Enhancing Human Resource Management in Healthcare: Integrating AI for Improved Work Efficiency and Reduced Burnout

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Abstract
Burnout among healthcare professionals continues to be a critical issue worldwide, affecting their psychological well-being, job satisfaction, and care quality. The integration of artificial intelligence (AI) in healthcare has emerged as a strategic solution to enhance human resource management (HRM) by improving work efficiency and reducing burnout. This systematic review searched recent literature from PubMed, ScienceDirect and Google Scholar including AI-related studies that measured burnout reduction or work efficiency among healthcare workers. The result showed the large language model was the most frequently applied approach across 13 countries. Burnout reduction via AI is most effective when systems are integrated with behavior-sensitive feedback or designed to offload documentation. AI's impact on work efficiency is well-supported such as time reduction and improved scheduling. Efficiency-focused AI interventions tend to yield faster observable benefits. Key challenges including system integration, clinician trust, interpretability of AI decisions, and ethical concerns. These findings offer valuable guidance of practical AI in healthcare that can support sustainable HRM practices by improving time efficiency, promoting workforce well-being, and maintaining care quality.

Keywords:
Artificial intelligence; Burnout; Healthcare; Human Resource Management; Work efficiency.

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INTRODUCTION

The Quadruple Aim in healthcare is an expansion of the previous Triple Aim framework, which consists of three goals: improving population health, reducing the rising cost of care, enhancing the patient’s experience of care and healthcare team well-being (Bodenheimer & Sinsky, 2014). This major challenge in human resource management (HRM) to continuously develop strategies that meet the growing global demand for healthcare (Joshi et al., 2024). One of the most strategies widely undertaken around the world is the integration of artificial intelligence (AI) (Sarraf & Ghasempour, 2025).

Artificial intelligence, the combination of science and engineering in intelligent algorithms, could mimics human cognitive functions, including learning and problem solving. Recognizing patterns and relationships from multidimensional datasets is the main capability of AI which is dynamic and autonomous. This technology represents several subfields as universal intelligence that has the potential to adapt through supply-and-demand challenges in healthcare (Bajwa et al., 2021). AI has become part of the healthcare 5.0 transformation, a significant evolution from Healthcare 4.0 (Raisa et al., 2025). This represents a shift toward a patient-centric approach to healthcare delivery, emphasizing personalized services by using advanced technologies one's life (Mbunge et al., 2021).

Despite its development over the past few decades, the adoption of AI in clinical practice on a global scale may still be far from reality. Many AI products for healthcare are still at the design and development stage. According to Wiens et al. (2019), this stage is still the beginning of building effective and reliable AI-augmented healthcare systems. There are still three further stages that need to be passed: Stage 2: Evaluate and validate the system and its utility statistically, clinically, and economically; Stage 3: Diffuse and Scale, which means policy design, development, and reimbursement system development; and Stage 4: Monitor and Maintain, including regular safety and performance assessments. Bajwa et al., (2021) suggest that AI systems in healthcare should be built without replacing the essential elements of the human interaction but rather to focus on its efficiency and effectiveness of that interaction. Therefore, AI integration in healthcare would operate with a human-centered approach to providing appropriate solutions to existing problems and understanding the complexity of patient care pathways.

Furthermore, traditional HRM remains a persistent challenge in healthcare organizations. It can be laborious, resource-intensive, and often inadequate in addressing the sector’s high workload demands (Dwivedi et al., 2021). The underlying concept is that every employee is a human, not a machine, and not merely a business resource. Effective human resource management is essential to enhance workforce efficiency within organizations while maintaining the well-being of employees (Chowhan et al., 2017). Ineffective management in balancing employee responsibilities has led to increased job demands, multitasking requirements, and the creation of stressful work environments (Marković et al., 2024). Consequently, elevated levels of stress, overwhelming feeling and burnout, which have detrimental effects on their emotional, mental, and physical well-being (Calhoun et al., 2020). In other words, the occurrence of burnout inevitably reduces employee motivation, job satisfaction, and work engagement, thereby disrupting the overall effectiveness of healthcare services.

The rapid evolution of AI as part of the technological transformation in healthcare presents a significant opportunity to enhance HRM. Artificial intelligence has a substantial impact on reducing the workload of employees and enhancing their engagement. It can mitigate repetitive and manual administrative tasks, providing practical solutions for completing complex duties efficiently while reducing burnout levels (Bundy et al., 2024; Cho et al., 2024; Sarraf & Ghasempour, 2025). Many clinical settings have begun adopting intelligent systems to assist in consultations, diagnosis, patient management, and health monitoring (Laing & Mercer, 2021; Petry et al., 2022; Ziegelmayer et al., 2022; Zielonka et al., 2025). By alleviating routine work and optimizing care services, this augmented technology have the potential to reduce inefficiencies, improve patient experiences, and enhance caregiver well-being which bringing healthcare closer to a more sustainable and balanced human resource management system (Bajwa et al., 2021).

However, despite various applications of these systems in both clinical and administrative environments, there is still no thorough synthesis of evidence showing how AI directly affect HRM through burnout reduction and work efficiency outcomes. A recent randomized controlled trial among nurses demonstrated that a tailored intervention using technology reduced personal and patient-related burnout significantly, but it did not fully explore work efficiency metrics such as task completion time or documentation burden (Omranian et al., 2025). Another review focusing on technologies related to electronic health records found positive effects on reducing burnout and improving workflow, but noted serious limitations such as small sample sizes and lack of follow-ups (Sarraf & Ghasempour, 2025). Therefore, this systematic review aims to critically examine existing studies on enhancing human resource management in healthcare, focusing on its effectiveness in reducing burnout and improving work efficiency, as well as identifying implementation barriers and potential strategies for optimization.

