Data-driven methods to improve quality assessment of intensive care units
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1.1 General Introduction

The interest in quality of care improvement has grown over the last decades and is essential to keep health care affordable, of good quality, and accessible for the public. From an economical perspective, there is a need for Dutch health care facilities to become aware and be critical about their expenditures. Health care expenditures are rising due to aging of the Dutch population [1], and there is more competition between health care facilities facilitated by the government. The health care inspectorate and the public ask for accountability and transparency about their quality of care. As a result, health care professionals are increasingly interested in and also performing internal quality assessment (QA). QA is a process where a health care improvement team internally compares their performance or externally with their peers for a specific quality of care measure, making use of data-driven QA tools. In the context of this thesis, data-driven implies methods that use data registered in a quality registry. The next step after assessment is that the improvement team investigates their internal processes after which they, if necessary, undertake actions to perform quality improvement (QI) initiatives.

Intensive Care Units (ICUs) treat the most critically ill patients at a hospital and provide the highest level of care. They also deliver the most expensive type of care. In the Netherlands, more than 90% of the ICUs participate in the National Intensive Care Evaluation (NICE) foundation [2], which was established in 1996 by a group of intensivists from six different hospitals. The NICE registry has the goals of facilitating QA and QI initiatives in Dutch ICUs. In NICE an ICU’s performance is compared to that of its peers, and accordingly it may start QI initiatives [3, 4]. For assisting ICUs in performing QA, and consequently improving their quality of care, the NICE registry has a toolbox. The methods in the toolbox are applied to various quality indicators and patient groups. An example is the method of case-mix adjustment and prognostic models applied to the quality indicator Standardized Mortality Ratio (SMR). The SMR is the ratio of observed and expected mortality, where an SMR greater than one implies worse performance of an ICU than expected with regard to risk-adjusted (RA) in-hospital mortality outcomes. An SMR less than one implies better than average performance. The NICE registry provides the results of these methods as feedback to their participants. ICUs can then use these results in for example the Plan phase of the Plan-Do-Study-Act (PDSA) cycle to determine where quality improvement is necessary. Another option is to use the results from the toolbox’s methods in the Study phase, and assess whether the interventions had the intended effect.

Results of some of the toolboxes’ methods are described in benchmark reports. The benchmark reports also include patient characteristics (age, gender, type of ICU admissions), and process measures such as percentage of ICU readmissions, ICU and hospital length of stay, mechanical ventilation duration, and glucose regulation. Outcome measures such as ICU mortality and in-hospital mortality are also included. The aforementioned information assists ICUs in interpretation of the results from the toolboxes’ methods and assists ICUs in the Plan and Study phase.

In recent years, new prognostic models have been developed, such as the Acute Physiology and Chronic Health Evaluation IV (APACHE IV) [5]. The new prognostic models give a more reliable estimate of the expected mortality resulting in higher
applicability with QA methods. There are also new visualization methods to report RA mortality, such as the variable life adjusted display (VLAD) [6], and Funnel plots [7]. Both these visualization methods are implemented in NICE registry’s toolbox. The combination of new prognostic models and QA pose many potential benefits, such as more accurate assessment of quality of care, timely detection of deteriorating performance, and benchmarking with other ICUs. However, there are pitfalls, such as incorrect construction or interpretation of the QA methods, and insufficient data quality of the mortality data used. This can lead to incorrect conclusions with regard to the quality of care.

Given the recent interest and increase in QA, clinical registries aim to expand the methods in their toolbox to satisfy the needs of their participants. The NICE registry is currently exploring more data-driven methods to add to the toolbox. However, currently the potential benefits and pitfalls of implementing and using these new additions to the NICE registry toolbox are unknown.

This thesis aims to answer the following research question:

**What is the potential of new data-driven methods that supplement the quality assessment toolbox for ICUs?**

The remainder of this chapter introduces the topics and more specific research questions addressed in this thesis. First, the NICE registry is introduced, followed by the topic of ICU data quality. Next, the topics of the new data driven-methods control charts and subgroup discovery are explained. Finally, we describe two categories of ICU patients for which the methods case-mix adjustment and prognostic models was applied from the NICE registry toolbox. The chapter concludes with an outline of this thesis.

