Examining Predictive Models for Burnout Detection among South African Medical Doctors: A Scoping Review

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This work is as much yours as it is mine.

Yours truly,

Ethan Terblanche

Abstract

Background:

Burnout among healthcare professionals is a multidimensional occupational phenomenon characterised by emotional exhaustion, depersonalisation, and diminished personal accomplishment. It contributes to reduced clinical performance, increased medical errors, and workforce attrition. Despite growing global concern, there remains limited synthesis of how predictive artificial intelligence (AI) models have been applied to detect burnout in healthcare settings

Objective:

To identify predictive models used for burnout detection in healthcare, and to examine which predictive models are most suited for early detection of burnout among South African medical doctors, based on available determinants and local context.

Methods:

Guided by the Joanna Briggs Institute (JBI) methodology and reported according to the PRISMA-ScR (2020) framework, the review addressed the research question: "What predictive models have been used for burnout detection in healthcare, and what evidence supports their suitability for South Africa?" Searches were conducted in PubMed, Scopus, PsycINFO and ProQuest (2018–2025, English language). Inclusion criteria followed the Population–Concept–Context (PCC) framework, and eight studies met eligibility requirements. Data was charted for model type, determinants assessed, and contextual relevance, then synthesised descriptively and thematically.

Results:

Studies from China, the United States, Italy, Colombia and South Africa employed algorithms including random forest, gradient boosting, neural networks, and deep learning. Psychological and organisational determinants, emotional exhaustion, fatigue, workload, and managerial support, was the strongest predictors, achieving accuracies between 68 and 94 per cent.

Conclusion:

Predictive AI models show promise for early burnout detection across healthcare settings. For South Africa, low-cost survey-based and organisational indicators appear most feasible, while future integration of physiological and digital data could enhance prediction accuracy as infrastructure advances.

Keywords: Artificial intelligence, burnout, early detection, medical doctors, predictive models, South Africa.

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List of Abbreviations

AI- Artificial Intelligence

EHR- Electronic Health Records

BO- Burnout

LMIC- Lower-Middle-Income-Countries

JBI- Joanna Briggs Institute

WHO- World Health Organisation

PRISMA-ScR- Preferred Reporting Items for Systematic Reviews and Meta-Analyses – Scoping Review extension

PCC- Population–Concept–Context framework

ML- Machine Learning

SVM- Support Vector Machine

ANN- Artificial Neuro Network

MBI- Maslach Burnout Inventory

HREC- Human Research Ethics Committee

LLMs- Large Language Model

Introduction

1.1 Background and Context

Burnout is recognised through depersonalisation, a diminished sense of personal achievement, and emotional tiredness (1)(2) . Among medical doctors, it manifests through psychological symptoms such as anxiety, depression and impaired concentration, as well as physiological signs including insomnia, fatigue and appetite disturbances (3)(4) . In South Africa, reported prevalence rates vary widely. Prior to the COVID-19 pandemic, Khan (2024) indicated burnout levels ranging between 4% and 84% among medical doctors, with prevalence escalating to nearly 78% during and after the pandemic. Burnout remains a pressing concern because it is consistently linked to increased medical errors, reduced productivity, diminished job satisfaction and higher rates of attrition (5)

Recent advances in artificial intelligence (AI) offer new possibilities for predicting and monitoring burnout. AI-based predictive models can integrate diverse data, from electronic health records (EHR) (6)(7) to surveys (8)(9), and wearable devices (10) to identify individuals or groups at heightened risk. Internationally, predictive models have achieved varying levels of success. Ensemble models such as random forests and gradient boosting often perform best when combining organisational and psychological determinants (8)(9) while models relying only on digital trace data, such as EHR logs, have demonstrated limited predictive power (6)(7).

While promising, the South African context remains underexplored. To date, limited work has been conducted locally. One study applied machine learning to survey data among nurses, identifying fatigue and managerial support as critical predictors of burnout(9). This highlights the importance of context-specific drivers in resource-limited settings and signals the need to systematically scope what predictive models exist and to assess their applicability to South African medical doctors.

1.2 Problem Statement

Burnout remains a major challenge in South Africa's healthcare system, aggravated by staff shortages, heavy workloads, and constrained resources. While predictive AI models have shown promise internationally (7)(8) there is limited evidence on which models are most suitable for South Africa, where data systems are uneven and contextual determinants (e.g. leadership support, working conditions, socioeconomic stressors) play a larger role(11). The lack of contextually validated predictive models restricts the country's ability to implement early detection and preventive interventions. Without such tools, burnout risks going unnoticed until it results in severe outcomes such as staff attrition, reduced quality of care, and adverse health impacts on medical doctors.

1.3 Research Question

What predictive models have been used for burnout detection in healthcare, and what evidence supports their suitability for South Africa?

1.4 Aim of the Study

The aim of this scoping review is to explore the main types of predictive models used for burnout detection in healthcare and to assess their suitability for early detection among South African medical doctors, considering psychological, physiological, and organisational determinants.

1.5 Research Objectives

To identify predictive models used for burnout detection in healthcare.

To examine which predictive models are most suited for early detection of burnout among South African medical doctors, based on available determinants and local context.

1.6 Significance of the study

This review contributes to the field of health systems science and digital health innovation by examining AI-based predictive models for burnout detection. It highlights which approaches have been successful internationally, identifies contextual gaps, and evaluates their potential relevance for South Africa. By doing so, it provides evidence to guide the development or adaptation of locally appropriate predictive models that can enable early detection and intervention. Given the high rates of burnout among South African doctors and the critical role they play in sustaining the healthcare system, developing predictive tools that can identify early warning signs is essential. This study can contribute to identifying the early signs of burnout, by looking at predictive AI models and determinants such as psychological, physiological and organisational determinants to examine their appropriateness for the South African context.

2. Literature Review

2.1 Definition and Prevalence of Burnout

Burnout (BO) is defined as a work-related syndrome involving emotional exhaustion, depersonalisation and reduced professional efficacy[(1)(2)]. Among doctors, it can manifest as irritability, depression and anxiety, as well as physiological outcomes such as chronic fatigue and disturbed sleep[(3,4)]. Burnout has significant consequences for patient safety, productivity and retention of healthcare professionals[(5)].

