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BEYOND BURNOUT: FROM MEASURING TO FORECASTING

Bart Blackburn
Tiffany Chan
Elizabeth Cherot
Richard B. Freeman
Xi Hu
Eric Matt
C. Aubrey Rhodes

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ABSTRACT

Burnout of physicians and other medical personnel is a major problem in the economics of healthcare systems, potentially costing billions of dollars. Knowledge of the determinants and costs of burnout at the organization level is sparse, making it difficult to assess the net benefits of interventions to reduce burnout at the level where arguably the greatest change can be affected. In this paper, we use data from a midsize healthcare organization with about 500 clinicians in 2021-22 to advance analysis of clinical burnout in two ways. First, we estimate the costs of clinician burnout beyond the widely studied losses due to turnover. Including hard-to-measure and potentially long-term costs that arise from reduced patient satisfaction and lower productivity of burnt-out clinicians at work, our analysis suggests a much higher cost of burnout per clinician than previous estimates that exclude these costs. Second, we use standard medical billing and administrative operating data to forecast turnover and productivity of clinicians to serve as an early warning system. Accurate estimates of both the cost of burnout now and of likely future costs should help decision-makers be proactive in their approach to solving the burnout crisis currently affecting the healthcare industry. While our empirical analysis relates to a particular healthcare organization, the framework for quantifying the costs of burnout can be used by other organizations to assess the cost-effectiveness of ameliorative policies.

Bart Blackburn
Atalan Tech
24 School Street
2nd Floor
Boston, MA 02108
USA
bart@atalantech.com

Tiffany Chan
Atalan Tech
24 School Street
2nd Floor
Boston, MA 02108
tiffany@atalantech.com

Elizabeth Cherot
March of Dimes
1550 Crystal Dr
Suite 1300
Arlington, VA 22202
echerot@marchofdimes.org

Richard B. Freeman
NBER
1050 Massachusetts Avenue
Cambridge, MA 02138
freeman@nber.org

Xi Hu
Labor & Worklife Program
Harvard Law School
50 Church Street
Cambridge, MA 02138
xhu@law.harvard.edu

Eric Matt
Axia Women's Health
227 Laurel Rd #300 Voorhees
Township, NJ 08043
eric.matt@axiawh.com

C. Aubrey Rhodes
Atalan Tech
24 School Street
2nd Floor
Boston, MA 02108
aubrey@atalantech.com

1 Introduction

Burnout is defined as the psychological syndrome emerging from a prolonged response to chronic interpersonal stressors on the job (Maslach and Leiter, 2016). It is estimated to impact half of all U.S. healthcare workers (Prasad et al., 2021). Burnout consists of three dimensions: an overwhelming exhaustion, feelings of cynicism and detachment from the job, and a sense of ineffectiveness and lack of accomplishment (Maslach and Leiter, 2016). The standard tool for assessing burnout is the Maslach Burnout Inventory, which was the first survey that measured all three dimensions of burnout. [1] Over two decades of research have identified a plethora of workplace and individual-level drivers of burnout that Maslach and Leiter (2016) usefully organize into six key domains of a workplace: workload, control, reward, community, fairness, and values.

While there is ample evidence on drivers of burnout and its relation to work behavior, the cost side of clinician burnout is relatively neglected. The well-known Han et al. (2019) paper gathers evidence from diverse sources on the cost of burnout in terms of reduction of clinical hours and turnover/replacement costs, and notes that physicians who feel burnt-out are twice as likely to leave their job as other physicians (Shanafelt et al., 2012). The American Medical Association STEPS Forward module on joy in medicine offers a calculator for organizations to project the cost of physician burnout, based on findings from Shanafelt et al. (2017). These estimates, while a useful starting point, are conservative. They exclude some hard-to-measure and potentially large costs such as the productivity loss from burnt-out working clinicians, costs associated with replacing a burnt-out clinician who leaves, and the ensuing lower medical care quality, increased malpractice risk, reduced patient satisfaction, and damage to the organization's reputation as it struggles to deal with clinician burnout.

In this paper, we develop a new method to quantify these costs and use machine learning algorithms to predict turnover probabilities for individual clinicians that carries the analysis to the individuals whose behavior identifies the problem. The method yields improved cost estimates for decision-making. We validate our models with historical data from a midsize healthcare organization of approximately 500 clinicians. Our method answers the call from the American Medical Association for more accurate and comprehensive models on the business impact of burnout (Berg, 2019), which can increase support for innovative policies for clinician well-being.

Our approach for estimating the impact of burnout is two-pronged. First, we quantify the full turnover cost when a clinician leaves by analyzing the net loss from a burnt-out clinician's absence, the cost of recruiting a replacement clinician, and the onboarding cost associated with getting a new clinician up to speed. Second, we quantify the impact of burnout on working clinicians' productivity, the satisfaction of their patients, and the subsequent cost to the organization. Compared to estimates in existing literature which focus solely on turnover costs, our estimates provide a more comprehensive measure of the cost of burnout in the medical setting that can guide discussion on how to budget wellness programs to alleviate burnout and turnover.

[1] Five other surveys - the Bergen Burnout Inventory, the Oldenburg Burnout Inventory, the Stanford Professional Fulfillment Index, the Mini Z instrument, and the Mayo Clinic Wellbeing Index - measure burnout in similar ways.

2 The Cost of Clinician Burnout

Although clinician burnout is associated with many identifiable negative outcomes, its economic impacts are poorly understood because many of the outcomes are multifaceted with costs that are difficult to measure. Some negative consequences directly impact the bottom line of healthcare organizations, while others affect patient safety and the individual clinician's well-being which are typically neglected in existing estimates of costs. Table A1 in the appendix summarizes the wide range of consequences of burnout documented in the existing literature, which we have organized into clinical and non-clinical impacts. Most studies examine the non-clinical cost of burnout related to turnover by surveying clinicians about their intention to keep practicing, change jobs, etc. and find that the intent to leave increases with burnout. The studies also show that burnout and intent to leave are related to actual turnover. For instance, Hamidi et al. (2018) found that at baseline, 26% of physicians reported experiencing burnout and 28% reported Intention to leave within the next two years. Two years later, when 13% of surveyed physicians had actually left, those who reported an intent to leave were more than three times as likely to have left than those who did not report an intent to leave. Those who reported experiencing burnout were more than twice as likely to have left than those who reported not experiencing burnout.

The cost of clinician burnout, however, goes beyond turnover. Other consequences exist which measurably affect the healthcare organization's productivity and revenue. Numerous studies have documented how clinicians suffering from burnout take more sick days, reduce clinical hours, produce less academic publications, and are less effective in teams (Soler et al., 2008; Shanafelt et al., 2016; Turner et al., 2017; Welp et al., 2016; Galletta et al., 2016). Patient satisfaction is likely to be significantly lower for those treated by burnt-out clinicians, which in turn affects customer loyalty and the reputation of the organization, both of which affect revenue growth (Windover et al., 2018; Halbesleben and Rathert, 2008). For individual clinicians themselves, burnt-out clinicians have lower career satisfaction, may increase the use of alcohol/drugs, and are more likely to retire early (Lu et al., 2015; Busis et al., 2017; Shanafelt et al., 2009; Kuerer et al., 2007; Nørøxe et al., 2019; Yao et al., 2021; Jackson et al., 2016; Shanafelt et al., 2002; Dewa et al., 2014).