RESEARCH METHOD

Study Design

A systematic review design is used in this study. It aims to critically identify, appraise, and synthesize existing studies from several databases related to the topic. The review focuses on summarizing published evidence exploring the effectiveness, challenges, and potential strategies associated with leveraging artificial intelligence (AI) in healthcare human resource management, particularly its role in mitigating burnout and enhancing work performance. This study was conducted using a design based on The SPIDER Research Question as below.

Table 1.
SPIDER Framework

Sample (S)	Healthcare professionals
Phenomenon of Interest (PI)	Application of various types of AI in healthcare settings,
Design (D)	Systematic review
Evaluation (E)	Burnout reduction and improvements in work efficiency
Research type (R)	Qualitative research

Source: Author(s) work

Study Design

A comprehensive search for relevant studies was conducted from August 23 to October 15, 2023. This review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines for systematic reviews and integrates inclusion criteria adapted from the SPIDER framework. The inclusion criteria were defined as follows.

- Study design: Observational and quasi-experimental studies.
- Study variables: Studies that examined artificial intelligence (AI) as the independent variable (intervention) and burnout reduction and/or work efficiency as the dependent outcomes in healthcare settings.
- Time and setting: Studies published between 2015 and May 2025, with no country restrictions, were eligible for inclusion

The literature search was performed across multiple databases, including PubMed, ScienceDirect, and Google Schoolar. Search strategies were customized for each database using Boolean operators (AND, OR) to ensure comprehensive coverage. The primary search string included key terms and their synonyms such as “Artificial Intelligence”, “Healthcare”, “Burnout”, and “Work Efficiency”, which were refined according to each database’s indexing system and aligned with the study objectives

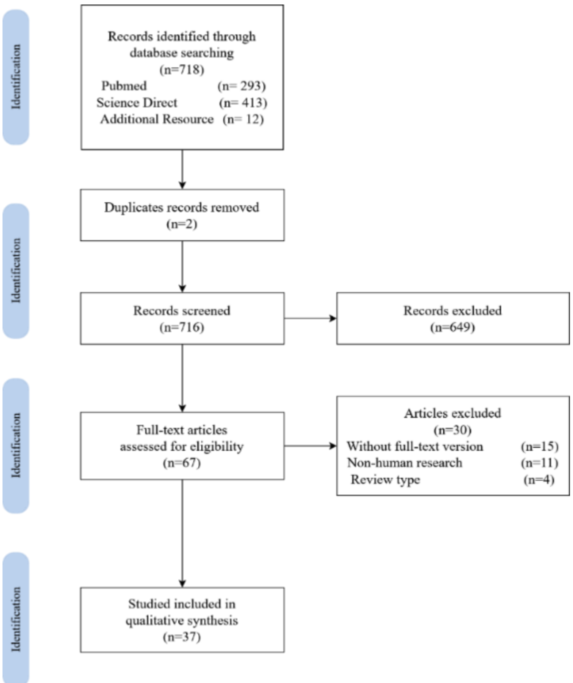
Critical Appraisal Tools

Studies that passed the screening stage were assessed for quality using the Joanna Briggs Institute (JBI) Critical Appraisal Tools, according to the appropriate study design. Consequently, two types of JBI critical appraisal tools were employed in this review, one for observational studies and another for quasi-experimental studies. Reviewers independently appraised each included study using the relevant JBI checklist to evaluate potential sources of bias, methodological rigor, and overall validity. The results of the quality appraisal were used to inform the interpretation of findings; however, no studies were excluded solely based on their quality scores

Data Screening and Framework

The comprehensive screening pathway of this review is illustrated in the PRISMA flow diagram (Figure 1). A total of 718 articles were identified across multiple databases, and 2 duplicates were removed. Following the identification phase, the remaining studies were reviewed in detail to confirm their eligibility, particularly regarding the influence of artificial intelligence (AI) on burnout reduction and work efficiency. During the screening process, 30 studies were excluded for not meeting the inclusion criteria, resulting in 37 studies being included in the final review. Data from the included studies were extracted based on key characteristics, including author and publication year, study design and country of origin, type of AI utilized, reported challenges, and suggested directions for future research. All extracted data are presented in a summary table, which serves as the main reference for the qualitative synthesis and as the basis for drawing conclusions, including the quality assessment of each study.

