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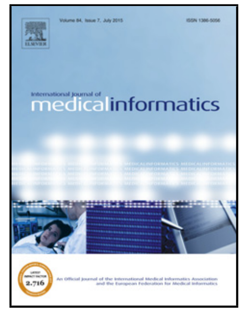

Automatic generation of minimum dataset and quality indicators from data collected routinely by the clinical information system in an intensive care unit

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Title page:

AUTOMATIC GENERATION OF MINIMUM DATASET AND QUALITY INDICATORS FROM DATA COLLECTED ROUTINELY BY THE CLINICAL INFORMATION SYSTEM IN AN INTENSIVE CARE UNIT

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Highlights:

- Automatic generation of MDS information and QIs in daily practice from quality electronic data reuse is possible.
- It will make feasible to develop a benchmarking model not based on manual registries and unsustainable human efforts.

ABSTRACT

Background: Quality indicators (QIs) are being increasingly used in medicine to compare and improve the quality of care delivered. The feasibility of data collection is an important prerequisite for QIs. Information technology can improve efforts to measure processes and outcomes. In intensive care units (ICU), QIs can be automatically measured by exploiting data from clinical information systems (CIS).

Objective: To describe the development and application of a tool to automatically generate a minimum dataset (MDS) and a set of ICU quality metrics from CIS data.

Methods: We used the definitions for MDS and QIs proposed by the Spanish Society of Critical Care Medicine and Coronary Units. Our tool uses an extraction, transform, and load process implemented with Python to extract data stored in various tables in the CIS database and create a new associative database. This new database is uploaded to Qlik Sense, which constructs the MDS and calculates the QIs by applying the required metrics. The tool was tested using data from patients attended in a 30-bed polyvalent ICU during a six-year period.

Results: We describe the definitions and metrics, and we report the MDS and QI measurements obtained through the analysis of 4546 admissions. The results show that our ICU's performance on the QIs analyzed meets the standards proposed by our national scientific society.

Conclusions: This is the first step toward using a tool to automatically obtain a set of actionable QIs to monitor and improve the quality of care in ICUs, eliminating the need for professionals to enter data manually, thus saving time and ensuring data quality.

Abbreviations

ICU: Intensive care medicine

CIS: Clinical information systems

SEMICYUC: Spanish Society of Critical Care Medicine and Coronary Units

Keywords: Clinical Information System, quality indicators, critical care, data quality.

1. INTRODUCTION

In recent decades, quality indicators (QIs) have been increasingly used in medicine to measure and compare processes and outcomes with the ultimate aim of improving care (1). Although the evaluation of healthcare systems should take into account various factors, including quality, costs, access, and patients' experiences (2), experts and medical societies have strongly recommended measuring QIs to assess the performance of intensive care units (ICUs) (1,3,4). This recommendation is based on the perception that integrating QIs into routine practice can improve quality and safety in ICUs and help ensure transparency (5).

Currently, QIs are assessed based on data collected manually; this process is time consuming and generates dissatisfaction among healthcare professionals (6). In practice, assessments of QIs are often based on measurements obtained in cross-sectional studies or from random samples or subsets of patients that may not be representative of the real situation.

In recent years, healthcare organizations have committed to computerizing ICUs, recognizing the intense and complex activity of these units. Clinical information systems (CIS) integrate data from patient monitoring systems, bedside equipment, and process-of-care information registered by healthcare professionals, offering advantages for the efficiency and quality of care. Our institution uses a commercial CIS (Centricity™ Critical Care Suite, CCC, GE Healthcare) configured by the work team and integrated with all bedside equipment, administrative software, and laboratory and radiology departments' information systems. ICU professionals add data by completing preconfigured forms. The CIS enables fast and secure access to all this information, displaying it clearly in an orderly interface. However, once patients have been discharged from the ICU, the rudimentary tool provided with the CIS to recover patients' information is inadequate for the purposes of quality control based on QIs. For this reason, our group used business intelligence techniques to develop a tool that can automatically extract the data needed to create a minimum dataset (MDS) from our CIS and measure some QIs. This tool uses methods that ensure the quality of data compiled in the CIS so that they can be used to measure QIs.