2.2 Determinants of Burnout in Medical Doctors

Psychological determinants include emotional exhaustion, impaired concentration and anxiety[(3)]. Physiological contributors include fatigue, somatic symptoms and disrupted sleep.[(4)]. Organisational drivers include excessive workloads, reduced autonomy, poor supervision and unsupportive workplace cultures[(5)(12)]. In South Africa, these issues are amplified by staff shortages and high patient loads[(13)]. The death of Dr Alulutho Mazwi in 2025 drew national attention to systemic shortcomings in protecting clinician well-being[(13)]. Dr Mazwi was a young medical intern in the department of paediatrics at Umlazi's Prince Mshiyeni Memorial Hospital. He suffered from diabetes, and unfortunately passed away after allegedly being made to work despite reporting that he was unwell[(13)].

The Health Professions Council of South Africa (HPCSA) states that junior doctors should work 40 hours per week, with a maximum of 20 hours overtime. However, these guidelines are ignored and in the overburdened South African health system junior doctors work between 80 and 120 hours per week. According to sources, Dr Mazwi had already collapsed twice before during working hours, which he told his supervisors about. Despite reporting his illness, he was told that if he did not report for duty he would have to redo his clinical rotation[(13)]. Predictive modelling studies reinforce the role of these determinants. Van Zyl-Cillié et al. (2024) found that fatigue and managerial support were the strongest predictors of burnout among South African nurses, indicating the importance of psychosocial and organisational influences in resource-constrained settings amongst medical professionals.

Therefore, this study is important as predicting or detecting burnout early can prevent further health problems and ensures an ethic of care for patients as they are treated by medically and psychologically fit professionals. By shifting from a pathological to a preventative approach of care, we could avoid tragic outcomes like the death of Dr Mazwi.

2.3 Artificial Intelligence in Mental Health and Early Detection

The application of artificial intelligence (AI) in mental health has expanded rapidly over the past decade, particularly in areas of diagnosis, prognosis, and early detection of psychological distress. The literature demonstrates that AI systems can synthesise diverse data sources, including clinical records, surveys, and physiological indicators, to identify individuals at elevated risk of mental health challenges, such as burnout, before symptoms become clinically apparent[(14)]. Recent studies illustrate the variety of AI methodologies being explored. For instance, research in China employed random forest models on self-reported survey data to classify burnout risk with notable accuracy[(8)].

Investigations in the United States have assessed electronic health record (EHR)-based predictors, showing that digital workload data can contribute meaningfully to prediction only when combined with baseline psychological variables[(6)(7)]. Further work integrating qualitative validation has emphasised that digital indicators alone cannot fully capture the psychosocial and organisational dimensions of burnout[(15)]. More recent advances, such as the EMBRACE model, have incorporated wearable sensor data to include physiological variables in predictive modelling[(10)]. These studies illustrate a growing movement towards multi-modal approaches in AI driven mental health monitoring.

2.4 Predictive Models for Burnout Detection

Across studies, model architecture varies widely, from traditional statistical methods, such as logistic regression, to advanced machine learning techniques capable of modelling complex, non-linear relationships[(8,9)]. Evidence suggests that tree-based algorithms, including random forests, decision trees, and gradient boosting, often outperform simpler linear models when handling heterogeneous datasets that include psychological and organisational variables[(9)(16)]. Neural networks have also been tested, particularly in clinical subfields such as anaesthesiology, where they have achieved moderate predictive accuracy[(17)]. Literature further indicates that predictive strength varies depending on the input data used. Models incorporating survey-based psychological and organisational measures typically achieve stronger performance than those relying exclusively on administrative or digital workload data[6][15]. These findings collectively underscore the importance of including multi-level determinants, psychological, physiological, and organisational, when developing burnout prediction models. At the same time, the literature highlights the need for contextually relevant models that can be adapted for resource-limited health systems such as South Africa's, where access to high-resolution digital or biometric data remains limited.

2.5 Consequences of Burnout and the Imperative for Early Detection

Burnout affects both clinicians and healthcare systems. It is associated with reduced performance, increased medical errors, higher attrition and, in severe cases, suicidal ideation[4]. For health systems, burnout reduces workforce resilience and raises costs due to absenteeism and turnover. Early detection is therefore essential. Predictive AI models can serve as early warning systems, but their success depends on contextual adaptation and the inclusion of relevant determinants.

2.6 International Perspectives and LMIC Contexts

Most predictive AI burnout modelling has been concentrated in high-income countries, particularly in the United States, where studies have emphasised EHR data. However, these models have generally struggled to predict individual-level burnout accurately[6][7]. In low- and middle-income countries, the literature suggests that psychosocial and organisational drivers play a greater role. Castro-Tamayo et al. (2025) examined burnout among support staff in a resource-limited Colombian hospital, identifying socioeconomic determinants, such as household income, as key predictors of emotional exhaustion. Similarly, van Zyl-Cillié et al. (2024) demonstrated that managerial support and fatigue were the strongest predictors among South African nurses. These findings underline the need for the contextual adaptation of predictive models rather than uncritical transfer from high-income settings.

2.7 Rationale for this Scoping Review

Although predictive AI models for burnout detection are gaining ground internationally, limited research exists in South Africa. Most models are developed in high-income countries with advanced digital infrastructure, which limits their direct applicability. Where LMIC contexts have been studied, psychosocial and organisational determinants emerge as particularly influential[9][11]. A scoping review, guided by the JBI framework[18] and reported in line with PRISMA-ScR [19], is therefore warranted to examine existing evidence. This will identify what predictive models have been developed globally, the determinants they incorporate, and their potential suitability for South Africa.

3. Methods

3.1 Research Design

This study employed a scoping review design, selected for its suitability in examining the available evidence on predictive artificial intelligence (AI) models for burnout detection among healthcare workers. A scoping review was deemed appropriate as the literature on this topic diverse and remains limited in the South African context. The review was conducted in accordance with the Joanna Briggs Institute (JBI) methodology for scoping reviews[18] and reported in line with the PRISMA extension for Scoping Reviews (PRISMA-ScR) checklist[19]. The review question and scope was structured using the Population–Concept–Context (PCC) framework, with the population defined as medical doctors and closely related healthcare professionals, the concept as AI-based predictive models for burnout detection, and the context as healthcare systems with a particular focus on South Africa. Studies published in English between 2018, and 2025 was considered eligible, this timeframe was selected because this showcased the most recent and relevant activity and development of AI. Searches were conducted in PubMed, Scopus, and PsycINFO, supplemented by grey literature sources such as ProQuest, OpenGrey, the World Health Organization and South African government reports.