Burnout also has adverse effects on clinical outcomes. Many studies stress that burnout compromises quality of care (Brunsberg et al., 2019; Williams et al., 2007; Shanafelt et al., 2010; Welp et al., 2016; Klein et al., 2010; Fahrenkopf et al., 2008; Zantinge et al., 2009; Kushnir et al., 2014). Notably, clinicians who are burnt-out have reported the tendency to discharge patients too early, not discuss treatment options properly, and order more tests than necessary (Lu et al., 2015). Hospital infections and patient recovery times have been shown to increase as burnout increases, and medical errors (such as procedure or medication mistakes) also rise with burnout (Galletta et al., 2016; Halbesleben and Rathert, 2008; Fahrenkopf et al., 2008). Finally, patient satisfaction is significantly lower for patients treated by burnt out clinicians (most likely due to the lower quality of care), which in turn affects their loyalty to the organization and its reputation, with adverse effects on revenue growth (Halbesleben and Rathert, 2008; Windover et al., 2018).

The absence of cost calculations for many of the documented impacts of clinician burnout can lead to erroneous decision-making and budgeting by healthcare organizations, such as deciding against implementing a policy that seems too expensive based solely on the cost of turnover when in fact the policy would pass a benefit-cost test based on the full costs of burnout. While the costs of some impacts such as patient satisfaction are long term and hard to quantify, ignoring them underestimates the burnout impact on the organization and the economic payoff from investing in programs to reduce burnout. The focus of most existing studies on what happens *after* a clinician leaves can also lead to erroneous decisions because that assumes clinician resignation is an inexorable event, when in fact policies exist which can reduce quitting. Being able to predict the probability of an individual's departure can help healthcare organizations plan for targeted interventions, which has proven to be a challenging task. Responding to this shortcoming, we developed a set of predictive models for forecasting turnover at the individual clinician level. Feeding these predictions into our cost calculations produces more realistic projections of turnover costs than using hypothetical scenarios which assume broad levels of turnover at the organizational level, while opening the door for developing cost-effective interventions.

3 Methods and Data

To better assess the economic impact of burnout at healthcare organizations, we develop a framework that examines the cost of burnout along two separate channels. The first channel is the effect of burnout on clinicians still working at the organization. To quantify this effect, we analyze the loss in productivity and reduced patient satisfaction among those clinicians experiencing burnout. We recognize there are likely additional costs due to spillover effects from the departure of the burnt-out clinician onto others in the health system, but we do not have the data available to support such an analysis. The second channel is the financial impact of a clinician quitting due to burnout. For each individual clinician, historical data allow us to estimate the replacement cost of their leaving the organization. Replacement cost here is defined as the sum of lost revenue from the number of months a position remains unfilled, recruitment costs, and the lower productivity during the onboarding/training of the new clinician. Combining the two channels gives a better estimate of the cost of the burnout an organization is facing. To compute a projected future replacement cost due to burnout, we factor in individualized quit probabilities (as computed by our machine learning models) with replacement cost and consider different levels of turnover due to burnout. We explain the calculations in greater detail below.

3.1 Machine Learning Models

The individual quit probabilities used in making cost projections were calculated using an ensemble of machine learning techniques, including tree-based learning algorithms. All computations were performed using R statistical software. The models were trained on 10 years of historical data from the partner health system, which included 678 clinicians in total (494 active and 184 resigned). Out-of-sample predictions for the work status (active or quit) of all 678 clinicians in the data set were made by using a 5-fold cross-validation as follows. First, the data were randomly partitioned into 5 folds. One of the folds was selected as a holdout/ test set, and the model was trained on the other four folds. Once the training was complete, the model was validated by making predictions on the status of the clinicians in the test set. The process was repeated four more times, each time selecting a different fold as the test set. In this manner, we made a prediction for each clinician in the data while avoiding overfitting. There were 184 clinicians who had quit in the data, and we correctly labeled 152 of them as quitters for a sensitivity of 82.6%. There were 494 active clinicians, and 380 of them were correctly labeled as active for a specificity of 76.96%. The models were calibrated to favor sensitivity over specificity since the cost of misidentifying a quitter is higher than the cost of misidentifying an active clinician. The balance between sensitivity and specificity can be easily adjusted if desired based on the relative costs of misidentifying resigning and active clinicians.

3.2 Burnout Assessment

To estimate the level of burnout at the partner health system, we developed and administered a comprehensive wellness assessment, composed of 15 items, covering the three theoretical dimensions of burnout: exhaustion, cynicism, and inefficacy (Maslach and Leiter, 2006). The literature describes exhaustion as wearing out, loss of energy, depletion, debilitation, and fatigue. The cynicism dimension was previously known as depersonalization (given the nature of human services occupations), and constitutes negative or inappropriate attitudes towards clients, irritability, loss of idealism, and withdrawal. The inefficacy dimension is described as reduced productivity or capability, low morale, and an inability to cope.

We used five items to reflect each of the dimensions, scoring each item on a six-point Likert scale (Likert, 1932) from “strongly agree” to “strongly disagree.” Each dimension included a combination of positively and negatively valenced items, with the latter reverse scored as appropriate. To test whether the data fit well with this theoretical framework, we conducted a confirmatory factor analysis (CFA) using Mplus software (version 8; Muthén and Muthén, 1998-2011). We computed a three-factor CFA in which the five items from each dimension were loaded onto the three dimensions of burnout for a total of 15 items. We retained all subscales with a factor loading greater than or equal to 0.4 (Stevens, 2012). If a factor loading was below the 0.4 cut-off, we removed the item and re-ran the CFA without it in the model. All of the items for the three-factor model met inclusion criteria with the exception of a positively-valenced (and reverse scored) item from the cynicism dimension and one negatively-valenced item from the inefficacy dimension. As such, the two items were removed from the model and the CFA was re-run with an improved fit. We calculated a composite score by averaging the 13 remaining items, which reflects wellness across all three dimensions of burnout. Composite scores above three indicate overall negative feelings (“slightly disagree”, “disagree”, “strongly disagree”) and higher burnout.

Finally, for simplicity we label clinicians with composite scores greater than three as burnt-out, and those with composite scores less than or equal to three as not experiencing burnout. We use this threshold throughout our various analyses when comparing groups. Recognizing that burnout can be experienced on a continuum and that the severity of the burnout matters, especially when interventions may aim to reduce the level of burnout an individual experiences versus eliminating it entirely, we also analyze burnout as a continuous variable. This provides us with estimates of the effects of incremental changes in burnout.

3.3 Cost Framework

Our framework separates clinicians experiencing burnout into two groups: those who continue to work at the healthcare organization as of July 1, 2022 (channel one) and those who left the organization between July 1, 2021 and June 30, 2022 (channel two). We estimate costs associated with active burnt-out clinicians by comparing the difference in productivity levels and rates of patient satisfaction of clinicians experiencing burnout versus those who are not. We estimate the costs from quitting by aggregating the net loss due to vacant positions, recruitment costs, and onboarding costs.

