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Hospital Effect Determinants and Stability Identification on Performance over Time

Evidence from regional heart failure data on mortality and readmissions

Ph.D. in Management Engineering

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Table of Contents

Tables

Figures

Chapter 1. Synopsis of the Dissertation

Introduction

Disruptive technologies and analytical methods are changing the way knowledge is generated and managed in healthcare. Hospitals are coping with both old and new challenges on lowering production costs while increasing safety and effectiveness for improving patient outcomes and the overall healthcare system.

Hospitals have been struggling traditionally with finding the best way to acquire workable insights on how to contain rising costs. In this debate, scholars of health economics and public management have tried to make sense of hospital production by designing and performing efficiency and effectiveness measurements in different international contexts. Informed by the microeconomics literature, many studies have been using efficiency analyses to understand if the resources (inputs) were allocated in the best way to obtain the superior results in term of the outputs. In the case of hospitals, the first attempts leveraged on parametric techniques to explain production process through cost analyses (e.g., Wennberg & Alan Gittelsohn 1973; Sherman 1984; Luft et al. 1987; Vita 1990).

Later on, due to the complexity of defining a production function for hospitals as a unit of analysis, other studies have tried to make a better framework of the production activity by including other parameters related to the "size" of their structure and activity. The literature is rich with studies using variables like as the number of beds, cost of capital and staffs for identifying the inputs to be used within analyses of technical and allocative efficiency (e.g., Peacock et al. 2001; Simar & Wilson 2007; Akazili et al. 2008; Barros et al. 2008; Smith et al. 2008). Although their value, they have been focused on certain variables related to the cost of production and there are rare studies dedicated to understanding the production process when considering quality indicators. Past studies (e.g., Delli Fraine et al. 2010; van Ineveld et al. 2016; Katharaki 2008; Garavaglia et al. 2011) showed that other indicators related to quality of care should be considered when adjusting inputs and outputs to measure the performance of a hospital from a clinical and organizational perspective.

Considering hospitals, during the last decade the general expectations of improving the current healthcare systems have been changed dramatically and it is now widely connected with improving managerial practices and hospital-related peculiarities. Studies using frontier analyses – like as Data Envelopment Analysis (DEA) – have provide a clear view of the hospitals' potential inputs, outputs and the production process, assuming the hospital as decision making unit. However, studies like as Shams et al. 2010 showed that separate wards inside the hospital may have different characteristics that must be taken into account for measuring hospital quality of care (e.g., avoidable readmissions). In this regard, hospital managers are in need of specific evaluation tools that might inform them where and how to improve both efficiency and effectiveness of their organizations.

Some countries such as United Kingdom and the United States are successfully encouraging their healthcare providers to adopt evidence-based decision-making approaches, targeting different stakeholders and practitioners (Bottle et al. 2018; Barends & Rousseau 2018). Today's healthcare providers such as hospitals can get the advantage of more advanced analytical tools and approaches to use real world data (Yang et al. 2014). Handling and merging big amounts of data such as hospital administrative data makes it possible to guide their day-to-day decisions and combine their value and experiences with more mature sources of information such as local datasets to provide better services and products in an attempt for improving the overall quality of care. In this regard, the healthcare systems of the most industrialized countries – through the action of provincial/federal authorities – are consolidating policy procedures for reporting the performance reviews of different healthcare providers (Park et al. 2011; Keenan et al. 2008; Renzi et al. 2012; Werner et al. 2009) to increase accountability through the capacity to collect and analyse large bodies of real world data.

The literature about hospital performance measurement is addressing this challenge and argues the need for such publicly available reports through the use of routinely collected data (e.g., Renzi et al. 2012; Taxis 2005; James 2012; Fung et al. 2008). However, concerns are still in place if – and to what extent – these reports would lead citizens, or general practitioners on their behalf, to compare actually providers and choose one against the others in search of receiving better care and treatment. Analyses like benchmarking hospitals are yet emerging topics to make sense of the data while answering to what extent a characteristic/variable might be relevant and promising to make the difference between hospitals that are performing under the same political or geographical discipline.

