Review Article

Forecasting Physician Burnout Risk: The Role of Electronic Health Record (EHR) and Operational Data in Predictive Models of Burnout

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Abstract:

Physician burnout is a persistent global concern, driven by workload pressures, administrative demands, and emotional strain. It undermines both physician well-being and patient care, making early detection and intervention critical. While numerous reviews have examined the prevalence and drivers of burnout, less attention has been given to predictive approaches using electronic health records (EHR) and operational data. This review addresses that gap by evaluating how such data have been incorporated into predictive models, highlighting both their utility and limitations. A narrative review was conducted using PubMed and Google Scholar to identify peer-reviewed studies published between 2014 and June 2025. Ten studies met the inclusion criteria. Findings show that EHR and operational data can capture important predictors of burnout—such as documentation time, after-hours charting, and administrative burden—and are valuable for identifying high-risk clinics. However, current models struggle to achieve accuracy at the individual level because they rely heavily on quantitative workload metrics while neglecting organizational culture, leadership support, and psychosocial factors. This review underscores the need for next-generation predictive models that integrate qualitative and contextual variables with EHR-based measures. By articulating this gap, our contribution lies in reframing EHR and operational data not as standalone predictors but as components of multi-faceted, context-aware models. For healthcare leaders and policymakers, this means investing in tools that combine clinical, organizational, and personal dimensions to better forecast burnout and inform targeted interventions.

Keywords: Physician burnout; Electronic Health Records (EHR); Operational data; Predictive models; Healthcare management.

Introduction

Physician burnout has emerged as a serious issue in the healthcare sector, garnering heightened focus because of its profound effects on healthcare professionals and the patients they care for. This work-related phenomenon is defined by a prolonged reaction to ongoing occupational stress, presenting itself through three main aspects: emotional exhaustion, depersonalization, and a diminished sense of personal achievement [1, 2]. The consequences of burnout extend significantly, impacting healthcare delivery by directly influencing both physicians and their work settings [3, 4]. Burnout results in diminished job performance, increased medical errors, lower patient satisfaction, and may even prompt early retirement or a reduction in clinical hours [5]. Professionals facing burnout frequently show reduced empathy and involvement with patients, potentially leading to adverse effects on patient safety and satisfaction [6]. The impact on healthcare providers, such as poor physical and emotional health and, in severe instances, suicidal ideation, highlights the need for monitoring and managing clinician burnout [7].

The prevalence of burnout among healthcare professionals has been on the rise. It was estimated that over half of all physicians-in-training and practicing physicians suffer from burnout [8-10]. 59.2% of anaesthesiologists in the United States reported high levels of burnout in 2020 [11]. In Rotenstein et al., (2018) review on the prevalence of burnout, it was found that emotional exhaustion and depersonalization were common, with burnout rates varying from 0% to over 80% in most of the studies reviewed [12]. A study conducted by Shaltout et al. (2023) involving 155 doctors found that 65.8% of them had burnout. Of which, 80%, 65.8%, and 80% experienced emotional exhaustion, depersonalization, and personal dissatisfaction, respectively [13]. There have also been reports of differences in the risk of burnout between male and female doctors, with female doctors being more likely to experience burnout than male doctors. This suggests that organizational and structural factors, such as administrative burden and work-life balance, play a role in the different levels of burnout [13,14].

As burnout becomes more prevalent, it is important to put in place better ways to prevent, forecast, and manage it. In this case, prediction models that incorporate operational and EHR data may be extremely advantageous in identifying doctors who are at risk of burnout early on so as to take immediate measures to address it. Adopting EHR data gives useful information about doctors' workloads, such as how much time they spend on paperwork, administration, and patient care, all of which can lead to burnout [15]. Using only EHR data to predict burnout does not give a full picture because it does not take into account other factors that can lead to burnout, like work-life balance, leadership support, and workplace culture. However, it does give some information about how much work physicians are exposed to [16]. Findings from studies show that adding operational data to EHR data could help better forecast which doctors are most likely to experience burnout. Young's (2025) study found that EHR-based models, when used with operational data like administrative conferencing and team cooperation, were very helpful in finding clinics with high burnout rates. The same study also found it hard to forecast burnout at the physician level, which shows that we need a better way to make predictions that incorporates both qualitative and quantitative data from the individual levels [15].