3.2 Methodology

The JBI framework outlines a structured approach consisting of five key stages: identifying the research question, identifying relevant studies, selecting eligible studies, charting the data, and collating, summarising and reporting the results. The use of the JBI framework ensured consistency and methodological transparency across all stages of the review. The review was reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) checklist[19]. The PRISMA-ScR framework provides a set of essential reporting items that enhance transparency, reproducibility and comparability across scoping reviews. The combination of JBI methodology and PRISMA-ScR reporting standards provided a robust foundation for the design and presentation of this review.

3.3 Eligibility Criteria

Studies was considered eligible if they met the following inclusion criteria. The population included medical doctors and, where relevant, closely related healthcare professionals such as nurses or residents, provided the findings was transferable to the context of doctors. The concept was the use of AI-based predictive models for the detection or early identification of burnout. Eligible studies also needed to consider at least one of the three broad categories of determinants: psychological, physiological or organisational. The context was healthcare settings, with a focus on applicability to South Africa and similar low- and middle-income country environments.

The review included peer-reviewed primary studies, secondary analyses, and reviews published between 2018 and 2025 in English. Excluded was non-healthcare domains, opinion pieces, conference abstracts without full texts, studies published before 2018 and those not available in English.

Table 1: PCC framework for eligibility criteria

Table 1 shows the PCC framework for the eligibility criteria for the selection of included studies of this scoping review.

PCC	Criteria
Population	Medical doctors and closely related healthcare professionals (e.g. residents, interns, nurses) where findings are transferable to the context of doctors
Concept	Predictive AI (Artificial intelligence) models using psychological, physiological, or organisational as predictors for early burnout detection
Context	Artificial intelligence (AI)-based predictive models for the detection or early identification of burnout, incorporating psychological, physiological, or organisational determinants

3.6 Information Sources

The literature search was conducted across three bibliographic databases: PubMed, Scopus, and PsycINFO, supplemented with grey literature sources including ProQuest Dissertations & Theses, OpenGrey, and targeted searches of organisational websites such as the World Health Organization and the South African Department of Health.

Search strategies was developed using combinations of controlled vocabulary (e.g. MeSH terms) and free-text keywords relating to burnout, predictive models, artificial intelligence, and healthcare professionals. Boolean operators (AND/OR) and truncation was applied to ensure comprehensive retrieval. The final search strategy was adapted to the syntax of each database, the final search was done on 14 October 2025.

Full Boolean strategies for each database are presented in ***Appendix A.***

3.7 Study Selection

Search results from each database was screened independently. No specialised software (e.g. Covidence or Rayyan) was used due to the relatively small number of studies retrieved. Instead, all records was managed manually and documented in an Excel spreadsheet, which also formed the basis for the subsequent data extraction and charting process.

The initial screening was conducted at the title level, followed by title and abstract screening, and finally by assessing the title, abstract and full text of potentially relevant studies. Filters was applied within databases at the search stage (e.g. limiting to English-language publications, 2018–2025, and relevant subject categories such as medicine, health professions, mental health, psychological stress, and prediction).

A total of 15 articles was identified for full-text review. Of these, seven was excluded as they did not employ AI-based predictive models, was descriptive only, or fell outside the date and language criteria. Eight new studies met the inclusion criteria and was incorporated into the review. For transparency of this scoping review, no second reviewer was used for the review of the articles included and excluded. The overall selection process, including numbers of records screened, excluded and included, is illustrated in the PRISMA-ScR flow diagram ***see Figure 1***

3.8 Data Charting

Data from the eight included studies was charted using an Excel sheet. For each study, information was extracted on the author and year of publication, country of origin, study design, population and sample size, and the main findings. In addition, determinants of burnout were categorised into psychological, physiological, and organisational, and the type of predictive AI model employed in the study was recorded. Finally, attention was given to whether the findings and methodological approaches was considered appropriate to South African context. Data extraction was carried out manually and cross-checked for accuracy to ensure consistency and reduce the risk of error. The completed data extraction sheet is provided in ***Appendix B***.

3.9 Data Synthesis

Extracted data was synthesised using both descriptive and thematic approaches to identify trends across determinants of burnout, and applicability to the South African context.

a) Descriptive Synthesis

The eight included studies was published between 2022 and 2025 and varied in design, population, and analytical approach. Most employed cross-sectional survey designs integrating machine learning models, while others used retrospective electronic health record (EHR) analyses, qualitative validation interviews, or pilot wearable-based models. Study sample sizes ranged from 24 participants [(15)] to over 1,100 healthcare workers[(8)]. Geographically, five studies was conducted in high-income countries (United States, China, Italy), one in a middle-income setting (Colombia), and one within South Africa.

The predictive models used across studies included random forest, gradient boosting, logistic regression, artificial neural networks (ANNs), support vector machines (SVMs), and a deep learning multitask model (EMBRACE). Tree-based algorithms such as random forest and gradient boosting was the most common, reflecting their strength in handling complex, nonlinear data and identifying variable importance in burnout prediction.

b) Thematic Synthesis

Thematic synthesis focused on three broad determinant categories, psychological, physiological, and organisational, to capture the multidimensional nature of burnout and the predictive role of AI in each, and whether it would be suitable for South African context.

Psychological determinants emerged as the most consistently represented across studies. Emotional exhaustion, depersonalisation, perceived stress, and low job satisfaction was repeatedly identified as key predictors of burnout. These variables was measured primarily through validated instruments such as the Maslach Burnout Inventory (MBI) and the Stanford Professional Fulfilment Index. For instance, Liu et al. (2025) and Cascella et al. (2025) both found emotional exhaustion to be the strongest predictor of burnout among healthcare staff and anaesthesiologists respectively, while Tawfik et al. (2025) confirmed through qualitative analysis that loss of autonomy and chronic stress exacerbate burnout in physicians.

Physiological determinants was less frequently incorporated across studies. Fatigue, self-reported or inferred through workload intensity, was a key predictor in several models[8][9]. Only one study, Alam et al. (2024), integrated objective physiological metrics using wearable sensor data such as sleep quality, heart rate variability, and physical activity. These data, processed through an explainable deep learning model (EMBRACE), achieved 94% accuracy in burnout prediction, highlighting the potential of multimodal physiological monitoring for early detection. However, such methods remain largely infeasible in low-resource settings where wearable technology is not widely available.