Studies from different theoretical and methodological disciplines are confirming the need of hospital performance measurement and evaluation. Contributions from operations management (e.g., Ramanathan 2005; Elg et al. 2013; Asplund et al. 2015; Pfeffer et al. 2006), operations research (e.g., Rouyendegh et al. 2016; Brennan et al. 2016), medical statistics (e.g., Ross et al. 2008; Wang et al. 2007), health economics (e.g., Hollingsworth & Smith 2003), and public policy and management (Heitmueller et al. 2014) addressed the issue of hospital performance measurement and evaluation. However, they gathered partial – and often conflicting – evidence about that learning from the past data/practices might be a value-added for hospital performance improvement. It was in the late 90s that the promising adoption of evidence-based practices came out successful in clinical practice (Sackett et al. 1996) and shortly after this made researchers and professionals questioning its usability for decision making and problem-solving in other fields (Walshe & Rundall 1999; Briggs & McBeath 2009).

The trend finds its way in management and policy disciplines with different meanings yet inspired by the original approach to systematically improve the current situation of data collection, data analyses, and distribution of information for better decision making. Respectively, this adaptation required new justifications to fit the Evidence-Based Management (EBMgt) approach for the managerial or political usage (Morrell 2011; Botterill & Hindmoor 2012). By definition, EBMgt is the attempt to extract knowledge from different sources of data and information to transform it to practice in an effective and efficient way (HakemZadeh & Baba 2016; Aron 2015; Guo et al. 2017; Barends & Rousseau 2018). One aspect of using such an approach is about monitoring hospitals' production and compare them on their efficiency scores. Despite the many studies dedicated to the translation of the concept and models of EBMgt to managerial decisions, the actual implementation of such models in hospitals has slower trend than expected (Jaana, Vartak, et al. 2014; Aloini et al. 2018; Rousseau 2006), thus raising questions about which are the real users of these models, for which decisions, and if they are improving the way of managing, organizing, and delivering healthcare to citizens.

Past studies (e.g., Raghupathi & Raghupathi 2015; Chassin & Chassin 2013; Rouyendegh et al. 2016; Bram et al. 2015; Berenson et al. 2013) made clear the point that analysing hospital performance in terms of quality and efficiency is critical, and it concerns a variety of decision-makers, ranging from health professionals to hospital managers, from citizens to policy makers. Respectively, based on the health economic literature, hospital performance measurement and frameworks for effective production functions (Hollingsworth & Street n.d.; Hollingsworth 2014) are attempts to clarify the path of evaluating hospitals and individuals considering different sets of inputs and outputs.

As with the other service-based industries such as education, managers aim to make sense of the information and datasets available and come up with workable solutions, or insights, for improving their decisions. As an example about hospitals, improving quality of care needs decisions based on the most recent knowledge extracted from the available datasets to add value to their decisions by learning from the past and thus achieve superior outcomes. Similarly, considering operational problems concerning managers in hospitals, using organizational data and efficiency analyses can crystalize the current situation of production flow and help a manager to predict the future demand and plan for the needed process improvements or new policy establishments (Maestre et al. 2018).

European countries, such as UK, have been setting several priorities and investments to advance the knowledge on performance measurement and make hospitals responsible for their results and raise transparency through national healthcare reviews and reports. In Italy, the institutional foundation of the Italian National Healthcare System (NHS) – as for other tax-based NHSs in the most developed Countries – grounds on the ethical assumption that all citizens, regardless of their social and economic characteristics and where they live, will receive high-quality hospital care. One challenge addressed in such reviews and reports is that hospitals are assumed as homogeneous and able to deliver similar care. However, citizen claim that it is not the case and that hospital performance shows significant variance among the Italian Regions and districts. This claim founds support from a growing evidence coming from national audit programs – e.g., the National Program on Outcomes (*Programma Nazionale Esiti*) – or private initiatives that provide citizens with benchmarking data about hospital performance – among the others, www.doveecomemicuro.com – to base their decisions about where to receive care. In Italy, because of the present variance in hospitals performance in the same region, growing number of citizens are by-passing the closest hospital in search of receiving a higher quality of care. This behavior, even if welcome by those scholars who endorse competition among hospitals as a virtuous mechanism for granting superior performance over time, has significant shortcomings in terms of equality, quality and efficiency of care (e.g., oversaturate vs. spare capacity in the different health districts). In this view, understanding the role that management practices and hospital characteristics play to shape hospital performance is a priority to design and implement improvement strategies that might guarantee the achievement of superior performance given patients' and hospitals' characteristics.