With the aim of helping other ICUs exploit their routinely collected data for quality control, this paper describes the tool we created and details the methods used to curate the dataset.

2. MATERIALS AND METHODS

2.1 Extraction, Transform, and Load (ETL) process

Once collected through the CIS, data are stored in the CIS database, which consists of different tables. Each variable is stored in a specific table depending on its type and source. The ETL process (Figure 1) consists of connecting to the CIS database, extracting the data for the target variable from the table where they are stored, applying transformation processes if required, and creating a new associative database (group of tables with common key fields) to feed the ICU data management tool. This new database is stored as common separated values (.csv) files in the ICU server within the hospital network. The ETL process was implemented using Python 3, and all data flow occurs between hospital severs that meet the required security conditions for working with clinical data. Detailed information about the source and type of the items needed to create the MDS and QI of the present study can be found in Appendix (A.1 and A.2).

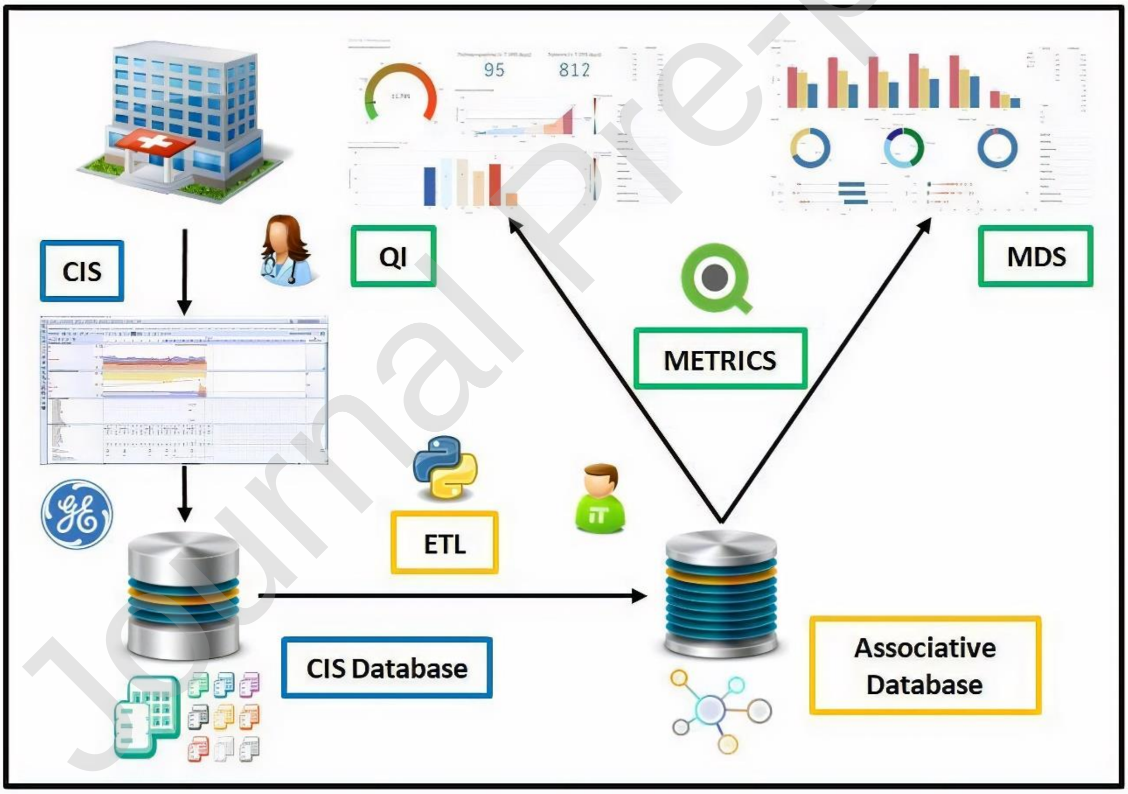


Figure 1. Data flowchart. The CIS collects the data and stores them in various tables in the CIS database. An ETL process is implemented with Python to create a new associative database. This new database is uploaded to Qlik Sense, which builds the MDS and calculates the QI by applying the required metrics. CIS: clinical information system; QI; quality indicators; MDS: minimum dataset; ETL: extraction, transform and load process.

