

Beyond order-based nursing workload: A retrospective cohort study in intensive care units

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Abstract

Introduction: In order to be positioned to address the increasing strain of burnout and worsening nurse shortage, a better understanding of factors that contribute to nursing workload is required. This study aims to examine the difference between order-based and clinically perceived nursing workloads and to quantify factors that contribute to a higher clinically perceived workload.

Design: A retrospective cohort study was used on an observational dataset.

Methods: We combined patient flow, nurse staffing and assignment, and workload intensity data and used multivariate linear regression to analyze how various shift, patient, and nurse-level factors, beyond order-based workload, affect nurses' clinically perceived workload.

Results: Among 53% of our samples, the clinically perceived workload is higher than the order-based workload. Factors associated with a higher clinically perceived workload include weekend or night shifts, shifts with a higher census, patients within the first 24 h of admission, and male patients.

Conclusions: The order-based workload measures tended to underestimate nurses' clinically perceived workload. We identified and quantified factors that contribute to a higher clinically perceived workload, discussed the potential mechanisms as to how these factors affect the clinically perceived workload, and proposed targeted interventions to better manage nursing workload.

Clinical Relevance: By identifying factors associated with a high clinically perceived workload, the nurse manager can provide appropriate interventions to lighten nursing workload, which may further reduce the risk of nurse burnout and shortage.

KEYWORDS

intensive care unit, nurse burnout, nursing workload

INTRODUCTION

The unprecedented volume and severity of COVID-19 patients over the past 4 years have emphasized the critical and specialized contributions of nurses who provide continuous care in hospital inpatient care, especially the intensive care units (ICUs). These high patient volumes and acuity levels placed extraordinary stress on

the healthcare system overall and, specifically, on the nursing workforce, because of the prolonged and elevated nursing workload. Increased nursing workload has been associated with nurse burnout and patient safety issues (Griffiths et al., 2020), requiring focused strategies to support nursing staff and alleviate nursing workload. Recognizing specific approaches to decrease nursing workload requires a data-driven understanding of factors that contribute to the

workload, such as the availability of supporting resources and staffing choices on nights and weekends. Identifying the factors that are associated with increased nursing workload could also help with the development of improved nurse–patient assignment policies, aiming for more equitable workload allocation and fostering a fair and secure working environment (Sir et al., 2015).

Patients in the ICU exhibit high levels of severity and are at higher risk of experiencing deterioration. An accurate workload measure in the ICU can help inform safer nurse staffing and assignment decisions that may also reduce the risk of nurse burnout (Liu et al., 2018; Spence Laschinger & Leiter, 2006). However, accurately measuring nursing workload is challenging. Order-based measures, derived from the total number or weighted sum of physicians' orders for a patient, are widely used (Cullen et al., 1974; Miranda et al., 1996, 2003; Reis Miranda et al., 1997) but are inherently limited and may not be able to adequately incorporate some important aspects of nursing practice, and therefore may not be an accurate reflection of nursing workload (Hart & Staveland, 1988; Moghadam et al., 2021). Nursing workload consists of various factors such as the quantity of time devoted to activities related to patient care; the degree of nursing expertise needed to manage diverse patient conditions, states, and activities; the amount of direct patient care required for a given patient or patients; the level of physical efforts to perform patient care tasks; the complexity of care related to patient condition, states, and/or acuity; etc. (Alghamdi, 2016). There is a need for more comprehensive workload measures, potentially grounded in the informed professional judgment of the nurses encountering the workload.

Clinically perceived workload is a measure that was captured by nurses in real time in our study hospital. Analyses of this workload measure can provide insights into various factors that contribute to nursing workload and identify opportunities to support nurse staffing. In our staffing system (Kronos Workforce Scheduler for Healthcare), two types of workload intensity measures were recorded. In addition to an order-based workload measure, data-driven classification (DDC) intensity, which was automatically calculated by the system based on a list of patient care orders entered by prescribing providers, there was also a workload classification, professional judgment (PJ) intensity, determined by the charge nurse in coordination with the staff nurse toward the beginning of the shift, which we refer to as clinically perceived workload. The system was introduced at our study hospital with the intent to support charge nurses in making data-driven patient care assignment decisions in each shift to balance nursing workload (Sir et al., 2015).

