Research and Applications

Using nursing notes to improve clinical outcome prediction in intensive care patients: A retrospective cohort study

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ABSTRACT

Objective: Electronic health record documentation by intensive care unit (ICU) clinicians may predict patient outcomes. However, it is unclear whether physician and nursing notes differ in their ability to predict short-term ICU prognosis. We aimed to investigate and compare the ability of physician and nursing notes, written in the first 48 hours of admission, to predict ICU length of stay and mortality using 3 analytical methods.

Materials and Methods: This was a retrospective cohort study with split sampling for model training and testing. We included patients ≥18 years of age admitted to the ICU at Beth Israel Deaconess Medical Center in Boston, Massachusetts, from 2008 to 2012. Physician or nursing notes generated within the first 48 hours of admission were used with standard machine learning methods to predict outcomes.

Results: For the primary outcome of composite score of ICU length of stay ≥7 days or in-hospital mortality, the gradient boosting model had better performance than the logistic regression and random forest models. Nursing and physician notes achieved area under the curves (AUCs) of 0.826 and 0.796, respectively, with even better predictive power when combined (AUC, 0.839).

Discussion: Models using only nursing notes more accurately predicted short-term prognosis than did models using only physician notes, but in combination, the models achieved the greatest accuracy in prediction.

Conclusions: Our findings demonstrate that statistical models derived from text analysis in the first 48 hours of ICU admission can predict patient outcomes. Physicians' and nurses' notes are both uniquely important in mortality prediction and combining these notes can produce a better predictive model.

Key words: natural language processing, critical care, risk prediction, nursing, retrospective cohort study

INTRODUCTION

While intensive care unit (ICU) patient outcomes are difficult to predict despite closely monitoring patients and using physiological parameters,[1–4] outcome prediction is necessary to inform treatment decision making. To date, ICU mortality prediction has primarily been based on structured clinical data, including the Sequential Organ Failure Assessment (SOFA) score, which is used to describe the time course of multiple organ dysfunction using a limited number of routinely measured variables,[5,6] and the Elixhauser Comorbidity Index, which quantifies the effect of comorbidities on patient outcomes.[7–9] These structured data are frequently documented in the electronic health record (EHR) and are often incorporated when making ICU mortality predictions. However, using only structured, coded approaches for data entry may result in the loss of significant clinical information typically contained in narratives (free-text data).[10] Free-text data represent 70% to 80% of all data in EHRs and often provide more contextual information than structured data.[11,12]

When predicting patient outcomes, such as mortality, it is beneficial to incorporate as much available EHR data as possible, including both structured and free-text data. EHR data generated by members of the interdisciplinary ICU team result in a wealth of critical care information for risk predictions. However, these large amounts of free-text data, particularly those from nurses, remain underutilized in clinical outcome prediction models.[13–15]

There are also key differences in nursing documentation compared with other clinician notes. For example, nursing documentation is more like a picture that describes a patient's status illustratively, whereas physicians' documentation is more like a headline due to focus on problem-oriented summarization and abstraction.[16] Additionally, nursing notes describe aspects of the patient's condition that are not addressed in the flowsheet or other structured data, such as change in status, nursing interventions, and patient responses (ie, precipitating factors of pain, patients' response to symptom management, or discussion about plan of care in a family meeting).[17] In summary, nurses and physicians focus on different aspects of patient care[18] and need integration of these clinical notes to gain a comprehensive understanding of the patient's health status.

Significance

While nursing notes contain descriptive information about the patient, specific interventions that have been completed, and patient responses to the interventions,[10] few studies have been conducted to extract EHR data from nursing notes for purposes such as patient safety and quality of care.[10] Moreover, data from nursing notes are often not included into clinical prediction models,[15] and there is no systematic way to incorporate these free-text data into clinical decision making for predicting ICU mortality.[19–22]

Free-text data from clinical notes may improve performance of models predicting adverse ICU outcomes (length of stay [LOS] ≥7 days or in-hospital death),[1] but it is unclear how much of that additional predictive power is provided by nursing or physician notes. In this article, *free-text data* refers to narrative notes in EHR nursing documentation rather than free-text comment boxes in specific documentation fields such as vital signs. Accordingly, we sought to demonstrate the role of nursing notes in clinical predictive modeling, using narrative notes rather than any other additional structured or unstructured data such as SOFA and Elixhauser scores. Therefore, this study aimed to investigate and compare the ability of physician and nursing free-text narrative notes, written in the first 48 hours of an ICU admission, to predict ICU LOS and mortality using 3 different analytical methods. We hypothesize that including free text from clinical nursing notes provides better predictions of ICU outcomes than including physician notes alone.