2.2 Description of the ICU data management tool

The tool was designed by a team of intensivists, the final users, but was developed by a team of data scientists. In the backend layer (blind for the user), the tool builds the associative database using the .csv files created in the ETL process and stores it in memory. The data in the tool can be updated whenever necessary by clicking a reload button. Data loading takes about 4 minutes. In the frontend layer (visible and interactive for the user), each object contains a specific metric to calculate each MDS item or QI from the data stored in the associative database. The MDS and QI are displayed in different objects (mainly tables and charts) and data can be exported into PDF files or Excel spreadsheets. Moreover, all data used to generate each object can be used as filters, allowing physicians to explore the MDS and QI according to different clinical criteria.

2.3 Definitions

Table 1 shows the variables included in the MDS. For the variable *Main diagnosis* we used the International Classification of Disease (ICD), ninth revision (ICD-9), until January 2018 and ICD-10 thereafter.

Minimal Dataset
Age
Sex
Hospital admission, date and time
ICU admission, date and time
ICU readmission (<48 hours)
Type of admission (urgent/scheduled)
Type of patient (medical/surgical)
Source of admission (ED, ward, OR)
APACHE II Score
SEMICYUC reason for admission
Main diagnosis
Procedures
Days on mechanical ventilation
Days on continuous renal replacement
Days in isolation
ICU discharge date and time
ICU discharge destination
Hospital discharge date and time
Status at hospital discharge

Table 1. List of Minimal Dataset variables. ICU: Intensive Care Unit; ED: emergency department. OR: Operating room and recovery room); APACHE: Acute Physiology Age Chronic Health Evaluation; SEMICYUC: Spanish Intensive Care Society (*Sociedad Española de Medicina Intensiva y Crítica y Unidades Coronarias.*

Table 2 shows the QIs measured and the metrics used to calculate them, based on the definitions proposed by the Spanish Society of Critical Care Medicine and Coronary Units (SEMICYUC) on 2017 (4). For unscheduled extubation we used 2011's definition.

Quality indicator	Metric
Incidence of barotrauma	$\frac{Nº\ of\ patients\ >12h\ on\ MV\ +\ barotrauma}{Nº\ of\ patients\ >12h\ on\ MV}$
Unscheduled extubation	$\frac{Total\ Nº\ of\ unscheduled\ extubations}{ETT\ days}$
Reintubation	$\frac{Nº\ of reintubations}{Nº\ of\ patients\ in\ MV}$
ICU-AW	$\frac{Nº\ of\ patients\ >7\ days\ in\ ICU\ +\ ICU-AW}{Nº\ of\ patients\ >7\ days\ in\ ICU}$
Ventilator-associated pneumonia (VAP)	$\frac{Nº\ of\ episodes\ of\ VAP}{Days\ of\ MV}$
Catheter-related bloodstream infections (CRBI)	$\frac{Nº\ of\ CRBI}{Days\ of\ central\ venous\ catheter}$
Severe hypoglycemia	$\frac{Nº\ of glycemia\ values\ >40mg/dl}{Nº\ of\ total\ glycemia\ determinations}$
Diagnosis of brain death	$\frac{Nº\ of\ patients\ diagnosed\ with\ brain\ death}{Nº\ of\ deaths}$
Brain-dead donors	$\frac{Nº\ of\ patients\ diagnosed\ with\ brain\ death\ +\ organ\ donors}{Nº\ of\ patients\ diagnosed\ with\ brain\ death}$
Delays in discharge	$\frac{Nº\ of\ stays\ with\ delayed\ discharge}{Total\ Nº\ of\ stays}$

Table 2. List of quality indicators and metrics used to define them. ICU-AW: Intensive care unit-acquired weakness; VAP: ventilator associated pneumonia; CRB: catheter related bloodstream infection; MV: mechanical ventilation; ETT: endotracheal tube.