MATERIALS AND METHODS

Design

A retrospective cohort study was used on a dataset collected by the Medical Intensive Care Unit (MICU) at the New York-Presbyterian/Columbia University Irving Medical Center. This study was approved by the Columbia University Institutional Review Board, study

#AAAR9189. The collected data were analyzed using R software version 4.0.2 program.

Data sources and study population

By utilizing linked data from three sources, a retrospective cohort study was conducted. Our data sources include (1) hospitalization and patient flow data for patients who were admitted to the MICU after January 1, 2018, and subsequently discharged from the hospital before December 31, 2018. These data contained patient demographic information and detailed time stamps on patient activities (e.g., ED admission time, ICU admission time, ICU discharge time, etc.). (2) Nurse staffing and nurse-to-patient assignment data at the nurse-shift level for all MICU nurse-shifts in 2018. For each nurse-shift, these data contained the nurse's scheduled start time, the nurse's actual punch-in and punch-out times, and which patient(s) were assigned to the nurse. (3) Kronos workload intensity data with two types of workload intensity measures—PJ intensity and DDC intensity for each patient-shift in 2018.

PJ intensity is a clinically perceived workload intensity measure based on nurses' professional judgment. The PJ intensity score represented the clinical or psychosocial circumstances(s) that most accurately characterized the patient's condition according to the expert judgment of the nurse who most recently cared for the patient. PJ intensity could take on four levels: low (1), medium/average (2), high (3), and extreme (4). The charge nurse, in coordination with the staff nurse, would classify patients as low, medium, high, or extreme according to their relative place on the continuum of patient intensity for that unit. Occasionally, patients had care needs beyond the normal resource requirements for the unit and would be classified as extreme (Shaha & Bush, 1996).

DDC intensity is a data-driven order-based workload intensity measure. It was automatically assigned by the Kronos system based on an accumulation of points that depended on the number of nursing orders placed for that patient in the focal shift. It could take on four values: low (1), medium/average (2), high (3), and extreme (4).

The PJ intensity together with the DDC intensity were used to inform staffing and nurse–patient assignment decisions at our study hospital.

Our study was at the patient-shift level. The Kronos workload intensity data provide us with the main outcome measure—the nurse's clinically perceived workload (PJ intensity). We used the hospitalization and patient flow data and the nurse staffing and nurse-to-patient assignment data to construct variables that may have affected nursing workload. We focused on patient-shifts from February to November 2018 (due to some missing information on patients who were admitted earlier than January 2018 or discharged after December 2018, we excluded data in January and December 2018). We excluded shifts and patient-shifts with missing variables (e.g., missing nurse-to-patient assignments, missing workload measures, etc.). See the online Appendix [Figure S1](#) for more details of our data cleaning and sample selection process. Our final cohort contained 9483 patient-shifts.

Factors for association with PJ intensity score

We constructed a comprehensive list of factors that could potentially be associated with PJ intensity. We classified the factors associated as the shift factors, patient factors at the patient record level and patient-shift level, and nurse factors.

Shift factors: For each shift, we controlled for day of the week; day versus night; and measures of the busyness of the shift at the unit level, including the total number of patient admissions in the shift, the total number of discharges in the shift, average patient census, average DDC intensity of all patients in the unit, and average patient-to-nurse ratio.

Patient factors at the patient record level: For each patient, we controlled for age; gender; comorbidity burden measured by the Elixhauser score (an aggregated comorbidity measure based on a weighted summation of comorbidity indicators) (Elixhauser et al., 1998); and whether the patient was admitted to MICU directly from the emergency department (ED).

Patient factors at the patient-shift level: At the patient-shift level, we controlled for the severity/resource intensity of the patient, including DDC intensity, average hourly Laboratory-Based Acute Physiology Score (LAPS) (Escobar et al., 2008), whether the shift was within 24 h of the patient's ICU admission, and whether the patient was discharged during the shift.

Nursing factors at the patient-shift level: At the patient-shift level, we examined several factors associated with the specific nurse assigned to the focal patient for that shift. These included the number of patients assigned to the focal nurse; a continuity of care flag, that is, whether the focal nurse had taken care of the focal patient before; and a measure of the focal nurse's historical workload, that is, the fraction of assignments with a DDC intensity larger than or equal to 3 that the focal nurse had over the last 2 weeks prior to the current shift.