MATERIALS AND METHODS

Data sources

The Multiparameter Intelligent Monitoring of Intensive Care III (MIMIC-III) database, developed by the Massachusetts Institute of Technology and Beth Israel Deaconess Medical Center (BIDMC), provides de-identified administrative, clinical, and survival outcome data for admissions to 5 distinct BIDMC ICUs[23,24]: medical , cardiac, surgical, trauma surgery, and cardiac surgery. The MIMIC-III dataset contains 8984 total ICU admissions during 2008 to 2012. These data include all free-text notes from clinicians (eg, physicians, nurses, nurse practitioners, physician assistants). The Institutional Review Boards of BIDMC and Massachusetts Institute of Technology have approved use of the MIMIC-III database by any investigator who fulfills data-user requirements. This research was deemed exempt by the Partners HealthCare Institutional Review Board.

Study population

We included patients ≥18 years of age who were admitted to the ICU at BIDMC during 2008 to 2012 (Figure 1). Patients with ICU LOS <48 hours and those lacking MIMIC clinical notes due to potential privacy disclosures were excluded. For patients with multiple ICU admissions during a single hospitalization, only the first admission was used for analysis.
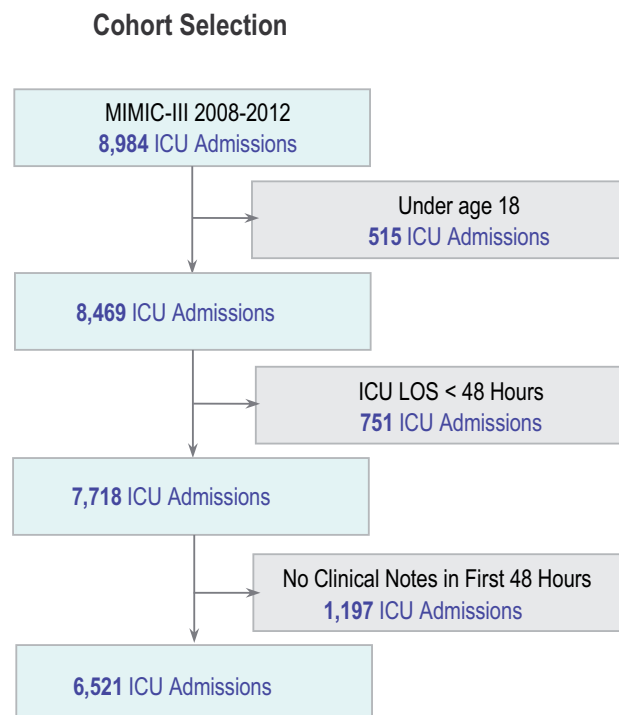
Cohort Selection

Figure 1. Flow Diagram. ICU: intensive care unit; LOS: length of stay; MIMIC-III: Multiparameter Intelligent Monitoring of Intensive Care III.

Measures

Similar to past literature,[1] we built clinical prediction models from data obtained early in the course of hospitalization. Data from the first 48 hours of the ICU stay were used to predict the primary outcome, ie, a binary composite score of ICU LOS ≥ 7 days or in-hospital mortality. We chose this composite outcome because LOS cannot be assessed validly without tandem consideration of mortality,[25] and because both mortality and prolonged ICU LOS represent unfavorable outcomes that might prompt early decisions around clinical care or hospital resource allocation.[1] Also, early accurate prognosis of this composite could have a large impact on decision making and patients' outcome trajectories.[1,25]

Text processing

All nursing and physician notes for these patients were extracted from the EHR. We followed standard preprocessing, such as removing stop words (eg, *and*, *the*, *is*), and aggregated the notes into a single large document for each admission. Each patient had a "bag of words," containing their entire clinical notes for the first 48 hours. Structured data (ie, vital signs or laboratory results) were excluded, and only free-text data used for analysis. For prediction, we selected the top 3000 frequent words in the corpus and applied the bag of words to obtain a 3000-sized vector for each admission with each entry tallying a given word. We calculated the correlation matrix of the 3000 bag-of-words features, and correlations between features were low. The mean correlation score is 0.04 with an SD of 0.07, suggesting high quality of features selected. To identify top predictive words, we used 5 independent data splits. We averaged the feature weight across 5 runs, which resulted in a final list of important variables.