3.3.1 Channel One: Burnt-Out but Actively Employed

Hypothesis 1: Clinicians experiencing burnout are less productive on the job.

We computed composite burnout scores for 195 clinicians at the partner midsize health system. A clinician's composite burnout score is the average of their scores on the three dimensions: exhaustion, cynicism, and inefficacy. Each of the three dimensions is scored on a six-point Likert scale as follows: strongly agree (1), agree (2), slightly agree (3), slightly disagree (4), disagree (5), strongly disagree (6). Given the negative valence beyond three on the Likert scale used here, we classify a clinician as burnt-out if the composite burnout score is greater than three. There were 90 clinicians thus categorized as experiencing burnout and 105 categorized as not. We use the total RVU (relative value unit) sum from the previous 12 months as a proxy for a clinician's productivity. RVUs provide a standard measure of the time, effort, and resources required for a clinician to perform a service or procedure. Both the Centers for Medicare & Medicaid Services (CMS) and private payers use the RVU system to determine clinician payment. In September 2022, the conversion factor for a single RVU was $34.6062/RVU (AASM, 2022). Taking the yearly sum of the total RVU for each clinician and multiplying by the conversion factor enables us to quantify the clinician's annual productivity in dollars (Samuel et al., 2020).

Hypothesis 2: Clinicians who are burnt-out have lower patient satisfaction.

We test the hypothesis that clinicians who experience burnout engage with patients less effectively as those who do not experience burnout and thus register a lower patient satisfaction score. To estimate the effect of burnout on patient satisfaction, we obtained patient survey data from September 2021 through April 2022. After each patient encounter, the partner healthcare organization sent a survey to the patient asking them to rate their experience. The survey contains 13 inquiries ranging from comfort levels surrounding COVID-19 protocols to in-office wait time. To gauge patient satisfaction with the attending clinician, we looked at responses to the following three items:

- "Quality of your medical provider (or tech, if not seen by a provider)"
- "Quality of your medical care"
- "Please rate your overall experience with us"

We chose these three items because they directly relate to the attending clinician, while all other items relate to things outside the influence or control of the clinician. Patients rated each item by choosing one of the following five descriptors: poor, fair, good, very good, or excellent. In our analysis, we used the percentage of "excellent" reviews each clinician received for the three items above as the response variable [2]. The percentage of excellent reviews is a natural choice to measure patient satisfaction that is widely used in literature (Richter and Muhlestein, 2017). We also recognize the potential spillover effects burnt-out clinicians have on their coworkers, but we lacked the data available to undertake such an analysis.

3.3.2 Channel Two: Burnt-Out and Quit

We estimate the *ith* individual clinician's quitting probability, Q_i, based on the clinician's attributes and work behavior. The individual level estimates allow for more accurate projections of turnover and burnout costs at the organizational level. We estimate the likely cost consequences of individuals leaving based on their replacement cost according to their role and the regions they operate in. We define individual replacement cost, C_i, as the sum of revenue lost if the clinician leaves the organization (L_i), the recruitment cost (R_i), and the onboard/training cost (T_i) for his/her new hire:

$$C_i = L_i + R_i + T_i$$

L_i, the total revenue lost, is computed by multiplying the average number of months, M_i, it takes to fill the vacancy (depending on job role and region) and the difference between the monthly revenue, RVU_i, brought in by the clinician less the clinician's monthly salary, S_i. That is,

$$L_i = (RVU_i - S_i) \times M_i$$

Monthly revenue, RVU_i, is calculated by converting the monthly RVU sum of the clinician to dollars. In many healthcare systems, the loss in revenue from a leaving clinician can be mitigated by moonlighting physicians or traveling nurses. However, the partner health system who provided the data for this study rarely, if ever, employed any of these temporary services. Some of the workload from the quitting clinician was likely shifted to existing

[2] We also considered the percentage of "poor" or "fair" reviews, but those were so sparse as to make analysis infeasible (only 2.26% of reviews on the items above were rated "poor" or "fair").

clinicians nearby, but it was not possible for us to estimate how much nor the risk of increased burnout from the shift.

Recruitment cost, R_i, comes from a variety of sources (O'Brien-Pallas et al., 2006; Hawkins, 2019). In addition to revenue lost and recruitment cost, new hires typically take a full year to reach normal productivity levels. The productivity lost over the time it takes a clinician to reach full productivity is considered onboarding or training costs, T_i. To calculate the onboarding/training cost, we work on a rolling 12 month window. We first compute the highest 12 month RVU total for each individual given their employment history, H_i, which indicates the full productivity the clinicians have at our partner healthcare organization. We then calculate the first 12 month RVU total, F_i, for each individual. We define the onboarding/training cost to be:

$$T_i = H_i - F_i$$

The actual annual turnover cost for an organization is then $\Sigma_N C_i$, where the summation is taken over the N clinicians who actually quit. The projected annual turnover cost factors in the individual quit probabilities, Q_i; this is $\Sigma_A (C_i \cdot Q_i)$ where the summation here is taken over all active clinicians, A. We test our method by comparing the actual turnover costs during a one-year period to the projected costs for that time period (see Table 6). Given the assessment of burnout at the partner healthcare organization, we then estimate what percentage of turnover can be attributed to burnout and quantify costs accordingly.

4 Results

4.1 Burnout Assessment

Using our dichotomous division of clinicians by whether their composite burnout score was above or below three, we estimate that 46.2% (90/195) of respondents suffer from burnout. This percentage is in line with the national estimates of 38.2% - 62.8% between 2011 and 2021 (Shanafelt et al., 2022). Figure 1 shows that the distribution of the composite burnout scores has the approximate shape of a normal distribution, and the center and spread of the distribution indicate a wide range of severity on the burnout continuum.

Table 1 shows that exhaustion and cynicism are the main aspects of burnout at this organization, though we will see that inefficacy also has a large impact despite being less frequent. It should not be surprising that the three dimensions of burnout do not mirror each other. Leiter and Maslach (2016) note that the three dimensions of burnout are interrelated but distinct and do not always correlate. Indeed, Thomas et al. (2020) posit that burnout "begins with exhaustion and ends with inefficacy," implying that the fewer clinicians who suffer from inefficacy may be in more severe, later stages of burnout. As the composite score is an average of the three dimensions of burnout, it is reasonable to get the approximately normal shape of Figure 1 even with the skewed distributions of each dimension.

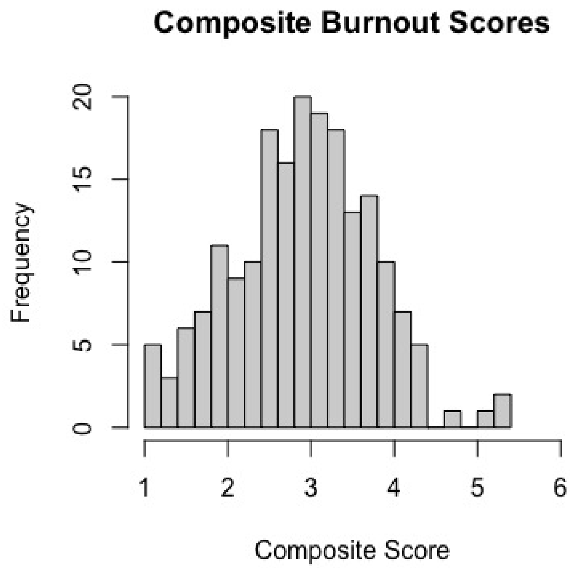

Figure 1: Distribution of composite burnout scores at the partner healthcare organization. The composite score is the average of the three dimensions: exhaustion, cynicism, and inefficacy.

