Temporal Associations Between EHR-Derived Workload, Burnout, and Errors: a Prospective Cohort Study

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BACKGROUND: The temporal progression and workload-related causal contributors to physician burnout are not well-understood.

OBJECTIVE: To characterize burnout's time course and evaluate the effect of time-varying workload on burnout and medical errors.

DESIGN: Six-month longitudinal cohort study with measurements of burnout, workload, and wrong-patient orders every 4 weeks.

PARTICIPANTS: Seventy-five intern physicians in internal medicine, pediatrics, and anesthesiology at a large academic medical center.

MAIN MEASURES: Burnout was measured using the Professional Fulfillment Index survey. Workload was collected from electronic health record (EHR) audit logs and summarized as follows: total time spent on the EHR, after-hours EHR time, patient load, inbox time, chart review time, note-writing time, and number of orders. Wrong-patient orders were assessed using retract-and-reorder events.

KEY RESULTS: Seventy-five of 104 interns enrolled (72.1%) in the study. A total of 337 surveys and 8,863,318 EHR-based actions were analyzed. Median burnout score across the cohort across all time points was 1.2 (IQR 0.7–1.7). Individual-level burnout was variable (median monthly change 0.3, IQR 0.1–0.6). In multivariable analysis, increased total EHR time (β=0.121 for an increase from 54.5 h per month (25th percentile) to 123.0 h per month (75th percentile), 95%CI=0.016–0.226), increased patient load (β=0.130 for an increase from 4.9 (25th percentile) to 7.1 (75th percentile) patients per day, 95%CI=0.053–0.207), and increased chart review time (β=0.096 for an increase from 0.39 (25th percentile) to 0.59 (75th percentile) hours per patient per day, 95%CI=0.015–0.177) were associated with an increased burnout score. After adjusting for the total number of ordering sessions, burnout was not statistically associated with an increased rate of wrong-patient orders (rate ratio=1.20, 95%CI=0.76–1.89).

CONCLUSIONS: Burnout and recovery were associated with recent clinical workload for a cohort of physician trainees, highlighting the elastic nature of burnout. Wellness interventions should focus on strategies to mitigate sustained elevations of work responsibilities.

KEY WORDS: graduate medical education; physician wellness; burnout; workload; electronic health record.

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INTRODUCTION

Burnout is a work-related phenomenon affecting nearly 50% of physicians, and is associated with negative consequences for physician health and patient safety.[1,2] Previous studies on risk factors have highlighted the link between perceived work-related stressors and burnout.[3–5] However, studies using self-reported workload are subject to recall and response bias, creating uncertainty about the degree to which workload causes burnout versus burnout causing a negative perception of workload.

Recent advances in clinical informatics have allowed for the quantification of clinician workload based on electronic health record (EHR) use. Several EHR vendors provide platforms for monitoring clinician workload and efficiency in ambulatory settings.[6,7] This has enabled studies assessing the relationship between EHR-based workload measures and burnout; for example, increased inbox volume and after-hours work have been associated with increased risk for burnout among outpatient physicians.[8–12]

However, there are several gaps in the previous research on EHR-based clinical workload measures and burnout. First, reliance on vendor-derived workload measurements has limited previous research to ambulatory care settings, whereas the effect of inpatient workload has remained relatively unexplored. Second, previous studies have been cross-sectional in nature, with limited assessment of the temporal relationship between workload and burnout. Third, the temporal evolution of burnout itself has not been well-studied, especially over short time intervals, owing to the limitations of the most commonly used survey instrument;[13] as a result, little is known about the time course over which clinicians develop or recover from burnout.

In addition, the downstream clinical consequences of burnout are not well-understood. Studies have reported an association between burnout and self-reported medical error;[3,4,14,15] however, such self-reports are subject to recall bias. The relationship between burnout and objective measures for medical error is less clear. Decision rules in the EHR allow for the objective identification of errors, and several heuristic measures have been developed. One example is retract-and-reorder events,[16] a proxy for wrong-patient errors.

To address these gaps, we conducted a longitudinal study of burnout among a cohort of intern physicians. Trainees suffer from a higher rate of burnout compared to physicians in practice,[17] have little autonomy over their workload or schedules, and have to adjust their workflows on a monthly basis as they switch between clinical rotations. We used monthly variation in intern workload as a natural experiment to examine the contribution of specific types of workload measures to changes in burnout. Our primary hypothesis was that monthly workload contributes to burnout, and secondarily that burnout might contribute to an increased rate of wrong-patient errors (Fig. 1a).