Model development

We modeled the outcome using standard machine learning methods, including penalized logistic regression, gradient boosting, and random forest. As different machine learning methods consider various types of signals derived from input, we used 3 methods instead of 1 to show result consistency. Ten percent of the patient dataset was set aside as the holdout test set (ie, not used in model building) and the remaining 90% divided into 9:1 training and validation sets randomly split 5 times. For each model, we applied nursing notes, physician notes, and combined physician and nursing notes to explore differences in predictive performance. The best model was selected based on the validation set receiver-operating characteristic area under the curve (AUC) score and applied to the test set to determine performance on data not used in model building. To prevent overfitting, we adopted early stopping. For logistic regression, we tune the regularization weight among 0.01, 0.001, and 0.0001. For gradient boosting, we tuned the number of boosting stages among 100, 300, 500, and 1000 and the learning rate from 0.1, to 0.01, to 0.001. For random forest, we tuned the number of trees from 100, to 300, to 500, to 1000. After obtaining the optimal hyperparameter set, we used the same hyperparameter set to run each experiment 5 times on different training and validation split. We then reported the average and SD metrics. After hyperparameter tuning, we found the following set of parameters had consistently optimal performance across all settings: for logistic regression, it was L2 norm with 0.0001 regularization weight; for gradient boosting, it was 500 boosting stages with 0.01 learning rate; and for random forest, it was 500 trees in the forest and we set the maximum depth of the tree to be 20.

RESULTS

Patient characteristics

During 2008 to 2012, there were 8984 qualifying ICU admissions with both physician and nursing notes in the MIMIC-III dataset. Of these, 8469 admissions included patients ≥ 18 years of age, and 7718 admissions included ICU LOS >48 hours. After excluding patients lacking clinical notes due to privacy concerns, the final cohort included 6521 admissions with clinical notes documented within the first 48 hours of the ICU stay. Within the cohort, the medical ICU was the most common admitting unit and contained 3239 (46.8%) ICU admissions (Table 1). Additionally, more clinical notes within the first 48 hours of ICU admission were from nurses (average of 9.6 notes per patient) than physicians (average of 6.5 notes per patient). A large majority of all ICU admissions were for emergencies (n = 5553, 85.2%), compared with urgent (n = 69, 1.1%) and elective (n = 899, 13.8%) admissions.

Model performance

Across 3 machine learning methods, the result pattern was consistent: content from nursing notes was more likely to predict mortality and ICU LOS than content from physician notes (Table 2). Using gradient boosting, nursing notes achieved an AUC of 0.826 while physician notes had an AUC of 0.796. When both physician and nursing notes were combined, the AUC was 0.839, indicating improved performance over models from physician or nursing notes alone.

Variable importance

For each type of note (ie, nursing, physician, or combined), we generated words that most strongly predicted the outcome and identified sentences in the clinical notes that contained predictive words (Table 3). The overlap rate was 0.38 between gradient boosting models of physician and nursing notes, demonstrating distinctly unique types of words and phrases related to prediction outcomes found in clinical notes by discipline. The physician notes and nursing notes included distinctly different types of words related to patient condition that may predict clinical outcomes.