Table 1: Burnout severity at the partner healthcare organization

Burnout Dimension	Clinicians Afflicted
Exhaustion	55.4% (108/195)
Cynicism	62.6% (122/195)
Inefficacy	6.7% (13/195)
Composite Score	46.2% (90/195)

4.2 Burnt-Out but Active

To test Hypothesis 1 that clinicians experiencing burnout are less productive on the job, we first compare the mean productivity of the non-burnout group, $\bar{x}_N$ (n=102), to the mean productivity of the burnout group, $\bar{x}_B$ (n=90). [3] Productivity in this case was measured as the total RVU output of a clinician over the one-year period beginning at the start of Q3 2021. A simple test for the difference in means shows that $\bar{x}_N - \bar{x}_B =$ \$80,979 ($p = .08$ from the two-sided t-test). Hence, on average, clinicians suffering from burnout are nearly \$81,000 less productive per year at this particular healthcare organization. Assuming the proportion of clinicians experiencing burnout in the assessment (46.2%) holds across the organization of 494 clinicians, we estimate that approximately 228 clinicians are burnt-out. With the estimated average loss in productivity due to burnout at \$80,979, this would put the aggregate productivity loss due to burnout at \$18,463,212 annually.

[3]Note that three clinicians, all from the non-burnout group, were unable to be included in our analysis due to missing work records.

The second approach is to view burnout as a continuous outcome. Measuring burnout along a continuum allows us to assess the effects of incremental changes in burnout levels and thus to examine potential interventions which may mitigate the severity of burnout rather than "flip" a clinician from one group to another. We measure productivity as described above, using the same data as in the analysis of burnout as a dichotomous variable. We control for age and clinician type when analyzing RVU output. It must be noted that the relationship between productivity and age is non-linear due in large part to the fact that working clinicians tend to decrease their hours in a non-linear fashion as they get older and approach retirement. Figure 2 displays the age-productivity curve, controlling for clinician type. The curve shows that productivity begins to decrease around age 50, with the drop-off becoming more precipitous as age increases.

Because age is an important factor with a highly non-linear relation to productivity, we use a Generalized Additive Model (GAM). GAMs are a generalization of linear regression which allow for non-linear dependencies. Here, the relation to age is estimated from the data using multiple curves. The effective degrees of freedom (edf) for age is 2.147 (p-value = .0453). This value indicates what Figure 2 displays, a highly non-linear relationship with productivity. The relationships between productivity and all other dependent variables are assumed linear and have the standard interpretation of their coefficients. In our model, the response variable is the total RVU output of a clinician over the one-year period beginning at the start of Q3 2021. In addition to age and clinician type, we regress on the individual dimensions of burnout: exhaustion, cynicism, and inefficacy. Our model has a particularly good fit with 89.9% of the deviance explained.

Table 2: Summary of Generalized Additive Model (Model 1). Annual RVU totals are regressed on the three dimensions of burnout and clinician type, as well as age which has a non-linear relationship. The effective degrees of freedom (edf) of age is 2.147, indicating a roughly quadratic relationship. Because the GAM deals with non-linearity, R^2 is an inappropriate measure of goodness-of-fit, and instead the deviance explained is used. The deviance explained is 89.8%, meaning the model is a good fit.

Term	Coefficient	p-value
Cynicism	-1032.2	0.264
Inefficacy	-1996.2	0.101
Exhaustion	1181.1	0.195
Associate Physician	27736.2	$< .001$
Certified Nurse Midwife	26108.0	$< .001$
Nurse Practitioner	14939.4	$< .001$
Physician Assistant	31886.9	$< .001$
Senior Physician	29767.1	$< .001$
Age	edf = 2.147	$p = .0453$
deviance explained = 89.8%		

Table 2 shows the results of the GAM (Model 1). The model examines the relation between productivity and the three components of the burnout while controlling for age and clinician type. The estimated coefficients for cynicism and inefficacy show that they are associated with lower productivity. On average, an increase of one unit on the cynicism score reduces annual RVU output by 1032.2 RVUs, which amounts to $35,720.52 annually per clinician using

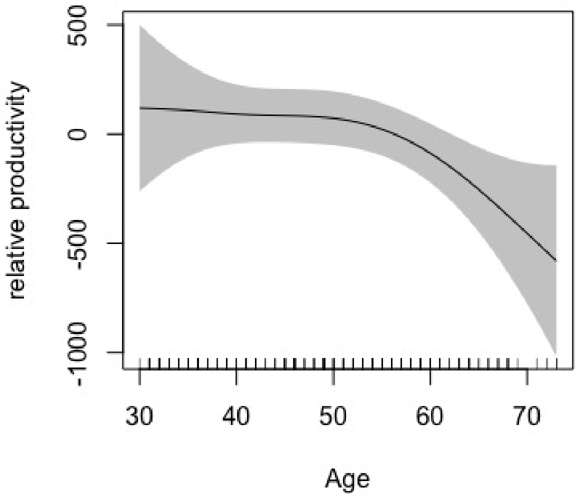

Figure 2: Productivity versus age curve, controlling for clinician type, where shading indicates confidence intervals. The scale on the y-axis is arbitrary as it measures relative productivity. The relationship between age and productivity is clearly non-linear, which justifies the use of a Generalized Additive Model.

the conversion factor above. Similarly, an increase of one unit on the inefficacy score reduces annual RVU output by 1996.2 RVUs, which amounts to $69,080.9 less revenue per clinician. By contrast, exhaustion is positively associated with productivity: an increase of one unit on the exhaustion scale is associated with an increase in productivity of 1181.1 RVUs or $40,873.38 per clinician per year. The likely reason for the positive coefficient of exhaustion is that the cause and effect may be reversed: a heavy workload will almost surely raise exhaustion.

While the impact of cynicism and inefficacy dominate the overall negative link from burnout to productivity found in the comparison of means given earlier, probing beneath the difference in mean productivity in the dichotomous burnout measure highlights the need for going beyond the burnout variable in analysis of cause and effects. Absent a model that deals with the dual causality of exhaustion and workload, we estimated an alternative GAM (Model 2 of Table 3) which removes exhaustion, given the opposite association exhaustion has with burnout. Inefficacy obtains a substantial negative coefficient while cynicism has only a modest and statistically insignificant coefficient. Additional work on the effect of burnout on productivity of working clinicians should concentrate on inefficacy, probing the measures going into it, and seeking other measures, as well as estimating more structured models than ours.

