uncertainty regarding how the ventilator algorithm processes the EAdi signal ("black box"). In addition, artifacts may look different when originating from cardiac or catheter movements (mechanical artifact) or when being secondary to inefficient filtering of the QRS complex (electrical artifact). This requires specific analysis of the raw diaphragm electromyography signal, and indeed, complex mathematical techniques might offer a solution. As the diaphragm electromyography is not available to the clinician to test this approach, we reason that using a threshold $>2\ \mu V$ as proposed by Aquino-Esperanza and colleagues is an appropriate practical solution for automatic detecting of ineffective efforts in large datasets. However, one should keep in mind that artifacts of larger amplitudes can be present and that careful consideration of the EAdi catheter position and signal quality is required when using EAdi for clinical decision-making and research. ■

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Network Analysis Subtleties in ICU Structures and Outcomes

To the Editor:

We were extraordinarily pleased to read "The Structure of Critical Care Nursing Teams and Patient Outcomes: A Network Analysis" conducted by Dr. Costa and colleagues (1). This is a timely study using methodologic approaches to measuring structure in complex healthcare systems, such as critical care teams. In this letter, we feel there are additional approaches Dr. Costa's team can consider, which we believe will improve the quality of the following network analysis in critical care.

The excellent way Dr. Costa and colleagues created connections among nurses has an unfortunate potential risk of building a high-density network, which may lack structural information, such as k-core and betweenness (2, 3). This Michigan team defined a connection (tie) between two nurses as they provided direct care for the same patient during the patient's ICU stay. In this way, nurses caring for one patient within a period (the patient's ICU stay) will form a complete subnetwork, within which all nurses are interconnected. The complete subnetwork has less structure information. Such a phenomenon becomes even worse (i.e., almost all nurses are interconnected in the nurse network) when *1*) the patient's ICU stays are prolonged (e.g., over 30 d) and *2*) each nurse cares for a majority of patients in the ICU. As a consequence, most nurses will have the same values of k-core and betweenness (2), respectively. The downside here is disabling the exciting opportunity of investigating associations between network structure and mortality risk.

Understanding the evidence to validate that nurses are randomly assigned to a patient, regardless of their mortality risk, would augment this fine work. Currently, it is hard to determine if the low mortality risk is because of core and high-betweenness nurses or the strategies used to assign nurses to patients. If the majority of nurses are assigned to care for a higher percentage of low-mortality-risk patients than that of high-mortality-risk patients, then they will have more connections in the nurse network, and they have the potential to be core and high betweenness. Generally speaking, there are a larger number of low-mortality-risk patients than high-mortality-risk patients in the neurosurgical and surgical ICUs, so nurses caring for a higher percentage of low-mortality-risk patients have more connections. Therefore, the finding would be that nurses caring for patients with a higher percentage of low mortality risk have more connections in the network, so they are core and high betweenness.

To let researchers understand such a complicated situation deeply, we provide an example. Assume we have a scenario in which 50 nurses from group A and 50 nurses from group B cared for both high-mortality-risk and low-mortality-risk patients. Nurses in group A cared for 90% of patients with low mortality risk and 70% of patients with high mortality risk. Nurses in group B cared for 70% of patients with low mortality risk and 90% of patients with high mortality risk. In this hypothetical scenario, a low-mortality-risk patient was cared for by more nurses in group A than those in group B. Assuming there were 920 patients, 900 of them were low mortality risk, and 20 were high mortality risk. Nurses in group A would care for 810 patients with low mortality risk and 14 patients with high mortality risk, whereas nurses in group B would care for 630 patients with low risk and 18 patients with high risk. Based on the way Dr. Costa and colleagues built the nurse network, nurses in group A had more dense connections, and thus they are potentially core and high betweenness. An explanation of the finding would be that because group A nurses cared for more patients with low mortality risk, they were core and high betweenness. In short, if Dr. Costa and colleagues can provide the percentages of low- and high-mortality-risk patients cared for by high core and betweenness nurses, then it will improve the quality of this already high-value paper.

Dr. Costa and colleagues used the number of high-betweenness or core nurses involved in individual patient care rather than the

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ratio of those nurses in their finding, which we think provides some but limited evidence on effective staffing interventions. For instance, beyond being cared for by more high-betweenness nurses, a patient with low mortality risk can also be cared for by more low-betweenness nurses. Moving forward, we believe that a study focusing on the percentages (percent of core and high-betweenness nurses of all nurses caring for a patient), instead of the raw numbers, can supply more comprehensive suggestions to ICU staffing. ■

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Reply to Chen *et al.*

From the Authors:

Thank you to Dr. Chen and colleagues for their thoughtful letter in response to our recent paper "The Structure of Critical Care Nursing Teams and Patient Outcomes: A Network Analysis" (1). We conducted an exploratory, hypothesis-generating study using network analysis methods to more deeply understand and examine ICU nurse staffing. We very much appreciate Dr. Chen and colleagues' helpful comments to further advance the field of network science in health care.

We acknowledge the potential limitations of defining a connection between nurses if they provided direct care for the same patient during the patient's ICU stay. Defining a connection among clinicians as to whether they shared the same patient is the most commonly used approach in healthcare network analyses (2–5). Nonetheless, we agree that defining connections this way may be problematic when patients have prolonged ICU stays (i.e., 30 d or more). However, in our sample, the mean length of stay was 4.7 days (SD, 6.8), indicating that the majority of our patient sample had ICU stays of 11 days or less, and that prolonged ICU stays are less of a concern in our sample. In other studies in which patients have prolonged ICU stays, considering alternative definitions of a connection between healthcare clinicians, such as whether a nurse handed off a patient to another nurse, might be a possible way to measure connections among clinicians. Additionally, in our study, an average patient was cared for by only seven different nurses, further ameliorating the concern that our measure may not be sufficiently discriminative. Our sociogram also demonstrates that there is enough variability in the coreness and betweenness measures to identify significant associations with outcomes of interest.

The authors rightfully point out the possibility of a selection bias from nonrandom assignment of nurses to patients in our work. This bias is a limitation in all cross-sectional analyses of healthcare variables and patient outcomes. However, among all the selection bias present in healthcare studies, nurse-to-patient assignment bias has been least likely to occur. Previous studies by our team and others show that nurse assignments are based on staffing availability, patient case-mix, and other unit-level factors (6, 7) and are near random at the patient level (8). In addition, in studies by our team, when nurse assignments were nonrandom, better-prepared, qualified nurses tended to be assigned to sicker patients (8)—a negative bias that works to weaken the results of our findings. However, we agree that unobserved selection could be confounding our findings, particularly considering the exploratory nature of our study; we acknowledged unobserved selection bias in our limitations section (1). In addition, we are unable to adjust or account for patient acuity measures, such as the Acute Physiology and Chronic Health Evaluation score (9), and therefore we are unfortunately unable to examine mortality risk and nurse network positions, as suggested by Chen and colleagues.

Lastly, we favored modeling the exposure variable as the number of core and high-betweenness nurses in a patient's care team instead of a percentage as suggested by Chen and colleagues. We chose to measure the number of core and high-betweenness nurses because a percentage measure is calculated as a ratio of two variables (percentage core nurses = number of core nurses over the total number of nurses); both of these variables are stochastic (or random) and both are collinear with ICU length of stay. Including a stochastic variable nonlinearly (e.g., as a denominator of another stochastic variable) could bias the model.

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