

A Model for Work Intensity in a Pediatric Training Program

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ABSTRACT

Background The Accreditation Council for Graduate Medical Education (ACGME) requires residency programs to monitor scheduling, work intensity, and work compression.

Objective We aimed to create a model for assessing intern work intensity by examining patient and clinical factors in our electronic health systems using multiple linear regression.

Methods We identified measurable factors that may contribute to resident work intensity within our electronic health systems. In the spring of 2021, we surveyed interns on pediatric hospital medicine rotations each weekday over 5 blocks to rank their daily work intensity on a scale from -100 (bored) to +100 (exasperated). We queried our electronic systems to identify patient care activities completed by study participants on days they were surveyed. We used multiple linear regression to identify factors that correlate with subjective scores of work intensity.

Results Nineteen unique interns provided 102 survey responses (28.3% response rate) during the study period. The mean work intensity score was 9.82 (SD=44.27). We identified 19 candidate variables for the regression model. The most significantly associated variables from our univariate regression model were text messages ($\beta=0.432$, $P<.0009$, $R^2=0.105$), orders entered ($\beta=0.207$, $P<.0002$, $R^2=0.128$), and consults ordered ($\beta=0.268$, $P=.022$, $R^2=0.053$). Stepwise regression produced a reduced model ($R^2=0.247$) including text messages ($\beta=0.379$, $P=.002$), patient transfers ($\beta=1.405$, $P=.15$), orders entered ($\beta=0.186$, $P<.001$), and national patients ($\beta=0.873$, $P=.035$).

Conclusions Our study demonstrates that data extracted from electronic systems can be used to estimate resident work intensity.

Introduction

Considering a growing body of research linking physician workload to fatigue and burnout,¹⁻³ the Accreditation Council for Graduate Medical Education (ACGME) updated guidance in 2017^{1,4} requiring programs to monitor “trainee work intensity.”⁴ Trainee work intensity is impacted directly and indirectly by various subjective, objective, patient, and clinical factors, making the concept difficult to define and challenging to assess.⁵⁻⁸ Existing data within electronic health records (EHRs), residency management systems, and other clinical information can be reexamined to understand physician behavior, and ideally to help plan for better resource allocation and utilization.⁷⁻¹⁰ This data can also be used to better identify areas for further instruction of residents, like task prioritization or gaps in clinical exposure.^{6,10-14} One study examining inpatient admissions demonstrated an increase in both patient complexity and the EHR data burden over a 15-year period, suggesting an increase in the workload for trainees caring for these patients.⁷ Another, looking

specifically at pediatric trainees, showed considerable workload variability between residents based on order entry and note documentation, but was unable to correlate these findings with subjective impressions of work intensity.⁶

This study looked more broadly at patient and clinical factors within the EHR and other electronic systems to identify factors associated with increased work intensity, as reported by pediatric interns.

Methods

This study occurred at an urban, quaternary care, free-standing children’s hospital. Pediatric interns were surveyed on weekdays over a 4-week hospital medicine rotation to minimize work pattern variability from December 16, 2020, to May 4, 2021. Surveys were distributed via an email link at the same time near the end of each day’s shift. Periodic email reminders from the study team were used to encourage participation. The survey asked trainees to rank their same day work intensity on a continuous scale from -100 (boredom) to +100 (exasperated) to highlight the full spectrum of potential work intensity. At the lowest level, there may be so little to do that the intern is bored. On the contrary, at the highest level the intern may be so overwhelmed that any

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Editor’s Note: The online version of this article contains the survey used in the study and further data.