2.4 Patients

This analysis included data from all non-coronary patients attended in our 30-bed polyvalent ICU during the period comprising January 1, 2014 through December 31, 2018. Although the CIS also contains information about coronary patients, we excluded them because they are attended by cardiologists rather than intensivists.

All patients or their legal representatives provided written informed consent, and our center's research ethics committee approved the study protocol (CEIC Institut d'Investigació Sanitària Pere Virgili.Reference: 41/2016).

3. RESULTS

From 2014 through 2018, our ICU admitted 4546 noncardiac patients (64% men; median age, 63 years). Table 3 shows some MDS variables for this population. Median APACHE II score was

21 with a standardized mortality rate of 36%. Real ICU mortality was 15% and hospital mortality was 19.3%. The most common ICD-10 main diagnosis at admission was cardiocirculatory disease, accounting for 24%. Most (51.2%) patients were admitted from the emergency department, and most (77.3%) were discharged to general hospital wards.

Minimal Dataset Variables	
Sex, male – n (%)	2932 (64.5)
Age, years - median (IQR)	63 (50-73)
Type of patient - n (%)	
Medical	3309 (72.8)
Surgical	1237 (27.2)
Type of admission - n (%)	
Urgent	4278 (94.1)
Scheduled	268 (5.9)
ICU LOS, days - median (IQR)	4 (2-8.1)
ICU Readmission - n (%)	114 (2.5)
Hospital mortality – n (%)	877 (19.3)
ICU mortality – n (%)	679 (15)
APACHE II – median (IQR)	21 (15-27)
Standardized mortality - %	36.7
Main diagnosis at ICU admission – n (%)	
Cardiocirculatory disease	1092 (24)
Traumatic injuries and poisoning	842 (18.5)
Gastrointestinal tract disease	681 (14.9)
Source of admission – n (%)	
Emergency department	2230 (51.2)
OR	802 (17.6)
Destination at discharge– n (%)	
General ward	3517 (77.3)

Table 3. Minimal dataset results. ICU: intensive care unit; LOS: length of stay; APACHE: Acute Physiology and Chronic Health Evaluation; OR: operating and resuscitation room

Table 4 reports QIs extracted and calculated automatically by the tool for our ICU for each year included in the study.