Figure 1.
Prisma Flow



Source: Author(s) work

FINDINGS AND DISCUSSION

Characteristics of Included Studies

By Years

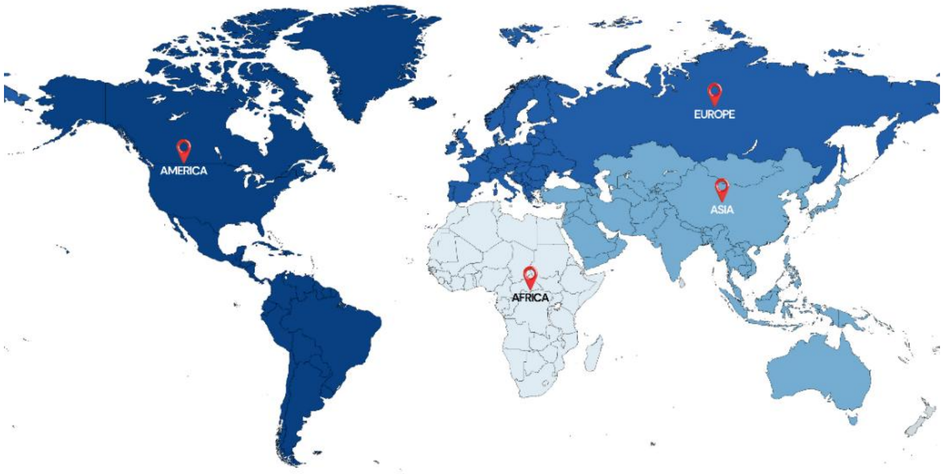
The recent research trend on the contribution of AI to burnout reduction and work efficiency among healthcare professionals has shown a continuous increase over the past decade. The year 2024 had the most publications, followed by a notable rise in mid-2025, when this review was conducted (Table 2). Most studies primarily focused on work efficiency, followed by burnout reduction, while a smaller number explored both outcomes simultaneously. Xie et al., (2025) emphasized that artificial intelligence has provided a significant boost in healthcare. Furthermore, a growing global trend in AI research within the medical field has been reported, from only 15 publications in 1995 to 310 in 2015, and reaching 5,297 publications by 2023.

By Country

Various countries have made valuable contributions to their respective research. Figure 2 shows the global distribution of published studies, with darker areas representing regions where more studies have been conducted. Based on the continent, America has the largest contribution, with 14 studies from the United States and 3 from Canada. Asia ranks second with 12 studies, including 5 from China, 2 from South Korea, and one study each from Taiwan, Vietnam, India, Australia, and Iran. Europe contributed 6 studies, originating from Switzerland, Poland, the Netherlands, Germany, and Italy. Finally, South Africa only includes 1 study. This pattern aligns with the trend reported by Xie et al. (2025) where the United States, China, and the United Kingdom top the list for AI research in healthcare. Additionally, one multinational study by Bharadwaj et al., (2024) was conducted collaboratively in the United States and Germany.

Figure 2.

Global Distribution of AI in Healthcare Studies



Source: Author(s) work

By Study Quality

Most of the included studies demonstrated good methodological quality. Twenty-seven studies were appraised using the JBI Checklist for observational studies, while ten studies employed the quasi-experimental checklist. Among the observational studies, moderate scores (4–6 out of 8 points) were observed in eight studies. This was mainly due to the lack of assessment for confounding factors (Q5 and Q6). Some studies also did not employ validated outcome measures (Q7), which may affect the reliability of their findings (Table 3). On

Table 2.
Characteristics of Included Studies

Author, Year	Country	AI Type	Key Finding	Challenges
Evidence Related with Burnout Reduction After AI Integration in Healthcare Settings				
Huo et al. (2025)	China	AI-assisted diagnostic	AI use indirectly enhances work well-being via psychological needs satisfaction (*β = 0.236, p < 0.01*). - Job complexity weakens autonomy/ competence satisfaction links (*β = -0.13, p < 0.05*).	High-complexity tasks reduce AI effectiveness Limited diagnostic accuracy for patient demographics. Physicians spend extra time verifying AI outputs (qualitative data).
Omranian et al. (2025)	USA	LLM (LLaMA 3), NLP	From 1501 narrative responses, 52.2% showed emotional exhaustion, 17.1% depersonalization, and 30.7% inefficacy. The AI classifier achieved micro-F1 of 0.91, macro-F1 of 0.89 for burnout detection. Burnout prevalence was significantly associated with perceived COVID-19 risk (OR 2.3, 95% CI 1.8–2.9).	Requires large annotated datasets; reliance on self-expressed language.
Nan et al. (2024)	USA	ML (N-of-1 models)	MAPE = 24.3% (wellbeing) and 13.6% (empathy), with anxious/depressed mood as top predictors (SHAP analysis). Wellbeing-empathy bidirectional prediction (64% cases).	Small sample size (*n* = 12); limited generalizability due to idiographic approach
Owens et al (2024)	USA	DAX™	lower burnout measured by Oldenburg Burnout Inventory (OLBI) disengagement sub-score (mean difference [MD] − 2.1; 95% confidence interval [CI]: −3.8 to −0.4); no significant differences in the OLBI exhaustion sub-score (MD − 1.0; 95% CI: −2.9 to 1.0) or the total OLBI score (MD − 3.0; 95% CI: −6.4 to 0.3); reduction in documentation time by 28.8% (1.8 min; 95% CI: 1.4 to 2.2)	Short follow-up; self-selection bias; unidentified confounders; generalizability to other primary care cohorts (limitation); predicting the provider characteristics for high adoption