TABLE 1

Measurable Variables of Workload Intensity

Data Source	Variable	Variable Type
Electronic health record	Geographical region–local	Patient
	Geographical region–regional	Patient
	Geographical region–national	Patient
	Geographical region–international	Patient
	Interpreter needed	Patient
	Language	Patient
	Pediatric Complex Chronic Conditions categories	Patient
	Pediatric Complex Chronic Conditions diagnoses	Patient
	Clinical events (notes, forms, handoffs)	Clinical
	Consult orders	Clinical
	Medication reconciliations (admit, transfer, discharge)	Clinical
	Orders entered	Clinical
	Patient admissions	Clinical
	Patient transfers (intra-hospital, sent, and received)	Clinical
	Patients discharged	Clinical
	Patients seen (any action)	Clinical
Residency management system	Hours worked	Clinical
Vendor analytics platform	Pages received	Clinical
	Text messages received	Clinical

additional task is exasperating. Interns who rated their intensity as >90 were sent a follow-up email encouraging them to utilize available support resources. Scores were bucketed into 5 groups to reduce nonresponse bias: $-2=-100$ to -61 ; $-1=-60$ to -21 ; $0=-20$ to 20 ; $1=21$ to 60 ; $2=61$ to 100 .

To identify contributing clinical factors, we queried our residency management system, vendor analytics platform, and EHR via our enterprise data warehouse for work hours, number of pages, and number of text messages received on work phones, and inpatient encounters where participants documented a note, form, order, or performed medication reconciliation (TABLE 1). We then gathered demographic data for those patients to identify which patient factors might contribute to work intensity, including Pediatric Complex Chronic Condition categories and diagnoses.¹⁵ Our study site serves as a referral center, so we included patient geographical region based on their home address (local=within the greater Boston area; regional=within one of the 5 New England states; national=within the United States but outside of New England; and international=outside of the United States). In total, there were 19 explanatory variables: 8 patient factors and 11 clinical factors (TABLE 1).

We used univariate followed by multivariate regression (with decision tree to account for interactions) to identify individual factors that correlate with subjective measures of work intensity. K-Nearest

Neighbors (KNN) cross-validation was used to determine the most statistically significant model. This study was deemed exempt from human subjects review by the Boston Children's Hospital Institutional Review Board.

Results

We surveyed 19 unique interns on 90 weekday shifts with a response rate of 28.3% (102 of 360). The average number of survey responses for any individual intern was 5.1 (SD=4.6). One intern rotated through pediatric hospital medicine twice during the study period and accounted for 27 of the total survey responses (26%), while 5 interns did not provide any survey responses. Work intensity scores ranged from -100 to 100 (mean=9.82, SD=44.27). Bucketed work intensity scores ranged from -2 to 2 (mean=0.2, SD=1.09). Three surveys prompted referral for support services. The online supplementary data FIGURE 1 shows the range of responses for each intern who participated.

Of the 19 explanatory variables studied, 5 were transformed from abnormal distributions. The variables most significantly associated with work intensity in the univariate analysis were text messages received, orders entered, and consults ordered (TABLE 2). Multivariate analysis with stepwise regression produced a Reduced Model ($R^2=0.247$, $F(4, 95)=7.78$, $P<.001$) containing the variables text

TABLE 2

Summary of Regression Models

Variable	Univariate Analysis			Multivariate Analysis (Reduced Model)		
	β	P Value	R ²	β	P Value	R ²
Clinical Factors						0.247
Clinical events ^a	0.053	.82	-0.010			
Consult orders	0.268	.022 ^b	0.043			
Hours worked	0.047	.67	-0.008			
Medication reconciliations	-0.060	.39	-0.002			
Orders entered ^a	0.207	<.001 ^b	0.120	0.186	<.001 ^b	
Pages received	-0.004	.78	-0.009			
Patient admissions	0.196	.43	-0.004			
Patient transfers	-1.212	.27	0.002	-1.405	.15	
Patients discharged	0.016	.79	-0.009			
Patients seen	0.051	.47	-0.005			
Text messages received ^a	0.432	<.001 ^b	0.096	0.379	.002 ^b	
Patient Factors						
Geographical region–international	0.104	.58	-0.007			
Geographical region–local	0.088	.20	0.007			
Geographical region–national	-0.745	.11	0.017	-0.873	.036 ^b	
Geographical region–regional	-0.082	.59	-0.007			
Interpreter needed	-0.023	.90	-0.010			
Language	-0.095	.53	-0.006			
Pediatric Complex Chronic Conditions Categories ^a	0.171	.53	-0.006			
Pediatric Complex Chronic Conditions Diagnoses ^a	0.121	.36	-0.002			