**1.2 Intensive Care and National Intensive Care Evaluation foundation**

Currently, 86 ICUs actively participate in the NICE registry consisting of more than 90% of all Dutch ICUs. More than 700,000 ICU admissions are currently included in the NICE registry database. For the core dataset of the NICE registry, participants register demographic, diagnostic and severity of illness data on the first 24 hours that patients are admitted to the ICU, as well as ICU and in-hospital mortality and length of stay. Other NICE registry modules include quality indicators (pertaining to e.g. bed occupancy and glucose regulation), SOFA score [8], complications and severe sepsis. In this thesis, the focus is on the core dataset, using mortality, readmission and case-mix data. To allow accurate benchmarking with mortality data, case-mix correction takes place using among others the APACHE IV prognostic model [5]. As mentioned previously, the NICE registry provides an SMR as feedback to the NICE participants, using the observed in-hospital mortality and the APACHE IV predicted in-hospital mortality. Good quality of data is necessary for providing a valid SMR to NICE registry participants.
1.3 Data quality of Intensive Care data

Correct mortality status registration is necessary for providing a valid and reliable SMR to an ICU. Sufficient data quality also ensures comparability between ICUs when benchmarking. Currently, the NICE registry assesses the data quality of each ICU with onsite visits [9]. During these visits, NICE registry staff scores all data items of the core dataset for 25 randomly selected patients according to the NICE registry definitions. The scored items are compared with what the NICE registry participant originally registered for the same records. However, the small random selection of 25 patients during an onsite visit does not reveal all possible in-hospital mortality registration errors made.

When using automated data registration systems, systematic errors can occur due to software errors. This can ultimately lead to incorrect data exported to the NICE registry. During automated data checks of the import process of a dataset, the NICE registry discovers most errors with regard to abnormal values. However, this is not the case for incorrect in-hospital mortality registration, which can only have two different values (deceased in the hospital yes/no after ICU admission). To assess the data quality of in-hospital mortality (and long term mortality of ICU admitted patients), the NICE registry has set up a linkage with an administrative insurance claims database, the Vektis registry [10], which records the vital status of each insured client. Additional investigation of the data quality of in-hospital mortality is possible with onsite visits.

With regard to in-hospital mortality registration, we answer the following research question: What is the reliability of in-hospital mortality registration in the Dutch National Intensive Care Evaluation (NICE) registry?

1.4 Control charts in the Intensive Care

Recently, the use of Shewhart control charts [11] in health care and Intensive Care has emerged [4]. Control charts monitor the values of a quality indicator over time, and investigate if changes have occurred in the underlying process. When the chart indicates that a particular indicator (e.g. ICU mortality) has adversely changed over time, this may be a starting point for QI initiatives. Therefore, Shewhart control charts can be a possible useful addition to the ICU QA toolbox.[11].

A prerequisite to using Shewhart control charts is that their construction follows specific methodological criteria. If this is not the case, control charts may fail to generate warning signals when there is an adverse change in the process being monitored, or could incorrectly generate warning signals when no change has occurred. Such errors will reduce the utility of control charts for healthcare QA, and will undermine the trust of its users in this method. Before Shewhart control charts are routinely applied for quality monitoring in the ICU, it is important to establish the methodological requirements for doing so.

Control charts are also able to incorporate observed and expected (by a prognostic model) mortality data. Control charts give an intuitive graphical representation of the risk-
adjusted (RA) in-hospital mortality over time. There exist many different types of RA control charts and they differ in their criteria for determining a structural decrease in ICU performance. Currently, we do not know which one performs best in the ICU domain. Additionally, if we implement the control chart in the NICE registry toolbox, it is important to know in which scenario the RA control chart performs well. Examples of scenarios include the degree in in-hospital mortality increase and the size of the ICU in terms of the number of patients.

In this thesis, we answer the following research question: **What are the methodological requirements for using control charts in healthcare, and what is their efficiency for monitoring trends in ICU mortality?**

### 1.5 Subgroup discovery

Although patient mortality is considered the most important indicator of ICU quality, it is often difficult to set up a concrete improvement plan when the observed mortality is worse than what we expected for a specific ICU. Mortality is the aggregated effect of a large number of care processes at the ICU, and mortality figures like the SMR do not tell us which of these processes caused the poor overall mortality. A possible way to tackle this problem is to investigate whether there exist specific subgroups of patients whose mortality percentages are excessively high, and thus cause the overall increased mortality. We have developed an algorithm for discovering such subgroups, based on a combination of regression tree analysis [12] and adaptive boosting [13]. The algorithm’s output consists of one or more subgroup descriptions that translate into patient characteristics available at ICU admission and measurements executed during the first 24 hours of ICU stay.

