Validation of an Intensive Care Unit Data Mart for Research and Quality Improvement

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Short Report

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Abstract

Data derived from the electronic health record (EHR) frequently undergo limited prospective validation. Efforts to perform validation often suffer from limited collaboration between clinicians and data analysts. In this manuscript, we describe the creation of a structured, rigorously validated intensive care unit (ICU) data mart based on data automatically and routinely derived from the EHR. This data mart includes high-quality outcomes data and other data elements commonly used for quality improvement and research purposes. These data elements were identified by physicians working closely with data analysts to iteratively develop and refine algorithmic definitions for complex outcomes and risk factors. We contend that this methodology can be reproduced and applied to other clinical domains to create high quality data marts, inclusive of complex outcomes data.

Background

The electronic health record (EHR) contains a vast quantity of data due to its observation nature, holding great promise as a valuable, efficient, and cost-effective tool. These data can inform quality improvement and research initiatives, especially those related to medical resources and patient outcomes.[1–3]. In its initial implementation, however, the EHR rarely captures outcomes of interest to key stakeholders reliably and accurately due to frequent limitations resulting from disorganized, incorrect, or missing variables that lack vigorous extraction methodologies. Together this limits the data's validity and utility.[4] In order to provide validated results for scientific interpretation, vigorous, reproducible, and validated techniques must be established for each EHR variable of interest.

Many institutions rely on a structured repository of data, drawn from the EHR, to facilitate ongoing access, a so-called data warehouse or data mart.[5, 6] This data repository is frequently created after the EHR has been created and, at many institutions, is created and maintained by data analysts working in isolation from front-line clinicians. The intensive care unit (ICU) is a particularly challenging area for creation of a data mart. Critically ill patients suffer life threatening organ pathology in at least one, if not many, organ systems. These patients are generally intensively monitored, with very high frequency of physiologic data capture. Laboratory data may be obtained multiple times per day. Multiple organ support modalities may be employed, with complex documentation and monitoring to quantify the degree of support. Once data are located though, they can support surveillance, decision support, and modeling of outcomes.[7]

We sought to define a methodology for the creation of a structured, rigorously validated intensive care unit (ICU) data mart based on data automatically and routinely derived from the EHR. We identified data elements commonly used for quality improvement and research purposes, including high-quality outcomes data, to refine the methodologies presented here. Importantly, data analysts and clinicians worked side-by-side throughout the process.

Methods
A multidisciplinary project team including clinical intensivists and data analysts met daily throughout construction, assembling a priority list of physiologic, laboratory, demographic, and billing data. The presence of data availability in routine clinical practice was confirmed using extensive chart review and validation. Data analysts worked to identify the location of variables within the data architecture underlying the EHR (Epic, Verona, WI). All elements were investigated for extent of chart documentation, frequency, duplication in different sites within the medical record, and agreement with patient clinical course. Variable extraction was initiated after location(s) of these key variables within the EHR were confirmed.

We created algorithmic definitions for complex data elements, including most outcomes, leveraging existing literature, when available. Test patients were extracted and algorithms iteratively refined at least weekly. The number of iterations required for each variable was variable dependent, influenced by fidelity of the variable within the EHR. Once shown to be reproducible in a broad cohort of patients, structured query language (SQL) was used to extract, transform, and load data from the EHR into a relational database housed on a departmental server. This same departmental server houses intraoperative variables within a perioperative data warehouse (PDW) that were obtained through similar methodologies.[8] The sensitivity and specificity of algorithmic definitions were then formally assessed using the finalized algorithms on random cohorts of 50–100 ICU patients. After formal assessments, patient outcome results were cataloged in tables for presentation and dissemination. This process is illustrated in Fig. 1.

Figure 1 Variables presented have been identified by clinicians as high-yield variables for quality improvement and research purposes. As these variables are located and validated within the electronic health record, they are added within the data mart. These data are then analyzable to be able to draw conclusive findings regarding outcomes including acute kidney injury, reintubation rates, and 7-day mortality, to name a few

Results

A total of 459,465 ICU patient encounters were identified and included in the ICU data mart. These patients include over 460,000,000 individual laboratory results and 4,610,776 vital signs (with 1-minute fidelity in the first 24-hours of admission). Using the above methodologies, a total of 26 outcomes were validated (Table 1). These data have been structured within 19 tables, all of which have a sensitivity and specificity of greater than 95%. The iterative construction of our processes allows for continual updates and validation of variables to maintain accuracy. When variables were not able to reach sufficient sensitivity or specificity despite iterations, data analysts formed collaborative meetings to review, check, and improve techniques. If it wasn’t possible to increase accuracy, variables were not advanced or included within final tables or projects due to lack of validity.
Table 1
Variables Currently Validated Organized by Variable Type