Statistical analysis

Multivariable linear regression was used to determine the patient, shift, and nursing factors associated with the PJ intensity of a patient in a shift. The linear regression equation is

$$\text{PJ Intensity} = \mathbf{X}^T \boldsymbol{\beta} + \epsilon,$$

where \mathbf{X} is the vector containing various patient, shift, and nursing factors that could potentially be associated with PJ intensity and ϵ is the error term capturing the effect of unobserved factors. Statistical significance was defined if p -value was less than 0.05 ($p < 0.05$).

Limitations

Our study had several limitations. First, we focused on a single institution and MICU only. This allowed us to collect very detailed

patient, nurse, and shift-level information. However, the robustness of our results to other institutions and ICUs of other specialties should be investigated in future research. Second, this was a retrospective cohort study. Even though we attempted to account for a rich list of covariates that could influence the workload of nursing staff, there were likely important factors that were not fully captured in our model. Third, there were only four levels for PJ intensity, which may not be sufficiently granular to have captured the more nuanced workload differences accurately. Lastly, the workload measures—DDC intensity and PJ intensity—along with the Kronos Workforce Scheduler for Healthcare, were developed primarily for clinical practice. Our study hospital utilized these tools to support nurse staffing decisions rather than for research purposes. It remains an important future research direction to develop more comprehensive measures of nurses' perceived workload, such as through psychological surveys.

RESULTS AND DISCUSSION

Study population

There were 905 unique patients, 73 unique nurses and 9483 patient-shift-level observations in the final cohort (Table 1). Among all the patients, 49.9% were male and 75% were admitted directly from the emergency department (ED). The median age was 60. The median LOS in the MICU was 3.5 days, and the interquartile range (IQR) was 5 days. At the shift level, the average unit census was 22.3 for a unit with 24 beds in total. The average patient-to-nurse ratio was 1.57. For the nurses, the average number of shifts each worked in our study period was 112. On average, 41.5% of their assignments had a DDC intensity equal to or higher than 3.

A small majority (53%) of the patient-shifts had a PJ intensity that was higher than their DDC intensity (PJ > DDC). A very small minority (5%) of the patient-shifts had a PJ intensity that was lower than corresponding DDC intensity. For the remaining patient-shifts, PJ and DDC intensities were equal. Figure 1 shows the compositions of day versus night shifts, and the patient-shifts in the first 24 h versus non-first 24 h in the MICU, stratified by different values of DDC intensity and PJ intensity. The size of the pie chart is proportional to the log-scaled sample size, so larger circles indicate larger sample sizes. Night shift and first 24 h were both associated with PJ intensity being larger than DDC intensity.

Factors associated with a higher PJ intensity

The coefficient of DDC intensity in multivariate regression analysis (line 7 in Table 2) demonstrated that 1 unit increase in DDC intensity is associated with 0.265 increase in the PJ intensity on average, which agrees with the fact that the Pearson correlation coefficient of DDC intensity and PJ intensity is 0.389 (positive). However, even after

TABLE 1 Summary statistics of patient, shift, and nursing factors in the regression analysis (905 unique patients, 74 unique nurses, and 9483 patient-shifts in 2018).

Variable	Mean	Stdev	Median	IQR
Patient-level information				
Age	58.2	18.6	60	27
Elixhauser	26.4	16.2	26	22
Gender—male	49.9%			
Admitted from ED	75%			
Mortality	21.7%			
Length of stay in MICU (days)	5.7	6.2	3.5	5
LAPS in admission shift (excluding expired patients)	70.2	29.9	68.1	42.2
LAPS in discharge shift (excluding expired patients)	64.7	27.2	61.7	37.3
Shift-level information				
LAPS score of all patients	79.94	7.13	80.38	10.17
DDC score of all patients	2.18	0.16	2.20	0.21
Number of admissions	1.75	1.11	2.0	1
Number of discharges	1.75	1.14	2.0	2
Patients census	22.31	1.17	22.58	1.5
Patient-to-nurse ratio	1.57	0.12	1.58	0.16
Nurse-level information				
Number of shifts worked in study period	112	34	112	31
Fraction of assignment with DDC ≥ 3	0.415	0.070	0.417	0.096

Abbreviations: DDC, data-driven classification; ED, emergency department; LAPS, laboratory-based acute physiology score.