Organisational determinants was the most dominant predictors across nearly all studies. Factors such as workload, administrative burden, inadequate staffing, limited managerial support, job insecurity, and resource constraints was consistently associated with burnout. Studies using EHR data [6][7] demonstrated that administrative metrics, such as after-hours documentation and inbox volume, correlated with higher burnout risk. The South African study by van Zyl-Cillié et al. (2024) reinforced these findings, revealing that unsafe staffing levels, management communication gaps, and fatigue was leading contributors to emotional exhaustion among nurses.

c) Relevance for South African context

In synthesising these findings, it became clear that AI-based predictive models provide valuable insights into the complex interplay of determinants contributing to burnout. The models' success across diverse healthcare systems indicates that burnout is a globally shared challenge, yet the contextual application of predictive tools differs.

For South Africa, psychological and organisational determinants identified internationally was highly transferable. Emotional exhaustion, low job satisfaction, and poor managerial support mirror patterns observed locally, where healthcare professionals face chronic workload pressure and emotional strain. Physiological determinants, however, was less applicable due to technological and infrastructural limitations, most South African facilities lack the capacity for continuous biometric monitoring or EHR-based data capture. Nonetheless, self-reported fatigue remains an accessible and reliable marker of burnout risk in resource-limited contexts.

Collectively, the synthesis illustrates that while predictive AI models can enhance early identification of burnout, their utility in the South African setting will depend on integrating affordable and contextually appropriate indicators such as workload, fatigue, and perceived support rather than technologically intensive metrics.

3.10 Ethical Considerations

As this study involved a review of previously published literature, no human participants was directly involved, and formal ethical approval was not required. An ethics waiver was, however, obtained from the relevant institutional review body, confirming that no ethical risks was associated with the conduct of the review ***(see Appendix D)***.

3.10.1 Ethical Usage of Artificial Intelligence (AI)

During the writeup of this research report I acknowledge and declare that I did make use of artificial intelligence (AI), more specifically LLM's large language models. Through the development of this scoping review research report I did make use of AI ethically and responsibly. I made use of ChatGPT (OpenAI, Premium version) and Perplexity AI as language models to support the research process. These tools were used in accordance with institutional and academic integrity guidelines.

The LLMs was used for idea generation to an extent, conceptual clarification, grammar editing, improving readability and document structuring. In some cases, text generation was used to refine phrasing and sentence structures, within sections such as the literature review, methodology, and discussion. However, all the work that is produced in this research report is my own intellectual contributions. The prompts, framing and final decisions regarding inclusion, synthesis and arguments made was personally developed by me as the researcher.

At all times during the research process, I made sure that the usage of AI did not replace my own originality nor my academic thinking. AI did also not disrupt my ability for critical reflection or adherence to ethical and responsible research standards. The language models were only used as writing and language support tools, not as sources of data or analysis of data. I made sure to verify the accuracy of the information produced by the LLMs, by ensuring that all sources used was independently reviewed, and then the ultimate decision was made by me.

4. Results

4.1 PRISMA-ScR Flow Diagram

This section of the results showcases the PRISMA-ScR flow diagram, illustrating the number of records identified across four databases.

