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EFFECTIVENESS OF ARTIFICIAL INTELLIGENCE-BASED TOOLS IN MONITORING AND REDUCING BURNOUT AMONG HEALTHCARE WORKERS: A SYSTEMATIC REVIEW

Aashima Magotra, MPH[1], Alok Arshey, Data Science[2], Shivam Sharma, MBBS[3], Shereen Khan, MPH[4], Shouunak Nandy, MBBS[5], Subir Magotra, MBA[6]

[1] Manipal Academy of Higher Education, Karnataka, India aashimamagotra1996@gmail.com, ORCID: 0009-0001-7477-1161
[2] Manipal Academy of Higher Education, Karnataka, India, alokarshey123@gmail.com
[3] All India Institute of health Sciences, Bhopal, India, drshvmshrm@outlook.com, ORCID: 0009-0007-1399-8219
[4]All India Institute of health Sciences, Bhopal, India, khanshereen2312@gmail.com, ORCID: 0009-0002-8297-8899
[5]Midnapur Medical College, West Bengal, India, shouunaknandy@gmail.com, ORCID: 0009-0000-3472-4670
[6]DY Patil University, Pune, India, subir22m@gmail.com
*Corresponding Author: Dr Shivam Sharma, MBBS, Email: drshvmshrm@outlook.com

ABSTRACT
Objectives: Burnout among healthcare workers adversely affects workforce well-being, healthcare delivery, and patient outcomes. Artificial intelligence (AI) has emerged as a promising approach for monitoring burnout risk and supporting interventions to reduce occupational stress. This systematic review evaluated the effectiveness of AI-based tools in monitoring, predicting, and reducing burnout among healthcare professionals.
Methods: A systematic review was conducted according to the PRISMA guidelines. Five electronic databases (Scopus, PubMed, Web of Science, CINAHL, and ProQuest) were searched for studies published between January 2014 and December 2024. Eligible studies involved healthcare professionals and evaluated AI-based approaches for burnout monitoring, prediction, or intervention. Data extraction and quality assessment were performed independently by two reviewers using the NIH Quality Assessment Tool.
Results: Twenty-five studies met the inclusion criteria. AI techniques included machine learning algorithms, natural language processing, large language models, wearable-integrated monitoring systems, electronic health record-based predictive tools, and chatbot interventions. Predictive models demonstrated moderate-to-high performance, with reported AUC values ranging from 0.72 to 0.91. Chatbot interventions and EHR-integrated population health management systems showed modest but statistically significant reductions in burnout, whereas AI-assisted documentation tools reduced administrative burden and improved workflow efficiency. However, most studies relied on self-reported outcomes, had limited follow-up periods, and demonstrated considerable methodological heterogeneity.
Conclusions: AI-based technologies demonstrate promising potential for identifying burnout risk and supporting interventions to reduce burnout among healthcare workers. Nevertheless, stronger longitudinal studies, standardized evaluation methods, and implementation across diverse healthcare settings are required before widespread adoption can be recommended.

KEYWORDS: Artificial Intelligence; Burnout, Professional; Health Personnel; Machine Learning; Occupational Stress

Introduction
Healthcare worker burnout is a critical issue characterized by emotional exhaustion, depersonalization, and a diminished sense of personal accomplishment. Burnout negatively impacts healthcare professionals and patient care, with prevalence rates ranging from 10% to 59% across various specialties [1]. A 2022 survey revealed that 46% of healthcare workers experienced frequent burnout, a rise from 32% in 2018 [2]. Burnout leads to decreased time with patients, increased medical errors, and higher hospital-acquired infection rates [3]. Additionally, affected individuals may reduce working hours or leave the profession, exacerbating staffing shortages. The COVID-19 pandemic has further intensified workloads and stress among healthcare workers [4]. Artificial Intelligence (AI) has emerged as a promising tool to alleviate burnout by automating administrative tasks, enhancing decision-making, and streamlining workflows. AI applications reduce cognitive and emotional burdens, allowing professionals to focus more on patient care [5]. For instance, AI-driven systems can handle routine documentation, schedule management, and data analysis, decreasing the time clinicians spend on non-clinical tasks [6].
Moreover, AI can support clinical decision-making by providing evidence-based recommendations, potentially enhancing job satisfaction and reducing burnout. A survey reported that 78% of physicians were optimistic about AI improving clinical efficiency [7]. However, integrating AI thoughtfully is essential to avoid complicating