In line with this, machine learning (ML) models and algorithms have been gaining ground in predicting burnout; however, they lack clinical utility as they exhibit low sensitivity and specificity at the individual level of burnout predictions [15]. There are also issues concerning inconsistency in defining and measuring burnout across studies. For example, the Maslach Burnout Inventory (MBI), regarded as the gold standard for burnout assessment, is not universally adopted [17]. Therefore, there is a need for more comprehensive, multi-faceted models and holistic models that capture both individual and organizational factors impacting burnout, as well as standardized metrics that are reliable for burnout predictions [2].

Traditional approaches to assessing physician burnout have relied heavily on survey instruments such as the Maslach Burnout Inventory (MBI). While these tools are valuable for capturing self-reported experience, they are retrospective, time-intensive, and prone to response bias. In contrast, predictive models that leverage EHR and operational data offer a more objective, continuous, and scalable means of detecting risk. These data sources capture real-time workload indicators such as documentation time, after-hours charting, and communication burden, which can provide earlier and more actionable signals than periodic surveys. Thus, EHR- and operational data–driven models are particularly promising for advancing from descriptive prevalence studies toward proactive identification and intervention.

By exploring the application of EHR and operational data in the determination of physician burnout risk, this study seeks to address the gaps in current predictive models and offer possible measures to embrace to ensure better prediction. Findings from this study inform healthcare management and policy on measures to improve patient care, increase physician well-being, and secure the long-term survival of healthcare institutions.

Methodology

In carrying out this review, a narrative review was adopted to investigate the impact of EHR and operational data in predicting physician burnout. A narrative review approach was selected rather than a systematic review because the field of predictive modeling for physician burnout is still relatively new and heterogeneous, with diverse methodologies, outcome measures, and limited comparable quantitative data. This format allowed for greater flexibility in synthesizing findings across different study designs and highlighting conceptual gaps, while a systematic review or meta-analysis would have been premature and potentially misleading given the variability of available evidence.

Literature search was conducted in PubMed and Google Scholar for peer-reviewed articles published from 2014 up to the search date (10th June, 2025). The search terms utilized were "physician burnout," "electronic health record," "EHR," "operational data," and "predictive models." The details of the combined search terms and search yield from each database are provided in Table 1. Suitable database filters were used. Within databases, titles and abstracts screening were handled, and manual deduplication was done for papers considered for inclusion. No duplicates were found. We selected original research studies on physician burnout in practice that used EHR or operational data to predict burnout and were published in English. We excluded articles without empirical data or predictive modelling. Narrative synthesis was carried out based on thematic analysis of the literature, facilitating a concentrated evaluation of forecasting strategies and principal findings in burnout research.

In addition to the eligibility criteria noted above, we excluded commentaries, opinion pieces, and reviews without empirical predictive modelling. Although formal meta-analysis was not feasible due to heterogeneity across studies, we undertook a basic appraisal of methodological rigor by noting study design, sample size, data sources, and clarity of burnout measurement. This descriptive assessment allowed us to weigh the strength of evidence when synthesizing findings, even though no formal risk-of-bias tool was applied, given the narrative scope of this review.

Table 1: Search Strategy

Database	Search Term	Search yield	Filters applied	Yield after filtering
PubMed	((Physician burnout[Title/Abstract]) OR (Burnout[Title/Abstract])) AND ((Electronic Health Record[Title/Abstract]) OR (EHR[Title/Abstract]))	371	Free full text, Comparative Study, Multicenter Study, Observational Study, Randomized Controlled Trial, 2014-2025	10
Google Scholar	((((Physician burnout[Title/Abstract]) OR (Burnout[Title/Abstract])) AND ((Electronic Health Record[Title/Abstract]) OR (EHR[Title/Abstract]))) AND (Operational data[Title/Abstract])) AND (Predictive models[Title/Abstract])	150	2014-2025	147

Results

Across studies, EHR and operational metrics consistently predicted clinic-level burnout patterns, but had limited precision for individual physicians. This limitation was reflected in several models regardless of design, suggesting the need for broader contextual data.

