Managed Critical Care: Impact of Remote Decision-Making on Patient Outcomes

Running head: Analysis of Tele-ICU Decision-Making Authority

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Article Summary: This work serves as a step toward better understanding the implications of remote, critical care intervention by evaluating levels of tele-ICU decision-making authority.

Clinical Relevance Statement

- Tele-ICU does not negatively impact patient outcomes or care processes.
- This work serves as a step toward better understanding the implications of remote, critical care intervention.
- Our results suggest that use of tele-ICU should be analyzed from a systems perspective to better understand the impact of remote intervention on critical care workflow.
- Practitioners should achieve collaborative communication between the bedside and remote ICU teams in combination with focusing on individual patient outcomes.

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Abstract

Objectives: Tele-ICU has become increasingly common as an extension of bedside care for critically ill patients. The objective of this work was to illustrate the degree of tele-ICU involvement in critical care processes and evaluate the impact of tele-ICU decision-making authority.

Study Design: Previous studies examining tele-ICU impact on patient outcomes do not sufficiently account for the extent of decision-making authority between remote and bedside providers. In this study, we examine patient outcomes with respect to different levels of remote intervention.

Methods: Analysis and summary statistics were generated to characterize demographics and patient outcomes across different levels of tele-ICU intervention for 82,049 critically ill patients. Multivariate logistic regression was used to evaluate odds of mortality, readmission, and likelihood of patients being assigned to a particular remote intervention category.

Results: Physician type influenced the level of remote intervention (aOR=2.42). The level of tele-ICU intervention was a significant factor for patient mortality (aOR=1.25). Sex (aOR=1.05), illness severity (aOR=1.01), and tele-ICU intervention level (aOR=1013) increased odds of ICU readmission while length of stay (aOR=0.93) and physician type (aOR=0.79) decreased readmission odds.

Conclusions: This study suggests higher levels of tele-ICU intervention do not negatively impact patient outcomes. Our results are a step toward understanding tele-ICU impact on patient outcomes by accounting for extent of decision-making authority and suggest that level of remote intervention may reflect patient severity. Further research

using more granular data is needed to better understand assignment of intervention category and how variable levels of authority impact clinical decision-making in tele-ICU settings.

Keywords: telemedicine; telecare; teleconsulting; critical care; medical informatics; intensive care units, decision-making, managed care, tele-intensivist managed care

1. Background and Significance

Critical care provided via telemedicine in the intensive care unit (ICU), or tele-ICU, is increasingly common to extend the reach of intensivists across geographically distinct ICUs and rural critical access hospitals. Studies show varying results of tele-ICU on patient-centered outcomes such as mortality and length-of-stay (LOS)[1]. Previous studies demonstrated decreased mortality and length-of-stay, increased adherence to best practices, and fewer preventable complications[2,3,4]; while others found minimal benefit except when adjusting for severity of illness[5,6,7]. Amongst those studies analyzing outcomes before and after tele-ICU implementation, the level of involvement by the tele-ICU ranges widely from consultation only to full decision-making authority. Thus, direct before-and-after analyses are difficult as the impact on patient outcomes varies across decision-making authority level[8,9,10].

Teamwork, communication, trust, and level of engagement are all proposed components for tele-ICU success, but are not sufficiently supported by evidence[11,12]. A major issue in previous analyses of tele-intensivist managed care is the assumption that tele-ICU adoption directly impacts patient outcomes. Based on Donabedian's model of structure-process-outcome[13], tele-ICU uptake changes the care system as it redefines the technological context in which care providers are embedded. Consequently, it also changes the process of how care providers conduct their tasks individually or collaboratively to deliver care, which could ultimately influence patient outcomes. Previous analyses of tele-ICU effect on patient outcomes were built on a simplified notion that the tele-ICU structure would directly impact outcomes while overlooking the role and impact of care process. Therefore, a complete evaluation of tele-ICU impact on patient outcomes should consider factors from both structure level (e.g., before and after tele-ICU uptake) and process level (e.g., different levels of decision-making authority) to account for the varied interpretations of tele-ICU impact.