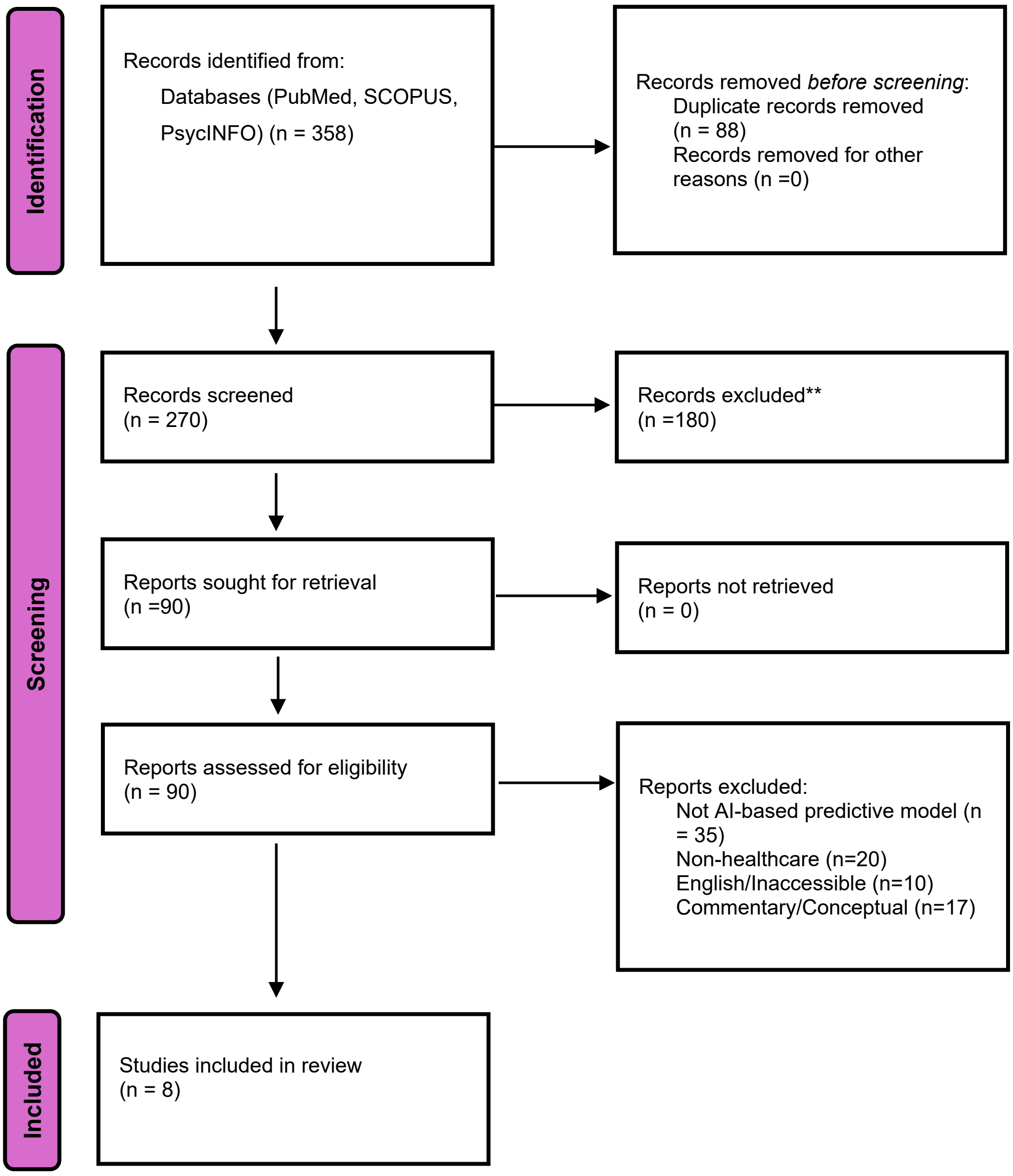

Figure 1Adapted from Page MJ, et al. BMJ 2021;372: n71. doi: 10.1136/bmj.n71.PRISMA-ScR flow diagram of the study selection process

4.2 Study Characteristics

Table 2 illustrates the characteristics of the 8 articles included in this scoping review, this table shows the author, country, study design, population and sample size, the AI tool used, key findings, determinants focused on, and its applicability to South African context.

Table 2: Study characteristics breakdown

Author (Year)	Country	Study Design	Population & Sample Size	AI Tool Used	Key Findings	Determinants Studied	Applicability to SA Context
Liu et al. (2025)	China	Cross-sectional survey with ML modelling	1,125 healthcare workers (doctors, nurses)	Random forest, SVM, logistic regression	Fatigue, job satisfaction and poor management support predicted burnout (~80% accuracy)	Psychological, physiological, organisational	Highly relevant, similar workforce stressors and fatigue patterns
Lou et al. (2022)	USA	Retrospective cohort using EHR data	~1,000 physicians	Logistic regression, XGBoost	After-hours screen time and inbox load predicted burnout	Organisational, psychological	Partially relevant, SA lacks integrated EHRs but admin overload parallels findings
Tawfik et al. (2024)	USA	Observational EHR analysis	1,300 physicians	Gradient boosting	Workload, inbox volume, and patient load strongest predictors	Organisational, psychological	High relevance, similar workload pressures but limited EHR feasibility
Tawfik et al. (2025)	USA	Qualitative validation interviews	24 physicians	ML-validated predictors (qualitative)	Workload, autonomy loss, admin burden confirmed by physicians	Psychological, organisational	Directly relevant, mirrors loss of autonomy and systemic inefficiency in SA
van Zyl-Cillié et al. (2024)	South Africa	Cross-sectional survey with ML analysis	1,165 nurses	Gradient boosting, decision trees	Fatigue, poor management support, and unsafe staffing predicted burnout	Psychological, physiological, organisational	Directly applicable, conducted in SA context
Cascella et al. (2025)	Italy	Cross-sectional ANN analysis	320 anaesthesiologists	Artificial neural networks (ANNs)	Emotional exhaustion and long hours predicted burnout	Psychological, organisational	Relevant, similar workload and exhaustion patterns in SA clinicians
Castro-Tamayo et al. (2025)	Colombia	Cross-sectional ML model	235 health managers & staff	Random forest, SVM	Job insecurity, low pay, family stressors predicted burnout	Psychological, organisational	Strongly relevant, parallels SA resource-limited context
Alam et al. (2024)	USA	Pilot wearable deep learning study	90 residents	Explainable deep learning model (EMBRACE)	Sleep disruption and high heart rate predicted burnout (~94% accuracy)	Psychological, physiological, organisational	Partially relevant, similar residency stressors, but limited access to wearables in SA

4.2.1 Review Findings

The eight included studies were published between 2022 and 2025 and represented a range of study designs, geographical settings, and analytical approaches. The majority of studies were conducted in high-income countries, including the United States, China, and Italy, with one study from a middle-income country (Colombia) and one conducted in South Africa. This distribution illustrate a strong concentration of research in technologically advanced settings, where access to electronic health data and computational resources facilitates the implementation of predictive artificial intelligence (AI) models.

In terms of study design, five studies employed cross-sectional survey-based methodologies that integrated AI modelling to identify determinants of burnout.[(8)(11)(17)] Two studies adopted retrospective analyses of electronic health record (EHR) usage metrics [6][7], while one study used qualitative interviews to validate previously developed machine learning (ML) predictors [15] .Sample sizes varied substantially, ranging from small qualitative cohorts of 24 participants to large-scale surveys of over 1,100 healthcare workers, reflecting diverse methodological scales and data collection strategies.

With respect to populations studied, most investigations focused on physicians and nurses, reflecting the occupational groups most at risk of burnout in healthcare. One study uniquely included health service managers and support staff within a resource-limited Colombian hospital[11], broadening the contextual understanding of burnout beyond direct patient care roles.

A wide range of AI tools was applied to predict burnout risk. Tree-based models such as *random forest* and *gradient boosting* was the most frequently used, offering interpretable variable importance measures for identifying key predictors[8][9]. Other studies employed *logistic regression* and *support vector machines (SVMs)*, while *artificial neural networks (ANNs)* and deep learning frameworks was used for complex data such as biometric or behavioural inputs[10][17]. Collectively, these models achieved predictive accuracies ranging from 75% to 94%, underscoring the feasibility of AI-based approaches for early burnout detection.

In examining determinants of burnout, three key domains emerged across studies- psychological, physiological, and organisational.

Psychological determinants such as emotional exhaustion, depersonalisation, loss of autonomy, and perceived stress were consistently associated with burnout across all settings. These factors were typically measured using validated scales like the Maslach Burnout Inventory (MBI). *Physiological determinants* were less commonly addressed, when present, they included fatigue (as a self-reported measure) and biometric data such as sleep quality and heart rate variability.[10] *Organisational determinants* were the most frequently cited and included workload, administrative burden, insufficient managerial support, job dissatisfaction, and resource limitations. These determinants was often quantified through surveys or objectively measured via EHR logs.