^a Transformed variable.^b Statistically significant.

messages received, patient transfers, orders entered, and national patients (TABLE 2). Our decision tree analysis combined the reduced model and a possible interaction between orders and text messages (online supplementary data FIGURE 1); however, KNN cross-validation ($k=10$) confirmed the original reduced model to be the most statistically significant and final model.

Discussion

In this study we were able to successfully identify variables from the EHR and other electronic sources that are significantly associated with intern perceptions of work intensity. Our survey suggests that interns on our hospital medicine rotation experienced the full spectrum of work intensity, though individual intern responses clustered around negative, neutral, or positive work intensity (online supplementary data FIGURE 2). Clinical factors including orders entered and text messages received were consistently associated with increased levels of work intensity. Clinical events (including notes written), work hours, and patients seen were not significantly associated with

the level of work intensity. Patient transfers to or from another hospital had a non-statistically significant negative association with work intensity. The only patient factor that was significantly associated with work intensity in the final model was out-of-area patients, which also had a negative coefficient. Though not entirely clear, it may be that patients referred from great distances within the United States sought care for a unique condition or had a care plan already in place. Other patient factors such as Complex Chronic Conditions, language spoken, and interpreter need did not reach statistical significance.

Our study supports evidence that the EHR can be used to measure trainee workload and that there is significant variation between trainees.^{6,9} Unlike Was et al, we were able to detect a statistically significant correlation between self-perceived work intensity and objective measures such as number of orders entered and number of text messages received.^{6,9} These data account for about 25% of the variability in subjective scores of work intensity, which is reasonable given the multitude of factors that may contribute to a trainee's experience. Models like this could provide a method for program

directors to passively monitor their trainees' workload, in addition to more invasive measures such as surveys and less specific measures like work hours.

Previous research in adults suggests that as patient complexity increased (rated using the Charlson Comorbidity Index), resident work intensity also increased⁷; however, we did not find an association between Pediatric Complex Chronic Conditions and work intensity. This could be because complex patients, while difficult to manage, also provide intellectual stimulation that provides meaning to one's work and tempers intensity. Work hours did not correlate, suggesting that it is the type of work that matters and not just the quantity, similar to findings in the nursing field.⁹ As our study focused on specific and measurable variables within our electronic systems, we are conscious that there may be other factors not studied that contribute meaningfully to work intensity. Importantly, these factors likely vary by clinical specialty and level of training, which may make it difficult to generalize across training programs. In addition, our study focused primarily on quantitative data in our electronic system, which might not capture the qualitative nature of what makes clinical care intense.

This study has limitations, most notably its narrow focus on pediatric interns on a hospital medicine rotation means the data may not be generalizable to other groups. The response rate was relatively low and, although a distribution of intensity scores was seen, there may be participation bias such that residents who experienced extremes of work intensity were more or less likely to fill out the survey. Similarly, because one resident represented about a quarter of the total survey responses, their perceived work intensity is overrepresented compared to others who filled out fewer or no surveys. Another limitation is that intensity scores were not measured on night shifts, weekends, and holidays, when interns cover more patients, and did not account for scheduling variability such as consecutive days worked. Lastly, while the quantity of orders and text messages were associated with work intensity, we did not examine the content of these factors, which may also play an important role in contributing to work intensity. For example, an order for parenteral nutrition could have a greater impact on subjective work intensity than an order for acetaminophen.

Conclusions

Our study demonstrates that data from electronic health records and other electronic sources can be used to model work intensity for pediatric interns.

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