In addition to the potential value of increasing the focus of research on inefficacy, the message we take from this calculation is that the burnout score, while an invaluable *indicator* of the problem that ties together its main features as a phenomenon, is not well-suited to assess what burnout does to productivity, absent a more complicated model and measures focused on the actual work behavior of clinicians. This leads us to consider other avenues beyond

Table 3: Summary of alternative Generalized Additive Model (Model 2). This time exhaustion is left out of the model and annual RVU totals are regressed on cynicism and inefficacy, controlling for clinician type and age. The effective degrees of freedom (edf) of age is 2.191

Term	Coefficient	p-value
Cynicism	-294.0	0.686
Inefficacy	-1682.1	0.159
Associate Physician	28251.6	$< .001$
Certified Nurse Midwife	27227.5	$< .001$
Nurse Practitioner	15826.6	$< .001$
Physician Assistant	32312.1	$< .001$
Senior Physician	30490.3	$< .001$
Age	edf = 2.191	$p = .0375$
deviance explained = 89.8%		

burnout surveys that we take in later sections.

To test Hypothesis 2 that burnt-out clinicians have lower patient satisfaction, we compare the percentage of "excellent" reviews a burnt-out clinician received to that of a clinician not experiencing burnout. We examined the differences between these two groups across all dimensions of burnout, including the composite score. Recall that inefficacy has been conjectured to indicate some of the most severe stages of burnout (Thomas et al., 2020). We find that the difference between the groups in this dimension is substantial, with clinicians who are burnt-out on the inefficacy scale significantly less likely to garner an "excellent" review from a patient encounter than those who are not burnt-out.

The plot of patient satisfaction versus clinicians categorized by their inefficacy score in Figure 3 shows a wide difference in the mean of the two groups. The mean patient satisfaction of the non-burnout group, $\bar{x}_{PN}$ (n=106), is 81.8% whereas mean patient satisfaction of the burnout group, $\bar{x}_{PB}$ (n=11), is 67.8% [4]. Despite the disparity in sample sizes of the two groups, this difference of $\bar{x}_{PN} - \bar{x}_{PB} = 14\%$ is highly significant ($p = .01$ from the two-sided t-test). Thus, on average we expect a clinician experiencing burnout on the inefficacy dimension to be 14% less likely to receive an excellent review than a clinician not experiencing burnout.

4.2.1 Moving Beyond Burnout Surveys

The results of the previous section establish the link between burnout and productivity, which quantifies some of the effects that are often discussed but rarely measured, while also highlighting the problem of using a broad indicator of the phenomenon to differentiate the causal links between feelings of burnout and productivity. To the extent that the productivity of a clinician reflects that person's current burnout level, it can serve as an early warning of the clinician leaving the workplace, and give an organization insight on potential burnout and future turnover absent another burnout survey. Indeed, productivity data has several advantages over surveys typically used for inferring how employees feel and may possibly behave in the future. Productivity data are objective and can be obtained for

[4] Note that here the sample size is 117 because patient reviews do not exist for every clinician.

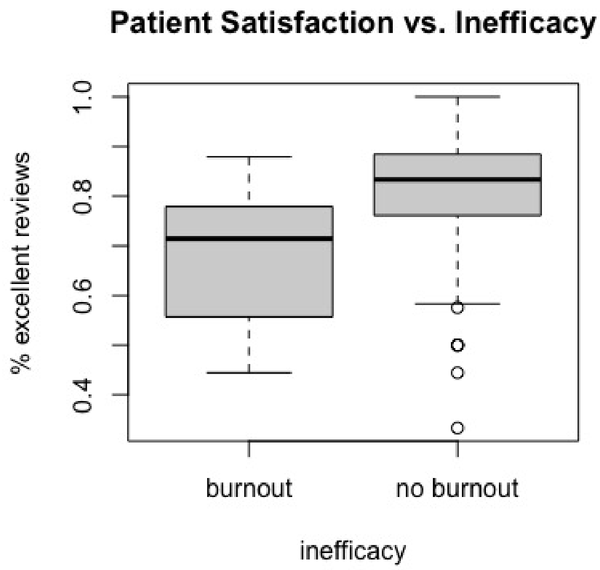

Figure 3: Patient satisfaction compared with burnout in the inefficacy dimension.

all clinicians within the health system, including those who do not fill out a burnout survey. Surveys can be costly to implement and process across an entire organization, especially when taking the clinician's time into account, whereas productivity data is collected at no additional cost to the organization and at no expense to the clinician. Finally, "survey fatigue" often leaves organizations with low response rates and unreliable estimates while the self-reporting aspect of burnout surveys also casts doubt on the accuracy of the results.

Following this line of thinking, we developed a machine learning algorithm to forecast future productivity from the past pattern of productivity. Using monthly RVU totals to measure clinician productivity, we use the monthly RVU sums from January 2021 to March 2022 to predict the RVU sum six months later in September 2022 for each clinician. We chose to predict RVU six months later so the forecasts would be plausibly actionable, giving leadership time to strategize and intervene if necessary. Tree-based regression was used to predict monthly RVU output six months in advance using the same standard data furnished by the partner health system. As in section 3.1, we cross-validated our models using a 5-fold scheme. We first randomly partition the data into 5 folds. One of the folds is chosen as a test set, and the other four folds are used to train the model. After the model was fit using the 4 folds, we use said model to predict RVU for the clinicians in the test set. This process was repeated four more times, enabling us to predict the RVU for every clinician in the data set. We then compared our predicted RVUs to the actual RVUs logged by the clinicians to assess the quality of our forecasts.

Table 4 breaks down the accuracy of the results by role type of the clinician. Our predicted values are strongly correlated with the actual values ($r = .77$) with a mean absolute error (MAE) of 474.89 RVUs. To put this number in context, the mean and standard deviation of the productivity totals for September 2022 are 1656.99 and 1080.90 RVUs, respectively. Note that in most cases the MAE is roughly half or less than half of the standard deviation. Accuracy of this caliber means leadership can feasibly predict when productivity will drop six months in advance, and given the association lower productivity has with burnout, this can serve as a proxy for burnout assessments. Indeed, this productivity monitoring and forecasting has the distinct advantage over surveys in that it allows leadership to be proactive in their approach to mitigating burnout.

Table 4: Monthly Productivity Forecasting Results

Role Type	Average Monthly Total (RVUs)	Standard Deviation (RVUs)	Mean Absolute Error (RVUs)
Senior Physician	2098.29	1014.26	534.12
Associate Physician	1727.19	1200.71	558.03
Certified Nurse Midwife	862.55	685.60	353.46
Nurse Practitioner	961.28	596.51	313.08
Physician Assistant	1132.02	857.91	411.24
All	1656.99	1080.90	474.89

Cross-validated correlation between predicted and observed values is $r = .77$.

4.3 Turnover and Burnout Cost

Table 5 shows the actual turnover costs from July 1, 2021 to June 30, 2022 at the partner healthcare organization. Note that during this time period, 55 clinicians left the organization, a turnover rate of 11.3%. The largest single turnover cost from an individual clinician's departure was measured at $391,000, and the total cost of all turnover during this time frame was $7.8 million. As clinicians may leave for reasons other than burnout, however, it would be wrong to associate all of that cost to burnout. Accordingly, we estimate the proportion of leaving clinicians likely due to burnout as opposed to other factors. Using the overall turnover rate (11.3%) together with the estimate of burnout at this organization (46.2%), and the assumption that burnt-out clinicians are twice as likely to have left (Shanafelt et al., 2012), we calculate the turnover rate of burnt-out clinicians to be 15.2%. Using these turnover rates, we further estimate that 35 of the 55 clinicians who quit (63%) were burnt-out. [5] Based on these calculations, a conservative estimate for the cost of turnover attributable to burnout is $4,912,510. This estimate is on the order of 2% of the total annual revenue of this midsize healthcare organization. Given that the labor cost of clinicians alone at this midsize health system was approximately 45% of revenue, the turnover costs due to burnout represent a significant portion of this health systems profits.