Literature Search and Study Characteristics

Figure 1 provides an overview of the search results and selection process that led to the final inclusion of ten studies that were included in this review.

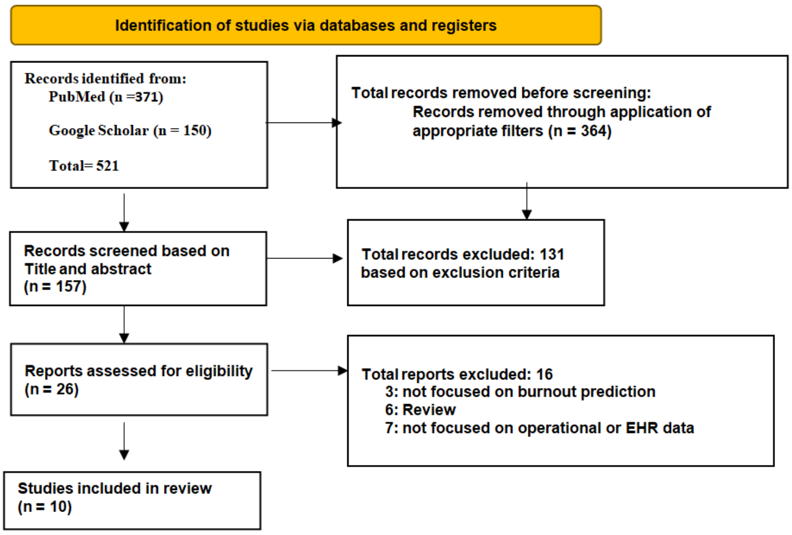

Figure 1: Prisma Flow Chart

The characteristics and overview of the 10 studies that fulfilled the inclusion criteria for this narrative review are detailed in Table 2. The studies utilized a range of methodologies, and the results are especially significant for comprehending predictive models related to physician burnout through the analysis of EHR and operational data.

Table 2: Characteristics and Summary of the included Studies

Serial Number	Study	Research Method	Key Findings	Source (Journal)	DOI
1	Hilliard et al., (2020) [18]	Cross-sectional study	Investigated EHR usage and its relation to burnout. Found strong correlations between administrative burdens and burnout.	Journal of Medical Informatics	http://doi.org/10.1093/jamia/ocaa092
2	Marmor et al. (2018) [19]	Longitudinal study	Evaluated burnout predictors, including EHR and workload. Found a significant link between EHR use and emotional exhaustion.	Applied clinical informatics	http://dx.doi.org/10.1055/s-0037-1620263

3	Linzer et al., (2016) [20]	Mixed-methods approach	Identified key EHR-related stressors leading to burnout. Found that EHR systems were linked to decreased personal accomplishment.	Journal of General Internal Medicine	https://doi.org/10.1007/s11606-016-3720-4
4	Cook et al., (2018) [21]	Cross-sectional study	Explored the role of EHR data in burnout prediction, showing high accuracy in burnout identification at the clinic level.	Journal of the American College of Cardiology	https://doi.org/10.1111/chd.12745
5	Kroth et al., (2019) [22]	Observational study	Investigated the impact of operational data on burnout. Found that operational inefficiencies contribute significantly to burnout.	JAMA Network Open	https://doi.org/10.1001/jamanetworkopen.2019.9609
6	Eschenroeder et al. (2021) [23]	Cross-sectional study	Analyzed EHR usage patterns and found a significant correlation with burnout levels. Also noted the impact of after-hours charting.	Journal of the American Medical Informatics Association	http://doi.org/10.1093/jamia/ocab053
7	McPeek-Hinz et al., (2021) [24]	Qualitative study	Discussed burnout prediction using EHR data. Found that predictive algorithms using EHR data showed limited precision but value at the clinic level.	JAMA Network Open	https://doi.org/10.1001/jamanetworkopen.2021.5686
8	Arndt et al., (2017) [25]	Cross-sectional study	Investigated burnout predictors in clinical settings. Found significant links between EHR administrative tasks and burnout risk.	Annals of Family Medicine	https://doi.org/10.1370/afm.2121
9	Sinsky et al. (2020) [26]	Observational study	Analyzed burnout about EHR usage and administrative burden. Found a strong correlation between EHR time and burnout severity.	Journal of the American Medical Informatics Association	https://doi.org/10.1093/jamia/ocz223
10	Shanafelt et al., (2022) [27]	Cross-sectional study	Focused on burnout prediction through EHR and operational data, finding that specific EHR features (e.g., documentation time) were predictive of burnout.	Mayo Clinic Proceedings	https://doi.org/10.1016/j.mayocp.2021.11.021