We had the following research aims: (1) characterize the evolution of burnout at a monthly timescale, (2) measure the association between time-varying clinical workload and burnout, and (3) determine whether burnout is associated with an increased risk for wrong-patient errors.

METHODS

Participants and Study Design

Intern physicians in Internal Medicine, Pediatrics and Anesthesiology ($N = 104$) at the Washington University School of Medicine were invited to participate through presentations at educational events and follow-up emails. This study was approved by the institutional review board of Washington University (IRB# 202004260).

Enrollment occurred between September and November 2020, with data collection occurring through April 2021. Participants agreed to complete monthly surveys for 6 consecutive months, and provide access to their EHR-based audit logs and related activities. This was a prospective cohort study, with repeated measurement of burnout, EHR-based clinical workload, and wrong-patient orders in 4-week intervals over a 6-month period (Fig. 1b). This study is reported using STROBE guidelines.[18]

Surveys

Interns at the study site rotated between different clinical assignments every 4 weeks across inpatient, outpatient, and elective or consult services. Therefore, participants were sent burnout surveys via email at 4-week intervals, timed to coincide with the end of each rotation. The initial survey included questions about demographic characteristics in addition to burnout as measured using the Stanford Professional Fulfillment Index (PFI).[19] Subsequent surveys consisted solely of the PFI.

The PFI is a 16-item scale that measures burnout and professional fulfillment, and has been validated against the Maslach Burnout Inventory (MBI).[13] The PFI was chosen because it allows for measurement of burnout at high temporal resolution—over 2-week intervals—in comparison to the yearly interval of the MBI.

Participants were paid \$10 for their initial survey completion, and \$5 for each subsequent survey completion. The survey instrument is available in the Supplemental Materials.

EHR-Based Workload Measures

All activities performed on an EHR are recorded in audit log files in order to monitor access to protected patient health information as mandated by the Health Insurance Portability and Accountability Act. Time, patient, activity, and the user responsible for each data access event are recorded. We used raw audit logs for all analyses. We did not use vendor-derived measurements (i.e., Epic Signal) because they might be subject to change over time,[20] and were not available for inpatient workflows. Audit logs have previously been used to describe clinician work hours and workflow.[10,21,22] We extracted audit logs for the study participants from the study site's EHR data warehouse (Epic Systems, Verona, WI).

Based on previous research, we determined that the primary work responsibilities of intern physicians included review of patient data, note writing, order placement, and review of clinical inbox messages.[21] Therefore, we categorized each audit log action as relating to patient data review, notes, orders, or inbox (Supplemental Appendix 2), and computed the time spent on each action as the difference in time stamps between that action and the subsequent one. Based on prior literature,[21] we characterized durations >5 min to represent inactivity.

We computed the following prespecified measures to summarize an intern's EHR-based clinical workload: total time spent using the EHR; time spent using the EHR after-hours, measured as the time spent between 6 pm and 6 am;[23] patient load, measured as the number of patients seen per day; time spent on the clinical inbox; number of ordering sessions per patient per day; time spent writing notes per patient per day; and time spent on chart review, i.e., reviewing patient notes, flowsheets, or results, per patient per day (see Table S1 for a detailed description). Each measure was aggregated over the month preceding each survey completion (Fig. 1b).

