Review

The Role of AI in Supporting Health Care Workers' Mental Well-Being: Scoping Review

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Abstract

Background: AI is increasingly transforming health care delivery and may offer new approaches to support the mental health and well-being of health care workers (HCWs). Mental health challenges faced by HCWs have gained recognition over the last decade, underscoring the need for continued exploration.

Objective: This scoping review explored the role of AI in enhancing or supporting the mental health and well-being of HCWs.

Methods: This scoping review followed the JBI guidelines and was reported according to the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) guidelines. The review included studies that directly addressed HCWs' mental health and well-being and excluded studies focusing on indirect AI applications such as workflow optimization. Academic and gray literature sources were searched without date restrictions. Two reviewers independently screened studies using Covidence, and the included studies underwent descriptive synthesis.

Results: Of 6587 records identified (6229 from databases), 5 studies met the eligibility criteria (4 from database searches and 1 from gray literature search), met the eligibility criteria. The studies applied AI-driven conversational systems, personalized recommendation tools, and mental health screening and prediction tools. Burnout was the most frequently addressed mental health concern, with nurses particularly vulnerable. A single-arm trial reported significant reductions in burnout scores following a personalized mobile intervention (t_{299}=8.692; P<.001). A prospective cohort study involving 816 HCWs reported 64.2% to 82% accuracy for machine learning–driven screening of anxiety, depression, and posttraumatic stress disorder. Empirical studies reported reductions in burnout and stress, whereas chatbot-based interventions demonstrated potential benefits for psychological support. However, the evidence remained constrained by small sample sizes, heterogeneous study designs, and short follow-up periods.

Conclusions: Current research suggests that AI may support HCWs' mental health by addressing burnout, stress, and anxiety through personalized support, chatbot-based interventions, and predictive screening. However, the evidence base remains limited and largely conceptual. Robust longitudinal studies and supportive policy frameworks are needed to evaluate the effectiveness, feasibility, and sustainability of AI-driven mental health interventions for HCWs.

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Keywords: artificial intelligence; AI; health care workers; mental health; burnout

Introduction

Enhancing the work experience of health care workers (HCWs) is crucial for improving the quality of health care delivery. HCWs remain highly susceptible to mental health issues such as stress, depression, insomnia, and burnout, primarily due to overwhelming cognitive demands [1]. High workload, inadequate resources, and exposure risks substantially contribute to these issues [2]. Evidence suggests that female HCWs, particularly nurses, display a higher risk of anxiety and depression [3]. A viewpoint article by Cho and Huang [4] emphasized how mental health–related stigma among physicians with burnout prevents them from seeking timely help [5]. This barrier may be stronger for female HCWs and nurses, who often hold limited power at work and are expected to display constant care and composure. The COVID-19 pandemic has further intensified these challenges, exposing gaps in support structures and prompting renewed attention to HCWs' mental well-being [6].

Rapid digitization over the last decade, primarily driven by the extensive use of electronic health records (EHRs) and clinical information systems, has created opportunities for novel technologies, such as AI, to influence health care delivery [7,8]. AI now supports a wide range of clinical functions, including diagnosis, treatment, genomic medicine, clinical decision support, therapeutic drug monitoring, and predictive analytics [9-11]. Within mental health, AI has demonstrated potential for early screening, personalized therapeutic support, and self-assessment for the general population, suggesting similar opportunities to enhance the mental health of HCWs [12].

Current research in this domain has advanced along 2 complementary pathways: workflow optimization and the direct provision of mental health support. Workflow optimization focuses on indirect support for HCWs' mental health by improving workflow processes in health care settings. Inefficient administrative processes, fragmented task coordination, and escalated documentation burden are recognized contributors to stress, anxiety, and burnout among HCWs [13]. To address these issues, AI-driven tools are leveraged to streamline workflows across clinical documentation, decision-making, and to facilitate communication between patients and HCWs [14]. These tools have demonstrated potential to reduce cognitive load, improve coordination, and mitigate burnout [15-17]. A scoping review by Alabi et al [18] identified 17 studies on strategies to reduce burnout among oncologists. The findings suggested that AI-driven tools effectively enhanced productivity in clinical settings, resulting in greater job satisfaction and improved teamwork, which ultimately mitigated burnout. Broader commentary highlights that such AI-mediated strategies represent scalable approaches to counter systemic pressures that contribute to burnout [19].