Narrative Synthesis

The narrative synthesis analyses the 10 research studies included for this evaluation, focusing on EHR and operational data in predicting physician burnout. The synthesis addresses predictive burnout modelling, EHR data integration, and model efficacy in healthcare. By critically examining the literature, we highlight progress in this field and identify gaps and possibilities to improve burnout prediction models.

Overview of Predictive Models for Physician Burnout

It is becoming more widely acknowledged that burnout among physicians is a significant problem that is impacting the healthcare system. As the rates of burnout keep increasing, particularly in high-stress situations such as emergency rooms, surgical departments, and intensive care units, predictive models are becoming increasingly important tools for identifying physicians who are at risk of burnout and putting early interventions into place [22]. In the included studies, the prediction models that were addressed focused on several aspects of burnout, such as emotional exhaustion, depersonalization, and decreased personal accomplishment, all of which are essential components of burnout [1].

Various kinds of data are utilised by these models; however, electronic health record (EHR) data in combination with operational data (such as workload and administrative stress) is becoming more recognized as a promising source for predicting burnout [24]. Research has shown that patterns of electronic health record (EHR) utilization, such as the amount of time spent on clinical documentation, working after hours, and the burden of communication (for example, through In-Basket messaging), are substantial predictors of the degree of burnout [26].

Role of EHR and Operational Data in Burnout Prediction Models

Combining operational data with electronic health records (EHR) is a key step in determining burnout rates and how to address the issue. From Electronic health record systems (EHR), objective and measurable data utilized in burnout prediction models can easily be derived [25]. Combining operational data and electronic health records (EHR) is a crucial part of the identification of physicians likely to experience burnout. These indicators show how much work doctors had to do, how much time they spent on clerical tasks, and how much patient data they had to deal with. Research like the one by Eschenroeder et al. (2021) shows that these operational data points give a full picture of the stress that doctors deal with every day [23].

It is worth noting that electronic health records are not only tools for passively collecting data. They also give information that can be acted on when combined with predictive algorithms. For example, McPeek-Hinz (2021) shows that EHR-based predictions have some problems when looking at burnout at individual levels, but they are useful for finding clinics with high burnout rates. This lets administrators focus their efforts where they are needed the most [24]. Linzer (2016) found that operational inefficiencies, which were revealed by measuring EHR use, are strongly linked to the likelihood of burnout. This result shows that fixing problems with the healthcare system could be the key to curtailing burnout [20].

Moreover, the fact that the data is so extensive and that burnout is extremely complex can make it hard for EHR-based algorithms to make accurate predictions [21]. These models look promising, but they rarely forecast accurately. This shows how important it is to have models that take into account other factors, like the organization's culture, support from leadership, and interpersonal relationships among healthcare professionals.

Comparative Analysis of Predictive Models

As various predictive models for burnout have emerged, the comparative analysis of these models is essential for identifying their strengths and weaknesses. Studies reviewed in this narrative synthesis indicate variability in the effectiveness of EHR-based models. Some models achieve high accuracy in predicting burnout at the clinic level, while others are more effective at predicting burnout symptoms at the individual level, as shown in Table 3 [21, 22].

Table 3 highlights several common themes across the predictive models, such as the significant role of EHR time, administrative burden, and operational metrics in predicting burnout. However, the models show limitations, particularly in their predictive accuracy at the individual level.