2. Objectives

To facilitate effective collaboration between onsite and tele-intensivists, the tele-ICU practice requires specification of decision-making authority. For example, the onsite physicians, either consulting or attending, can assign an *intervention category* to each patient to designate the level of decision-making involvement the remote staff is afforded for each patient. While this is not currently done at every institution, there is a need to examine the effects of tele-ICU decision-making to better understand the impact of tele-intensivist managed care on patient outcomes. Our study aims to explore the upstream process changes from tele-ICU that affect downstream patient outcomes by leveraging data from *intervention category* assignments and examine its association with patient outcomes.

3. Methods

3.1. Data Source

Data were extracted from a publicly available tele-ICU database – the Philips eICU Collaborative Research Database. The database contains structured data from adult (≥ 18 years) ICU patients from over 200 hospitals across the United States during 2014 and 2015 and includes demographics, diagnosis, treatments, vital signs, medications, lab values, nursing and respiratory therapy notes, and patient outcomes among others. Hospitals contributing to the dataset are from both academic and nonacademic settings and vary in size up to 500 beds. All major ICU types are included (e.g., medical, surgical, cardiothoracic, neurologic), and data contributions from each hospital depend on site-specific policies, procedures, and interfaces. Further details on data availability, quality, and patient characteristics are available in published descriptive studies[14,15]. Importantly, this data set also contains quantitative measures of intervention or decision-making authority for the remote team as designated by bedside physicians for individual patients.

3.2. Inclusion Criteria

All adult patients with at least one assigned intervention category record were included in analysis. Intervention categories are used to define the amount of oversight or authority given to tele-ICU clinicians by the bedside clinician for each patient. Our data include three designations: 1) emergency only (*category 1*), 2) emergency and best practices (*category 2*), and 3) full intervention authority (*category 3*). Best practices may be institution-determined or related to illness-specific, documented medical best practices[16,17], and emergency and full intervention authority may be interpreted differently across institutions.

In addition, implementation of these categories may vary. A patient that repeatedly requires intervention due to physiological decompensation may be assigned a higher decision-making authority, allowing the remote team to address the needs of the patient without consulting the bedside physician first (*category 3*). Whereas that same patient at another hospital may be assigned a lower decision-making authority (*category 1*), where the tele-ICU must consult with the bedside team unless an emergency occurs (e.g., cardiac arrest).

Patients without any intervention category records and those missing data for the following variables were excluded: Acute Physiology and Chronic Health Evaluation IVa (APACHE) severity score, ICU and hospital mortality, and length-of-stay. Some patients had multiple intervention category records for a single stay. Some of which remained in the same category and some changed categories during their stay. We included three cohorts for analysis corresponding to patients which remained in categories 1-3 consistently during their ICU stay. A fourth potential cohort for patients with more than one category during their ICU stay was excluded. This mixed group includes patients which moved to a higher or lower category one or more times during a single stay and warrants in-depth analysis in a subsequent study. This study was reviewed and approved by the University of Arizona institutional review board.

3.3. Statistical Analysis

We developed three multivariable logistic regression models to evaluate features within each cohort and their association to outcomes of mortality, levels of remote intervention, and ICU readmission, respectively. The first model evaluated demographics (i.e., age and gender), ICU and hospital lengths of stay, ICU readmission, and intervention category relative to hospital mortality as a binary, one-vs-one model. The second model evaluated input features relative to the assigned remote intervention category as a binary, one-vs-any model[18]. Input features included age, gender, severity score, ICU readmission, and either managing or consulting physician type at the bedside. The third model used readmission as a binary dependent variable in one-vs-one model.

Intervention category in all models was treated as a binary factor to compare the impact of remote intervention on patient outcomes. Emergency and best practices intervention (*category 2*) and full intervention and interaction (*category 3*) were combined into a single *intervention* group to selectively evaluate whether the voluntary decisions made by the remote team were the influential factors to patient outcomes. This single group was compared against category 1 (*emergency intervention only*) as a binary independent variable. Readmissions in the mortality and remote intervention category models were represented as numerical number of ICU visits. In the readmission model, however, a binary readmission factor indicating, simply, first admissions or readmissions was used (one-vs-one).