The direct provision of mental health support involves the application of AI-driven tools to support the mental health of HCWs. Emerging literature highlights the use of conversational agents (such as natural language processing [NLP]–based chatbots for mood monitoring and reflective dialogue) [20-23]. Another category of AI-driven mental health support includes tools trained on traditional therapeutic approaches, such as cognitive behavioral therapy (CBT) [20,24], mobile and web-based apps offering psychosocial support [21], chatbot-based triage, and navigation tools [22,23], and machine learning (ML)–driven predictive models for early screening and risk identification [25-27]. Although these avenues illustrate the wide range of innovation in this domain, a structured examination of the evidence base underpinning their effectiveness, safety, and applicability in health care settings remains lacking.

Research to date has primarily focused on AI-driven workflow optimization with indirect benefits for HCW mental well-being [16]. In contrast, AI-driven interventions designed to directly support the mental health of HCWs remain poorly understood. This scoping review therefore aimed to map the current landscape of AI-driven interventions intended to directly support the mental health and well-being of HCWs.

Methods

Overview

This scoping review was conducted in accordance with the JBI guidelines for scoping reviews [28] and reported using the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) [29] (Checklist 1). The steps in the review process included the search strategy, selection of evidence sources, data extraction, evidence analysis, and presentation of results [30]. The review protocol was registered with the Open Science Framework [31]. Since the use of AI to support HCWs' mental health is still emerging, a scoping review was appropriate to map the existing studies, approaches, and interventions. This method provided a broad overview of how AI has been used in this area and helped identify gaps and opportunities for future research.

Search Strategy

A preliminary search was conducted using the search terms "artificial intelligence," "mental health," and "health care worker," and their synonyms, with assistance from an information and evidence synthesis specialist (LL). This informed the subsequent development of an in-depth search strategy using search terms identified in the titles, abstracts, and index terms of the articles retrieved in the initial search. This led to a methodological search for the literature published in the Ovid MEDLINE, PubMed, CINAHL, Cochrane Library, Scopus, Embase, and PsycInfo databases. The gray literature search included ProQuest Dissertations &

Theses Global, Google, and the reference lists of the included studies. This search was conducted in March 2024 and later updated in September 2025. The first 100 search results from Google were screened. The gray literature search was subsequently updated in December 2025 to capture any newly available evidence. The search was limited to literature in English, and no date restrictions were applied. Only studies involving AI-driven tools designed to directly support the mental health of HCWs were included. Studies focusing on indirect effects, such as workflow optimization, were excluded. Full inclusion and exclusion criteria are provided in Table 1. The search strategy for all included databases is provided in Multimedia Appendix 1.

Table 1. Inclusion and exclusion criteria.

Criteria	Include	Exclude
Participants	HCWs[a]—allied health, medicine, nursing, and midwifery	Other types of HCWs; those in the prequalification or preregistration period, including students and interns
Concept	AI for supporting mental health: AI, neural networks, deep learning, natural language processing, and chatbots designed to improve or enhance mental health and well-being outcomes	Any other form of aide (eg, human interventions, diagnosis, patient care, and clinical decision-making) that does not directly support or enhance mental health and well-being outcomes
Context	Related to the mental health of HCWs working in health care settings	Physical health of HCWs; areas outside health care settings
Outcome	Stress, anxiety, depression, insomnia, and burnout.	Outcomes outside of those included
	Objective and subjective measures, and perspectives (eg, HCWs and managers)	
Study design	All primary designs (quantitative, qualitative, and mixed methods), secondary research (reviews), opinion pieces, and editorials	None

[a]HCW: health care worker.

Screening and Study Selection

Database search results were collated, uploaded to Covidence, and deduplicated. Records identified through citation searching and gray literature were screened separately against the same eligibility criteria. Two reviewers (among SSD, BD, MM, and LS) independently assessed the titles and abstracts of each result against the eligibility criteria. In the subsequent phase, the same step was followed by 2 independent reviewers (among SSD, BD, MM, and LS) to screen eligible full texts. Discrepancies were resolved through mutual discussion with a third reviewer (PM) to reach consensus.

Data Extraction

Given the small number of included studies (n=5), the data extraction form was applied to all included studies and refined as needed (Multimedia Appendix 2). The data extraction template was discussed and agreed upon by the review team prior to extraction. The extracted information included: authors, year of publication, country or region of origin, study design, professions involved, type of AI used, mental health challenge addressed, outcomes, barriers to and enablers of AI use, study limitations, and directions for future research and policy.