workflows. Ethical concerns, such as the potential prioritization of profit over patient care, highlight the need for careful deployment [8].
Many studies exploring AI interventions for burnout are observational or cross-sectional, limiting the ability to establish causality. Small sample sizes further constrain the generalizability of findings. A review noted that while AI can reduce cognitive and work burdens, implementation challenges necessitate more robust study designs [9]. There is limited longitudinal research assessing the long-term impact of AI interventions on burnout, making it difficult to determine whether AI solutions provide sustainable benefits or temporary relief. The deployment of AI raises ethical concerns, including data privacy issues, potential job displacement, and devaluation of professional skills. Healthcare workers fear that AI diagnostic errors may increase stress or lead to missed diagnoses [10]. Additionally, concerns persist that AI might perpetuate higher workloads, contributing to burnout, clinical errors, and poorer outcomes [6]. The effectiveness of AI systems relies heavily on data quality and availability. Limitations in these areas hinder AI's ability to address healthcare challenges [11]. Research in high-resource settings, such as South Korea and the United States, often overlooks challenges faced by healthcare workers in low- and middle-income countries (LMICs). Differences in healthcare infrastructure, workload distribution, and cultural attitudes toward mental health can significantly influence burnout factors [12]. The absence of studies from LMICs highlights the need for inclusive research accounting for diverse healthcare systems. Additionally, most AI interventions target narrow aspects of burnout, such as administrative tasks, without addressing complex determinants like interpersonal dynamics or institutional policies. The reliance on proprietary AI algorithms with limited transparency raises ethical concerns and challenges reproducibility [13]. The lack of longitudinal studies further exacerbates this issue, as the long-term effects of AI interventions on burnout remain largely unexplored.
Existing research often evaluates isolated AI tools without assessing their integrated impact on burnout. Studies focus on specific outcomes, such as task load reduction or predictive accuracy, while neglecting broader psychosocial dimensions. Emotional exhaustion and depersonalization, key components of burnout, are frequently underexplored in AI-related interventions [14][15]. Variations in the use of burnout measurement tools, such as the Maslach Burnout Inventory (MBI), and the reliance on self-reported data introduce inconsistencies [14]. Additionally, usability, training, and perceived workload redistribution are often overlooked.
While AI and machine learning algorithms have successfully observed or predicted burnout, active implementation to reduce burnout and enhance job satisfaction remains limited. Most studies evaluate AI model performance for predicting burnout but place minimal emphasis on leveraging AI for mental well-being or workplace outcomes. Concerns about job insecurity linked to AI integration further complicate its adoption. The lack of long-term studies exacerbates the challenge of assessing AI's sustained impact. This study aims to evaluate AI's predictive capabilities and its potential to deliver meaningful and lasting improvements in burnout reduction and job satisfaction.

METHODOLOGY

Protocol and registration

This systematic review was conducted in accordance with PRISMA guidelines. The protocol was registered in the PROSPERO (CRD-NIHR) database with Reference ID CRD42025642827.

Search Strategy

For this systematic search, we developed a search strategy to identify relevant literature. This search strategy was tailored to five major electronic databases: Scopus, CINAHL, Web of Science, ProQuest, and PubMed. These databases were chosen for their broad coverage of medical, nursing, and multidisciplinary literature. Search terms included were “artificial intelligence”, “machine learning”, “AI”, “algorithm”, “predictive analytics”, “healthcare worker”, “healthcare professional”, “doctor”, “nurse”, “clinician”, “burnout”, “emotional exhaustion”, “occupational stress”, “compassion fatigue”, “mental health”, “monitor”, “track”, “predict”, “evaluate”, “improve”, “reduce”, “mitigate”, “effectiveness”, “outcome”, “impact”, and “efficacy”. These terms were combined using Boolean operators AND or OR to obtain the final search string. The search was conducted for studies published between January 2014 and December 2024, ensuring that the review captures the most recent advancements and trends in the use of AI for mitigating healthcare worker burnout. To maintain consistency and relevance, the search was limited to articles published in English. Only full-text articles were considered, and reviews, editorials, and opinion pieces were excluded.