Guo et al. (2024)	China	ML classifiers (GBT, RF, SVM, LR) for burnout prediction	Gradient boosting trees (GBT) achieved the highest predictive performance (AUC = 0.821; accuracy = 73.9%) for burnout among 1235 nurses. Key predictors included job crafting and leisure activities, providing empirical support for precision-targeted well-being strategies.	Model transparency issues; generalizability limited by cultural/workplace factors.
Cho et al (2024)	South Korea	Nurse Healing Space	Significant burnout reduction after 2 and 4 weeks: $t = 7.012$, $P < .001$ and $t = 2.811$. Also reduced job stress ($t = 6.765$, $P < .001$) and stress responses ($t = 5.864$, $P < .001$).	App limitations included lack of notification system, limited customization, and moderate usability score (3.4/5).
Li et al (2024)	Australia	NLP & sentiment analysis on Twitter posts	Observed a shift to negative sentiment and high affect word use to identify increased burnout signals among younger nurses post-COVID.	Inferred outcomes from unstructured social media data without validated clinical instruments. Demographic verification was partially manual
Li et al. (2023)	China	ML (LR, RF, SVM)	LR model achieved AUC = 0.904 (test set), identifying sleep disturbance (OR = 2.1, $p < 0.001$) and chronic fatigue (OR = 3.4, $p < 0.001$) as key predictors.	N/A
Gupta et al. (2021)	India	ECG-based ML (Extra Tree Classifier)	Model AUC = 0.84; lower RMSSD/SDNN in burnout ($p < 0.001$). Chaotic work environment increased burnout risk (OR = 2.09, 95% CI: 1.14–3.85).	Single-item burnout measure (Mini-Z) may lack depth; HRV confounded by physical activity.
Ganeshan et al. (2020)	USA	AI-assisted workload distribution	Burnout scores in radiology decreased by 22% (OR = 1.9, 95% CI: 1.4–2.6) post-AI integration.	Self-reported burnout data (recall bias). may not apply to high-volume private practices.
Evidence Related with Work Efficiency After AI Integration in Healthcare Settings				
Renggli et al. (2025)	Switzerland	MIP, CP, RL, GA	Focus group ($n = 21$) revealed 85% emphasized fairness and 76% autonomy in scheduling. AI-MIP implementation in a 35-staff unit reduced last-minute shift changes by 30% and increased scheduling satisfaction, but did not include burnout as a measured variable.	Low interpretability of AI decisions; human trust in algorithmic fairness still developing; hybrid implementation preferred.
Zielonka et al. (2025)	Poland	AI diagnostic decision	Reduced ED decision time and increased triage precision	Unclear accountability in decision-making; AI performance highly

				dependent on local protocols.
Gustafson et al (2025)	USA	LLM (ChatGPT)	Many agreed that AI could enhance efficiency and productivity in their field (64.1%), with 21.1% strongly agreeing	Geographic bias
Allen et al. (2024)	USA	AI diagnostics, administrative	AI improved efficiency (e.g., reduced inbox burden) but risked workload escalation (70% feared "more work").	Participants reported differing interpretations of AI.
Barak-Corren et al (2024)	USA	ChatGPT-4	ChatGPT reduced documentation time by up to 43% in complex cases and decreased perceived effort by 33%. Summaries were completeness 7.6/10, readability 8.7/10	LLM sometimes missed critical negatives. Clinicians concern over lack of differential diagnosis and medicolegal accountability
Pavuluri et al. (2024)	USA	AI workflow	Early evidence showed 2.7× improvement in documentation efficiency.	Ethical risk if misapplied.
Miao et al. (2024)	USA	LLM (ChatGPT)	ChatGPT outperformed traditional dictation and typing in documentation quality. discharge summaries and consent forms were rated higher in completeness and empathy.	HIPAA compliance concerns; accuracy verification still human-dependent; ethical questions around authorship and disclosure.
Bharadwaj et al. (2024)	USA & Germany	Calantic (AI-powered radiology diagnostic)	451% ROI over 5 years, with 145 days saved in workflow tasks (e.g., 78-day reduction in triage time). Efficiency quantified via labor time savings and revenue increases ($3.56M revenue vs. $1.78M costs).	Limited to stroke-accredited hospitals. Dependency on scan volume and reimbursement rates.
Moryousef et al (2024)	Canada	ScribeMD, Heidi, Scribeberry, Tali, Nabla	clinical documentation as a significant source of burnout (75% of the respondents); 90% reported openness to using AI scribes; Nabla performed the best (with a favorable score of 68% and lowest critical error score of 28%);	Documentation accuracy; automation bias; medico-legal and privacy concerns; multicultural and multilinguistic considerations (e.g., different accents, dialects, and languages)
Champendal et al. (2024)	Switzerland	AI denoising algorithms	Focus groups with Nuclear Medicine Technologists (NMTs) revealed AI improved workflow efficiency (50% reduction in acquisition time, 30–50% lower radiotracer use). Barriers included workload increases (e.g., "assembly-line" workflows) and resistance due to lack of AI	IT infrastructure challenges