DISCUSSION

We investigated and compared the ability of physician and nursing notes to predict ICU length of stay (LOS) and mortality using 3 different analytical methods. The physician and nursing notes were written in the first 48 hours of an ICU admission. We assessed the top predictive words generated from each type of notes and examined their predictive power on ICU mortality and LOS using penalized logistic regression, gradient boosting, and random forest as the classifier. Nursing notes had higher predictive values than physician notes across all classifiers and all methods. Combining nursing and physician notes produced a superior predictive model. This validates our initial hypothesis that, in our study, free text clinical nursing notes provide better predictions of ICU outcomes such as LOS and mortality compared with physician notes alone. One such explanation for this could be that certain contextual information is usually assessed and managed by nurses and only brought to the attention of physicians if the data reach a certain threshold outside a normal range (eg, urinary/defecatory distress, restlessness or difficulty with sleep, patient complaining about discomfort). There were also stylistic differences: nursing notes were typically more frequent and shorter but appeared less structured than physician notes. Such

Table 1. ICU LOS ≥7 days or in-hospital death

Outcome Category	All	Deleterious Outcome	No Deleterious Outcome
Admissions	6521	2341	4180
ICU LOS ≥7 d	851 (13.1)	851 (36.4)	0 (0)
In-hospital death	1799 (27.6)	1799 (76.8)	0 (0)
Age, y	62.7 ± 16.5	66.2 ± 15.2	60.7 ± 17.0
Male	3703 (56.8)	1332 (56.9)	2371 (56.7)
Admission type			
Elective[a]	899 (13.8)	157 (6.7)	742 (17.8)
Emergency[a]	5553 (85.2)	2163 (92.4)	3390 (81.1)
Urgent	69 (1.1)	21 (0.9)	48 (1.1)
Ethnicity			
White	4896 (75.1)	1803 (77.0)	3093 (74.0)
Black	722 (11.1)	261 (11.1)	461 (11.0)
Hispanic/Latino	276 (4.2)	76 (3.2)	200 (4.8)
Asian	165 (2.5)	54 (2.3)	111 (2.7)
Other	462 (7.1)	147 (6.3)	315 (7.5)
ICU type			
CCU	753 (10.9)	442 (10.1)	311 (12.2)
CSRU	833 (12.0)	693 (15.8)	140 (5.5)
MICU	3239 (46.8)	1870 (42.7)	1369 (53.7)
SICU	1216 (17.6)	770 (17.6)	446 (17.5)
TSICU	886 (12.8)	604 (13.8)	282 (11.1)
Nursing notes within 48 h			
Word count	2352.6 ± 1729.7	2656.9 ± 1887.3	2182.0 ± 1609.7
Note count	9.6 ± 4.8	10.3 ± 5.0	5.9 ± 3.8
Physician notes within 48 h			
Word count	4852.7 ± 3488.2	5949.8 ± 3813.3	4241.3 ± 3130.6
Note count	6.5 ± 4.0	7.4 ± 4.1	9.1 ± 4.6

Values are n, n (%), or mean ± SD.

CCU: cardiac care unit; CSRU: cardiac surgery recovery unit; ICU: intensive care unit; LOS: length of stay; MICU: medical intensive care unit; SICU: surgical intensive care unit; TSICU: trauma surgery intensive care unit.

[a]An elective admission is defined as a typically scheduled admission not originating from the emergency room, and an emergency admission as a typically unscheduled admission originating from the emergency room.

Table 2. Performance metrics stratified by model and note types

	Logistic Regression	Random Forest	Gradient Boosting
ROC-AUC			
Nursing	0.795 ± 0.001	0.802 ± 0.009	0.826 ± 0.004
Physician	0.793 ± 0.003	0.793 ± 0.005	0.796 ± 0.006
Both	0.815 ± 0.002	0.809 ± 0.007	0.839 ± 0.003
PR-AUC			
Nursing	0.702 ± 0.004	0.686 ± 0.008	0.696 ± 0.009
Physician	0.690 ± 0.002	0.680 ± 0.010	0.698 ± 0.005
Both	0.735 ± 0.004	0.709 ± 0.003	0.715 ± 0.003
Accuracy			
Nursing	0.740 ± 0.006	0.730 ± 0.003	0.723 ± 0.022
Physician	0.728 ± 0.003	0.724 ± 0.012	0.720 ± 0.004
Both	0.754 ± 0.009	0.738 ± 0.009	0.742 ± 0.006
Precision			
Nursing	0.674 ± 0.012	0.628 ± 0.004	0.648 ± 0.007
Physician	0.656 ± 0.006	0.619 ± 0.014	0.640 ± 0.008
Both	0.677 ± 0.015	0.633 ± 0.012	0.661 ± 0.010
Recall			
Nursing	0.599 ± 0.007	0.706 ± 0.010	0.632 ± 0.007
Physician	0.602 ± 0.014	0.705 ± 0.018	0.604 ± 0.002
Both	0.671 ± 0.013	0.738 ± 0.005	0.659 ± 0.009