Regarding applicability to the South African context, organisational and psychological determinants was identified as the most transferable across settings. Studies consistently reported fatigue, administrative burden, and limited managerial support as primary predictors of burnout. One included study conducted in South Africa by van Zyl-Cillié et al. (2024)[9] identified fatigue and confidence in management as significant predictors among nurses, providing local evidence aligned with international patterns. Physiological determinants, including those derived from wearable or biometric data, were less frequently assessed and appeared less feasible for implementation in settings with limited technological infrastructure. Across all included studies, AI driven models demonstrated the capacity to identify psychological, organisational, and physiological predictors of burnout with varying degrees of accuracy.

5. Discussion

5.1 Overview of key findings

This scoping review examines current evidence on the use of predictive artificial intelligence (AI) models for burnout detection among healthcare professionals. Eight studies published between 2022 and 2025 were included, representing diverse methodological and analytical approaches across China, the United States, Italy, Colombia, and South Africa. Collectively, the studies demonstrated that AI-based models can effectively predict burnout risk, with reported accuracies ranging from 68% to 94%. The strongest models integrated psychological and organisational determinants, while physiological data contributed meaningfully only in a minority of studies where biometric inputs were available.

Most research originated from high-income countries, where access to electronic health records (EHRs) and advanced computational infrastructure facilitated model development. Only one study [9] was conducted in South Africa, underscoring the persistent under-representation of low- and middle-income contexts in predictive AI research. Despite this imbalance, the determinants identified internationally, particularly fatigue, workload, and managerial support, align closely with those reported in South African occupational health literature, suggesting a high degree of contextual transferability.

5.2 Determinants of Burnout and Predictive Relevance

5.2.1 Psychological Determinants

Across all eight studies, psychological factors emerged as central to burnout prediction. Emotional exhaustion, depersonalisation, and perceived stress consistently appeared as high-value predictors in models employing the Maslach Burnout Inventory (MBI) or comparable scales[8][17]. Psychological strain was particularly pronounced among early-career clinicians and anaesthesiologists, whose roles involve high cognitive and emotional demand. These findings reinforce Maslach and Leiter's (2016) model of burnout as fundamentally psychological, driven by prolonged exposure to unmanaged stress.

Studies also indicated that AI models incorporating validated psychological metrics outperformed those relying solely on behavioural or workload data[6][7]. This underscores that affective indicators, often accessible through survey instruments, remain indispensable for accurate prediction. The consistent predictive strength of emotional exhaustion suggests it could serve as a cornerstone variable for future South African model development, especially given the high prevalence of compassion fatigue and emotional strain reported among local clinicians[5].

5.2.2 Physiological Determinants

Physiological determinants were examined in relatively few studies but offered novel insight where included. Fatigue, disrupted sleep, and elevated heart rate were identified as strong correlates of burnout in the EMBRACE study [10], which used wearable sensor data and adaptive deep learning. Similarly, Liu et al. (2025) identified self-reported fatigue as a significant variable in models combining psychological and organisational indicators. The limited presence of physiological data reflects a methodological gap rather than irrelevance, such measures remain scarce because wearable and biometric technologies are not routinely integrated into clinical workflows, particularly in resource-limited settings. For South Africa, physiological data collection faces additional barriers, including equipment cost, data privacy concerns, and limited digital literacy among healthcare workers. As digital infrastructure expands, physiological monitoring may complement psychological and organisational predictors to enhance early-warning accuracy.

5.2.3 Organisational Determinants

Organisational variables consistently demonstrated the highest predictive strength. Workload intensity, administrative burden, inadequate managerial support, and lack of autonomy featured prominently across studies(7)(9). In the South African context, van Zyl-Cillié et al. (2024) found that fatigue and confidence in management were the two most important predictors of burnout among nurses, mirroring international findings, linking supervisory quality with emotional exhaustion. EHR-based studies in the United States (6)(7)(15) further validated administrative overload as a quantifiable burnout risk. Longer screen times, higher inbox volumes, and after-hours electronic documentation strongly correlated with burnout scores, reinforcing the role of organisational design in clinician distress. Although South African healthcare systems lack fully integrated EHR infrastructure, similar patterns arise through excessive paperwork, staff shortages, and managerial inefficiencies, suggesting that predictive frameworks grounded in workload metrics could still hold relevance if adapted to local data sources.

5.3 Integration of Determinants

The included studies collectively support a multi-determinant model of burnout, wherein psychological, physiological, and organisational factors interact dynamically. Tree-based algorithms such as random forest and gradient boosting most frequently achieved high predictive accuracy(8,9). Neural networks and deep-learning frameworks demonstrated similar or slightly lower accuracy, but offered advantages in capturing non-linear relationships among determinants(10)(17).Survey-based datasets produced more robust models than EHR-only datasets, likely because psychological and organisational variables provide richer, human-centred context than administrative metrics alone. The integration of explainable AI-illustrated by the EMBRACE model, also marks an important step towards ethical and transparent deployment in healthcare environments.

5.4 Applicability and Impact for South African Context

Although most studies included in this review were conducted in high-income settings, their findings hold valuable implications for South Africa. The evidence indicates that organisational and psychological determinants are the most influential predictors of burnout across all contexts. Variables such as workload, administrative burden, managerial support, and emotional exhaustion consistently produced strong model performance (7)(8)(9) .These determinants mirror the operational pressures described within the South African healthcare environment, suggesting that predictive frameworks built on similar constructs could be locally effective.

The single South African study by van Zyl-Cillié et al. (2024) provides direct evidence of this transferability. Using gradient-boosting models, it identified fatigue and confidence in management as the strongest burnout predictors among nurses, aligning closely with patterns observed internationally. The study demonstrated that reliable prediction is possible even in resource-constrained settings when organisational and psychosocial data are used.

Studies from high-income countries also offer guidance on potential data sources for adaptation. Lou et al. (2022) and Tawfik et al. (2024) used electronic health record (EHR) metrics such as after-hours documentation and inbox volume to quantify workload. While comprehensive EHR systems are not yet universal in South Africa, similar administrative data could be captured manually or through simplified digital logs. Alam et al. (2024) further showed that incorporating physiological variables, such as sleep disruption and heart-rate variability, improved model accuracy; however, such biometric inputs may remain impractical locally until digital infrastructure advances.