			literacy. Facilitators: training, "local champions," and interoperability.	
Liao et al. (2024)	Taiwan	Generative AI assistant (A+ Nurse)	The A+ Nurse platform enhanced communication and clinical documentation through real-time summarization. Improvements in care coordination and efficiency	Limited adaptability across specialties; lack of regulation for AI-generated content.
Baek et al. (2024)	South Korea	NLP (BERT)	BERT reduced triage time from 10.3 to 7.2 minutes per case ($p < 0.001$). Classification accuracy improved to 91.3%; inter-rater agreement rose to $\kappa = 0.87$. Physician satisfaction improved significantly (mean 4.3 vs. 3.7, $p = 0.02$).	Physician concern over over-reliance; requires model retraining for rare cases; interpretability limitations.
Van Zyl-Cilliers et al. (2024)	South Africa	AI-staffing prediction model	Patient wait time decreased by 23% with predictive workforce modeling. Improved inter-team coordination reported	Limited infrastructure in low-resource settings; dependency on continuous data input.
Laplante et al. (2023)	USA	AI-guided laparoscopic cholecystectomy (GoNoGoNet)	AI improved dissection accuracy (F1 score = 0.83) and reduced operative time by 18% ($p < 0.05$).	Dependency on high-quality endoscopic imaging; poor performance in low-resource settings.
Li (2023)	China	Chatbots	Reduced triage time by 30% ($p < 0.01$) and improved diagnostic accuracy (F1 score: 0.82) in gastroenterology.	Lack of systems. Limited generalizability. Ethical concerns about AI replacing human judgment.
Mascagni et al. (2022)	Italy	Deep learning for critical view of safety in cholecystectomy	AI improved critical view of safety (CVS) identification accuracy to 95% (IoU = 0.71), reducing intraoperative errors by 40% ($p < 0.001$)	performance dropped in cases with severe inflammation (15% false negatives)
Laing & Mercer (2021)	Canada	Clinical Decision Support System (CDSS) for preventive care	CDSS saved 195.7s per chart review ($p < .001$), extrapolated to 82.6 annual hours saved. No impact on decision accuracy (78.4% vs. 80.9%, *$p = 0.41$*). High perceived usefulness (mean score: 6.69/7).	Interface concerns (e.g., confusing date formats); the inherent trust in the CDSS; data accuracy concerns; layout usability
Dang et al. (2021)	Vietnam	Digital health platforms	EHR integration improved workflow efficiency (time savings: 40%; $p < 0.05$). Qualitative feedback highlighted reduced administrative burden	Fragmented health IT infrastructure. Low digital literacy among rural providers. Privacy concerns with centralized data.
Vafaeezadeh et al. (2021)	Iran	Deep Convolutional	AUC = 0.99 (matching cardiologist performance). EfficientNetB3 (A4C	Limited differentiation between bioprosthetic and mechanical valves

		Neural Network (DCNN)	view) and EfficientNetB4 (PLA view) achieved >99% accuracy (F1-score = 0.9996). Ensemble models reached 100% accuracy. Time savings: Automated analysis reduced manual interpretation	(grouped as "prosthetic"). Computational cost of ensemble models. 4. Generalizability to 3D echocardiography or other views (A2C, A3C) untested
van Leeuwen et al. (2021)	Netherlands	AI for vessel occlusion detection in stroke	€2,100 savings per patient (95% CI: €1,800–€2,400). 25% reduction in interpretation time (p < 0.001).	Assumed linear time savings may not reflect real-world workflow disruptions. 4. Ethical concerns about over-reliance on AI
Evidence Related with Burnout Reduction and Work Efficiency After AI Integration in Healthcare Settings				
Shah et al (2025)	USA	DAX Copilot	Large statistically significant reductions in task load (−24.42, p < 0.001) and burnout (−1.94, p < 0.001); moderate statistically significant improved usability (+10.9, p < 0.001); positive utility outcomes	Recruitment; integration with existing workflows; rapid technological progression; diverseness of fi
Albrecht et al. (2025)	USA	Ambient AI (Abridge) for clinical documentation	Improved workflow ease (*OR = 6.91, p < .001*) and timely note completion (*OR = 4.95, p < .001*). 67% reported reduced burnout risk.	Survey differences; limited objective metrics; early adopter bias
Bundy et al. (2024)	USA	DAX Copilot	In semi-structured interviews (n = 12), physicians reported reduced documentation burden and better patient engagement. Concerns noted regarding automation errors and workload shifting. No statistical metrics were presented.	Inaccuracies in AI transcription; concern over patient consent; legal responsibility in auto-generated notes.
Liu et al. (2024)	China	ML (XGBoost, NLP)	AI-based burnout prediction reached AUC of 0.84. After deployment, emotional exhaustion scores (MBI) dropped by 23%, and task efficiency improved by 16% (p < 0.05). Burnout alerts led to intervention in 38% of high-risk staff.	Integration with EMR is complex; data privacy concerns.
Noble et al. (2022)	Canada	AI-guided mental health chatbot (MIRA)	Reduced clinician workload by 25% (OR: 1.8; 95% CI: 1.2–2.7) and burnout (CORE-10 scores ↓18%; p = 0.03). High user satisfaction (AES: 4.2/5).	Short follow-up (6 months). Dependence on self-reported data.

Petry et al. (2022)	USA	AI-augmented radiological triage system	Reduced length of stay (LOS) by 1.2 days for intracranial hemorrhage (ICH) ($p < 0.01$). Burnout decreased by 18%. Efficiency: 30% faster triage prioritization (AUC = 0.89).	Single-center study limits generalizability. 2. No long-term follow-up on burnout sustainability. High initial setup costs for AI integration.
Ziegelmayer et al. (2022)	Germany	AI in CT-based lung cancer screening	Cost-effectiveness ratio of €3,500 per quality-adjusted life-years (QALY) gained. AI reduced false positives by 15% (F1 score = 0.91) and reading time by 40% ($p < 0.01$).	Potential over-reliance on AI, risking missed diagnoses in edge cases. 3. High computational costs for real-time implementation. 4. Ethical concerns about data privacy in large-scale screening programs.

Source: Author(s) work

the other side, quasi-experimental studies showed more consistent quality scores. Only one study was rated as moderate because of insufficient reporting on control criteria (Q2), outcome measurements (Q5), and adequate follow-up (Q8) (Table 4). Overall, although the included studies generally demonstrated acceptable methodological rigor, limitations related to study design precision and reporting transparency should be taken into account when interpreting the findings

Table 3.