PR-AUC: precision-recall area under the curve; ROC-AUC: receiver-operating characteristic area under the curve.

stylistic differences may suggest that less structured clinical notes may be useful for conveying rich contextual information that may not be captured in structured, templated clinical documentation. A concern is that important information might not get documented when asking nurses to use templated or structured notes. Accordingly, there is a critical need in healthcare to recognize the unique and important value of nursing work and documentation such that standardization does not limit the content of nursing assessments and free-text notes.

Our study is consistent with previous work but provides some unique insights and implications for clinical practice. Several recent studies have investigated the use of risk prediction models on patient outcomes based on free-text data in the EHR[19,26,27] and demonstrated that nursing notes are good predictors of short-term clinical outcomes. However, these notes were not compared with physician notes for predictive accuracy.[19] If important prognostic information is contained in nursing notes, the flow of information from nurses to physicians should be enhanced, especially given that absence of interprofessional collaboration may result in more errors and omissions in patients' care.[21,28] While nurses typically review physician notes, the opposite is often not the case.[29] Both nurses and physicians should acknowledge the importance of effective communication and should develop and implement interprofessional teamwork interventions to improve collaboration.[21,29,30]

Table 3. Examples of top predictive words and contextual quotes from clinical notes

Nursing Notes	Physician Notes	Both
dl	**increase**	**failure**
"*bun: XX mg/**dl**: am creatinine: XX mg/dl: am glucose: XX mg/**dl**"*	"*plan to extubate but for now **increase** sedation as appears uncomfortable*"	"*Renal **failure**, end stage (end stage renal disease ESRD)*"
vent	**autoflow**	**metastat**
"*plan: maintain present **vent** settings, revert to ac overnight if pt tires.*"	"*Ventilator mode: CMV/ASSIST/**AutoFlow**"*	"*Prostate Ca—**metastat**ic to bone*"
levoph	**CMV**	**cancer**
"*unable to wean **levoph**ed*"	"*Ventilator mode: **CMV**/ASSIST*"	"*73 y/o female with breast **cancer** metastatic to the liver/lung/bones/CNS*"
abg	**floor**	**diet**
"*unable to maintain sat > XX. on nrb, increase rr and worsen **abg** pneumonia*"	"*Disposition: stable for transfer to **floor**"*	"*patient refuses diabetic **diet** and will only take regular **diet**"*
cmo	**norepinephrine**	**extub**
"*action: **cmo**, ivf/iv abx d/c, morphine drip start as directed and titrate to accommodate patient comfort level, palliative care nurse consult*"	"*Infusions: **Norepinephrine** - 0.01 mcg/Kg/min*"	"*patient was **extub**ated without difficulty*"

Key words were selected from top predictors from the gradient boosting method. The Nursing Notes and Physician Notes columns indicate the top 5 predictive words not found within the top 50 words of the other group. The Both column indicates the top 5 predictive words overall. Quotes have been lightly edited for clarity (abbreviations expanded; typos corrected).

abg: arterial blood gas; cmo: comfort measures only; CMV: continuous mandatory ventilation; vent: ventilator.

Our study findings have the potential to inform future work, particularly related to prompts ("triggers") for communication and timely responses to physiological changes that patients experience. For example, a hypothetical trigger system could inform care team members when clinical notes indicated that the patient was at a high risk of having a long LOS or in-hospital death, and prompt possible steps to address it (goals of care discussion, etc.). Trigger-based multidisciplinary care provides a clear structure and linkage to critical patient outcomes. In addition, such triggers could be built into the EHR to prompt early intervention and triage by clinicians if a patient's physical health deteriorates and facilitate a clinician's ability to prioritize care.[31] Future applications of this research are broad, yet findings from our study suggest the need for future innovations such as prospective surveillance of triggers for patient deterioration.[32] The CONCERN (Clinical Decision Support Communication for Risky Patient States) study is an app-based study that investigates nurses' judgment that a patient's clinical state may be deteriorating, in both narrative and structured information in acute and critical care.[33] The CONCERN study is an example of using free-text and structured data from nursing documentation in the EHR to identify early warning signs of rapid deterioration and poor outcomes from critically ill patients. Future studies are also needed to examine the use of EHR data from different clinical team members on mortality prediction and other important patient outcomes.