Data Analysis and Charting

The extracted data were analyzed descriptively to map key characteristics and concepts across the included studies. Charted data were reviewed iteratively by multiple reviewers (SSD, BD, and MM) to identify similarities and recurring concepts relevant to the review objectives. Given the small number of included studies and the convergence of findings, extracted concepts were grouped into a single overarching thematic category reflecting the focus of the available evidence. The charting framework and thematic categorization were refined through discussion among the review team, with disagreements resolved by consensus. The final charted data and thematic category were reviewed by the full team (SSD, BD, MM, and PM) to ensure consistency, transparency, and alignment with the review questions.

Ethical Considerations

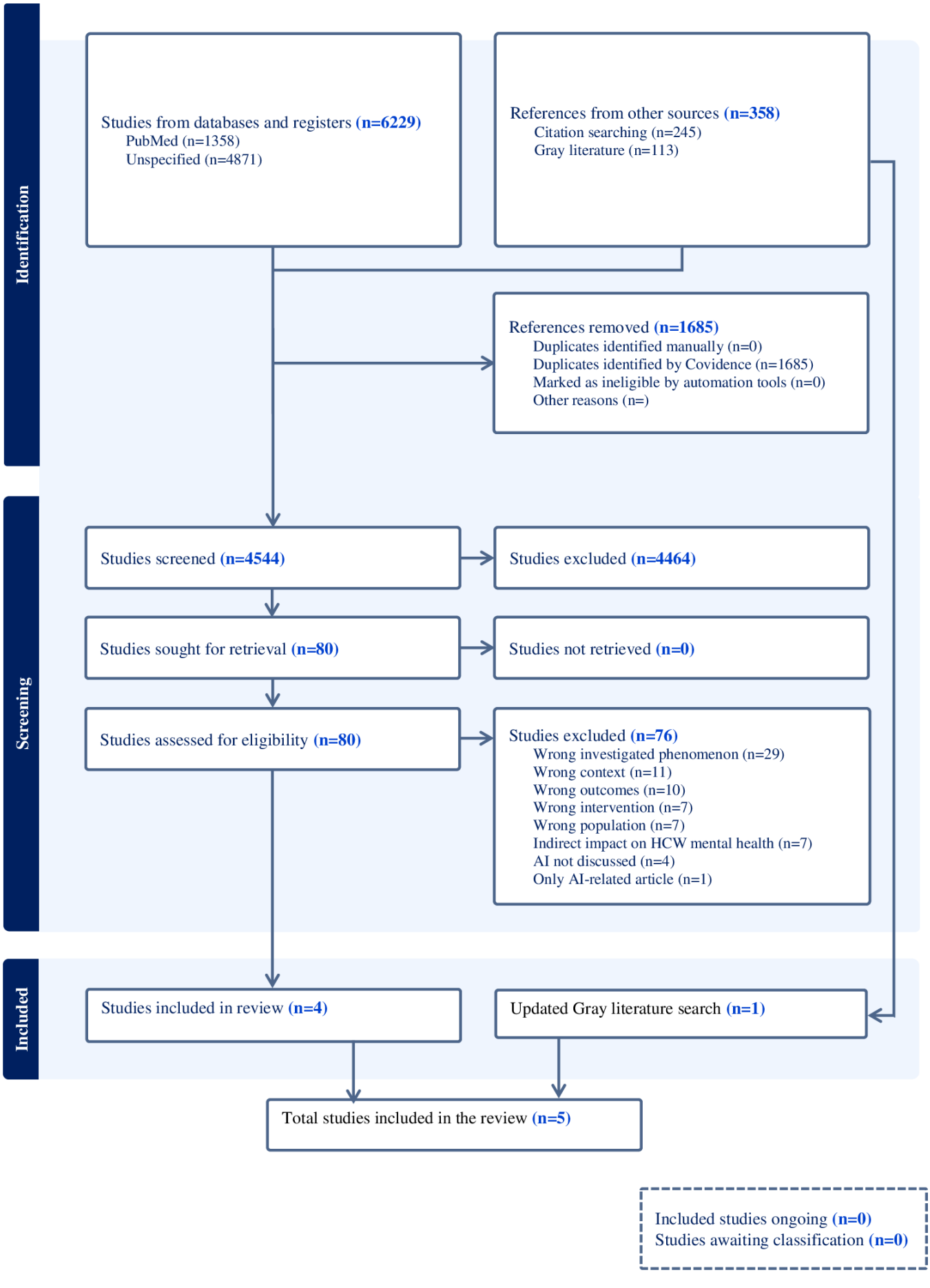
This scoping review did not require ethics clearance from an institutional review board.