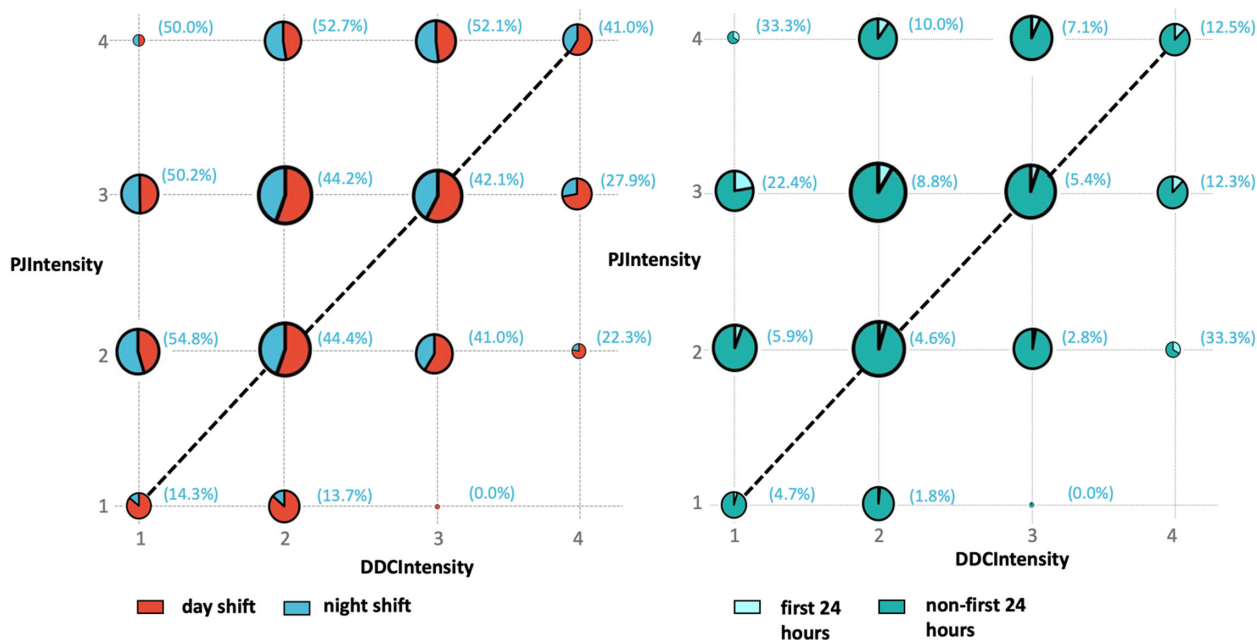


FIGURE 1 Distribution of day/shift night flag and first/non-first 24 h flag, stratified by the values of DDC intensity and PJ intensity (numbers in brackets denote the percentage of night shifts and first 24 h shifts at each level). DDC, data-driven classification.

controlling for DDC intensity, other shift, patient, and nursing factors were still correlated with PJ intensity, that is, their coefficients in the regression analysis are still significantly different from 0.

Shift-level characteristics: Night shifts and weekend shifts were associated with a higher PJ intensity. Shifts with a higher number of

admissions as well as shifts with a higher census were associated with a higher PJ intensity.

Patient-level characteristics: Younger patients, male-gendered patients (compared to female patients), patients admitted to the MICU within the first 24 h (compared to those who have already

TABLE 2 Multivariate linear regression results where we regress PJ intensity on various shift, patient, and nursing factors.

Variable	Estimation of β -coefficients	95% CI of β -coefficients
Night shift flag	0.074*** (0.012)	[0.050, 0.098]
Weekend shift flag	0.052*** (0.013)	[0.027, 0.077]
Age	-0.003*** (0.0003)	[-0.004, -0.002]
Gender—male	0.067*** (0.011)	[0.045, 0.089]
Admitted from ED	-0.079*** (0.012)	[-0.103, -0.055]
DDC intensity	0.265*** (0.011)	[0.243, 0.287]
Discharge flag	-0.178*** (0.023)	[-0.223, -0.133]
First 24 h flag	0.198*** (0.023)	[0.153, 0.243]
Average hourly LAPS score	0.0008*** (0.0002)	[0.0002, 0.0012]
Total admissions in shift	0.011* (0.005)	[0.001, 0.021]
Patient census in shift	0.014* (0.005)	[0.004, 0.023]
Number of agency nurses on shift	0.043*** (0.012)	[0.019, 0.067]
Number of patients assigned to the focal nurse	-0.410*** (0.014)	[-0.437, -0.383]
Fraction of DDC ≥ 3 in past 2 weeks	0.074*** (0.027)	[0.021, 0.127]

Note: Only significant variables are presented here and the full table is provided in the online Appendix (Table S2). In the “estimation of β coefficients” column, *0.01 < p -value < 0.05, **0.001 < p -value < 0.01, *** p -value < 0.001, the number in parenthesis is the corresponding standard error. Number of observations: 9483.