[5] The assumption that burnt-out clinicians are twice as likely to leave is actually a conservative one; other studies put the odds ratio of burnt-out clinicians leaving at 2.19 (Windover et al., 2018) and 2.68 (Hamidi et al., 2018). Using the odds ratios of 2.19 and 2.68 yields estimates of 65% and 70%, respectively, of turnover attributable to burnout.

Table 5: Turnover and Burnout Costs (Q3 2021 - Q2 2022)

	Turnover Cost	Clinician Churn Rate
Actual	\$7,778,140	11.3% overall
63% Attributable to Burnout	\$4,912,510	15.2% for burnt-out clinicians
65% Attributable to Burnout	\$5,074,715	15.7% for burnt-out clinicians
70% Attributable to Burnout	\$5,419,085	16.8% for burnt-out clinicians

4.3.1 Projected Turnover Costs

We break down the cost of a clinician quitting as the sum of the recruitment cost, onboarding cost, and revenue lost as outlined in Section 3.3.2. Using the quitting probability for each individual clinician generated by our predictive model, we can compute projected costs for the entire organization. We trained our predictive model on data provided by our partner healthcare organization up through the end of the second quarter 2022. We then projected costs for the next calendar year, July 1, 2021 through June 30, 2022.

Table 6: Projected Turnover Cost vs Actual Turnover Cost (Q3 2021 - Q2 2022)

Turnover Cost	Projected	Actual
Recruitment	\$1,470,683	\$1,505,000
Onboarding	\$2,860,469	\$2,754,309
Lost Revenue	\$4,649,753	\$3,518,831
Total	\$8,980,905	\$7,778,140

Table 6 shows how the projections for the calendar year from the beginning of third quarter of 2021 compared to the actual costs. The projection totals are off by 13.4%, with the largest discrepancy coming from the lost revenue calculations. The reason actual lost revenue was not as high as projected may be because other clinicians “pick up the slack” when a coworker has quit, which arguably may result in the burnout severity increasing for those clinicians who take on additional burdens. Nonetheless, the modest error here is further validation that the predictive model is accurate.

5 Discussion

Burnout in the medical field is widely studied, but its economic consequences have been only crudely estimated. This paper seeks to quantify these consequences through a novel conceptual and computational framework. We conceptualize burnout impacting a healthcare organization in two distinct ways, via the impact on active clinicians who are burnt-out and through the turnover costs of clinicians quitting due to burnout. Both impacts are difficult to quantify, but we have laid out a computational framework for better estimates of each. Furthermore, we go beyond just measuring burnout to forecasting burnout and its consequences. We show that accurate forecasts are possible using only the standard data health systems already possess. In this manner, decision-makers have the ability to plan ahead instead of being forced to look retroactively using traditional surveys.

Nearly half of reporting clinicians experience burnout at our partner healthcare organization, in line with national estimates (Shanafelt et al., 2022). Our findings indicate that the impact of burnout on active clinicians is sufficiently large to justify major interventions and workplace alterations to reduce this problem. On average, a burnt-out clinician is less productive than their non-burnt-out counterpart by nearly \$81,000 per year. Depending on the dimension, an increase of just one unit on the burnout scale is associated with a productivity loss of up to \$69,000 per year. Different dimensions of burnout have different relations to productivity, with inefficacy being most important and exhaustion showing a positive relation to productivity in the short term, likely reflecting the reverse impact of heavy work effort on exhaustion. Moreover, clinicians experiencing burnout as measured by inefficacy are 14% less likely to receive an "excellent" review after a patient encounter. Burnout is affecting not only the balance sheet of the healthcare organization, but also the quality of patient care.

The most burnt-out clinicians quit. We quantify the aftermath by calculating recruitment costs, onboarding costs, and lost revenue based on actual data from our healthcare partner. Depending on the type of clinician and the specific region, when a clinician quits it can cost the healthcare organization up to \$391,000. Aggregate turnover costs are well into the millions of dollars annually, and even conservative estimates of turnover due to burnout put the impact of quitting due to burnout at nearly \$5 million annually at our midsize partner health system.

Limitations of our study are as follows: at the time of administering the burnout assessment, 195 of the 487 active clinicians responded (seven more clinicians were hired subsequent to the completion of the assessment, bringing the total to 494). Possible nonresponse bias may exist. In certain cases, matching financial records were not available in the data (three non-burnt-out clinicians). Because patient reviews do not come in regularly and are sparse relative to the number of patient encounters, we were unable to generate a sample size large enough linking reviews to financial records. Furthermore, we attempted to quantify the monetary impact of lower patient satisfaction but were unable to do so with the existing data. Patient reviews do not come in regularly and are sparse relative to the number of patient encounters, so matching to existing profit/loss records did not yield a sample size large enough for analysis. There also could exist response bias from the patients leaving the reviews. Indeed, the limitations of our study are tied to the limitations of surveys in general. These limitations underscore the need to analyze burnout using non-survey data, which we have done by focusing on productivity measures. Surveys are necessary to guide interpretation of the productivity behavior, but using productivity data has the virtue of directly measuring the economic consequence of burnout via standard business reporting that does not require clinician input.

Future work should analyze the financial impact of lower patient satisfaction when data becomes available. Pending further longitudinal data on burnout, we would also want to study the long-term effects of burnout on clinicians, such as long-term productivity changes over time, and the likelihood of quitting based on burnout level.

Additionally, we would also like to investigate the redistribution of work to the coworkers of a quitting clinician after the clinician's departure.

Even with our limitations, these results justify an investment in clinician well-being. Han et al. (2019) used simulations at the national level to estimate the cost of burnout to be $7,600 per physician. Given the size of our healthcare partner (494 clinicians), this would place the aggregate cost of burnout at just over $3.75 million. According to our analyses, a conservative estimate of the cost of turnover from burnout alone is over $4.9 million; if we include costs of productivity loss from active burnt-out clinicians the total cost of burnout could be four times as high, on the order of $20 million annually at our midsize partner health system. Even this is likely to be lower than the real cost as it does not consider the effects of lower patient satisfaction, the impact of which we did not have sufficient data to quantify. Moreover, we have demonstrated that it is possible to get ahead of the burnout situation by estimating the probability individual clinicians leave and forecasting declining productivity as a proxy measure for burnout. This gives decision-makers an early warning of sorts so they may intervene, as opposed to accepting high rates of turnover and burnout as inevitable. It is our hope that the framework we have laid out here will be applied by other healthcare organizations when making the business case for investing in programs and preventive measures to mitigate clinician burnout.