Results

Study Characteristics

A total of 6587 records were identified, including 6229 (94.6%) from database searches and 358 (5.4%) from other sources, comprising 245 (3.7%) from snowball searches of reference lists and 113 (1.7%) from gray literature sources (Figure 1). After deduplication, 4544 database records remained for title and abstract screening. Of these, 4464 (98.2%) were excluded, whereas 80 (1.8%) progressed to full-text review. Following full-text assessment, 76 of 80 records (95.0%) were excluded for reasons outlined in Multimedia Appendix 3, leaving 4 studies (5.0%) for inclusion. One additional study identified through the updated gray literature search was added, bringing the total to 5 studies included in the final review. The PRISMA flowchart of study selection is presented in Figure 1.

Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart. HCW: health care worker.



The included studies were published between 2021 and 2025 (Figure 2). Geographically, out of the 5 studies, 2 (40%) originated from the United States [32,33], 2 (40%) from the Republic of Korea [21,34], and 1 (20%) from Quebec, Canada [35]. The included citations comprised 1 single-arm trial, 1 prospective cohort study [34,35], 1 commentary [32], 1 doctoral thesis presenting a conceptual framework [33], and 1 scoping review [21]. Further study characteristics are presented in Table 2.

Figure 2. Number of included publications by year.

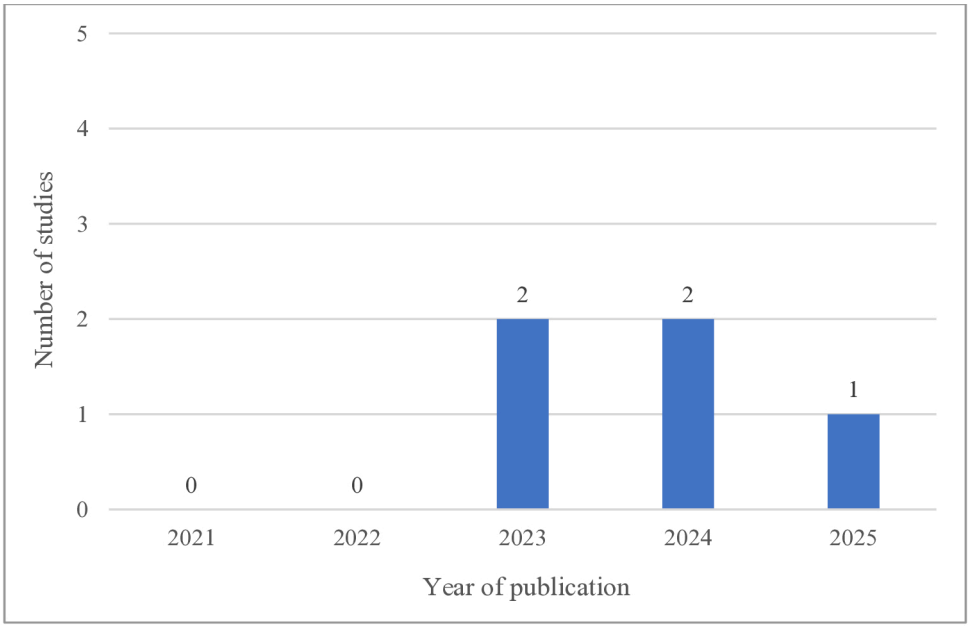


Table 2. Study characteristics.

Author (year)	Country	Setting	Participants	AI used	Mental health issues
Baek et al (2025) [21]	Republic of Korea	—[a]	Licensed health professionals (physicians or surgeons, dentists, medical doctors, registered nurses, licensed practice or vocational nurses, pharmacists) and allied health professionals	AI chatbots, NLP[b], and ML[c]	Anxiety, depression, and burnout
Cho et al (2024) [34]	Republic of Korea	Web-based nursing communities	Nurses	Use of AI as a program recommendation system	Burnout and ob stress
Geoffrion et al. (2023) [35]	Quebec, Canada	Eight health care centers across Quebec	Health care workers from different sectors of health and social services, including hospitals, long-term care, and local community services centers	ML, logistic regression, and support vector machines	Anxiety, depression, and posttraumatic stress disorder
Singh (2024) [33]	United States	—	Mental health workers	NLP	Stress and burnout
Ventura et al (2023) [32]	United States	—	Physicians	AI for screening, prediction, and personalized recommendation	Burnout

[a]Not applicable. A setting did not apply as these were secondary studies, including commentaries, reviews, and prospective frameworks.
[b]NLP: natural language processing.
[c]ML: machine learning.