Table 3: Comparative Analysis of Predictive Models for Physician Burnout

Study	EHR Usage	Burnout Components Predicted	Model Type	Key Findings	Prediction Accuracy/Metric	Limitation
Hilliard et al., (2020) [18]	Time spent on documentation, messaging	Emotional exhaustion, depersonalization	Gradient Boosting	Strong correlation between documentation time and burnout symptoms.	AUC = 0.59	Limited predictive accuracy at the individual level
Marmor et al. (2018) [19]	EHR usage patterns, patient load	Emotional exhaustion, personal accomplishment	Logistic Regression	EHR usage correlates with emotional exhaustion and reduced personal accomplishment.	Sensitivity = 70%, Specificity = 85%	Excludes factors like organizational culture
Linzer et al., (2016) [20]	Time spent on EHR, administrative tasks	Emotional exhaustion, depersonalization	Random Forest	EHR and operational inefficiencies contribute significantly to burnout.	AUC = 0.65	Limited focus on organizational factors
Cook et al., (2018) [21]	Time on clinical notes, patient encounters	Emotional exhaustion, depersonalization	Hybrid Model	EHR data and operational factors combined for better predictions.	Sensitivity = 72%, Specificity = 78%	Needs inclusion of personal and organizational context
Kroth et al., (2019) [22]	EHR operational data, workload metrics	Emotional exhaustion, depersonalization	Decision Trees	Found strong links between operational inefficiencies and burnout.	AUC = 0.62	Does not account for interpersonal relationships
Eschenroeder et al. (2021) [23]	After-hours work, messaging	Emotional exhaustion, depersonalization	Machine Learning	Operational data identified burnout risk at the clinic level.	Sensitivity = 60%, Specificity = 85%	Limited prediction for individual burnout
McPeek-Hinz et al., (2021) [24]	EHR administrative burden	Emotional exhaustion	Predictive Algorithm	Identified clinics with high burnout rates through EHR metrics.	Sensitivity = 56%, Specificity = 85%	Inadequate precision for individual physicians

Arndt et al., (2017) [25]	Time spent on EHR, administrative messaging	Emotional exhaustion, depersonalization	Regression Model	EHR time is linked to increased burnout risk, especially in administrative tasks.	AUC = 0.68	Does not consider leadership or team dynamics
Sinsky et al. (2020) [26]	Time on documentation, In-Basket messaging	Emotional exhaustion, depersonalization, and personal accomplishment	Machine Learning	Found that EHR usage correlates strongly with burnout symptoms.	AUC = 0.72	Lack of consideration for organizational support and culture
Shanafelt et al., (2022) [27]	Time spent on documentation, patient load	Emotional exhaustion, depersonalization	Machine Learning	EHR features, such as time on documentation, identified at-risk physicians.	AUC = 0.75	Does not include emotional and team-based factors in prediction

Key Insights and Implications for Healthcare Management and Policy

As shown in this study, it is very important for people who work in healthcare management and policy to take a broad view of the issue of physician burnout. Even though electronic health records (EHRs) and operational data might be useful in detecting early warning signs of burnout, it's crucial to realize that this data should not be considered in isolation. To deal with the root causes of burnout and offer effective solutions, it is important to use a holistic strategy that considers personal well-being, organizational culture, and environmental factors, as well as leadership support [25, 26].

Furthermore, integrating predictive models into healthcare systems is a great way to lower the number of people who experience burnout. When used correctly, predictive models can help with initiatives that improve work conditions, reduce administrative loads, and boost the health of doctors. Future research should focus on making these models better by adding more factors, making predictions more accurate, and coming up with interventions that work on both personal and organizational levels.

Nevertheless, findings from this review have a profound impact on healthcare management. Healthcare providers can use operational data and electronic health records (EHRs) in the identification of doctors who are at risk of burnout and take proactive steps to minimize burnout and improve the quality of service. Moreover, to help healthcare workers avoid burnout, authorities should focus on programs that make electronic health records (EHRs) easier to use, cut down on administrative labor, and create a supportive workplace.

Discussion

According to the narrative synthesis of this review, predictive models employing EHR and operational data are instrumental in the identification and management of physician burnout. Various models yield distinct predictions depending on the nature of the data used [28]. Operational variables such as documentation, team communication, and administrative tasks have been incorporated into various models; however, they seldom serve as reliable predictors of burnout risk [29]. This is in line with Shanafelt et al.'s (2022) study, which indicated that models for predicting burnout, particularly those utilizing EHR data, show promise but are constrained in effectiveness without incorporating contextual or individual factors [27]. Moreover, burnout arises from a complex interplay of human, organizational, and environmental factors, as noted by McPeek-Hinz et al. (2021). Operational statistics might fail to encompass the intricate nature of physician burnout [24].