With this respect, the progressive availability of real world data that are routinely collected might represent a promising source of evidence for running performance analysis (Moore et al. 2013, De Rosa et al. 2014). Real world data (RWD) by definition refer to a clinical data pool that when analysed will turn into available pieces of real-world evidence (RWE) to guide decisions in healthcare. As shown in Figure 1, the RWD pool contains a variety of data sources for different purposes and organizations that can be combined or used separately for a target decision.

Figure 1. Real-world data (RWD) sources in healthcare.

However, the emerging literature on EBMgt in healthcare shows that health professionals and hospital managers are still preferring sources with lower levels of evidence, such peer opinions, to adjust their decisions. This leaves the floor – since the need is still unmet – for those sources that are more robust for performance analyses.

Therefore, the evidence derived from hospital care measurement through available stored datasets – such as administrative data – is overlooked but rapidly attracting interest from health policy makers, administrative managers, and health professionals alike who are concerned with learning from past practices and data to better inform their day-to-day decisions. Knowing about which hospital variables affect the outcome of care the most can create empirical evidence for supporting better managerial practices and improvement strategies in the future. In this perspective, the integration of different RWD sources such as claims data and hospital (generated) data (Figure 1) offers new opportunities to use a significant amount of longitudinal information that has not been available in the (even recent) past. Based on the limitation of availability of these data sources in Italy for research, this dissertation gets an advantage of using a regional hospital administrative data repository containing hospital discharge forms for Heart Failure patients in the Lombardy Region (Northern Italy). Data about 200+ hospitals were collected by their Authority and have been checked for quality assurance.

The core topic of this PhD dissertation applies to healthcare management and is relevant for operations management in hospitals. By definition, operations management in hospitals includes a set of activities aimed at providing patients with services and products by transforming inputs into outputs/outcomes. Operations management contribute to hospitals' efficiency and effectiveness by improving their performance over time. Therefore, this dissertation, by means of the four papers of which is composed, contributes to the hospital quality of care measurement literature, trying to crystallize the effect of potential hospital related characteristics on quality of care provided for a single service and investigating the stability over time of these potential factors. Following, the rest of the Chapter 1 will give a brief but comprehensive overview of 1) the research context and objectives; 2) the research process and the structure of the dissertation; 3) the theoretical background; 4) the overall contributions; and 5) finally, the main conclusions after presenting study limitations and future directions.

Research context and objectives

Hospital performance measurement

In different research fields, the term "performance" has different meanings based on the focus of each study. In healthcare, defining performance is closely related to the specific goals and values of the target stakeholders, such as managers, professionals, patients, insurers, policy-makers. Considering hospital managers as the main decision-makers concerning with services performance, it is important to understand what affects most the efficiency and effectiveness of their organization and what could be learnt from their peers/rivals in the same institutional context (Gravelle et al. 2014). In Italy, hospitals are performing under the same regional reimbursement scheme which is based on tariffs that are independent of hospital performance. This can lead studies focusing on other variables that differ providers such as hospitals from one another free of considerations of treatment costs when comparing rival.

As necessitates by performance measurement steps, after adjusting specific performance indicators then managers need collecting information and data. Next, the process requires the use of relevant statistical modeling to determine results (Frolich 2012). Analysing organizational data such as those collected routinely through the organizational processes with help in presenting information for the specific issue and making evidence-based decisions.

This approach is coherent to what is known as the Evidence-Based Management (EBMgt) movement inspired by its match in clinical domain known as Evidence-Based Medicine (EBM). As stated by Aron (2015) and Briner ET all. (2009), when confronting a decrease in quality of care for certain patients, EBMgt approaches can provide hospital managers with a clear understanding of the current situation of their organization and of which variables are affecting this decrease, thus underlying a guide to action.