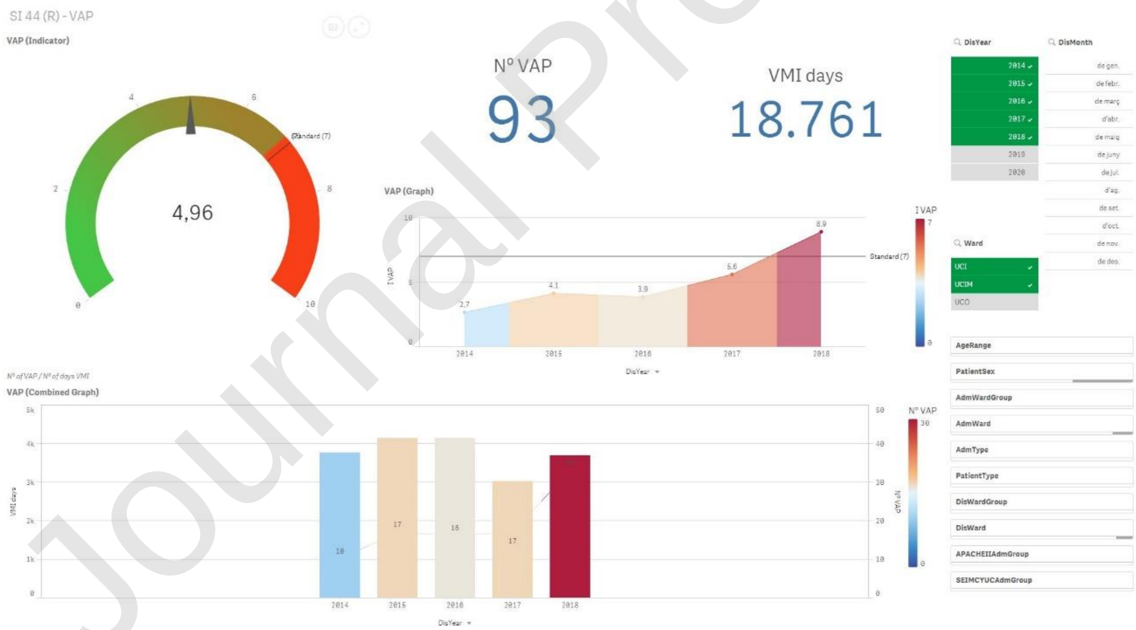
Quality Indicator	2014	2015	2016	2017	2018	Standard
Number of patients	846	860	876	973	991	
Barotrauma (‰)	0.6	0.3	0.2	0.3	0.6	< 3
Unscheduled extubation (‰)	6.1	4.8	6.8	7.3	7.6	< 15
Reintubation (%)	6.8	89	6.6	5.1	6.9	<1
ICU-acquired weakness (%)	0.8	9.4	10	15.7	20.3	< 25
VAP (‰)	2.7	4.1	3.9	5.6	8.9	< 12
CRBI (‰)	1.4	1.0	2.6	1.3	1.9	< 4
Severe hypoglycemia (%)	0.1	0.1	0.1	0.1	0.1	<0.5
Brain death diagnosis (%)	17	11.3	12.6	11.6	3.5	5-30
Brain dead donors (%)	38	80	68.7	80	50	60
Delayed discharge (%)	0.0	7.1	12.0	13.0	12.1	9

Table 4. Quality indicators per year. VAP: ventilator-associated pneumonia; CRB: catheter-related bloodstream infection. Standard values are based on the SEMICYUC's 2017 recommendations, except for unscheduled extubation, for which we used the 2011 standard.

Figure 2 shows two examples of the QI measured with our data management tool as displayed in the user interface: catheter-related bloodstream infection and ventilator-associated pneumonia.

A

B



4. DISCUSSION

Our data management tool allowed us to automatically obtain MDS information and some QIs to assess and improve the quality and safety of care given to our patients. Healthcare professionals have long been aware of the importance of measuring variables related to the quality of care and patient safety, and recent efforts to reorganize health systems to maximize "value" are increasing this awareness (6). Improving the quality of healthcare will require professionals from different backgrounds to work together to review processes and outcomes. In critical care, this approach requires the development of high-quality clinical databases, which will also constitute a rich source for clinical research and benchmarking. Clinical research networks are working with the data available in the CIS to answer clinical questions about care decisions and outcomes (5,8).

Various studies have shown that data can be used to reduce costs and improve the quality of care. Cismondi et al. (9) found that implementing a predictive model they created using the MIMIC II database could reduce the number of blood tests in ICU patients with gastrointestinal bleeding by 50%. Vranas et al. (10) found that a machine-learning approach could identify subgroups of patients with similar clinical trajectories despite different baseline characteristics such as diagnosis at admission or severity of illness. Bourdeaux et al. (11) found that using dashboards to alert clinicians when tidal volume exceeded the recommended value of 8ml/kg predicted body weight improved the management of this ventilatory parameter, increasing the proportion of time patients received both tidal volumes < 8ml/kg and tidal volumes <6ml/kg and decreasing the time it took for the tidal volume to drop below the threshold again after an alarm; moreover, this effect increased over time (12). The same group has also developed a decision-support tool based on machine learning algorithms that prompts clinicians to consider discharging patients who appear physiologically ready for discharge (13).