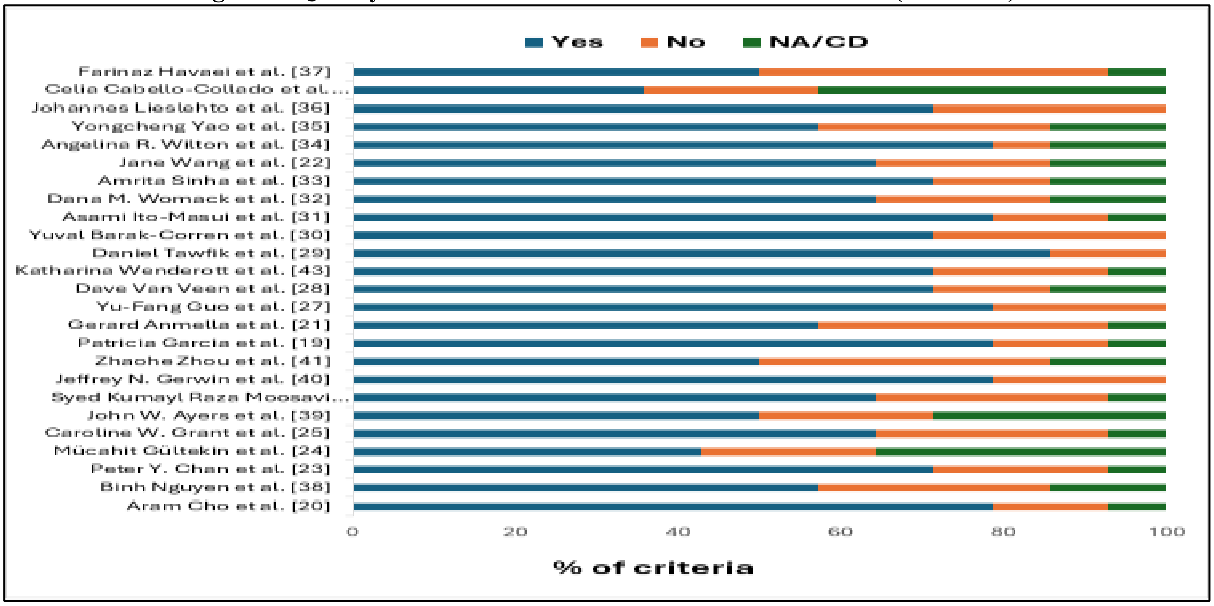
Selection Criteria

The selection criteria were developed in alignment with the PRISMA guidelines to ensure the inclusion of relevant and high-quality studies. The review focused on studies involving healthcare workers, including doctors, nurses, and allied health professionals, that utilized artificial intelligence (AI) technologies or tools for monitoring, predicting, and improving burnout. Only observational studies were included. Studies not involving healthcare workers, those using interventions unrelated to AI, or reporting outcomes unrelated to burnout were excluded. Additionally, opinion pieces, editorials, commentaries, and abstract-only papers were excluded.

Quality Assessment

The risk of bias of the included studies was assessed using the quality assessment of NIH Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies [16][17][18]. Given that most included studies were observational in nature, this tool was deemed appropriate for evaluating the risk of bias. The two reviewers used the tool in its standard form without any modifications. Each study was independently assessed by the reviewers to ensure an objective evaluation. Discrepancies in assessments were resolved through consensus discussions, and inter-rater reliability was calculated to ensure consistency, with Cohen's kappa (κ = 0.813) indicating strong agreement between reviewers. Cohen's kappa value was calculated using RStudio.

Figure 1. Quality Assessment Results for the Included Studies (NIH Tool)