Healthcare is facing nowadays a greater demand for collecting and assessing performance data gathered in hospitals (e.g., Abusharekh et al. 2015; Raghupathi & Raghupathi 2015; Dobrzykowski & Tarafdar 2015), data availability from different sources, and willingness to make sense of the performance information for public policy and decision making (Heitmueller et al. 2014). Investing in performance analyses for learning from the past processes and data will result in reducing the consequences of making poor decisions and better understanding of quality of care measures applications. Additionally, the availability of performance measures will benefit citizens in broader perspective with an increased public awareness on what should be important when choosing a hospital while reducing performance results/rankings misinterpretations when presented to the public audience.

For sure the topic of hospital performance is a broad theme with several different perspectives to consider, and it is beyond the scope of this dissertation to consider some at once. While past studies have investigated widely how patients' characteristics (age, gender, disease severity) shape hospital performance through the systematically collected data (administrative health data), hospital characteristics (public/private ownership, teaching/no-teaching structure, mean length of stay, number of complicated cased and operation, and etc.) have been widely overlooked, with very limited evidence provided with clinical perspective. This PhD research aims at shedding original and definite light on which (and how) hospital characteristics affect hospital performance and if there is any evidence of the effect consistency over time.

Coherent to this line of discussion, the first objective of this PhD dissertation is to improve the current understanding about which are the sources of evidence, analyses and kinds of managerial decisions/practices that different groups of decision-makers refer to when analysing performance. This objective was satisfied by conducting a systematic literature review and completing a content analyses of driven articles to shape a framework for using EBMgt approaches for decision making in healthcare. The findings helped me to identify the literature gaps and limitations addressed when considering hospital managers using of available data sources for decision making when measuring organization performance.

Based on the literature results together with expanding the literature on the topic of quality of care measurement (Barclay et al. 2018; Walshe & Rundall 1999), the second research objective was set to address the debate around which are the models and variables significant when considering mortality and readmission outcomes to the certain population for comparing hospitals. Moreover, some significant covariates have been tested considering patient's previous history and treatment during the hospitalization. Next, mortality and readmission models were analysed and compared together on the possibility of using a combined outcome and how much it depends on patient's history of treatment and care. This technical considerations were questioned using variety of administrative data in different countries and settings and choosing mortality and unplanned readmission like the one by US Centers for Medicare and Medicaid Services Hospital Compare Overall Hospital Quality Ratings (CMS 2016). As such, the composite outcome was suggested aiming at simplifying the complex information in rating hospitals. Later on, the findings of this primary step, helped in testing new covariates for predicting mortality and unplanned readmissions of HF patients and discuss the use of combined outcome by managers as an alternative to determine hospital performance.

Respectively, one general issue addressed in the literature and findings of the composite outcomes was concerned around the need for more clarification of not only patient-related covariates but also on hospital-related characteristics that potentially affect the quality of care. Using administrative data, the first step was learning from the data and make sense of the relation and priority of each potential determinants of quality of care might have when considering a certain population. What was clear from the literature was that different providers (in this thesis hospitals) have different performance rates and what makes them different in achieving a good efficiency and effectiveness is not only related to patient's characteristics but also the hospital itself. Besides its clinical importance, it is also crucial for managers to learn from the other peer's workable and good practices when providing services to transfer the knowledge. One example is whether considering different admission wards has a role in patient's treatment and services received during hospitalization or not.

The third research objective was shape around isolating the effect of the hospital related characteristics on performance. Respectively, the hospital determinants identifications empirically analysed by shaping new models with hospital related covariates to explain different outcomes. The results shape my third paper and were confirming of existence of such an effect specially when considering readmission rate. Respectively, the focus of the following study was set on considering 30-day unplanned readmission rate as the most relevant quality of care outcomes concerning managers and policy-makers for hospitals for examining the stability of 'hospital effect' over time which has been set for the last objective to complete the previous ones. The last paper (number four) is an attempt to answer the question if hospitals show any consistency of maintaining the quality of care over time while connecting all path have been undertaken over previous three papers to raise understanding of what works for hospitals to improve their performance over time and what they can learn from one another.

Thus, the structure of current thesis research was based by the findings of each research objective and followed by focusing interest for the identified literature gaps and limitations and innovative contributions for the next ones in order. In the next section, a brief description on each paper derived based on these assumptions is provided connecting to the main research objectives (shown in Figure 2).