Statistical significance and adjusted odds ratios (aOR) are reported for all models. Gender, intervention category, and managing or consulting physician were categorical variables while age, severity score, lengths-of-stay, and number of ICU visits were continuous variables. While some statistical tests are appropriate for smaller sample sizes, they do not allow for adequate evaluation of sample sizes above 10,000[19,20]. Our approach allows for interpretability of individual features and sufficiently characterizes the decision-making factors in the large patient population well in excess of 10,000 patients. Coefficients comparing characteristics across subgroups illustrate the change in log-odds ratio for binary outcomes or the change in log-odds ratio with one unit change of continuous independent variables.

Variables in all three models were selected based on potential impact they may have over the primary predictor variable of interest. For example, the intervention category assigned to a patient by a physician might be influenced by the severity score at the time of assignment but not by mortality as the outcome of mortality occurs after the intervention category assignment. Data preprocessing and analyses were performed using Python Language Reference version 2.7.14 (Python Software foundation, Delaware, USA) and R version 3.4.3 (R Foundation for Statistical Computing, Vienna, Austria).

4. Results

4.1. Summary Statistics

Of the 139,367 patients in the database, a total of 82,049 patients met initial inclusion criteria for analysis, i.e., patients had at least one intervention category record (online supplement Figure 1). The average number of intervention category records per patient was 2.86. Most patients (85.2%) remained in a single category through the entirety of their ICU stay (Cohorts 1-3) (Table 1), and 12,127 patients (14.8%) had records in multiple categories and were excluded. Readmissions accounted for 12.5% on average across all categories. Minimal demographic differences were seen between cohorts. Interestingly, the readmission rate was highest for patients in cohort 3 (full intervention and interaction).

The distribution of primary ICU admission diagnoses across all four patient groups was representative of the sample population with sepsis, heart failure, myocardial infarction, and cerebrovascular stroke among the most common admission diagnoses accounting for >21% of admissions in all four categories (online supplement Figure 2).

4.2. Logistic Regression Results

In the regression model with mortality as the outcome of interest, all features other than *gender* were statistically significant (Table 2). There are increased adjusted odds of mortality for higher APACHE score (aOR=1.04, 95% CI: 1.04-1.05), older age (aOR=1.01, 95% CI: 1.01-1.02), longer ICU LOS (aOR=1.07, 95% CI: 1.06-1.07), and readmission to the ICU with (aOR=1.40, 95% CI: 1.34-1.47). Higher intervention category level (aOR=1.25, 95% CI: 1.17-1.33) also resulted in increased odds of mortality suggesting that *category 3* is used for the sickest of patients which tend to have higher mortality rates.

In evaluating features related to the level of remote intervention (Table 3), we found that older patients were generally assigned a lower intervention category (aOR=0.99, 95% CI 0.99-0.99). Sex (female) (aOR=1.13, 95% CI: 1.09-1.16), increased severity (aOR=1.01, 95% CI: 1.01-1.01), and ICU readmissions (aOR=1.05, 95% CI 1.02-1.08) slightly increased adjusted odds of a patient being assigned to *category 2 or 3* rather than *category 1 – emergency intervention only*. Interestingly, the managing physician type (managing or consulting) was also influential with adjusted odds ratio of 2.42 (95% CI: 2.32-2.52). If assigned by a consulting physician, the odds were greater of an intervention *category level of 2 or 3* rather than *category 1.*

We found that sex (female) (aOR=1.05, 95% CI: 1.01-1.10), higher severity (aOR=1.01, 95% CI: 1.007-1.008), and higher intervention category (aOR=1.13, 95% CI: 1.08-1.19) increased adjusted odds of readmission (Table 4). ICU LOS (aOR=0.93, 95% CI: 0.93-0.94) slightly decreased odds of readmission. Perhaps patients discharged from the ICU too quickly tend to result in additional ICU visits. Lastly, consulting (as opposed to managing) physician also decreased the odds of readmission with adjusted odds ratio of 0.79 (95% CI: 0.75-0.83).