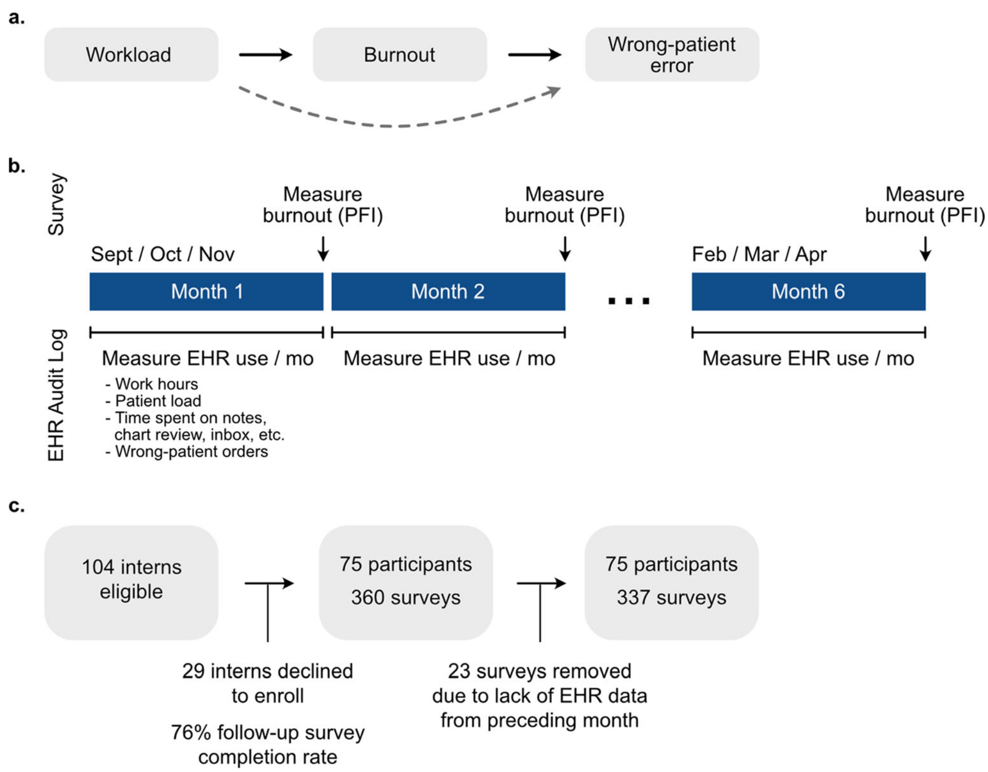

Figure 1 Overview of study design and data collection. a Conceptual framework for the study. b Illustration of study design. Participants completed one survey each month for 6 months to measure burnout. EHR use was collected in the background. For each survey, EHR use for the preceding month was summarized and used in a multivariable linear mixed-effects model to explain burnout score. c CONSORT diagram of study enrollment and data collection.

Wrong-Patient Orders

Wrong-patient orders were captured by measuring retract-and-reorder (RAR) events for the month preceding each survey completion. A RAR event is defined as any order—laboratory, medication, or imaging—that is placed on a patient, canceled within the first 10 min, and then re-ordered by the same clinician on another patient within the next 10 min.[16,24] RAR events have a 76.2% positive predictive value for being a wrong-patient order,[16] and have been recommended as a patient safety measure by the Office of the National Coordinator for Health IT and the National Quality Forum.[25]

Outcomes

The primary outcome was the 10-item burnout subscale score of the PFI.[19] PFI burnout scores range from 0 to 4, where scores ≥1.33 are typically used to dichotomize burnout to align with the MBI; however, an exact cut-off score for the PFI remains currently under study. Therefore, PFI burnout score was used as a continuous variable in regression models to increase statistical power, and to represent burnout as a continuous state; scores were approximately normally distributed in our sample.

The secondary outcome was the frequency and rate (as a ratio of total ordering sessions) of wrong-patient orders as measured by RAR events.

Statistical Analysis

Descriptive statistics were calculated as median and interquartile range (IQR) for continuous variables and frequencies and percentages for categorical variables. Collinearity for workload metrics was assessed using variance inflation factors (Table S2). A multivariable linear mixed-effects model was used to examine the relationship between EHR-based clinical workload measures and continuous burnout scores. Random intercepts were included to control for repeated measures within individuals, representing the per-individual average level of burnout. Fixed effects for specialty, gender, total inbox time, and after-hours EHR time were controlled for in the model based on previous literature.[1,8–10] The remainder of the EHR measures were included as additional fixed effects, and stepwise backwards elimination was used to identify variables that were significantly associated with burnout scores. Only EHR measures that were significant after backwards elimination were included in the final model. Effect estimates for the final model are presented as changes in magnitude of the EHR measure from the 25th percentile observed in the sample to the 75th percentile and associated 95% confidence intervals (CIs).

Interns were sometimes assigned to locations where Epic was not used for clinical care, and thus audit log data was not available. Months with insufficient audit log data were excluded by removing all months where fewer than 3000 actions were recorded (N = 23) (Fig. 1c). Several alternative cutoff points for minimum actions were evaluated and found not to meaningfully change the results.

A Poisson regression was used to assess the relationship between burnout and wrong-patient orders after adjusting for specialty and total number of ordering sessions in the associated month. In particular, the count of wrong-patient orders was the dependent variable, burnout score was the independent variable, and an offset representing the total number of ordering sessions was used such that model estimates reflected ratios for the overall rate of wrong-patient errors. Effect estimates are presented as rate ratios (RR) and 95%CIs.