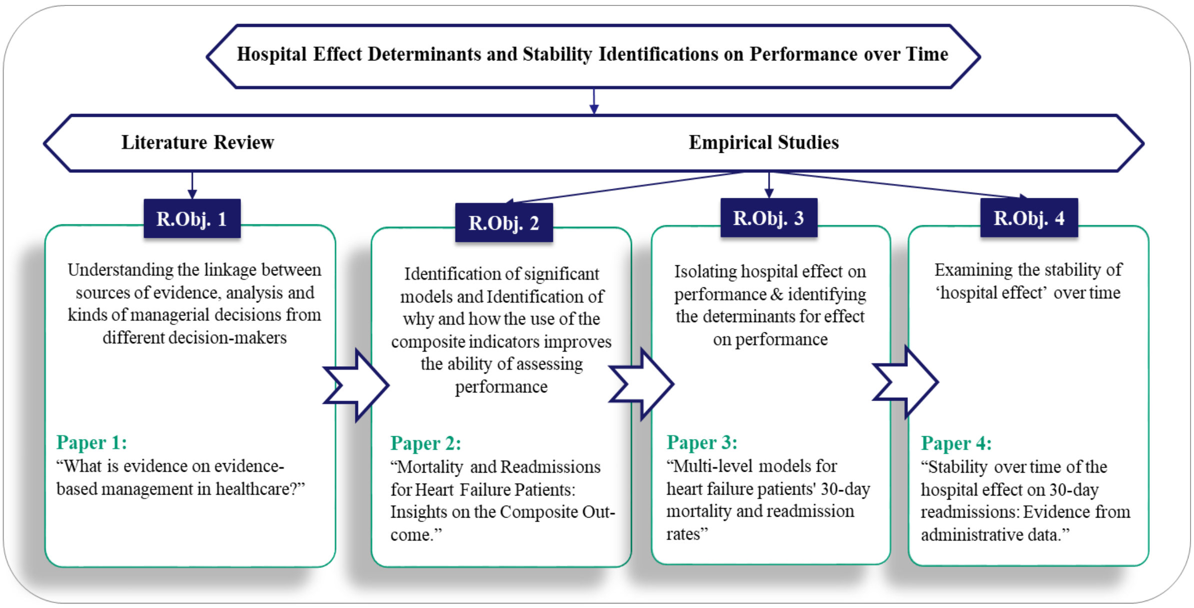

Figure 2. Publication order based on the research questions

Research process and structure of the dissertation

This PhD dissertation is composed of four stand-alone papers, which are fully presented in the second chapter. The order of presenting papers is according to the research process undertook for achieving each research objective that are connected and are were identified consecutively one after the other by research findings and expanding the relevant literature. Therefore, each paper, which is a complete piece of work in itself and provides its own contributions to previous knowledge, sets also the stage for the one that comes next. Following in this section, a summary of each paper will be presented to clarify how the findings of each paper helped researcher to expand the work and make sense of the data for answering more focused research questions.

Paper 1: "What evidence on evidence-based management in healthcare?"

The first study investigates the ongoing debate on whether and how evidence-based management (EBMgt) practices should be developed and implemented in healthcare by conducting a systematic literature review and analyzing the results based on an Inputs-Processes-Outcomes framework. EBMgt has been reinforced by the increasing availability of massive datasets from very heterogeneous sources coupled with an improved capacity to analyse them. Scholars of healthcare management and decision management as well as policy-makers and healthcare professionals are investigating to what extent the consolidating bodies of knowledge and practices about EBMgt are informing and supporting managerial decisions in healthcare.

Respect to past contributions and reviews on EBMgt topic in healthcare (e.g., Young 2002; Jaana et al., 2014; HakemZadeh and Baba 2016), this study have focused on the overlooked relationship between managerial decisions and sources of evidence, with specific reference to different groups of decision-makers by adopting a process perspective that has been incorporated into a novel theoretical framework based on the Input-Process-Output (I-P-O) model (McGrath, 1964). Using Scopus database, we (me and my colleagues) carried out a systematic literature review on EBMgt in healthcare. Inclusion and exclusion criteria have been crystallized and applied. Only empirical journal articles and past reviews have been included to consider only well-mature and robust studies.