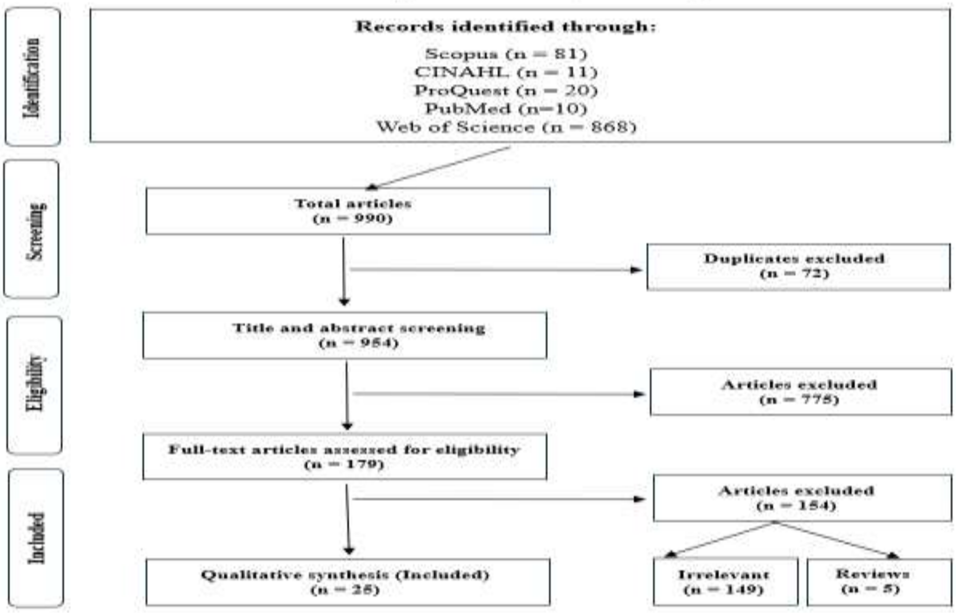


Source: Prepared by the authors based on the study data

Data Extraction

Two independent reviewers screened the titles and abstracts of the articles to assess eligibility, followed by a full-text review of the selected studies. The reasons for excluding articles were documented. Additionally, the references of the included articles were hand-searched to identify any potentially relevant studies. Discrepancies between the reviewers were resolved through discussion and consensus. The following details were extracted from the included studies into a pilot worksheet by the two reviewers: (1) author names; (2) year of publication; (3) country; (4) sample size; (5) study design; (6) improvements in burnout; (7) reported burnout metrics; and (8) types of AI techniques or tools utilized. The extracted information was cross verified independently by both reviewers to ensure accuracy and reliability. Any inconsistencies were resolved collaboratively

FIGURE 2. Flow diagram of the study selection process



Source: Prepared by the authors based on the study data

RESULTS

The search yielded 990 articles from various electronic databases. After removing duplicates, 954 articles were screened by title and abstract. Of these, 179 met the inclusion criteria for full-text review, and 25 studies were ultimately included in this systematic review. A PRISMA flow diagram outlining the selection process is provided in Figure 2.

The 25 included studies were conducted between 2018 and 2024, involving healthcare professionals such as physicians, nurses, allied health workers, and mixed clinical populations across countries including the United States, China, Spain, Finland, Japan, Germany, and Canada. Sample sizes ranged from 10 in pilot studies to over 4,000 in large cross-sectional surveys.

Burnout was assessed using various instruments, with the Maslach Burnout Inventory (MBI) and its variants (MBI-GS, MBI-EE) being the most common (n = 13). Other tools included the Copenhagen Burnout Inventory (CBI), Stanford Professional Fulfillment Index (PFI), and single-item validated measures.

AI-based tools used in these studies included machine learning classifiers (e.g., logistic regression, random forest, gradient boosting, support vector machines), natural language processing (NLP) models for chatbot-based screening and documentation summarization, large language models (e.g., GPT-4), wearable device integration, population health management algorithms embedded in EHRs, and chatbots for psychological support.

Seventeen studies used AI for monitoring or predicting burnout. Monitoring strategies included analysis of EHR usage to detect work exhaustion [29, 33]. The stratifying burnout risk using population health management tools and detecting strain among nurses using wearable sensors and operational data [22, 32, 34]. Predictive modeling studies used demographic, psychological, workplace, or digital trace data to forecast burnout risk with reported accuracies ranging from 57% to 90% and AUC values from 0.72 to 0.91 [27, 35, 36]. Gradient boosting and random forest models were most effective, especially in predicting job crafting behaviors and resilience [27, 36]. NLP and LLM-based tools showed promise in reducing administrative burden but did not directly assess burnout outcomes [28, 30, 44].

Six studies included interventional or quasi-interventional AI applications. These involved chatbots for mental health support, AI-personalized iCBT for shift workers, population health tools in clinical workflows and AI-assisted diagnostics [21, 22, 31, 43]. Effects varied: the Vickybot chatbot showed a moderate reduction in burnout ($z = -2.07$, $P = .04$, $r = 0.32$), and clinicians who valued population health tools reported 15–30% lower burnout odds [21, 22]. Other interventions showed mixed or non-significant effects.