| Variable Type         | Variables                                                                 |
|-----------------------|---------------------------------------------------------------------------|
| Patient Variables     | Date of birth, Height, Weight, BMI                                         |
|                       | Ethnicity, Gender, Sex, Race                                               |
|                       | Date of surgery/anesthesia                                                 |
|                       | Primary admission diagnosis                                                |
|                       | Insurance type, Smoker History                                             |
|                       | Mortality scores: Charlson, Elixhauser, Romano                             |
|                       | ICU discharge location                                                     |
|                       | Hospital admission and discharge dates                                    |
|                       | ICU admission and discharge dates                                          |
|                       | Readmission date within 7 days                                            |
|                       | ED visits within 7 days of discharge                                      |
|                       | Death date                                                                 |
| Laboratory/Imaging Variables | Approximately 4100 unique lab test variables (e.g., BUN, drug levels)   |
|                       | Hematocrit values                                                          |
|                       | INR values                                                                 |
|                       | Partial thromboplastin values                                              |
|                       | WBC count min/max                                                          |
|                       | CT head scans                                                              |
|                       | Pathology results                                                          |
| Variable Type          | Variables                                                                                                                                 |
|-----------------------|------------------------------------------------------------------------------------------------------------------------------------------|
| Medication Variables  | Crystalloid IV fluids (normal saline, LR, plasmalyte)                                                                                     |
|                       | 575 unique transfusions                                                                                                                   |
|                       | Albumin                                                                                                                                  |
|                       | Parenteral nutrition                                                                                                                       |
|                       | Enteral nutrition                                                                                                                           |
|                       | Blood transfusion (pRBCs, FFP, platelets, cryoprecipitate)                                                                                   |
|                       | 750 Infused medications, including nutrition (e.g., electrolytes, dextrose,) diabetic control (e.g., insulin, dialysates, etc) and medications (e.g., fentanyl, propofol, dexmed) |
|                       | 400 Antibiotics (e.g., ampicillin, vancomycin, cefazolin)                                                                                   |
| Variable Type               | Variables                                                                 |
|----------------------------|---------------------------------------------------------------------------|
| Hospital Course Variables  | First recorded time of dialysis treatment:                                |
|                            | CRRT, HD, PD                                                              |
|                            | Mechanical Ventilator variables:                                          |
|                            | Ventilator Mode, SpO2, FiO2                                               |
|                            | Mandatory Respiratory Rate, SpO2r                                         |
|                            | Tidal (Observed), PEEP/CPAP (cm H2O)                                      |
|                            | Central venous pressure values                                            |
|                            | Assessment scores:                                                        |
|                            | GCS, SOFA, RASS, CAM-ICU, Peds NLP score                                  |
|                            | Peds PEW score                                                            |
|                            | Arterial pressure min/max                                                 |
|                            | Pulse min/max                                                             |
|                            | Systolic BP min/max                                                       |
|                            | Temp min/max                                                              |
|                            | Urine Output min/max                                                      |
|                            | Central Line and Cath durations                                           |
|                            | Chest effort flag                                                         |
|                            | Wheeze flag                                                               |
|                            | ECMO RPM                                                                  |
|                            | O2 lpm                                                                    |
|                            | Intubation duration                                                       |
|                            | Extubation time                                                           |
|                            | Reintubation date                                                         |

Validated data are used to interpret patient outcomes for all patients within the ICU and ICU data mart. Additionally, these data can be joined to the 120 tables including more than 1900 unique variable columns within the existing perioperative data warehouse.

**Discussion**
We present a methodology for building a robust and highly granular ICU data mart, leveraging the synergistic expertise of clinicians and data analysts. Optimizing the quality of data obtained from large databases will improve accuracy, results, and confidence within informatics research for quality improvement and research purposes.

These processes can be adapted to new variables as they present to provide real-time clinical data on large populations of patients within our ever-changing clinical environment. Several hospital systems involved in data informatics research have already established similar organizational methodologies to ensure quality of data obtained within their data warehouses.[6, 9, 10] Together, these structured and validated methodologies strengthen the results obtained and the validity and trust within our research community. Even after establishing these methodologies, there is a need for consistent upkeep and maintenance of systems. Continual data maintenance and validation is not included within these methods but are equally essential to ensuring continuation of valid data collection. The major value for this established methodology lies in the additional variables and patient markers that are added to the EHR and identified as priority for inclusion within the data mart. These same processes are adapted to ensure quality data collection and trust of information obtained. Within our workgroups, we are validating the accuracy of a variable or variables that will identify positive coronavirus 2019 (COVID-19) test results into our variable lists using the presented methodology to confirm accuracy within results obtained across a variety of available laboratory data.

Similar to much of informatics research, our results are limited by the quality of data entered into the EHR. Missingness and inaccurate data elements can be screened and eliminated when detected, but such errors are difficult to prevent entirely. The ability of our algorithms and methods to detect data accuracy with sensitivity and specificity > 95% on repeated queries is evidence of the rigor of our data extraction method. We recognize, however, this number is not 100% and thus a low level of inaccuracies cannot be eliminated. As our systems change and update within our underlying EHR architecture, aspects of our data extraction and validation may need to be updated as well to ensure continued validity.

Our methodology and accuracy provides a strong foundation for the results obtained through our large ICU data mart. As we plan to add patient data throughout the hospitalization and perioperative periods, we will continue to establish structured methodologies to ensure data accuracy. Future uses of these formats will aim to target validation of variables across multiple health care centers to create multicenter perioperative data warehouses with validated patient variables for quality improvement and research purposes.

Declarations

Conflict of Interest: The authors declare no competing interests.

Clinical Trial Number: Not applicable

Acknowledgments: Not applicable
Compliance with Ethical Standards

Conflict of interest statement: Dr. Boncyk is a consultant for Sedana Medical. This manuscript does not reference any activities related to this consultancy and Dr. Boncyk declares no conflict of interest. Dr. Freundlich declares no conflict of interest. Pamela Butler declares no conflict of interest. Karen McCarthy declares no conflict of interest.

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Ethical Approval: This project received local Institutional Review Board (IRB) approval (#220897).

Informed Consent: A waiver of informed consent was obtained with IRB approval.

Authors Contributions: CB contributed to project design, data interpretation, and construction of manuscript. PB contributed to data collection and construction of manuscript. KM contributed to project design, data collection, data interpretation, and construction of manuscript. RF contributed to project design, data collection, data interpretation, and construction of manuscript.

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Figures

![Diagram](image)

**Figure 1**

Progression Through Variable Identification or Validation of Patient Outcomes