Appendix

A.1 Literature Review

Table A1: Summary of Documented Impacts of Clinician Burnout

Type	Category	Impact	References
Non-clinical	Turnover	burnt-out clinicians are less likely to intend to keep practicing	Hoff et al. (2002)
Non-clinical	Turnover	burnt-out clinicians are more likely to intend to change jobs	Soler et al. (2008)
Non-clinical	Turnover	burnt-out clinicians are more likely to intend to leave	Moreno-Jiménez et al. (2012)
Non-clinical	Turnover	burnt-out clinicians are more likely to leave	Hamidi et al. (2018); Shanafelt et al. (2012)
Non-clinical	Productivity	burnt-out clinicians take more sick days	Soler et al. (2008)
Non-clinical	Productivity	burnt-out clinicians have less work ability (self-reported)	Ruitenburg et al. (2012)
Non-clinical	Productivity	burnt-out clinicians reduce clinical hours	Dewa et al. (2014)
Non-clinical	Productivity	burnt-out clinicians reduce academic publications	Turner et al. (2017)
Non-clinical	Productivity	burnt-out clinicians engage less in teamwork	Welp et al. (2016); Galletta et al. (2016)
Non-clinical	Patient-focused	burnt-out clinicians have lower patient satisfaction	Halbesleben and Rathert (2008); Windover et al. (2018)
Non-clinical	Clinician-focused	burnt-out clinicians have less career satisfaction	Shanafelt et al. (2009); Yao et al. (2021)
Non-clinical	Clinician-focused	burnt-out clinicians are more likely to increase alcohol/drug use	Jackson et al. (2016)
Non-clinical	Clinician-focused	burnt-out clinicians are more likely to retire early	Dewa et al. (2014)
Clinical	Care Quality	burnt-out clinicians give suboptimal care	Lu et al. (2015)
Clinical	Care Quality	burnt-out clinicians have higher referral rates	Kushnir et al. (2014)
Clinical	Care Quality	burnt-out clinicians have lower perceived quality of care from patients	Klein et al. (2010)
Clinical	Care Quality	Hospital infections increase in patients with burnt-out clinicians	Galletta et al. (2016)
Clinical	Care Quality	Psychological evaluations and consultation lengths increase with burnt-out clinicians	Zantinge et al. (2009)
Clinical	Care Quality	Recovery times are longer for those who were treated by burnout clinicians	Halbesleben and Rathert (2008)
Clinical	Patient-safety	burnt-out clinicians are associated with decreased patient safety measures	Welp et al. (2016)

A.2 List of Data

The following data was furnished by the partner health system for the analyses in this paper. Note that all data was de-identified to protect the identities of all clinicians.

- Demographic data: age, gender, ethnicity, marital status
- Average commute time to and from work
- Employment data: role type, date of hire, date of termination
- Medical billing data: procedure type, RVU totals, time and date
- Financial data: profitability of departments, compensation of clinicians
- Departmental data: region, number of employees
- Scheduling data: dates and times clinicians worked
- Patient satisfaction data

References

AASM (2022), "CMS revises Medicare physician fee schedule conversion factor for 2022," `https://aasm.org/cms-revises-medicare-physician-fee-schedule-conversion-factor-2022/`, accessed: 2022-10-14.

Berg, S. (2019), "AMA honors 22 organizations' commitment to cutting doctor burnout," https://www.ama-assn.org/practice-management/sustainability/ama-honors-22-organizations-commitment-cutting-doctor-burnout, accessed: 2022-10-14.

Brunsberg, K. A., Landrigan, C. P., Garcia, B. M., Petty, C. R., Sectish, T. C., Simpkin, A. L., Spector, N. D., Starmer, A. J., West, D. C., and Calaman, S. (2019), "Association of pediatric resident physician depression and burnout with harmful medical errors on inpatient services," *Academic medicine: journal of the Association of American Medical Colleges*, 94, 1150.

Busis, N. A., Shanafelt, T. D., Keran, C. M., Levin, K. H., Schwarz, H. B., Molano, J. R., Vidic, T. R., Kass, J. S., Miyasaki, J. M., Sloan, J. A., et al. (2017), "Burnout, career satisfaction, and well-being among US neurologists in 2016," *Neurology*, 88, 797–808.

Dewa, C. S., Loong, D., Bonato, S., Thanh, N. X., and Jacobs, P. (2014), "How does burnout affect physician productivity? A systematic literature review," *BMC health services research*, 14, 1–10.

Fahrenkopf, A. M., Sectish, T. C., Barger, L. K., Sharek, P. J., Lewin, D., Chiang, V. W., Edwards, S., Wiedermann, B. L., and Landrigan, C. P. (2008), "Rates of medication errors among depressed and burnt out residents: prospective cohort study," *Bmj*, 336, 488–491.

Galletta, M., Portoghese, I., D'Aloja, E., Mereu, A., Contu, P., Coppola, R. C., Finco, G., and Campagna, M. (2016), "Relationship between job burnout, psychosocial factors and health care-associated infections in critical care units," *Intensive and critical care nursing*, 34, 59–66.

Halbesleben, J. R. and Rathert, C. (2008), "Linking physician burnout and patient outcomes: exploring the dyadic relationship between physicians and patients," *Health care management review*, 33, 29–39.

Hamidi, M. S., Bohman, B., Sandborg, C., Smith-Coggins, R., De Vries, P., Albert, M. S., Murphy, M. L., Welle, D., and Trockel, M. T. (2018), "Estimating institutional physician turnover attributable to self-reported burnout and associated financial burden: a case study," *BMC health services research*, 18, 1–8.

Han, S., Shanafelt, T. D., Sinsky, C. A., Awad, K. M., Dyrbye, L. N., Fiscus, L. C., Trockel, M., and Goh, J. (2019), "Estimating the attributable cost of physician burnout in the United States," *Annals of internal medicine*, 170, 784–790.

Hawkins, M. (2019), "The Cost of a Physician Vacancy," https://aasm.org/cms-revises-medicare-physician-fee-schedule-conversion-factor-2022/, accessed: 2022-10-14.

Hoff, T., Whitcomb, W. F., and Nelson, J. R. (2002), "Thriving and surviving in a new medical career: the case of hospitalist physicians," *Journal of Health and Social Behavior*, 43, 72.

Jackson, E. R., Shanafelt, T. D., Hasan, O., Satele, D. V., and Dyrbye, L. N. (2016), "Burnout and alcohol abuse/dependence among US medical students," *Academic Medicine*, 91, 1251–1256.

Klein, J., Grosse Frie, K., Blum, K., and von dem Knesebeck, O. (2010), "Burnout and perceived quality of care among German clinicians in surgery," *International Journal for Quality in Health Care*, 22, 525–530.

Kuerer, H. M., Eberlein, T. J., Pollock, R. E., Huschka, M., Baile, W. F., Morrow, M., Michelassi, F., Singletary, S. E., Novotny, P., Sloan, J., et al. (2007), "Career satisfaction, practice patterns and burnout among surgical oncologists: report on the quality of life of members of the Society of Surgical Oncology," *Annals of surgical oncology*, 14, 3043–3053.

Kushnir, T., Greenberg, D., Madjar, N., Hadari, I., Yermiahu, Y., and Bachner, Y. G. (2014), "Is burnout associated with referral rates among primary care physicians in community clinics?" *Family practice*, 31, 44–50.