Some countries have developed national registries that provide participating ICUs with feedback and benchmarking on patient outcomes, enabling them to compare their results against national standards and similar hospitals, for example, the ANZICS registry in Australia and New Zealand, ICNARC in England, and NICE in the Netherlands (14–16).However, unlike our tool, these registries offer only an MDS and clinical data obtained on the first day of admission. In Spain, the SEMICYUC has developed a national registry where participating ICUs enter data regarding MDS and nosocomial infections in ICU patients (17). Participating ICUs can use their data to obtain infection QIs and compare their results with those obtained at national level. The NICE registry includes some data integrated from the CIS, but the other registries require local investigators to enter all data manually, representing a huge time investment that risks discouraging investigators and maybe even compromising data quality.

According to the Agency for Healthcare Research and Quality, good QIs should be relevant, actionable, and reliable; importantly, it should be feasible to collect the data needed to measure them (18). Our ICU uses QIs as recommended by the SEMICYUC (4). The QIs selected for the initial development of the tool described here had to be suitable for electronic data extraction, an important prerequisite for the feasibility of data collection. The specific algorithms used for this purpose might need to be adapted for use in other settings. For example, to assess the rate of reintubation in our ICU, the denominator we used was the number of days of mechanical ventilation instead of the number of scheduled extubations as proposed by the SEMICYUC, because our CIS does not register scheduled extubations. We realize that this represents a change in the standard definition of reintubation rate, but we think that it is justified because it simplifies data collection and makes benchmarking more feasible. Along these lines, in a study using a modified-RAND Delphi method to develop actionable QIs for appropriate antibiotic use in ICUs, Kallen et al. (19) decided that suitability for electronic data extraction should be a prerequisite for the QIs they aimed to develop.

Rather than focusing on obtaining QIs directly from the CIS, our efforts should focus on creating tools that integrate information stored in different platforms to enable automatic measurement. The huge amount of information stored in the CIS is insufficient to measure many QIs because they are based on data that is not available. Our dataset needed to incorporate information from different sources; thus, our data management tool extracted information from CCC©, our ICU CIS, and from SAP-ARGOS, the electronic health record (EHR) used in the rest of the hospital and configured at the institutional level, where we obtained administrative information regarding final outcome and hospital discharge. Other groups have dealt with this issue. McWilliams et al. (15) recently published the methods they used to curate a research dataset from routinely collected data by linking information contained in their CIS with data from a national audit dataset to obtain real-time clinical dashboards.

If ICUs make decisions and define improvement actions based on information obtained from the CIS, it is important to ensure the quality of the data when generating quality metrics. Kahn et al. (20) found a very low rate of agreement in race assignment between two electronic databases, one of which was an EHR. Some years later, this group harmonized data quality terms to a comprehensive unified terminology with definitions and examples and organized into a conceptual framework to support a common approach to defining whether EHR data are suitable for specific uses (21). Our group recently used this framework to classify discrepancies observed when comparing the MDS and quality metrics for our ICU automatically generated by our data management tool during a two-month period against gold standard values extracted from our CIS by physicians. We found that there were no significant differences between the values for any of the variables tested collected by our data management tool and those collected manually by trained staff; moreover, the 6 discrepancies observed in the data were distributed among 5 variables and were due to solvable errors (22). Similarly, Dziadzko et al. (23) found good agreement (100% sensitivity) between values of 11 key quality metrics calculated automatically with a near real-time data management tool and those obtained by a trained investigator in a comprehensive EHR review.

Reusing data from EHRs has also proven useful in research. MIMIC-III is a large, single-center database that integrates anonymized, comprehensive clinical data of patients admitted to the Beth Israel Deaconess Medical Center (Boston, MA, USA). Under a data use agreement, researchers around the world can access this database, and it has been widely used in academic and industrial research (24). The Critical Care Health Informatics Collaborative, a database that integrates EHR from adult ICUs from different centers in the UK, is also available for healthcare researchers (25). Although our data management tool was created to automate the measurement of QIs, it also allows *ad hoc* queries, making it useful for research. It is important to guarantee the quality of the data before using them in research to develop predictive models.