Two protocol or conceptual studies lacked complete outcome data but illustrated emerging uses of AI that warrant further evaluation [31, 44]. Overall, predictive models achieved moderate to high accuracy, and interventional tools showed modest but significant effects on burnout, although follow-up durations were short and most relied on self-reported measures.

Table 1. Interventional or Quasi-Interventional AI Studies

Study (Author, Year)	Country	Sample Size	AI Intervention	Burnout Instrument	Main Outcome
Anmella G et al. (2023)	Spain	34	Vickybot chatbot for self-assessment & tailored psychological modules	MBI (EE subscale)	Moderate burnout reduction ($z = -2.07$, $P = .04$, $r = 0.32$)
Wang J et al. (2024)	USA	4,257	Population health management tools embedded in EHR	Single-item MBI validated	15–30 % lower odds of burnout among high-tool-importance users
Ito-Masui A et al. (2021)	Japan	70	iCBT app + ML personalization for shift workers	PSQI & burnout proxy	Protocol: aims to improve sleep & well-being
Wenderott K et al. (2024)	Germany	9 residents	Quantib Prostate CAD system	NASA-TLX, STAI	No significant stress reduction; ↑ diagnostic time
Garcia P et al. (2024)	USA	162 clinicians	GPT-4 draft replies for inbox messages	NASA TLX + Work Exhaustion	Task load ↓ from 61.3 to 47.3 ($p < .001$); exhaustion ↓ ($p < .001$)
Dong S et al. (2024)	USA	81	HRVEST wearable + simulation	HRV metrics (stress proxy)	Improved HRV post-intervention

					indicating stress reduction
Gültekin M et al. (2024)	Turkey	13	Various AI tools (chatbots, VR, diagnostic support)	Perceptions (interviews)	Reduced workload & stress; qualitative findings
Van Veen D et al. (2024)	USA	10	GPT-4 summarization (evaluated for impact)	N/A	81 % preference for AI summaries; ↓ documentation burden

Source: Prepared by the authors based on the study data

Supplementary Material

Table 2. Quality Assessment of Included Studies Using the NIH Tool DISCUSSION

Author	**1.Research question or objective clearly stated?**	**2. Study population clearly defined?**	**3. Study participation rate ≥50%?**	**4. Study subjects consistently selected/recruited?**	**5. Study sample size justification provided?**	**6. Exposure measured before outcome measurement?**	**7. Sufficient timeframe to detect association?**	**8. Different exposure levels related to outcome?**	**9. Exposure measures clearly defined and consistent?**	**10. Exposure assessed multiple times?**	**11. Outcome measures clearly defined and consistent?**	**12. Outcome assessors blinded to exposure?**	**13. Loss to follow-up ≤ 20%?**	**14. Confounders measured and statistically adjusted?**	**Quality rating (Good, Fair, Poor)**
Aram Cho et al. [20]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	CD	Good
Binh Nguyen et al. [38]	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	No	Yes	CD	NA	No	Fair
Peter Y. Chan et al. [23]	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	NA	Yes	Good
Mücahit Gültekin et al. [24]	Yes	Yes	CD	Yes	No	NA	NA	Yes	Yes	No	Yes	No	NA	NA	Fair
Caroline W. Grant et al. [25]	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	No	Yes	No	NA	Yes	Fair
John W. Ayers	Yes	Yes	NA	Yes	Yes	NA	NA	No	Yes	No	Yes	Yes	NA	No	Fair

et al. [39]														
Syed Kumayl Raza Moosavi et al. [26]	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	NA	No	Fair
Jeffrey N. Gerwin et al. [40]	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Good
Zhaohe Zhou et al. [41]	Yes	Yes	CD	Yes	No	No	No	Yes	Yes	No	Yes	No	NA	Yes	Fair
Patricia Garcia et al. [19]	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	CD	Yes	No	Good
Gerard Anmella et al. [21]	Yes	Yes	No	Yes	No	Yes	Yes	No	Yes	Yes	Yes	No	No	CD	Fair
Yu-Fang Guo et al. [27]	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Good
Dave Van Veen et al. [28]	Yes	Yes	CD	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	NA	No	Good
Katharina Wenderott et al. [43]	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	NA	No	Good
Daniel Tawfik et al. [29]	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Good
Yuval Barak-Corren et al. [30]	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No	Good
Asami Ito-	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	CD	Yes	No	Good