Regarding study settings, Geoffrion et al [35] conducted a prospective cohort study across 8 health care centers in Quebec, Canada. Cho et al [34] conducted a single-arm trial involving nurses recruited through web-based nursing communities. For the remaining studies, the setting was either not reported or not applicable because the study was conceptual or commentary-based.

AI-driven interventions were proposed for various health care disciplines, including nurses [21,34], physicians [32],

surgeons, dentists, pharmacists, allied health professionals [35], and mental health workers [33]. Most included studies focused on burnout as the primary mental health concern, whereas Geoffrion et al [35] examined anxiety, depression, and posttraumatic stress disorder (PTSD) among HCWs. Across the included studies, a range of AI approaches, including ML and neural network–based methods, were used. The application domains included NLP-driven conversational systems, personalized recommendation systems, and predictive screening tools (Table 3).

Table 3. Types of AI reported in the reviewed literature.

Author (year)	Types and approaches to AI	Application domain
Cho et al (2024) [34]	ML[a] and neural network optimization	Personalized recommendation system
Geoffrion et al (2023) [35]	ML, logistic regression, and support vector machines	Screening tool
Baek et al (2025) [21]	Rule-based systems, ML, and NLP[b]-enabled approaches	Chatbots
Singh (2024) [33]	NLP	Mental health app (MHApp)
Ventura et al (2023) [32]	ML	Predictive screening and risk stratification

[a]ML: machine learning.
[b]NLP: natural language processing.

Effectiveness of AI in Promoting HCWs' Mental Health

Findings from the included studies suggested that AI-driven tools may offer preliminary benefits for reducing burnout among HCWs. A single-arm trial by Cho et al [34] introduced Nurse Healing Space, a mobile app that delivered personalized well-being sessions on mindfulness meditation, laughter therapy, storytelling, reflective writing, and acceptance and commitment therapy (ACT). These modules were tailored using a similarity-based recommendation algorithm that analyzed individual burnout profiles using the Copenhagen Burnout Inventory, job stress, stress-response indicators, coping patterns, and demographic characteristics. The development process included a pilot phase involving 10 participants, followed by algorithm optimization with a sample of 300 users. Over the 4-week intervention, overall burnout scores significantly decreased from a baseline mean of 62.36 (SD 18.00) to 55.22 (SD 18.79) following the first intervention phase (t_{299}=7.012; P<.001). They further decreased to 52.70 (SD 20.15) after the second intervention phase (t_{299}=8.692; P<.001). Significant reductions were also observed in personal burnout (t=6.134; P<.001), work-related burnout (t_{299}=6.816; P<.001), and client-related burnout (t_{299}=6.439; P<.001). In addition, participants demonstrated reductions in job stress (t_{299}=6.765; P<.001) and physiological stress responses (t_{299}=5.864; P<.001). Among the intervention components, ACT was associated with the largest reduction in burnout (12.3%), followed by laughter therapy (10.4%). The trial concluded that the app effectively reduced nurse burnout, job stress, and stress responses through personalized interventions, which reduced nurse attrition and enhanced the quality of health care services.

The included studies also explored AI-driven chatbots as scalable tools to support HCWs' psychological well-being. Baek et al [21] conducted a scoping review that synthesized 10 studies evaluating AI chatbots designed to support the psychological well-being of HCWs. The studies included chatbots such as Vickybot, iChatBot, PeerChat, Wysa, Viki (Vitalk Virtual Mental Health Assistant), and Mood Disorders Information Resource Assistant (MIRA). Six chatbots were delivered through mobile apps and 4 through web-based platforms. These chatbots incorporated features of CBT, mindfulness-based strategies, stress-management exercises, crisis-support functions, and mood tracking and primarily used NLP-driven algorithms. Several chatbots also incorporated ML and rule-based programs. The therapeutic capacities included problem-solving exercises, dialectical behavior strategies, behavioral activation, psychoeducation, gratitude training, and supportive functions (such as reminders and gamification). Anxiety, depression, and burnout were the most frequently assessed mental health outcomes. Among the included studies, 1 reported substantial improvement in anxiety, 1 in depression, and 2 demonstrated reductions in burnout. The remaining studies that focused on resilience, compassion fatigue, and loneliness showed mixed or nonsignificant effects. User perceptions of chatbots were generally positive, with several studies reporting high perceived usefulness, satisfaction, and ease of use. However, the authors observed substantial variation in engagement and completion rates. Barriers to usability included time constraints, notification fatigue, and low sustained engagement. Heterogeneity across study designs, intervention duration, and user engagement further limited comparability. Through the review, Baek et al [21] emphasized the need for standardized evaluation frameworks, methodological rigor, stronger clinical validation, and a focus on digital health equity for the safe and effective deployment of chatbot-based mental health tools for HCWs.