The eight studies suggest that predictive AI models can be adapted to South African healthcare by emphasising variables that are measurable with existing resources, psychological screening data, organisational metrics, and workload indicators. Local implementation should therefore focus on low-cost, survey-based models similar to those used by Liu et al. (2025) and Castro-Tamayo et al. (2025), which achieved high predictive accuracy using self-reported data. Together, these findings illustrate that while sophisticated physiological monitoring may remain aspirational, robust burnout prediction is attainable through the thoughtful use of psychological and organisational information already available within healthcare institutions.

5.5 Strengths and Limitations

This scoping review possesses several strengths. It is the first review of its kind to systematically map predictive artificial intelligence (AI) models for burnout detection among healthcare professionals with explicit consideration of their applicability to the South African context. By integrating the Joanna Briggs Institute (JBI) methodological framework and adhering to the PRISMA-ScR reporting guidelines, the review maintained methodological transparency and reproducibility throughout. The inclusion of multiple databases (PubMed, Scopus, and PsycINFO) and grey literature sources such as ProQuest and OpenGrey, strengthened the breadth of the evidence base and reduced the risk of publication bias. Moreover, the use of the Population–Concept–Context (PCC) framework ensured a structured and conceptually consistent approach to defining inclusion criteria.

A further strength lies in the comprehensive thematic synthesis that captured burnout as a multidimensional phenomenon encompassing psychological, physiological, and organisational determinants. This approach allowed for an integrated understanding of how predictive AI models operationalise different aspects of burnout risk. The inclusion of both international and South African studies also provided valuable comparative insight, highlighting shared global challenges while emphasising contextual nuances relevant to resource-limited healthcare systems.

Despite these strengths, several limitations should be acknowledged. The review was limited to English-language publications from 2018 to 2025, which may have excluded relevant studies published in other languages or before this timeframe. The limited availability of studies from low- and middle-income countries (LMICs) restricted the ability to fully assess the contextual transferability of AI models to settings such as South Africa. Although the search strategy was comprehensive, the reliance on three primary databases may have omitted relevant studies indexed elsewhere.

Additionally, no critical appraisal of methodological quality or risk of bias was undertaken, in line with the purpose and scope of scoping reviews, however, this limits the capacity to evaluate the robustness of individual studies. Furthermore, the heterogeneity of AI models, study designs, and burnout measurement tools complicated direct comparisons across studies. Finally, while physiological determinants were identified, the scarcity of studies using objective biometric data constrained the synthesis of this domain. The review provides a rigorous and transparent mapping of the emerging evidence base but acknowledges that further empirical validation and contextual adaptation are required to inform practical implementation within South African healthcare settings.

5.5 Research Gaps and Future Directions

Three major gaps emerge from this review. Geographical imbalance is the first gap that emerges. There is an urgent need for research from low- and middle-income countries to validate AI models in resource-limited environments. Secondly, the integration of multi-modal data**:** few studies combine psychological, physiological, and organisational variables into a single predictive framework. Lastly, ethical and implementation challenges are emerging. The development of explainable and equitable AI systems remains limited, particularly concerning data privacy and clinician trust. Future studies should pursue longitudinal designs to track burnout trajectories over time and test interventions based on predictive alerts. Mixed-methods approaches, combining quantitative AI prediction with qualitative insights into lived experiences, could bridge the gap between algorithmic accuracy and clinical relevance.

6. Conclusion

This scoping review sets out to identify and map existing evidence on predictive artificial intelligence (AI) models for the detection and early prediction of burnout among medical doctors and related healthcare professionals, and to consider their applicability within the South African context. Guided by the Joanna Briggs Institute (JBI) methodology and reported in accordance with the PRISMA-ScR framework, the review synthesised eight peer-reviewed studies published between 2022 and 2025. Collectively, these studies demonstrated that AI has considerable potential to predict burnout through the integration of multidimensional determinants, particularly those related to psychological and organisational domains.

Across the evidence base, emotional exhaustion, perceived stress, and job dissatisfaction consistently emerged as key psychological indicators of burnout. Organisational factors such as workload, administrative burden, managerial support, and job insecurity were found to be the most influential and readily measurable determinants across predictive models. Physiological factors, though less frequently studied, offered additional predictive value when included, especially when combined with data derived from wearable sensors. These findings affirm the multidimensional nature of burnout and highlight the ability of AI models to capture complex, non-linear interactions between personal, occupational, and environmental stressors.

The review also revealed a striking imbalance in the geographic distribution of research. The majority of predictive AI studies have been conducted in high-income, data-rich health systems, with only one study originating from South Africa and few from other resource-limited contexts. This gap underscores the urgent need to develop and validate predictive models that are contextually appropriate, affordable, and ethically implemented in low- and middle-income settings. Within South Africa, psychological and organisational determinants identified internationally are highly transferable and align with findings from prior national studies that highlight emotional exhaustion, fatigue, and structural inefficiencies as principal contributors to burnout.

Predictive AI models offer a promising tool for the early detection of burnout among healthcare professionals, yet their successful adaptation in South Africa will require pragmatic, context-specific strategies. Future research should prioritise hybrid models that draw on accessible data sources, such as validated burnout inventories and workload indicators, while progressively integrating physiological and digital data as technological infrastructure advances. By combining human-centred insight with computational innovation, South Africa can leverage AI not only as a diagnostic or predictive instrument but also as a catalyst for systemic improvement in healthcare workforce well-being.

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8. Appendices

8.1 Appendix A Search Strategies

Database/Source	Platform	Search String/Query	Filters Applied	Limits (Date/Language)	Results Retrieved (n)
PubMed	NCBI	("Burnout, Professional"[Mesh] OR burnout[Title/Abstract]) AND ("Artificial Intelligence"[Mesh] OR "Machine Learning"[Mesh] OR "Deep Learning"[Title/Abstract] OR "predictive model*"[Title/Abstract] OR algorithm*[Title/Abstract]) AND ("Physicians"[Mesh] OR physician*[Title/Abstract] OR doctor*[Title/Abstract] OR clinician*[Title/Abstract])	Human Participants Free Full Text	2018-2025 English Only	75
Scopus	Elsevier	("burnout" OR "emotional exhaustion" OR "depersonalization" OR "personal accomplishment" OR "stress" OR "mental health") AND ("healthcare workers"	Medicine Health Professionals Mental Health Physician Burnout	2018-2025 English Only	215