Abbreviations: DDC, data-driven classification; ED, emergency department; LAPS, laboratory-based acute physiology score.

been in the MICU for more than the first 24-h window), and patients with a higher average hourly LAPS score were associated with a higher PJ intensity. Patients admitted from the ED (compared to those admitted from other inpatient units) or who were being discharged in the focal shift were associated with a lower PJ intensity.

Nursing-shift-level characteristics: Nurses who had a heavier historical workload (measured by fraction of shift with DDC intensity equal to or larger than 3 in the past 2 weeks) were associated with a higher PJ intensity.

DISCUSSION

In this study, we analyzed ICU nursing workload. We compared an order-based workload (DDC intensity) that was automatically calculated based on a list of physician orders to a nurse’s clinically perceived workload (PJ intensity) that was entered by the charge nurse in coordination with the staff nurse based on their informed professional judgment. Among the 9483 patient-shifts, 42% of them had equal PJ intensity and DDC intensity, and 53% of them had a PJ intensity higher than the DDC intensity, indicating that order-based workload measures tended to underestimate clinically perceived nursing workload. This observation is consistent with prior studies of order-based workload measures in the literature (Cullen et al., 1974; Hart & Staveland, 1988; Miranda et al., 1996, 2003; Moghadam et al., 2021; Reis Miranda et al., 1997). However, to the best of our knowledge, our work is the first to investigate the differences between PJ intensity and DDC intensity. We further studied how various factors affected PJ intensity. Previous studies have shown that factors such as shift type (day vs. night), patient gender, admission sources

(ED vs. general wards), and case complexity were associated with nursing workload (Hart & Staveland, 1988; Moghadam et al., 2021). However, very few studies in the existing literature have examined as comprehensive a list of shift, patient, and nurse-level factors as our work. The multivariable regression analysis helps us more accurately single out the association of each of the factors.

Based on our analysis, timing of the shifts, specifically nights and weekends, was associated with a higher PJ intensity. Even though in the ICU setting, the hospital maintains similar nurse staffing levels (i.e., nurse-to-patient ratio) across different shifts, night and weekend shifts are often associated with lower levels of multidisciplinary staff availability (fewer physicians and supporting staff). Since care needs are intense in the ICU, the resource scarcity effect may play a major role in clinically perceived workload. Also, shifts that had more admissions or higher census—that is, shifts that were busier at the unit level—were associated with a higher PJ intensity. This may similarly be due to the resource scarcity effect. Since a lot of resources (e.g., physicians, supporting staff, X-ray machines, etc.) were shared, when the unit was busy, the nurses’ work may have been affected by the shortage of these shared resources. For example, diagnostic tools can become overwhelmed due to high demand. This might lead to delays in obtaining results and further impede the ability of nurses to make progress in patient care. A shortage of supporting staff such as technicians or even food service means that nurses have to fill these roles, diverting their time from direct patient care. Alleviating the pressure from resource scarcity by scheduling more supporting staff (such as technicians and patient care assistants), increasing capacity of the bottleneck resources, or increasing other unit-level supports are potential interventions that could be effective at reducing clinically perceived workload strain.