Quality Assessment for Observational Studies according JBI Checklist

Author, Year	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Score
Dang et al. (2021)	yes	yes	yes	no	no	no	yes	yes	5/8 (63%)
Noble et al. (2022)	yes	yes	yes	yes	no	no	yes	yes	6/8 (88%)
Li (2023)	yes	yes	yes	yes	no	no	yes	yes	6/8 (88%)
Bharadwaj et al. (2024)	yes	yes	yes	yes	yes	yes	yes	yes	8/8 (100%)
Champendal et al. (2024)	yes	yes	yes	yes	yes	yes	yes	yes	8/8 (100%)
Gustafson et al (2025)	yes	yes	yes	yes	yes	yes	yes	yes	8/8 (100%)
Allen et al. (2024)	yes	yes	yes	yes	yes	yes	yes	yes	8/8 (100%)
Guo et al. (2024)	yes	yes	yes	yes	no	no	yes	yes	6/8 (88%)
Miao et al. (2024)	yes	yes	yes	yes	no	no	no	no	4/8 (50%)
Nan et al. (2024)	yes	yes	yes	yes	no	no	yes	yes	6/8 (88%)
Li et al (2024)	yes	yes	yes	yes	yes	yes	yes	yes	8/8 (100%)
Liao et al. (2024)	yes	yes	yes	yes	no	no	unclear	no	4/8 (50%)
Pavuluri et al. (2024)	yes	yes	yes	yes	no	no	unclear	no	4/8 (50%)
Bundy et al. (2024)	yes	yes	yes	yes	no	no	unclear	no	4/8 (50%)
Liu et al. (2024)	yes	yes	yes	yes	yes	yes	yes	yes	8/8 (100%)
Van Zyl-Cillie et al. (2024)	yes	yes	yes	yes	yes	yes	yes	yes	8/8 (100%)
Zielonka et al. (2024)	yes	yes	yes	yes	unclear	no	yes	yes	6/8 (88%)
Renggli et al. (2025)	yes	yes	yes	yes	unclear	no	no	no	4/8 (50%)
Omranian et al. (2025)	yes	yes	yes	yes	no	no	yes	yes	6/8 (88%)
Owens et al (2024)	yes	yes	yes	yes	yes	yes	yes	yes	8/8 (100%)
Moryousef et al (2024)	no	yes	yes	yes	no	no	yes	yes	5/8 (63%)

Huo et al. (2025)	yes	yes	yes	yes	yes	yes	yes	yes	8/8 (100%)
Mascagni et al. (2022)	yes	yes	yes	yes	yes	yes	yes	yes	8/8 (100%)
Ziegelmayer et al. (2022)	unclear	unclear	yes	yes	no	no	yes	yes	4/8 (50%)
Ganeshan et al. (2020)	yes	yes	yes	yes	yes	yes	yes	yes	8/8 (100%)
van Leeuwen et al. (2021)	yes	yes	yes	yes	yes	yes	yes	yes	8/8 (100%)
Petry et al. (2022)	yes	yes	yes	yes	yes	yes	yes	yes	8/8 (100%)

Table 4.

Quality Assessment for Quasi-Experimental Studies according JBI Checklist

Author, Year	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Score
Albrecht et al. (2025)	yes	no	yes	yes	yes	no	yes	yes	yes	8/9 (89%)
Laing & Mercer (2021)	yes	unclear	yes	yes	yes	no	yes	yes	yes	8/9 (89%)
Vafaeezadeh et al. (2021)	yes	no	yes	yes	yes	yes	yes	no	yes	7/9 (78%)
Gupta et al. (2021)	yes	no	yes	yes	yes	yes	yes	no	yes	7/9 (78%)
Li et al. (2023)	yes	yes	yes	yes	yes	yes	yes	no	yes	8/9 (89%)
Cho et al (2024)	yes	yes	yes	yes	yes	yes	yes	yes	yes	9/9 (100%)
Baek et al. (2024)	yes	yes	yes	yes	yes	yes	yes	yes	yes	9/9 (100%)
Shah et al (2025)	yes	no	yes	yes	no	yes	unclear	yes	yes	7/9 (78%)
Laplante et al. (2023)	yes	no	yes	yes	no	yes	yes	no	yes	6/9 (67%)
Barak-Corren et al (2024)	yes	no	yes	yes	yes	yes	yes	yes	yes	8/9 (89%)

Source: Author(s) work

By Study Aim

This study focuses on the role of AI in reducing the incidence of burnout and increasing work efficiency. Among the included studies (Table 1), 17 studies focus on the impact of AI on burnout reduction while 24 studies focus on work efficiency. The rapid evolution of artificial intelligence (AI) in healthcare presents an unparalleled opportunity to address burnout workforce shortages. spanning from 2014 to 2021, and showing an increasing trend year by year, research expanding on medical records and management, besides the most studies on clinical field (Sarker, 2022). Across multiple studies, these systems demonstrated evident benefits including reducing the workload healthcare staff face, reduced after-hours documentation, improved workflow efficiency, enhanced clinician satisfaction, and even modest reductions in self-reported burnout. This could also have knock-on effects on staff retention, as fewer staff feel the need to leave or retire due to health reasons (Awasthi et al., 2024; Nguyen et al., 2016; Rajkomar et al., 2018).