		OR "healthcare professionals" OR "physicians" OR "nurses" OR "support personnel" OR "health services managers" OR "intensive care professionals" OR "emergency department workers" OR "long-term care workers") AND ("predictive model" OR "machine learning" OR "artificial intelligence" OR "random forest" OR "gradient boosting" OR "logistic regression" OR "deep learning" OR "wearable devices" OR "biometric data" OR "electronic health records" OR "EHR" OR "heart rate variability" OR "HRV" OR "surveys" OR "Maslach Burnout Inventory")	Psychological Stress Job Stress Prediction Frontiers in Psychology		
PsycINFO	EBSCOhost	(AB (burnout OR “burnout syndrome”) OR SU(Burnout)) AND (SU (“Artificial Intelligence”) OR AB (“artificial intelligence” OR “machine learning” OR “deep learning” OR “predictive model*”	Linked Full Text Scholarly (Peer Reviewed) Journals	2018-2025 English Only	26

		OR algorithm* OR wearable* OR “activity log*”)) AND (SU(Physicians) OR AB (physician* OR doctor* OR clinician* OR resident* OR intern*))			
ProQuest Dissertations & Theses	ProQuest	(burnout among health professionals) AND (predictive AI models) AND "healthcare professionals"	Artificial Intelligence Machine Learning Medicine Physicians	2018-2025 English Only Linked Full Text Peer Reviewed	42

8.2 **Appendix B** Data Extraction Sheet

The link below allows viewing access to anyone within the University of Witwatersrand. This full data extraction sheet showcases the type of data extracted. The extraction sheet has a logical flow focusing on the author/s, intext reference, year of publication, title, country of origin, study type/design, abstract, population and sample size, and then findings. The findings were then broken down further into the three determinants studied psychological, physiological, and organisational. The type of predictive AI-tool was also included, and then the appropriateness for South African context.

Ethan_Terblanche_3020408_DataExtraction_Sheet

8.3 Appendix C PRISMA ScR Checklist

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
TITLE			
Title	1	Identify the report as a scoping review.	i
ABSTRACT			
Structured summary	2	Provide a structured summary that includes (as applicable): background, objectives, eligibility criteria, sources of evidence, charting methods, results, and conclusions that relate to the review questions and objectives.	iii
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known. Explain why the review questions/objectives lend themselves to a scoping review approach.	1
Objectives	4	Provide an explicit statement of the questions and objectives being addressed with reference to their key elements (e.g., population or participants, concepts, and context) or other relevant key elements used to conceptualize the review questions and/or objectives.	2
METHODS			
Protocol and registration	5	Indicate whether a review protocol exists; state if and where it can be accessed (e.g., a Web address); and if available, provide registration information, including the registration number.	N/A
Eligibility criteria	6	Specify characteristics of the sources of evidence used as eligibility criteria (e.g., years considered, language, and publication status) and provide a rationale.	5
Information sources*	7	Describe all information sources in the search (e.g., databases with dates of coverage and contact with authors to identify additional sources), as well as the date the most recent search was executed.	6
Search	8	Present the full electronic search strategy for at least 1 database, including any limits used, such that it could be repeated.	6

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
Selection of sources of evidence†	9	State the process for selecting sources of evidence (i.e., screening and eligibility) included in the scoping review.	6
Data charting process‡	10	Describe the methods of charting data from the included sources of evidence (e.g., calibrated forms or forms that have been tested by the team before their use, and whether data charting was done independently or in duplicate) and any processes for obtaining and confirming data from investigators.	6/7
Data items	11	List and define all variables for which data was sought and any assumptions and simplifications made. **Not included in this scoping review**	N/A
Critical appraisal of individual sources of evidence§	12	If done, provide a rationale for conducting a critical appraisal of included sources of evidence; describe the methods used and how this information was used in any data synthesis (if appropriate). **Not appropriate for this scoping review**	N/A
Synthesis of results	13	Describe the methods of handling and summarizing the data that was charted.	7/8
RESULTS			
Selection of sources of evidence	14	Give numbers of sources of evidence screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally using a flow diagram.	10
Characteristics of sources of evidence	15	For each source of evidence, present characteristics for which data was charted and provide the citations.	11
Critical appraisal within sources of evidence	16	If done, present data on critical appraisal of included sources of evidence (see item 12). **Not included in this scoping review**	N/A
Results of individual sources of evidence	17	For each included source of evidence, present the relevant data that was charted that relate to the review questions and objectives.	11-13
Synthesis of results	18	Summarize and/or present the charting results as they relate to the review questions and objectives.	11-13
DISCUSSION			

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
Summary of evidence	19	Summarize the main results (including an overview of concepts, themes, and types of evidence available), link to the review questions and objectives, and consider the relevance to key groups.	13-17
Limitations	20	Discuss the limitations of the scoping review process.	15/16
Conclusions	21	Provide a general interpretation of the results with respect to the review questions and objectives, as well as potential implications and/or next steps.	17/18
FUNDING			
Funding	22	Describe sources of funding for the included sources of evidence, as well as sources of funding for the scoping review. Describe the role of the funders of the scoping review. **No Funding was needed or given for this scoping review**	N/A

Adapted from: Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMAScR): Checklist and Explanation. Ann Intern Med. 2018; 169:467–473. doi: 10.7326/M18-0850.

8.4 Appendix D HREC Ethics Waiver

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

HUMAN RESEARCH ETHICS COMMITTEE (MEDICAL)

Office of the Deputy Vice-Chancellor (Research & Innovation)

HUMAN RESEARCH ETHICS COMMITTEE (MEDICAL)

ETHICS WAIVER

Ref: W25/07/36

TO WHOM IT MAY CONCERN

Waiver:	This certifies that the following research has received a waiver from the full Human Research Ethics Committee (Medical) review and approval
Investigator:	Mr Ethan Terblanche Student Number: 3020408
Supervisor:	Ms S. Makings and Dr H. Roos
School: **Department:**	School of Clinical Medicine Department of Family Medicine and Primary Care Division of Health System Sciences
Degree:	BHSc (Hons) Health System Sciences
Project title:	Predictive Models for Burnout Detection in South African Medical Doctors: A Scoping Review Protocol
Reason:	For a review of information in the public domain No human participants will be involved in the study.

Professor P. Ruff
Chairperson: Human Research Ethics Committee (Medical)

Date of Approval: 02 September 2025

This waiver certificate is valid for 5 years from date of approval. Extension may be applied for.

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REC-250208-004