4.3. Readmissions and Discharge

As was shown in the intervention model (Table 3), readmissions are more likely to be associated with a higher intervention category indicating potentially more oversight by the remote team leading us to believe that intervention categories, generally, are used to increase oversight for worse or worsening patients. We found that patient severity scores upon admission, however, were comparable for patients assigned to a single category regardless of which category (online supplement Figure 3). Additionally, most patients transitioned from the ICU to the medical-surgical floor, however, cohort 1 had proportionally higher number of patients discharge to a *step down unit* and lower number of patients discharge to *death* (Figure 1). This is not to imply that providing care at sites with different costs and staff skillsets is less favorable, but rather the spectrum of discharge locations from *death* to *home* should be considered. While certainly there are underlying decisions as potential confounders behind providing care at various locations, cohort 2 and 3 nevertheless had higher proportions of patients that discharged to *death* as opposed to location-specific care considerations that are not necessarily related to an escalation of care due to patient state.

5. Discussion

Results from this study provide insight into how intervention category assignments for tele-ICU influence clinical practice and clinical outcomes. Our results show that the degree of intervention authority given to the remote team by the beside physician is, to some extent, a reflection of the trajectory of patient severity of illness (i.e., improving or worsening) and physician type (i.e., managing or consulting). While this may not be true for each individual institution, the tele-ICU broadly was permitted more oversight and treatment authority for readmissions irrespective of severity of illness upon initial admission to the ICU. Alternatively, oversight may be related to external factors such as ICU capacity or resource limitations[21] which are not captured in our data.

We observed differences in patient outcomes between the intervention categories and influential factors related to underlying use of tele-ICU. Given that worsening patients were assigned to higher categories (i.e., more tele-ICU intervention), differences in mortality and ICU length-of-stay between cohorts may reflect patient severity and illness trajectory rather than a result of tele-ICU intervention throughout an ICU visit as was seen in prior severity adjusted studies[5,6]. A 2021 systematic review comparing tele-ICU “decision-making authority” to “tele-consultation” found that tele-ICU implementation with decision-making authority resulted in significant reduction in ICU mortality[22]. Hospital mortality, ICU LOS, and hospital LOS, however, showed a minimal advantage of tele-ICU implementation regarding patient outcomes. In addition, tele-ICU functions evolve over time and changes should be closely monitored to avoid any potential negative impacts to patient outcomes[23].

Our study provides more context to levels of decision-making authority and includes potentially confounding factors related to patient outcomes. However, more granular case-matching and mixed methods studies are required because severity of illness and subsequent treatment path likely change the trajectory of patient outcomes. Though, our results suggest that remote oversight by the tele-ICU for those patients requiring continuous monitoring are less likely to have a negative impact on care processes.

As might be expected, patient age and ICU LOS increase odds of mortality across intervention categories. In addition, the physician type making the tele-ICU intervention category selection was a factor. Consulting physicians lead to increased odds (aOR=2.42, 95% CI: 2.32-2.52) of patients being assigned a higher category and decreased the odds (aOR=0.79, 95% CI: 0.75-0.83) of ICU readmission. It is possible that consulting physicians defer to additional tele-ICU oversight or that consulting physicians are more often involved with more severely ill patients which also tends to result in higher intervention categories with additional oversight resulting in lower readmission rates.

Alternatively, consulting physicians may not be as invested in the patient as a managing physician and tend to cede control to the tele-ICU to minimize involvement or liability. This is highly institution specific and may depend entirely on prognosis, required treatment, and mode of interprofessional care[24], but aligns with previous work suggesting that physician-specific factors correlate with patient outcomes[25]. Thus, for those institutions in our study that utilized intervention category assignments, the physician type was the most influential factor in the intervention model (Table 3) and the readmission model (Table 4) with adjust odds ratios of 2.42 (95% CI: 2.32-2.52) and 0.79 (95% CI: 0.75-0.83), respectively.