The key perspective that must be emphasized here is that AI is unlikely to replace doctors but may transform the nature of work. It's been quite an issue that the risk of job displacement in various fields, especially health and social care due to AI. On the other hand, fewer healthcare roles consist of wholly automatable tasks and demand for care is continuing to rise (Davenport & Kalakota, 2019). Another possibility that the healthcare jobs most likely to be automated would be those that involve less contact with patients, such as radiology, digital information, and pathology. This also won't happen any time soon. AI systems in radiology perform a single task of reading and interpreting images but this needs to be confirmed by radiologists on diagnosis. Therefore, AI should be expected to transform, rather than replace, healthcare jobs by automating routine tasks and improving work efficiency (Langlotz, 2019).

By AI Model

Various AI models have continued to develop over the past few decades. In this review, we classified the distribution of AI models used across the included studies. Generative AI, typically LLMs like GPT and BERT, emerged as the most prominent, used in 10 studies. Narrow AI, AI systems trained for a single, well-defined task such as NLP for triage, scribing, and classification, was already used in 9 studies. Finally, classical ML (decision trees, random forests, SVM) and Optimization AI (MIP, GA) contributed to 7 and 5 studies, respectively. Furthermore, we have seen the use of multimodels or hybrid AI in healthcare publications (6 publications). A similar study by Awasthi et al. (2024) reported DL (Deep Learning) and ML (Machine Learning) as separate groups and had more publications than NLP (Natural Language Processing). However, DL is a unit within ML, which is also a subset of AI. ML is a learning method based on data or past experience that automates analytical model building. Meanwhile, DL performs computation through multi-layer neural networks and processing (Sarker, 2022).

Mitigating Burnout and Enhancing Well-being among Healthcare Professional Through AI

Healthcare has been the subject of studies on job happiness and burnout (Konlan et al., 2022; Kumaş et al., 2019). The prevalent issue of burnout, characterized by emotional exhaustion and disconnection, has been reported to stem from the dynamic nature of the healthcare industry, marked by high-pressure demands and heavy workloads (Çelik & Kılıç, 2019). Kloutsiniotis et al. (2022) found that HRM strategies that support worker health and safety are essential for preventing burnout. Creating a safe and supportive workplace is critical to prevent burnout, eventually improving healthcare workers' health and safety and leading to better patient care.

With the rapid advancement of technology, AI offers solutions that may help reduce the burden of burnout in several ways. Results show that AI can detect factors contributing to burnout in healthcare workers, such as unbalanced shift allocation and administrative burdens commensurate with professional responsibilities (W. Li et al., 2024; Nan et al., 2024; Omranian et al., 2025). Various burnout predictors using AI tools have been reported to have high accuracy, with AUCs ranging from 0.84 to 0.90 (Guo et al., 2024; Liu et al., 2024; Owens et al., 2024). During the COVID-19 pandemic, Gupta et al., (2021) developed the Extra Tree Classifier, a predictive machine learning (ML) model, to detect heart rate variability reflective of stress and burnout among healthcare workers. It reported burnout rates with good accuracy and identified associated features, such as feeling dissatisfied with the current job, a stressed, chaotic, and hectic environment, and feeling that COVID-19 had significantly impacted mental well-being. Furthermore, AI was able to detect sleep disturbance and chronic fatigue in healthcare workers with good accuracy (L. Li, 2023).

The positive impacts of AI integration directly influence both employee performance and the quality of patient care, which constitute the core objectives of HRM in healthcare systems (Athamneh, 2024; Cavanagh et al., 2023). Specifically, the role of AI within HRM strategies emphasizes fairness and autonomy in workload and shift allocation, leading to increased job satisfaction, reduced emotional exhaustion, enhanced task efficiency, and improved patient engagement (Bundy et al., 2024; Cho et al., 2024; Ganeshan et al., 2019; Petry et al., 2022). Job complexity and task load can be reduced by AI assistance, which indirectly enhances work well-being through psychological needs satisfaction ($p < 0.01$) (Huo et al., 2025; Shah et al., 2025). Overall, Albrecht et al. (2024) in the USA reported that the risk of burnout decreased by 67% after using Ambient AI for clinical documentation. In another country, Noble et al. (2022) in Canada reported reduced clinician workload by 25% and burnout risk by 18% ($p = 0.03$).

Improved Human Resource Management Outcomes through AI-Supported Work Efficiency

Having figured out that AI has significant potential in identifying and reducing burnout in healthcare workers, this will undoubtedly play a role in achieving the primary goal of human resource management: work efficiency. As that happens, it provides employees with additional time to learn about novel practices, enhance their abilities, and further increase their productivity in more dynamic job positions (Nawaz et al., 2024). Notably, various studies have reported impressive results that AI supports good workflow, thereby simultaneously increasing efficiency. Most of the results concern time savings and revenue increases.

AI tools predominantly promote automation in repetitive and manual tasks. As a part of HRM technology, it can reduce administrative errors, expedite decision-making processes and enhancing employee productivity. In other words, achieving the desired outcomes can be accomplished with minimal time, effort, and resource expenditure (Meshram, 2023). Studies reported that AI could supports on scheduling shifts with MLs, triage with NLPs and helping on discharge summaries and consent forms with LLMs (Baek & Cha, 2025; Miao et al., 2024; Renggli et al., 2025; Zielonka et al., 2025). Specific AI models, such as narrow and hybrid models, can enhance imaging results and its interpretation and increase accuracy in patient diagnostics and surgery (Champendal et al., 2024; Laplante et al., 2023; L. Li, 2023; Mascagni et al., 2022; Ziegelmayer et al., 2022). Petry et al. (2022) used AI-augmented radiological worklist triage system and found efficiency on triage prioritization increased by 30% with AUC = 0.89. Clinical Decision Support System (CDSS) for preventive care by Laing & Mercer (2021) reported a significant time saving up to 195.7s per chart review, extrapolated to 82.6 annual hours saved.