5. CONCLUSION

The results of our study are a first step toward the automatic measurement of actionable QIs to monitor and improve the quality of care in ICUs. Our approach will help professionals select the improvement strategies that work best in their setting, based on real data. Automatic generation of QIs in daily practice from quality electronic data reuse will make it feasible to develop a benchmarking model not based on manual registries and unsustainable human efforts; this change will also favor reliable research using artificial intelligence models.

Summary Table

What was already known on the topic:

- Integrating QIs into routine practice can improve quality and safety in ICUs and help ensure transparency
- QIs are assessed based on data collected manually; this process is time consuming and generates dissatisfaction among healthcare professionals

What this study added to our knowledge:

- Automatic generation of MDS information and QIs in daily practice from quality electronic data reuse is possible.
- It will make feasible to develop a benchmarking model not based on manual registries and unsustainable human efforts; this change will also favor reliable research using artificial intelligence models.

Authors' contributions

All authors contributed to the intellectual content, interpretation, and writing of the manuscript.

Statement of conflicts of interest

None of the other authors have competing interests.

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John Giba edited the manuscript.

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A.1. Abbreviation, name and description of each item

Abbreviation	Name	Description
Pats	Patients	An automatic ID code is created when a patient is admitted
Stays	ICU stays	Calculated by subtracting admission date from discharge date
MV	Mechanical ventilation	Checked in each nursing shift (each 8h approx)
DD	Discharge delay	Checked once per day when a patient is ready to be discharged but remains in the ICU
BDDon	Brain dead donors	Selected from a multi-choice panel created by the CIS configuration team of physicians
Gly	Glycemia values	Numeric value filled in by a nurse at each glycemia observation
HypoGly	Glycemia values <40	Label created in the ETL process depending on Gly
CVC	Central venous catheter	Times of insertion and removal recorded by nurses
BT	Barotrauma	Selected from a multi-choice panel of adverse events when the event takes place
USE	Unscheduled extubations	Selected from a multi-choice panel of adverse events when the event takes place
ReI	Reintubations	Selected from a multi-choice panel of adverse events when the event takes place
AW	Acquired weakness	Selected from a multi-choice panel of adverse events when the event takes place
VAP	Ventilator-associated pneumonia	Selected from a multi-choice panel of adverse events when the event takes place
CRB	Catheter-related bacteremia	Selected from a multi-choice panel of adverse events when the event takes place
Death	Death	Selected from a multi-choice panel with all ICU discharge options
BDDiag	Brain death diagnosis	Selected from a multi-choice panel with CIE-9 (until 2018) and CIE-10 (from 2018) catalogs
Gender	Gender	Automatically provided by the Hospital Electronic Health Record system at ICU admission
Age	Age	Automatically provided by the Hospital Electronic Health Record system at ICU admission
PT	Patient Type	Selected from a multi-choice panel created by the CIS configuration team of physicians
AT	Admission Type	Selected from a multi-choice panel created by the CIS configuration team of physicians
ReA	Readmission	Selected from a multi-choice panel created by the CIS configuration team of physicians
HM	Hospital Mortality	Automatically provided by the Hospital Electronic Health Record system at hospital discharge
HER	Electronic Health Record	Systematized collection of patient health information in a digital format
CIS	Clinical Information System	Computer-based system for collecting, storing, and manipulating clinical information
APACHE II	Severity of illness score APACHE II	Automatic calculation by the CIS

SM	Standardized Mortality	Automatic calculation by the CIS

This table presents an abbreviation, a name and a brief description of what each item is and how they are recorded into the system database.

A.2. Source and collection type of each item

	Collection type						
Source	Automatic assignment	Checklist	Multi-choice panel	Start-End fields	Numeric values	CIS calculation	Hospital EHR
Demographics	Pats			Stays			Gender/Age/HM
Observed Records		MV time/DD	BBDon/PT/AT/ReA		Gly/HypoGly		
Insertions				CVC time			
Adverse Events			BT/USE/ReI/AW/VAP/CRB				
Diagnoses			Death/BBDiag				
Derived Values						APACHE II/SM	

This table spots each item in terms of collection type and source. Items are represented by their abbreviation (see Table ST1.