Beyond intervention studies, Singh [33] proposed a conceptual model for an AI-human partnership–based mental health app (MHApp) specifically designed for mental health workers. The model was developed through a structured, multiphase process involving needs assessment, literature-based gap analysis, evaluation of existing organizational support systems, and assessment of AI's potential to enhance accessibility and personalization. Grounded in the job demands–resources model [36] and perceived organizational support theory [37], the conceptual model aims to combine AI's analytical capabilities with empathy to deliver personalized psychological support, reduce job-related stress, and promote resilience among mental health workers.

Alongside therapeutic interventions, predictive modeling approaches were recommended for screening and prediction of various mental health conditions. A commentary by Ventura et al [32] suggested using AI-driven screening and prediction models to identify HCWs at heightened risk of adverse mental health outcomes, particularly burnout. The commentary further highlighted that AI-driven systems could analyze individual data to flag emerging risk profiles, enabling timely and personalized support. Similarly, a prospective cohort study by Geoffrion et al [35] of 816 HCWs (Time 1) from clinical and social sectors across 8 health care centers in Quebec showed the effectiveness of ML models for screening anxiety, depression, and PTSD using only 2 questions on the level of stress and quality of life, alongside biological sex. Logistic regression and support vector machine models produced 64.2% to 82% overall accuracy. The highest-performing model for depression achieved an accuracy of 82.0%, sensitivity of 82.1%, and specificity of 81.8% using cumulative 3-week measures (n=693). The anxiety screening models reported accuracies of approximately 64.2% to 77.2%, with sensitivities approaching 79.7%. However, the positive predictive values did not exceed 50% in any model, underscoring the need for further model tuning with larger datasets. These findings suggest the feasibility of low-burden, ML-driven screening systems for identifying psychological distress using minimal user input. Collectively, these studies demonstrated the growing application of AI across intervention delivery, screening, personalized support, and predictive mental health management for HCWs.

Discussion

Principal Results and Comparison With Prior Literature

The review explored the current landscape of AI-driven interventions designed to directly address the mental health of HCWs. While AI is widely applied across diagnostics, screening, risk analysis, workflow management, and robotic surgery [38-40], its application to enhance the mental well-being of HCWs remains relatively underdeveloped. The included studies focused on reducing burnout [32,33], providing intervention-based support via chatbots [21], mobile apps [34], and predictive screening [32,35]. The studies also reported reduction in stress [34], and improvements in anxiety and depressive symptoms [21,34]. Findings suggest that current research remains heterogeneous, comprises conceptual frameworks, predictive modeling approaches, and early-stage intervention studies [33-35]. These developments reflect a growing recognition of the importance of HCW well-being for safe and effective health care delivery.

Burnout was the most prevalent mental health concern within the included studies. The *International Classification of Diseases, 11th Revision* (*ICD-11*), describes burnout as an occupational phenomenon resulting from chronic workplace stress that has not been successfully managed [41]. Burnout among HCWs is linked to adverse outcomes in clinical performance, patient experience, and overall organizational functioning [42-46]. Burnout and stress are recognized as critical targets for mental health innovation within health care systems, aligning with global research priorities [6]. This is particularly relevant because individual barriers, organizational constraints, and social stigma often prevent HCWs from adequately addressing their psychological concerns.

Personalized AI-driven tools, particularly Nurse Healing Space [34], demonstrated early effectiveness in alleviating emotional exhaustion and depersonalization and enhancing mental well-being through individualized support [35]. These findings, although preliminary, suggest a shift from reactive, episodic support toward personalized, proactive strategies that may address the time pressures and workload demands of HCWs. Chatbots represent another emerging category of personalized AI-driven interventions [47]. Evidence synthesized by Baek et al [21] indicates growing interest in these technologies, which reflect a broader shift toward proactive psychological support. Chatbots offer low-burden, scalable mental health support, which might be particularly useful in high-demand health care settings with limited access to conventional psychological support [47,48]. However, the chatbots included in this study largely relied on rule-based or limited NLP-driven conversational systems, which differ from newer generative AI systems capable of more adaptive and context-aware interactions. Additional implementation constraints include small sample sizes, short-term interventions, and limited evaluation measures. This gap highlights the need for more rigorous, longitudinal research to determine the sustained impact of these tools [27,33,34].