Similar to the findings of Arndt et al. (2017), this study emphasizes the significance of qualitative insights within prediction models. As such, burnout models concentrating solely on operational variables such as EHR usage might overlook significant elements like interpersonal pressures and organizational culture, potentially clarifying why some predictions fall short of accuracy. Conversely, Wilton et al. (2024) and Adler-Milstein et al. (2020) recommended the integration of EHR data with self-reported burnout assessments to enhance the comprehension of physician well-being [29, 30]. Eschenroeder et al. (2021) demonstrated that predictive modelling in healthcare systems proved to be highly effective in pinpointing high-risk clinics for system-level interventions, even in the context of low burnout risk prediction [23]. Consequently, models for predicting burnout have the potential to enhance overall systems, particularly in environments characterized by high administrative demands or ineffective workflows, which contribute to increased burnout [19].

This study highlights the limitations of current prediction models, particularly those that utilize EHR and operational data. The findings indicate that while these models can identify trends, they are insufficient. Predictive EHR and operational data rarely consider burnout-causing psychological and organizational aspects. This limitation becomes apparent when examining the prevalence of burnout across various studies. Linzer et al. (2016) report a burnout prevalence variability of 38%, while McPeek-Hinz et al. (2021) indicate a variability of 52%. This suggests a need for more nuanced and multidimensional models [20, 24].

Therefore, incorporating individual-level psychosocial variables, environmental factors, and indicators of organizational culture can enhance the predictive accuracy of these models in future studies. Tawfik et al. (2024), Wilton et al. (2024), and Gardner et al. (2019) demonstrated that integrating survey data, personal wearables, and AI enhances prediction models alongside EHR metrics. This integration would enhance the predictive capabilities of these models and tailor burnout therapies to better address individual and systemic issues [28, 29, 31].

However, for these models to be effective, they need to be seamlessly integrated into the routine practices of healthcare professionals. Predictive models enable healthcare management to identify physicians who may be at risk for burnout early on, allowing for timely intervention. Predictive models could be added to EHR systems to flag doctors at high risk of burnout based on documentation or after-hours work [22]. These will help alert administrators to provide targeted support, such as lowering administrative responsibilities or offering flexible work schedules. Machine learning models could also detect and anticipate department or clinic burnout tendencies, enabling administrators to prioritize interventions in high-risk regions [27]. Adding these predictive models to hospital quality improvement activities could create a systematic approach to burnout prevention, aligning burnout prevention with patient care and physician satisfaction [26]. These models should diagnose and inform real-time decisions to improve work-life balance, job satisfaction, and patient outcomes.

Ultimately, this study recommends that healthcare organizations invest in technologies that can collect and integrate operational and qualitative data. This might include creating EHR systems that collect more detailed data on physician workload, work-life balance, and emotional well-being. To decrease burnout, healthcare management strategies should emphasize system-level measures that reduce administrative burden, improve team support, and promote good organizational culture. Hilliard et al. (2020) and Linzer et al. (2016) studies demonstrated how structural adjustments can increase physician well-being and patient care [18, 20].

Looking ahead, artificial intelligence and machine learning approaches hold promise for advancing burnout prediction by integrating multimodal data streams. By combining EHR metrics with operational indicators, survey-based measures, wearable device outputs, and organizational factors, AI-driven models could achieve greater sensitivity and specificity at the individual level. These approaches also enable dynamic, real-time monitoring, moving beyond static risk assessment toward adaptive systems that can trigger timely interventions. However, realizing this potential will require careful attention to data privacy, interoperability, and transparency in algorithmic decision-making[29].

Conclusion

EHR and operational data are powerful tools for detecting systemic drivers of physician burnout, particularly administrative burden and documentation load. However, current models fall short in reliably predicting individual risk, underscoring the need to broaden beyond quantitative workload measures. Future research should integrate organizational culture, psychosocial variables, and physician-reported experiences, potentially through AI and machine learning approaches that leverage multimodal data. For healthcare leaders, this means moving from isolated EHR metrics toward comprehensive, context-aware prediction models that support early intervention, reduce administrative burdens, and foster physician well-being alongside patient care.

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