Data processing and visualization was performed using Python 3.8.5 (Python Software Foundation, Wilmington, DE) and R 4.0.3 (R Foundation, Vienna, Austria). Statistical analysis was conducted in SAS 9.4 (SAS Institute, Cary, NC).

RESULTS

Cohort Characteristics

Seventy-five of 104 (72.1%) eligible interns enrolled and completed at least one survey. Participant demographics are shown in Table 1. The median number of surveys completed per participant was 6 (interquartile range (IQR), 4–6). Surveys were completed a median of 0.88 (IQR 0.11–3.21) days after initial receipt. We observed a 76.0% (285/375) subsequent survey completion rate across follow-up surveys.

Thirty-two of 75 (42.7%) participants met criteria for burnout at study enrollment (PFI score ≥1.33). Median burnout score across the study was 1.2 (IQR 0.7–1.7). Although median burnout score was relatively stable over time (Fig. 2a), individual burnout scores varied considerably month-to-month (Fig. 2b). Median absolute change in an individual's burnout score between consecutive months was 0.3 (IQR 0.1–0.6). Thirty of 69 (43.5%) participants who completed ≥2 surveys experienced ≥1 transition in burnout status; 20 of 64 (31.3%) participants who completed ≥3 surveys experienced ≥2 transitions in burnout status.

Table 1 Characteristics of the Study Cohort. Demographic Data and Average Monthly EHR Workload Metrics Collected from Study Participants. Count and Percent Presented for Categorical Variables, While Median and Interquartile Range (IQR) Presented for Continuous Variables

	n (%) for categorical/ median (IQR) for numeric
Specialty	
Medicine	35 (47%)
Pediatrics	23 (31%)
Anesthesiology	17 (23%)
Gender (= male)	34 (45%)
Married (= yes)	23 (31%)
Children (= yes)	4 (5%)
PFI burnout score	1.2 (0.7–1.7)
Avg total EHR time per month (h)	85.4 (54.5–123.0)
Avg after-hours EHR time per month (h)	9.9 (4.3–26.2)
Avg patient load per day	6.1 (4.9–7.1)
Avg inbox time per month (h)	0.8 (0.3–2.4)
Avg ordering sessions per patient per day	3.3 (2.6–4.1)
Avg note time per patient per day (h)	0.51 (0.37–0.72)
Avg review time per patient per day (h)	0.49 (0.39–0.59)

EHR-Based Workload Measures

Participants performed a median of 23,584 (IQR 14,607–33,873) audit log actions each month across 1,652 unique action types, with a total of 8,863,318 audit log actions analyzed. Participants cared for a median of 6.1 (IQR 4.9–7.1) patients per day and spent a median of 85.4 (IQR 54.5–123.0) hours using the EHR each month, with a median of 9.9 (IQR 4.4–26.2) hours per month spent after-hours. A median of 0.51 (IQR 0.37–0.72) hours and 0.49 (IQR 0.39–0.59) hours per patient per day were spent on notes and chart review, respectively.

Multivariable Model for Workload and Burnout

After accounting for repeated measures among individuals and controlling for specialty, gender, inbox time, and after-hours EHR time, we found that increased total EHR time, increased patient load, and increased chart review time in the preceding month were associated with higher burnout scores (Fig. 3, Table S3). For example, an increase of total EHR time from 54.5 h (25th percentile) to 123.0 h (75th percentile) per month was associated with a 0.121 (95%CI 0.016–0.226) point increase in burnout score; an increase in patient load from 4.9 (25th percentile) to 7.1 (75th percentile) patients per day was associated with a 0.130 (95%CI 0.053–0.207) point increase in burnout score; and an increase in chart review time from 0.39 (25th percentile) to 0.59 (75th percentile) hours per patient per day was associated with a 0.096 (95%CI 0.015–0.177) point increase in burnout score. A post hoc analysis controlling for temporal trends in burnout found similar results (Table S4). We did not find a statistically significant association between after-hours EHR time or inbox time and burnout.

Burnout and Wrong-Patient Orders

There were 35 wrong-patient orders during the study period. After adjusting for the role of specialty and for order volume, we did not find a statistically significant relationship between burnout scores and the rate of wrong-patient orders (rate ratio [RR] 1.20 per unit increase in burnout score, 95%CI 0.76–1.89, p=0.431).