At the patient level, younger patients, male patients, the first 24 h of admission to the MICU, or higher LAPS scores were associated with a higher PJ intensity. Some of the patient-level factors (e.g., first 24 h and higher LAPS score) were associated with a higher acuity level, and their positive associations with PJ intensity after controlling for the DDC intensity indicated that order-based workload measure may not accurately capture all acuity-related clinical needs. While there are always activities that are autonomous aspects of nursing practice and are not reflected by physician's orders, the first 24 h of admission to the MICU may be a particularly intense period for autonomous nursing practice, there are typically several important tasks/considerations that are not fully reflected by orders, such as the work to acclimate the patient and family to the ICU environment, in-depth patient assessments and histories, and establishing nursing care plans. For the LAPS score, we note that expired patients tend to have higher LAPS scores (see [Table 1](#)). The occurrence of a patient's death can significantly increase the nurses' stress levels and perceived workload. This is due, in part, to the additional responsibilities they must undertake, such as engaging with the deceased patient's family and handling additional documentation. The finding that lower age was associated with higher clinically perceived workload is interesting since the risk of morbidity and mortality is usually associated with higher age. Nurses may sense a greater burden and anxiety over taking care of the younger critically ill patients. This association could also be attributed to different medical conditions or diagnoses that prompt the admission of younger patients to the ICU, which can be more critical compared to those of order patients. Being able to accurately identify these factors can help guide nurse staffing decisions, including staffing more nurses when necessary and balancing the shift-to-shift patient care needs and nursing workload.

Some nurse-level factors were shown to be associated with clinically perceived workload. For example, a greater historical workload was linked to an increased clinically perceived workload. This suggests we need to properly balance the nursing workload over time. In addition, there was an inverse relationship between the number of patients assigned and the perceived workload. This is likely due to omitted variable bias since our model may not capture some patient severity and nurse competency information that can affect both nurse-patient assignment and clinically perceived workload. For example, it is probable that patients with less acute conditions are more likely to be collectively assigned to a single nurse. Consequently, the number of patients assigned to a nurse may implicitly convey information about the patients' severity levels.

In related work utilizing the same dataset, the causal relationship between historical workload and the difference between clinically perceived workload and order-based workload was further explored (Chan et al., 2023). The study also suggested policies for matching nurses to patients to temporally balance the nursing workloads. However, in contrast to this manuscript, it did not examine additional factors beyond historical workload that contribute to the clinically perceived workload. This work found factors in a number of

different categories that are associated with the clinically perceived workload.

More than ever, staffing shortages and burnout among health-care workers are at an all-time high (Shah et al., 2021). Order-based workload measures can help inform staffing decisions but are an incomplete reflection of nursing practice and therefore the true nursing workload. By examining a comprehensive list of shift-, patient-, and nurse-level factors, we have found many important factors associated with a higher clinically perceived workload. We can classify these factors into two categories: potentially modifiable factors and less modifiable factors. Potentially modifiable factors include night or weekend shifts, busier units with a higher number of admissions or a higher census. As discussed before, the higher clinically perceived workload during these shifts may have been due to resource/staffing scarcity (fewer physicians and supporting staff). For these factors, we could add more supportive personnel (e.g., technicians and patient care assistants) to lighten the clinically perceived workload during such shifts. Less modifiable factors include various patient-level characteristics. When dealing with high patient acuity and care needs, it is essential to appropriately elevate staffing levels and carefully balance the nursing workload.

CONCLUSIONS

To better manage nursing workload and improve nurse job satisfaction and patient safety, accurately quantifying nursing workload and understanding the contributing factors are critical. Although order-based workload measures are commonly used, they may underestimate the nurse's clinically perceived workload. Weekend shifts, night shifts, and shifts with a higher census are associated with a higher clinically perceived workload. These are likely to be associated with a lack of supporting resources. Alleviating the pressure from resource scarcity by scheduling more supporting staff could help reduce the clinically perceived workload. Patients within the first 24 h of admission, patients with a higher LAPS score, young patients, and male patients are also associated with a higher clinically perceived workload. This requires properly adjusting the nurse staffing level and the patient-to-nurse assignment when dealing with high patient acuity and care needs.

CLINICAL RESOURCES

American Nurses Association—Nurse Staffing Guideline, <https://www.nursingworld.org/practice-policy/nurse-staffing/>.

UKG for Healthcare Clinical Scheduling Extensions, <https://www.ukg.com/resources/product-info/ukg-healthcare-solution-guide>.

American Association of Critical-Care Nurses—Resources for Staffing in Acute & Critical Care, <https://www.aacn.org/clinical-resources/staffing>.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

Our research data were collected by the Medical Intensive Care Unit (MICU) at the NewYork-Presbyterian/Columbia University Irving Medical Center. This study was approved by the Columbia University Institutional Review Board, study #AAAR9189. However, the data are not publicly available due to patient privacy considerations.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Appendix S1:

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