The findings of this research showed that from the several sources of evidence available, two of them had been used by healthcare managers for decision making so far; namely: published studies and experts' opinions. Evidence is analysed through: literature reviews, data analysis of empirical studies, workshops with experts. Main kinds of decisions identified as: performance assessment of organization units, staff performance assessment, change management, organizational knowledge transfer and strategic planning. Finally, the most users of evidence-based approaches in healthcare are still professionals like physicians and nurse leaders. Health professionals like physicians are used to refer to "expert opinion"– according to the well-established EBM discipline – for health-related issues and decision-making, they refer to evidence with lower robustness when dealing with managerial practices. Also, both health professionals and hospital managers, used administrative data and medical records in a limited number of cases which will left the debate of using such a sources to design and implement EBMgt initiatives to improve hospital performance.

Driven findings necessitate further investigation on the topic when focusing on performance measurements using organizational data sources such as administrative data that are available data sources and routinely collected without any pre-adjusted political objectives and include a wide variety of information regarding the patients, wards, and hospitals. In Italy such data were collected for almost two decades and contain information as regard of the patients, wards, and hospitals (Patient level: age, sex, length of stay, comorbidity weight, and etc. Hospital level: number of admission, mean length of hospital stay, % surgical DRGs, type of hospital, and etc.)

As such, the empirical parts of this dissertation are conducted around hospital performance measurement with a special focus on quality determinants and the possible role of management practices to shape performance. I get advantage of the data sources available for research by Lombardy Region including hospital claims data and discharge abstracts for different groups of patients. At this time by expanding the literature on using administrative data for performance analyses, I find out that such analyses need me to focus my interest on a single service provided within hospitals. This focus will allow me to use mature and well-developed data analyses such as multi-level logistic models to make sense of the data and have a deep look at the current situation of hospitals Lombardy in Italy while identifying the current connection and importance of quality of care determinants like 30-mortality, 30-day unplanned readmission rate, mean length of stay, and etc.

Paper 2: "Mortality and Readmissions for Heart Failure Patients: Insights on the Composite Outcome."

Literature review findings show that, although the undoubtable importance of quality of care measurements for hospital managers, patients, practitioners and regulators, there is not enough attention in implications for care outcomes and managers and practitioners still using peer opinions rather than using more reliable sources such as administrative data to learn and highlight management practices.

The second study is an attempt to do so by first focusing on a single service provided by hospitals and quality determinant. Yet, the performance of a hospital is closely related to a variety of topics and fields and literature recommends choosing a specific single service for such quality measurements.

This study gets an advantage of administrative data which contains data from countable hospitals inside Lombardy Region and by the single service, the focus is on the heart failure (HF) patient's admissions over 2010-2012. These data were available for this research from Italian Ministry of Health and Lombardy Region Welfare General Directorate and have been recently opened to approve studies with the aim of unfolding the informative value stored in them and informing evidence-based improvement strategies.

HF is a common cardiovascular condition in the aging population of the most developed Countries including Italy. These patients are a priority for both healthcare regulators and professionals and despite the significant technological advancements experienced in the last years, when admitted in hospital, they show a high risk of 30-day mortality (Vaartjes et al. 2010; Teryl K. Nuckols 2015) as well as a high probability of incurring in multiple unplanned 30-day readmissions (Chiang et al. 2011; Gu et al. 2009; Au et al. 2012; Keenan et al. 2008). The statistical model investigates the effect of patient characteristics on mortality and/or readmission using a multivariable logistic model. We estimated the predictive model using a random sample of about 70% of our dataset and presented the results in details in the paper in the next chapter regarding the 30-day mortality, 30-day unplanned readmission and for both outcomes combined.

Findings on the combined outcomes showed that some variables are significantly predicting the combined outcome like Length of stay and renal diseases; which were associated with readmissions but not with mortality. Based on the findings, this focus had the undoubted value of allowing the researchers to go more in-depth and thus improving the predictive ability of their models (e.g., (Lim et al. 2015)), there is also the need for academicians, healthcare regulators, and professionals to consider that mortality and readmissions are competing outcomes and for adjusting models for including hospital characteristics, it is thus critical to understand the specific contribution of each of the two outcomes to the combined one.