DISCUSSION

In this longitudinal study of physician trainees, we characterized the evolution of burnout at monthly intervals and found it to be highly variable. Using EHR-derived measures for clinician workload that are applicable across both inpatient and ambulatory care settings, we showed that changes in burnout were associated with variations in clinical workload in the

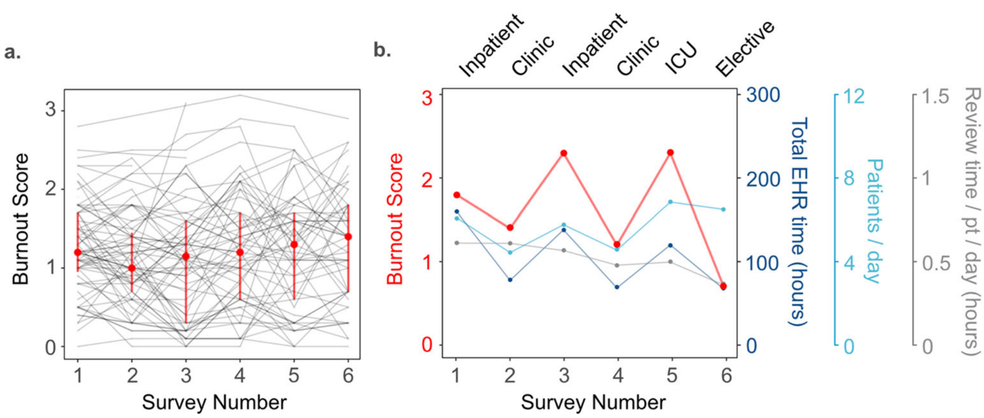

Figure 2 Burnout is highly variable over time. a Trajectories of burnout score over time for all participants in the study shown in gray. Median burnout score per survey shown as red dots, with bars representing interquartile range. b Example burnout trajectory and selected EHR workload measures observed for a participant over the course of the 6-month study. Burnout trajectory shown in red with axis on the left. Total EHR time per month shown in dark blue, patient load per day shown in light blue, and chart review time per patient per day shown in gray, with axes on the right. Monthly rotation schedule for this participant shown above the plot.

preceding month, specifically, total EHR usage time, patient load, and chart review time. Furthermore, we did not find a statistically significant association between burnout and errors using an empirically validated measure for wrong-patient orders. These findings have important methodological, pragmatic, and translational implications.

Prior studies of burnout have relied on measurements that occurred, at best, at 6-month to 1-year time intervals.[26–31] For example, burnout has been shown to be low among intern physicians at the beginning of intern year, high by the end of the year, and remain high throughout residency,[28–31] with few transitions between burnout states after initial onset of burnout.[28] Thus, burnout is often conceptualized as being relatively static over long time intervals; there is limited understanding about its time course, progression, or recovery. In contrast to prior work, we measured burnout at monthly time intervals, aligned it with associated EHR-based workload, and characterized the fluctuations in burnout over time (Fig. 2a, b). Our methodological approach demonstrated that clinicians can both develop and recover from burnout over short time intervals, illustrating the elastic nature of burnout.

Higher levels of EHR-based workload—measured by patient load, EHR usage time as a proxy for total work hours, or chart review time as a proxy for patient complexity or provider inefficiency—were associated with burnout (Fig. 3). Prior research has shown that persistent stressors, such as increased workload over long periods of time, can have cumulative effects on employee wellness.[32] Periods of high clinical workload can also minimize opportunities for recovery activities such as sleep, exercise, or other self-care practices,[33–35] thus reducing the propensity for recovery.[36] Our results emphasize the importance of workload management as a strategy for mitigating the effects of chronic burnout.

Taken together, our results have several practical implications for the design of wellness interventions. First, burnout mitigation is potentially best achieved by reductions in workload. Even if overall workload cannot be reduced, sustained elevation in burnout can be avoided by interleaving periods of

