, limiting causal inference and resulting in predominantly low-to-moderate certainty of evidence according to the GRADE assessment. Second, considerable heterogeneity existed across healthcare technologies, implementation strategies, healthcare settings, and outcome measures, precluding quantitative meta-analysis. Third, many studies relied on self-reported outcomes, introducing the possibility of recall, reporting, and social desirability biases. Therefore, future research should prioritize well-designed prospective and multicenter studies with longer follow-up periods to evaluate the long-term effectiveness, sustainability, and cost-effectiveness of healthcare technologies. Standardized workforce and quality-of-care outcome measures should also be adopted to improve comparability across studies. Additionally, future investigations should focus on implementation strategies that address infrastructure readiness, interoperability, workforce training, ethical governance, and equitable access to ensure that digital transformation contributes to resilient, efficient, and sustainable healthcare systems in middle-income countries.

Conclusion

Healthcare technology integration has the potential to enhance workforce optimization in MICs. However, its effectiveness is likely influenced by factors such as infrastructure preparedness, workforce competency development, and institutional support capacity. Further research using longitudinal and technology-specific approaches with standardized outcome indicators is needed to strengthen the current evidence base.

Ethics approval

Not required.

Acknowledgments

The authors extend their sincere gratitude to Dr. Zoel Hutabarat for his expert guidance and supervision throughout this systematic review.

Competing interests

The authors declare no competing interests regarding the conduct or publication of this study.

Funding

No external funding was received for this study.

Underlying data

Derived data supporting the findings of this study are available from the corresponding author on request.

Declaration of artificial intelligence use

Artificial intelligence (AI)-based language tools, including ChatGPT, were used to assist with language refinement, readability improvement, and manuscript structuring. All AI-assisted outputs were critically reviewed, revised, and validated by the authors, and all final interpretations and conclusions remain the sole responsibility of the authors.

How to cite

Syifa RSA, Akram M, Hutabarat Z. Navigating technology integration for workforce optimization in healthcare settings: A systematic review of strategies, barriers, and outcomes from middle-income countries. Narra X 2026; 4 (2): e275 - <http://doi.org/10.52225/narrax.v4i2.275>.

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