Masui et al. [31]															
Dana M. Womack et al. [32]	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	CD	NA	No	Fair
Amrita Sinha et al. [33]	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	CD	NA	Yes	Good
Jane Wang et al. [22]	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	No	Yes	CD	NA	Yes	Fair
Angelina R. Wilton et al. [34]	Yes	Yes	CD	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	CD	Yes	Good
Yongcheng Yao et al. [35]	Yes	Yes	Yes	Yes	No	No	NA	Yes	Yes	No	Yes	No	NA	Yes	Fair
Johannes Lieslehto et al. [36]	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Good
Celia Cabello-Collado et al. [44]	Yes	Yes	CD	Yes	No	NA	NA	No	Yes	No	Yes	NA	NA	CD	Fair
Farinaz Havaei et al. [37]	Yes	Yes	No	Yes	No	No	No	Yes	Yes	No	Yes	No	NA	Yes	Fair

"Yes", Low risk of bias; "No", High risk; "NA", not available; "CD", cannot determine
Source: Prepared by the authors based on the study data

Although a meta-analysis was initially considered, it was not feasible due to significant heterogeneity across the studies included. The studies differed in terms of their designs, AI tools utilized, burnout measurement methods, and outcome reporting. These differences precluded meaningful statistical pooling; therefore, a narrative synthesis was conducted.

This systematic review provides a comprehensive overview of current evidence on the role of AI-based tools in monitoring and reducing burnout among healthcare professionals. The 25 included studies encompassed diverse healthcare settings and employed various AI techniques, including machine learning classifiers, natural language processing (NLP), large language models (LLMs), wearable-integrated prediction systems, and population health management tools. These technologies primarily targeted key drivers of burnout, such as excessive workload, administrative burden, and emotional fatigue.

Some AI-enabled interventions, particularly chatbot-based tools and EHR-integrated dashboards, demonstrated statistically significant improvements in burnout-related metrics. However, findings across studies were mixed, and many effects were modest or preliminary. Predictive models achieved moderate to high accuracy (AUC 0.72–0.91) in identifying individuals at risk of burnout, especially when combining workplace, psychological, and behavioural data [27, 35, 36]. AI-driven documentation support tools, such as GPT-4 based summarization systems, effectively reduced administrative workload, although their direct impact on burnout was not assessed [28, 30, 44]. Chatbot interventions like Vickybot produced moderate reductions in burnout symptoms, while population health management dashboards were associated with lower reported burnout odds [21, 22].
Despite these promising results, several limitations should be considered. Most studies relied on self-reported burnout measures, which are subjective and susceptible to bias. Few studies included long-term follow-up or objective clinical outcomes, limiting understanding of sustained impact. Many interventions were pilots or protocols with small sample sizes, reducing generalizability. The lack of standardized burnout assessment tools further hindered direct comparisons across studies.
In addition to methodological limitations, broader challenges remain. Ethical considerations including data privacy, algorithmic bias, and fairness must be addressed to ensure safe and equitable implementation of AI tools. Moreover, most of the studies were conducted in high-income settings with robust digital infrastructure, limiting applicability to low-resource contexts where burnout is equally prevalent but structural barriers to AI adoption are greater.
Future research should prioritize standardized evaluation metrics, incorporate objective outcome measures, and employ large-scale, longitudinal designs across diverse healthcare settings. Equitable access, user-centered design, and contextual adaptation will be critical to ensure the successful and ethical integration of AI tools into healthcare systems worldwide.

CONCLUSION

This systematic review highlights the growing potential of AI-based tools to monitor and reduce burnout among healthcare workers. AI technologies including predictive modeling, LLM-driven documentation aids, chatbots, and EHR-integrated population health tools show promise in addressing key contributors to burnout, particularly workload and administrative burden. However, high heterogeneity in study design, reliance on self-reported outcomes, limited follow-up periods, and lack of standardization limit the strength and generalizability of current evidence. Additionally, the concentration of studies in high-income settings raises concerns about global applicability. Future research should focus on developing robust, standardized, and inclusive evaluation frameworks to ensure that these tools are effective, scalable, and equitably accessible across diverse healthcare environments.

Conflicts of Interest
The authors declare no conflicts of interest.

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