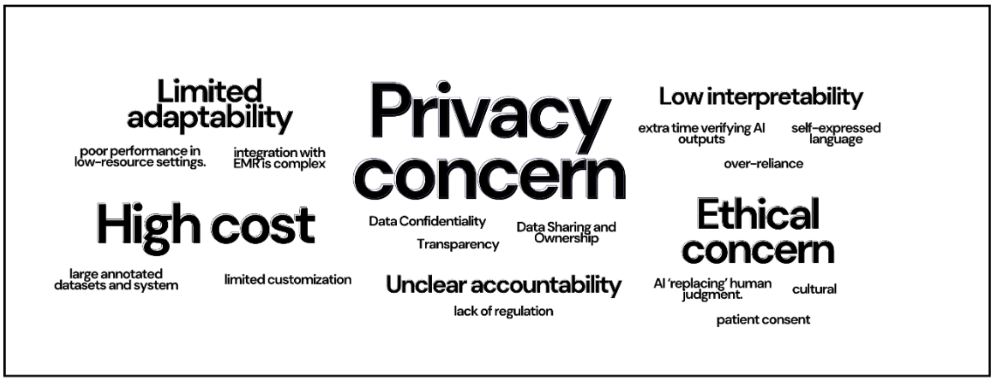
The impact of AI on healthcare management is increasingly evident. Studies have reported that documentation time can be saved up to 43% and efficiency improved by 2.7x (Barak-Corren et al., 2024; Liao et al., 2024; Pavuluri et al., 2024). Clinician workload has been decrease by 25%, while patient waiting times were reduced by 23% (Noble et al., 2022; Van Zyl-Cillié et al., 2024). Beyond hospital settings, primary care physicians and pharmacists have also experienced improvements in efficiency and productivity following AI implementation (Allen et al., 2024; Gustafson et al., 2025).

Using AI in the healthcare system, especially HRM, will simplified all operations and is cost-effective. Eventually, financial benefits further reinforce AI's value (Mansor et al., 2018; Nawaz et al., 2024). For instance, AI-assisted detection of vessel occlusion in stroke patients can save approximately €2,100 per patient (95% CI: €1,800–€2,400) (Van Leeuwen et al., 2021). In a multiregional study, Bharadwaj et al. (2024) reported that 451% ROI over 5 years, with 145 days saved in workflow tasks (e.g., 78-day reduction in triage time). In addition, Efficiency is quantified via labor time savings and revenue increases ($3.56M revenue vs. $1.78M costs). Therefore, time-saving AI systems become a strategic muscle for strengthening HRM performance, financial sustainability, and workforce well-being in healthcare sector

Overview of Potential Barriers Affecting AI Adoption in Healthcare

The major concern in implementing AI in healthcare lies in protecting patient rights and ensuring adherence to ethical principles (Figure 3). Healthcare serves an inherent and inseparable framework that governs all patient-centered care, as known healthcare bioethics. As AI become increasingly capable of supporting or even replicating clinical decision-making, there is a growing risk that bioethical dilemmas and professional accountability may be diminished. This raises important questions about transparency, informed consent, data privacy, and the extent to which AI should be allowed to influence decisions that directly affect patient outcomes.

Figure 3.
Potential Barriers Affecting AI Adoption in Healthcare



Source: Author(s) work

Despite demonstrating in reducing burnout and enhancing work efficiency, AI still faces substantial challenges in real-world implementation, particularly in rare cases and low-resource healthcare settings. High-complexity patient cases often diminish AI effectiveness and may increase the likelihood of missed or delayed diagnoses in edge scenarios. On the other hand, the integration of AI systems across facilities with varying levels of technological presents additional barriers to achieving the desired outcomes.

Another concern is the high initial setup cost required for AI integration, which cannot be overlooked. Developing an effective AI system requires substantial customization, robust infrastructure, and access to large, well-annotated datasets to ensure accuracy, reliability, and adaptability within diverse healthcare environments. In addition, evolving government policies must continue to strengthen regulatory oversight and ensure comprehensive protection of public health data against misuse by private entities. Overall, although the adaptability of AI across different demographics and clinical contexts remains limited, the growing body of research offers complementary insights that can collectively advance the quality, safety, and performance of AI in healthcare management

CONCLUSIONS

The adoption of AI system has reduced administrative burdens, improved psychological well-being and increased work efficiency among healthcare professionals. AI represents a transformative shift in how healthcare organizations manage and optimize their human resources. Despite these positive outcomes, variations in implementation quality, data integration, and ethical concerns remain key challenges that hinder large-scale adoption. Overall, these improvements enable healthcare managers to redirect human capital toward more value-driven and patient-centered tasks, reinforcing the strategic function of HRM as potential support system.

LIMITATION & FURTHER RESEARCH

The heterogeneity of AI models and implementation settings complicates direct comparisons, as performance outcomes may depend on organizational maturity, data quality, and technological readiness. Therefore, future research should focus on standardizing evaluation metrics and integrating workforce well-being indicators into system design to ensure that technology serves as a supportive tool rather than a replacement, fostering sustainable HRM system in healthcare and workforce resilience.

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