In addition to burnout, the included studies also addressed other important mental health concerns among HCWs, including work-related stress, cognitive burden, anxiety, depression, and PTSD [35]. These findings align with recent literature promoting ML as an effective method for augmenting psychological assessments using minimal or passively collected data. For instance, a comparative review by Arora and Joshi [49] reported that ML models could accurately predict anxiety and depression using minimal input features from wearable devices and brief self-report questionnaires. These findings support the feasibility of scalable, low-burden screening tools, especially in resource-constrained settings. Ventura et al [32] further suggested that AI-driven screening could help identify HCWs at risk of psychological distress and guide timely support. However, a lack of generalizability and database bias remain prominent concerns. Cruz-Gonzalez et al [50] expanded on this by reviewing AI applications across diagnosis, monitoring, and intervention, offering a domain-specific structure for integrating AI into organizational mental health strategies. While these advances provide an important foundation, most of the frameworks remain largely conceptual and require empirical validation.

Among the occupational groups represented, nurses appeared particularly vulnerable to burnout [21,34]. This is a critical issue, given that nurses constitute the largest segment of the global health care workforce, with a stock of 32.7 million [51]. Nurses report substantial levels of anxiety, depression, and stress, which makes accessible digital mental

health support particularly relevant [52,53]. Burnout among nurses is associated with higher nurse turnover rates, which, in turn, impacts the quality of care and increases the financial burden on hospitals [45,54]. Cho et al [34] developed Nurse Healing Space to support nurses' mental health by reducing burnout. A subsequent randomized controlled trial by Baek et al [55] demonstrated a reduction in both personal and client-related burnout among nurses compared with the control group. These findings are consistent with a systematic review by Askarizadeh et al [56], which showed that mobile-based self-care apps significantly reduced anxiety among HCWs. Broader evidence from the general population suggests that mobile apps serve as standalone self-management interventions for anxiety and depression, indicating potential for tools customized to HCWs [57]. Singh's [33] AI-human conceptual model for MHApp, specifically designed for mental health professionals, extends this work by advocating a shift from task-oriented AI systems to emotionally intelligent, collaborative interventions.

The included studies were published between 2021 and 2025, reflecting the emerging nature of AI-driven mental health applications for HCWs. Although the field has seen an increase in primary studies, a large portion of the available literature remains conceptual in nature [21,32,33]. The limited number of included studies and the predominance of conceptual literature highlight both the novelty of this research area and the need for further empirical investigation into AI-driven mental health interventions. Notably, all the studies originated in high-income countries. This finding is consistent with the large-scale digitalization of health care in these countries, characterized by advanced infrastructure, the regular and systematic use of EHRs, and the availability of large, high-quality clinical databases [58,59]. Future research should explore the potential of AI-driven mental health support for HCWs in low- and middle-income countries, particularly in the context of advancing universal health coverage, furthering a key United Nations Sustainable Development Goal [60].

Limitations Reported Within the Included Studies

Despite the promising nature of these findings, the current evidence remains constrained by several methodological and implementation limitations. Methodological limitations include small, nonrepresentative samples, absence of a control group, and self-reported measures [21,34,35]. Short intervention durations and limited follow-up periods further restrict conclusions regarding long-term effectiveness, while non-representative samples limit generalizability. The predictive modeling study by Geoffrion et al reported several implementation limitations, such as incomplete data, low positive predictive values, limited validation procedures, and the absence of hyperparameter tuning, which limited the clinical utility of predictive models [35]. These limitations collectively emphasize the need for larger, longitudinal, and methodologically rigorous evaluations to determine the clinical effectiveness and equitable implementation of AI-driven mental health interventions for HCWs.

Implications for Practice, Policy, and Research

The findings of this review underscore the need for interdisciplinary collaboration to advance AI applications in HCWs' mental health. Partnerships between AI developers, clinicians, and policymakers are essential to ensure that AI tools are clinically relevant, ethically sound, and aligned with health care priorities. As the empirical evidence base for the use of AI solutions to enhance and promote HCWs' mental health is still evolving, possibilities for generalization are limited, both for practice and for the advancement of methodological approaches. There is a need for further research to advance the evidence in this aspect of AI. Future studies could use participatory design methods to actively engage HCWs in cocreating AI tools that support their mental well-being. Rigorous implementation science frameworks are crucial to evaluate the real-world scalability of interventions, especially in resource-constrained settings where digital infrastructure is underdeveloped.