The research question addressed here is: **Can we automatically discover subgroups of ICU patients responsible for poor in-hospital mortality outcomes?**

### 1.6 Quality of care for readmissions to the ICU

Premature discharge of an initial ICU admission to a ward or poor care provision at such a ward may lead to unplanned readmission to the ICU. Readmissions also cause a high burden on ICU resources. Therefore, unnecessary readmissions should be avoided as much as possible [14, 15]. The original APACHE IV prognostic model currently excludes readmissions to avoid counting more than one non-survival for the same patient and because their physiologic parameters might be influenced by treatment and hence no longer represent true severity of illness. As a result, the in-hospital mortality of readmitted patients is not part of the benchmark reports given to the participants of the NICE registry. To provide a comprehensive overview of the quality of care for readmissions, case-mix adjustment of the in-hospital mortality is necessary. A modification of the APACHE IV prognostic model is thus required. However, the adjustment is possible in various ways. For example, should the altered APACHE IV include information about the initial admission
and first readmission, or also include the second readmission. Therefore, it is first necessary to investigate the performance when altering the APACHE IV prognostic model in different ways.

The following research question is addressed: **What is the quality of care, based on the risk-adjusted in-hospital mortality, of patients readmitted to the ICU?**

### 1.7 Use of ICU data for influenza surveillance

The World Health Organization (WHO) stimulates countries to explore possibilities for Severe Acute Respiratory Infections (SARI) and influenza like illness (ILI) surveillance. During the early onset of an influenza epidemic, weak (e.g. in case of multiple comorbidities or of high age) patients will develop more severe influenza related diseases such as pneumonia. A consequence is a higher admission rate to the ICU of patients with a respiratory infection. Thus, there is a relation between the presence of an influenza epidemic and the number of ICU patients admitted with a respiratory infection. The National Institute for Public Health and the Environment (RIVM), responsible for ILI surveillance, search for possibilities for early detection of epidemics. One of their sources is the sentinel general practitioners (GP) registry. Including ICU data in their surveillance could improve the early detection of epidemics. Before combining these registries, an investigation of the relation between ILI data of the GP registry and ICU respiratory infection data of the NICE registry is necessary.

The final research question answered in this thesis is: **Can data of an ICU quality registry be used for surveillance of influenza like illness outbreaks?**

### 1.8 Outline of the thesis

Chapter 2 investigates the quality of in-hospital mortality data, as they are recorded in the NICE registry database. To this end, we linked the NICE registry data to an external administrative insurance claims database, and performed onsite visits to re-abstract, from the list of discrepancies, in-hospital mortality from different information sources. Based on the results, we assessed the reliability of in-hospital mortality as a quality indicator.

In chapter 3, we review methodological criteria for the application of Shewhart control charts in the health care domain. In addition, the literature was systematically searched for applications of Shewhart control charts in health care QA initiatives, and the methodological soundness of these applications was evaluated.

Chapter 4 describes a statistical simulation study that we conducted to assess the suitability of control charts for monitoring RA in-hospital mortality of ICU patients. In particular, we investigated the efficiency of such charts in detecting upward shift in in-hospital mortality. We compared seven different types of control charts, and investigated
the influence of both patient volume and in-hospital mortality increase rate on detection speed.

Chapter 5 evaluates the impact of different prognostic model calibration methods on the warning signals given by a RA control chart monitoring in-hospital mortality. The two options evaluated were internal and external risk-adjustment of the APACHE IV prognostic model, which predicts the in-hospital mortality. Internal risk-adjustment in this study implies using historic data of the ICU itself. External calibration uses historic data of all Dutch ICUs. In both cases, first level recalibration [16] was applied. We evaluated the warning signals given by the best performing control chart resulting from chapter 4.

Chapter 6 evaluates the ability of a subgroup discovery algorithm to detect subgroups of ICU patients responsible for an ICUs’ poor performance. The methods’ performance was evaluated by examining the number and descriptions of subgroups found for ICUs that had different levels of performance.

Chapter 7 alters the APACHE IV prognostic model to include patients readmitted to the ICU. With the altered APACHE IV prognostic model, calculation of the RA inhospital mortality outcomes of readmitted patients becomes possible.

Chapter 8 links the data of the NICE registry to the sentinel GP registry. With both sources combined, we investigated whether ICU data on respiratory infections reflected ILI activity in the general population, which relevant time lag existed between both data sources, and the predictive ability of ICU data in detecting influenza epidemics.

This thesis concludes with chapter 9, giving a general discussion. The discussion addresses the major results of this thesis, and answers the research questions.
1.9 References