Our study will significantly contribute to the growing body of evidence that machine learning models can provide a more accurate outcome prediction to support early treatment decision making when caring for individuals with critical illness. The study findings show that there are different models that are consistent in terms of providing parallel insight about patients' risk for mortality in the ICU setting. Model findings highlight the need to incorporate all available free-text data in the EHR to analyze the role of knowledge and content sharing from nursing and physician notes within the first 48 hours of ICU admission. Data in nursing notes, combined with physician notes, could be integrated into technology (ie,

computers and apps) to provide early warning signals, notably shortly after ICU admission, that the patient's health is deteriorating and to prompt the care team to intervene quickly.

Limitations

This study has several important limitations. First, we examined care during 2008 to 2012, so our findings may not generalize to more recent years. However, the study period is still relatively recent and can serve as a baseline for comparing the effect of changes in policy and practice on documentation possibly associated with mortality risk. Second, we focused on nursing and physician notes generated within the first 48 hours of ICU admission and thus cannot evaluate the predictive relevance of clinical notes taken outside this 2-day window. However, similar to other literature, we limited the sequence of past events to the most recent 48-hour period because it is expected to be sufficient for assessment of medical condition of ICU patients with respect to patient mortality.[1,34] Third, we focused on documentation by only nurses and physicians, but critical care is a broad, interdisciplinary specialty. The role of other clinicians' documentation in predicting mortality in the ICU setting is not known. Future studies also should analyze clinical documentation of bedside nurses, respiratory therapists, advanced practice clinicians (eg, physician assistants and nurse practitioners), and physicians. Fourth, our goal was not to develop the most accurate model possible, but rather to explore text information contained in each type of note. For this reason, we excluded structured clinical data (eg, vital signs or laboratory results) from our model. Models that incorporate elements of structured clinical data are needed for comprehensive understanding of the impact of both structured and free-text data on predicting clinical outcomes. Last, clinical practices, particularly documentation practices and choice of wording in the EHR, are notoriously dependent upon local and institutional culture. Therefore, more work is needed to compare mortality prediction models based on clinical notes from specific ICU settings. As we examined data from a single tertiary care hospital in the northeastern United States,

future studies are needed to determine if similar results are obtained within other datasets and from institutions.

CONCLUSION

ICU patient outcomes are difficult to predict but necessary for medical decision making. To date, ICU mortality prediction has primarily been based on structured clinical data. However, free-text clinical data seem to perform as well as or better in mortality prediction than structured clinical data. Our study findings demonstrate that statistical models derived from text analysis of clinical notes collected in the first 48 hours of ICU admission can predict patient outcomes, ie, length of stay and mortality. Our study underscores the notion that physicians' and nurses' notes are both uniquely important in mortality prediction, and combining these notes can produce a better predictive model. Early analysis and discussion of notes from the entire ICU care team, especially nursing notes, can inform goals of care conversations, prognostic planning, realistic goal setting, family involvement, and future planning. Additional studies are warranted to determine whether mortality prediction and decision tools based on word triggers can improve multidisciplinary team communication and patient outcomes. In summary, free-text data in the EHR could be leveraged to develop predictive models that can be incorporated into clinical practice and research to provide feedback to clinicians.

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AUTHOR CONTRIBUTIONS

KH, TFG, and CL conceived the study design and contributed to data collection. KH, TFG, SR-B, JAT, and CL performed data analysis and interpretation of the results. All authors contributed to the writing and review of the manuscript.

ETHICS APPROVAL

The Institutional Review Board of Beth Israel Deaconess Medical Center and Massachusetts Institute of Technology have approved use of the MIMIC-III database by any investigator who fulfills data-user requirements. This research was deemed exempt by the Partners HealthCare Institutional Review Board.

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CONFLICT OF INTEREST STATEMENT

None declared.

DATA AVAILABILITY STATEMENT

De-identified data are available at MIMIC Critical Care Database (physionet.org)

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