Longitudinal studies with extended follow-up periods are crucial for assessing the sustained impact of AI-driven interventions to reduce burnout and improve mental health outcomes. Although burnout, stress, and depression among HCWs warrant further exploration, the mental health of HCWs is an underrepresented area in AI research. Targeted interventions at the individual and systemic levels may be necessary to address these issues. Challenges such as data privacy and confidentiality need to be considered as AI's role continues to grow. The use of AI in real-world health care settings also presents potential risks that need to be explored, and strategies for seamless integration must be formulated.

Review Strengths and Limitations

This is among the first scoping reviews to specifically synthesize evidence on AI-driven interventions designed to directly support the mental health of HCWs. The review addresses a critical gap in the field, as existing AI research centers on workflow optimization or patient-facing applications. The review team is transdisciplinary, comprising professionals from health care (SSD, MM, BD, LL, LW, SK, LS, and PM), public health, digital health (LW), and engineering (TC), thereby enhancing the comprehensiveness of the review processes, findings, and interpretation. The review integrates empirical interventions, reviews, predictive modeling approaches, and conceptual AI-human hybrid frameworks to provide a comprehensive understanding of current research in the field.

However, the review has some limitations. First, the review is limited by the exclusion of non–English-language papers, which may have led to the omission of relevant evidence from non–English-speaking regions. Second, only 5 studies met the inclusion criteria, reflecting both the novelty of the topic and the scarcity of empirical research directly examining AI for HCW mental health. This limits the breadth of the findings. Third, all included studies were conducted in high-income countries (the United States, Canada, and South Korea), limiting the review's ability to capture the state of

AI-driven mental health research in low- and middle-income settings, where digital infrastructure and workforce needs may differ substantially. Finally, the search strategy did not explicitly include emerging generative AI terms such as "large language model," "LLM," or "ChatGPT," which may have limited the identification of some recent studies.

Conclusions

AI holds promise for improving the mental health of HCWs, offering new avenues to detect distress early, mitigate burnout and stress, personalize support, and streamline access to care. Although the current evidence base remains limited and heterogeneous, the potential for AI to enhance well-being and transform mental health support for HCWs is clear and gaining momentum. The use of AI in the predictive space is recognized, but research on its role in mitigating burnout and stress among HCWs is at a relatively nascent stage. The included studies suggest that AI-driven systems, including mobile apps, chatbot-based interventions, and ML-driven screening approaches, may support more proactive, accessible, and individualized mental health care for HCWs. However, there is a strong need to strengthen the empirical base through robust, contextually grounded studies that evaluate the effectiveness, feasibility, and sustainability of AI-driven interventions specifically designed to support HCWs' mental health.

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Generative AI Use

The authors used Grammarly (version 1.147.0.0) and Microsoft Copilot (GPT-5.2) for text generation, proofreading, and editing under full human supervision. The authors reviewed and approved the final manuscript and take full responsibility for its content.

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Data Availability

All data generated or analyzed during this study are included in this published article and its supplementary information files.

Authors' Contributions

Conceptualization: LL, TC, SK, PM
Data curation: SSD, BD, MM, LS, PM
Formal analysis: SSD, BD, MM, PM
Investigation: SSD, BD, MM, LL, LW, TC, SK, PM, LS
Methodology: LL, LW, SK, PM
Resources: TC, PM
Supervision: TC, PM
Writing—original draft: SSD, BD, MM, PM
Writing—review and editing: SSD, BD, MM, LL, LW, TC, SK, PM

Conflicts of Interest

None declared.

Multimedia Appendix 1

Search strategies for all databases.
[DOCX File (Microsoft Word File), 27 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Data extraction form.
[DOCX File (Microsoft Word File), 16 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Reasons for exclusion at full-text screening.
[DOCX File (Microsoft Word File), 42 KB-Multimedia Appendix 3]

Checklist 1

PRISMA-ScR checklist.
[DOCX File (Microsoft Word File), 33 KB-Checklist 1]

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Abbreviations

ACT: acceptance and commitment therapy
CBT: cognitive behavioral therapy
EHR: electronic health record
HCW: health care worker
***ICD-11*:** *International Classification of Diseases*, *11th revision*
NLP: natural language processing
PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews
PTSD: posttraumatic stress disorder

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