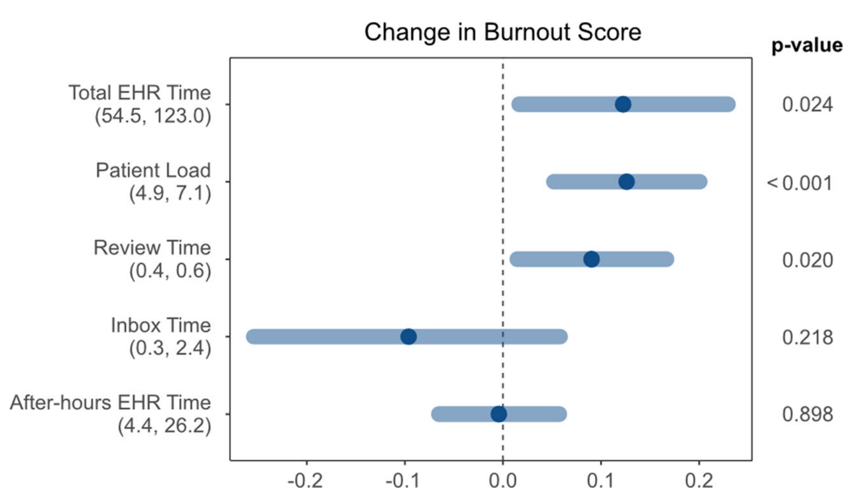

Figure 3 Multivariable model for burnout score as a function of monthly EHR-derived workload measures. A linear mixed-effects model was used to examine the relationship between EHR-derived workload and burnout score, controlling for repeated measures per participant and the role of specialty and gender. Shown is the estimated effect (dot) and 95%CI (shaded area) of a 25th to 75th percentile change (shown below each variable) in each EHR workload measure. Dotted line indicates zero effect.

relatively reduced workload. For trainees, this may mean alternating inpatient rotations with outpatient or elective blocks where possible. Alternatively, recent studies have showed that providing non-clinical time within weekly schedules or flexible time-off programs improved overall wellness among trainees.[37] Second, consideration should be given to interventions that improve provider efficiency, such as personalized EHR training,[38–40] or allocation of support staff including scribes and medical assistants.[41] Finally, as our results suggest that recovery from burnout can occur rapidly, evaluation of the efficacy of any wellness intervention could be assessed in as little as 1 month, allowing for more rapid testing of various interventions.

We did not find a statistically significant association between burnout and wrong-patient orders. Previous literature suggests that physicians who are burned out tend to self-report a higher rate of medical error.[19,42–45] In contrast, studies that used observed medical error did not find an association between burnout and error,[31,46–48] and our results are consistent with the finding that burned out physicians are actually not any more likely to commit errors than their non-burned out peers. However, the low wrong-patient order rate observed limited our power to detect an association between burnout and errors, and we may have missed a small but clinically important effect.

Limitations

This work has several limitations. By measuring workload using EHR audit logs, we were unable to capture non-EHR-associated work such as time spent caring for patients in person. Nonetheless, our measurements are consistent with previous reports of EHR usage and clinical workload that included direct observation,[21,49,50] and thus likely correlated with true workload. We defined "after-hours" as work occurring between 6pm and 6am,[23] which included both night-shift work as well as extended day-shift work; measuring true after-hours work was impractical due to variability in intern schedules. We occasionally had incomplete workload measurements due to participants being assigned to clinical locations for which EHR audit log data was not available. We excluded months with <3000 recorded EHR actions; however, this threshold is somewhat arbitrary. We performed a sensitivity analysis and found our results to be robust to changes in this threshold. Finally, burnout is highly personal and we were unable to capture the effect of interpersonal relationships, working environment, the emotional toll of patient care, or other subjective aspects of our participants' work experiences. We acknowledge that our model's estimated effect size for workload variation may not fully explain the median ±0.3-point change in burnout score between months we observed, likely for the above reasons.

This was a single-center study conducted among intern physicians whose responsibilities alternated between inpatient and outpatient care, and our results may not generalize to other physicians. Workload observed for interns in this study may not apply to trainees at other institutions. Interns may not be performing the job responsibilities they aspire to have in the future, which may prompt more negative responses to their current work. Although we found a statistically significant effect of workload on burnout score, a minimal clinically significant change on the PFI scale has not been determined. Our participation rate was high, but we did not have complete recruitment and completion of all surveys, which potentially could lead to response bias. Finally, although RAR events allow for objective measurement of error, these events capture only a small part of all the errors that may have occurred.

CONCLUSIONS

We found that burnout varied considerably over time and was associated with recent EHR-based clinical workload. These findings provide insight into the temporal evolution of burnout, and suggest that future interventions designed to improve physician wellness should focus on mitigating overall workload, or periods of sustained workload.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11606-022-07620-3.

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Declarations:

Conflict of Interest: *The authors declare that they do not have a conflict of interest.*

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