Overall, patients readmitted to the ICU are assigned their original or higher intervention category. Much work has been done to predict patient readmissions[26,27]. As noted in our readmission model, longer ICU LOS decreased odds (aOR=0.93, 95% CI: 0.93-0.94) of readmission. Existing readmission prediction models in combination with tele-ICU intervention categories could be used to determine which patients discharge too quickly and should stay in the ICU.

5.1. Socio-technical Considerations

Although our results did not indicate that higher tele-ICU intervention categories significantly improve patient outcomes, especially among those with higher severity, results still conveyed an optimistic message from healthcare technology implementation perspective that the care system socio-technical balance and care processes was minimally disrupted or impacted by the tele-ICU uptake. If it did, patients would likely experience worse outcomes due to communication interruptions resulting in decreased best practice adherence[28,29]. Mixed-methods research from a systems perspective, in combination with this work, is required to specify tele-ICU success mechanisms and best practices for interconnected and collaborative care. This is especially important for preparing healthcare systems to leverage tele-ICU in response to public health emergencies such as the COVID-19 pandemic where certain clinical needs may be better routed through remote operations[30].

To our knowledge, there is not currently a shared, collaborative decision-making framework specific to the tele-ICU beyond high-level implementation models[31,32,33] and ICU operating guidelines provided by the Leapfrog Group[34]. Data and information exchange between the bedside clinicians and the patient are expected and occur regularly[35], but the addition of the tele-ICU changes the dynamics of decision-making and patient monitoring[36]. Studying decision-making authority in the context of guideline adherence could provide more evidence of tele-ICU impact on patient outcomes[37,38]. Individual institutions must define and reinforce the level of interaction the remote team has with both the bedside team and the patient or guardian[39]. Most importantly, metadata related to either team and the decisions that are made should be systematically recorded to enable retrospective research and quality improvement studies.

What is not known within our dataset, is the underlying reason for intervention category assignment. It appears higher intervention categories are used for sicker patients and consulting physicians are more likely to assign higher intervention categories. We are unable to validate the reasons for category assignment or any additional communication between bedside and remote teams. Possible reasons for assignment are (1) that a patient is improving, and the managing physician is comfortable releasing decision-making authority to the remote team, (2) that a patient is worsening and requires constant oversight that the managing physician alone cannot provide, or (3) combinations of clinical factors regarding the patient status and managing physicians practicing tendencies.

5.2. Limitations and Future Work

To avoid group-level biases, we did not select group characteristics as model inputs such as hospital type (teaching or non-teaching)[41]. In addition, we used patients across the United States rather than from a single institution or geographic region. Patients which share group characteristics could otherwise introduce group-level biases and require multilevel regression or other mixed methods to alleviate potential bias[42]. Multilevel regression models could be used in future work at single institutions to evaluate decision-making within the confines of that particular institution's protocols and procedures but is not necessary given the breadth of our input data.

Future work should include analyzing intervention categories through case matching by diagnosis further stratified by patient severity to highlight tele-ICU impact on outcomes more granularly. This could be used to identify workflow disruptions related to the tele-ICU within single ICU types (e.g., medical surgical ICU have a lower mortality post-elective surgery) and provide further insight to the direction of change for patients that move to a higher or lower category during a single ICU visit. Regionalization studies and investigations of staffing data and patient census at individual institutions or group of institutions under a single healthcare system using intervention categories could provide similar insight. Lastly, temporality of intervention categories, for example daytime vs. nighttime and whether patients are improving, or worsening could also be insightful[40].

6. Conclusion

Our results suggest that higher tele-ICU decision-making authority is used for worsening patients and highly dependent on bedside physician type. Tele-ICU also does not negatively impact the care processes collaboratively carried out by both remote and bedside teams at the expense of patient outcomes. While there is room for investigation around the impact of tele-ICU on patient outcomes, evaluation of intervention category assignments in the tele-ICU is a step toward better understanding workflow success mechanisms and may guide design of future mixed-methods studies.

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Conflicts of Interest

None declared.

Protection of Human and Animal Subjects (blinded)

Abbreviations

APACHE: acute physiology and chronic health evaluation

ICU: intensive care unit

IQR: inter-quartile range

LOS: length of stay

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