Leiter, M. P. and Maslach, C. (2016), "Latent burnout profiles: A new approach to understanding the burnout experience," *Burnout Research*, 3, 89–100.

Likert, R. (1932), "A technique for the measurement of attitudes." *Archives of psychology*.

Lu, D. W., Dresden, S., McCloskey, C., Branzetti, J., and Gisondi, M. A. (2015), "Impact of burnout on self-reported patient care among emergency physicians," *Western Journal of Emergency Medicine*, 16, 996.

Maslach, C. and Leiter, M. (2006), "Burnout. Stress and quality of working life: Current perspectives in occupational health, 37, 42–49," .

Maslach, C. and Leiter, M. P. (2016), "Understanding the burnout experience: recent research and its implications for psychiatry," *World psychiatry*, 15, 103–111.

Moreno-Jiménez, B., Gálvez-Herrer, M., Rodríguez-Carvajal, R., and Vergel, A. I. S. (2012), "A study of physicians' intention to quit: The role of burnout, commitment and diffi cult doctor-patient interactions," *Psicothema*, 24, 263–270.

Nørøxe, K. B., Vedsted, P., Bro, F., Carlsen, A. H., and Pedersen, A. F. (2019), "Mental well-being and job satisfaction in general practitioners in Denmark and their patients' change of general practitioner: a cohort study combining survey data and register data," *BMJ open*, 9, e030142.

O'Brien-Pallas, L., Griffin, P., Shamian, J., Buchan, J., Duffield, C., Hughes, F., Laschinger, H. K. S., North, N., and Stone, P. W. (2006), "The impact of nurse turnover on patient, nurse, and system outcomes: a pilot study and focus for a multicenter international study," *Policy, Politics, & Nursing Practice*, 7, 169–179.

Prasad, K., McLoughlin, C., Stillman, M., Poplau, S., Goelz, E., Taylor, S., Nankivil, N., Brown, R., Linzer, M., Cappelucci, K., et al. (2021), "Prevalence and correlates of stress and burnout among US healthcare workers during the COVID-19 pandemic: A national cross-sectional survey study," *EClinicalMedicine*, 35, 100879.

Richter, J. P. and Muhlestein, D. B. (2017), "Patient experience and hospital profitability: Is there a link?" *Health Care Management Review*, 42, 247–257.

Ruitenburg, M. M., Frings-Dresen, M. H., and Sluiter, J. K. (2012), "The prevalence of common mental disorders among hospital physicians and their association with self-reported work ability: a cross-sectional study," *BMC health services research*, 12, 1–7.

Samuel, L. T., Grits, D., Acuña, A. J., Piuzzi, N. S., Higuera-Rueda, C. A., and Kamath, A. F. (2020), "Work relative value units do not adequately support the burden of infection management in revision knee arthroplasty," *JBJS*, 102, 230–236.

Shanafelt, T., Goh, J., and Sinsky, C. (2017), "The business case for investing in physician well-being," *JAMA internal medicine*, 177, 1826–1832.

Shanafelt, T. D., Balch, C. M., Bechamps, G., Russell, T., Dyrbye, L., Satele, D., Collicott, P., Novotny, P. J., Sloan, J., and Freischlag, J. (2010), "Burnout and medical errors among American surgeons," *Annals of surgery*, 251, 995–1000.

Shanafelt, T. D., Balch, C. M., Bechamps, G. J., Russell, T., Dyrbye, L., Satele, D., Collicott, P., Novotny, P. J., Sloan, J., and Freischlag, J. A. (2009), "Burnout and career satisfaction among American surgeons," *Annals of surgery*, 250, 463–471.

Shanafelt, T. D., Boone, S., Tan, L., Dyrbye, L. N., Sotile, W., Satele, D., West, C. P., Sloan, J., and Oreskovich, M. R. (2012), "Burnout and satisfaction with work-life balance among US physicians relative to the general US population," *Archives of internal medicine*, 172, 1377–1385.

Shanafelt, T. D., Bradley, K. A., Wipf, J. E., and Back, A. L. (2002), "Burnout and self-reported patient care in an internal medicine residency program," *Annals of internal medicine*, 136, 358–367.

Shanafelt, T. D., Dyrbye, L. N., Sinsky, C., Hasan, O., Satele, D., Sloan, J., and West, C. P. (2016), "Relationship between clerical burden and characteristics of the electronic environment with physician burnout and professional satisfaction," in *Mayo Clinic Proceedings*, Elsevier, vol. 91, pp. 836–848.

Shanafelt, T. D., West, C. P., Dyrbye, L. N., Trockel, M., Tutty, M., Wang, H., Carlasare, L. E., and Sinsky, C. (2022), "Changes in Burnout and Satisfaction With Work-Life Integration in Physicians During the First 2 Years of the COVID-19 Pandemic," in *Mayo Clinic Proceedings*, Elsevier.

Soler, J. K., Yaman, H., Esteva, M., Dobbs, F., Asenova, R. S., Katić, M., Ožvačić, Z., Desgranges, J. P., Moreau, A., Lionis, C., et al. (2008), "Burnout in European family doctors: the EGPRN study," *Family practice*, 25, 245–265.

Stevens, J. P. (2012), *Applied multivariate statistics for the social sciences*, Routledge.

Thomas, S. P., Liao-Troth, S., and Williams, D. F. (2020), "Inefficacy: the tipping point of driver burnout," *International Journal of Physical Distribution & Logistics Management*.

Turner, T. B., Dilley, S. E., Smith, H. J., Huh, W. K., Modesitt, S. C., Rose, S. L., Rice, L. W., Fowler, J. M., and Straughn Jr, J. M. (2017), "The impact of physician burnout on clinical and academic productivity of gynecologic oncologists: a decision analysis," *Gynecologic oncology*, 146, 642–646.

Welp, A., Meier, L. L., and Manser, T. (2016), "The interplay between teamwork, clinicians' emotional exhaustion, and clinician-rated patient safety: a longitudinal study," *Critical Care*, 20, 1–10.

Williams, E. S., Manwell, L. B., Konrad, T. R., and Linzer, M. (2007), "The relationship of organizational culture, stress, satisfaction, and burnout with physician-reported error and suboptimal patient care: results from the MEMO study," *Health care management review*, 32, 203–212.

Windover, A. K., Martinez, K., Mercer, M. B., Neuendorf, K., Boissy, A., and Rothberg, M. B. (2018), "Correlates and outcomes of physician burnout within a large academic medical center," *JAMA internal medicine*, 178, 856–858.

Yao, H., Wang, P., Tang, Y.-L., Liu, Y., Liu, T., Liu, H., Chen, Y., Jiang, F., and Zhu, J. (2021), "Burnout and job satisfaction of psychiatrists in China: a nationwide survey," *BMC psychiatry*, 21, 1–11.

Zantinge, E. M., Verhaak, P. F., de Bakker, D. H., van der Meer, K., and Bensing, J. M. (2009), "Does burnout among doctors affect their involvement in patients' mental health problems? A study of videotaped consultations," *BMC family practice*, 10, 1–10.