Respectively, the model allowed us to consider both outcomes by including proposing variables in two levels adding hospital-level covariates to analyze the effect of management practices on health-related outcomes. Details of this step are presented briefly as follow and presented in the second chapter of this dissertation in details.

Paper 3: "Multi-level models for heart failure patients' 30-day mortality and readmission rates: the relation between patient and hospital factors in administrative data."

Based on the second paper findings, hospitals show differences in terms of quality of care. Past researches have investigated extensively how to implement risk-adjustments based on inputs, case-mix or other patients' characteristics to limit potential biases when benchmarking hospital performance (Wallmann et al. 2013; Lingsma et al., 2018). Despite the value of these contributions, three limitations still puzzle our understanding of how to provide regulators and hospital managers with evidence-based guidelines about how to improve quality of care. First, past contributions underemphasized the role of management practices, privileging patients-related covariates (Au et al. 2012; Wallmann et al. 2013) or hospital resources (Häkkinena et al. 2013). Second, past studies that investigated the relationship between management practices and quality of care proved it through either self-reported surveys or expert opinion. In this view, regulators and hospital managers pointed out that current evidence about the existence of this relationship is not enough robust as studies on hospital performance based on administrative data (e.g., Bottle, Sanders, et al. 2013; Murdoch & Detsky 2013; Cook & Collins 2015)–even if limited to patient-related covariates. Third, 30-day mortality and 30-day unplanned readmission are competing outcomes (Di Tano et al. 2015). While the mainstream approach is to analyze them as a single outcome (Au et al. 2012), an increasing number of scholars (Krumholz et al. 2006; Wallmann et al. 2013) analyzed them separately to better understand what explains different quality of care and the role played by different managerial alternatives (Bonow 2008; Glance et al., 2017).

With this study, we developed and empirically tested, through administrative data, an original hierarchical logistic model that combines individual-level covariates about patients' characteristics with hospital-level ones about management practices to gather more robust evidence about the role that management practices play. Data comes from the hospital discharge abstracts for Heart Failure (HF) patients in the Lombardy Region (Northern Italy). As indicators of hospital quality of care, we considered the well-established measures of quality of treatment on short-term outcomes for Heart Failure (HF) patients (Bonow 2008; Bottle, Middleton, et al. 2013): 30-day mortality and 30-day unplanned readmission.

Our results confirm that hospital-level covariates do affect the quality of care and that 30-day mortality and 30-day unplanned readmission are affected by different managerial choices paving the way for the design and implementation of evidence-based improvement strategies. While some variables like percentage of surgical DRG and the hospital type are significant for mortality, the mean length of stay is significant for unplanned readmission, showing that mortality and readmission rates might be improved through different strategies.

Paper 4: "Stability over time of the "hospital effect" on 30-day readmissions: Evidence from administrative data."

This study investigates the stability over time of the "hospital effect" (i.e., covariates at the hospital level) on 30-day unplanned readmissions. Based on the findings demonstrate through the previous papers, hospital managers and professionals can affect positively (or negatively) hospital performance through the adoption (or not) of management practices that we refer to it as 'hospital effect' in this work.

When dealing with similar cohorts of patients, hospitals can organize themselves to achieve superior performance in terms of effectiveness, safeness, and efficiency. In fact, evidence about what makes the hospital work (or do not work) would inform the design and implementation of effective policy initiatives – as well as improvement strategies – aimed at not only narrowing the gap between the best and the worst performers (Cadarette & Wong 2015; Kiivet et al. 2013; Roos et al. 2004) but also reducing variation in the performance distribution in general perspective.

In this study, analyses have been done over three years (2010-2012) separately for comparing hospital performance in term of 30-day unplanned readmissions. Best/worst providers were identified through a multi-level model and distance function that combines both patient and hospital covariates in each year. Our results confirm that even if hospital covariates (and the connected managerial choices) affect 30-day unplanned readmissions, their effect, contrary to expectations, is not stable in the short-term (three years). The results are interesting as they raised the question of what makes the difference between these providers in the same region through the years. These results called for further investigation using data for decisions regarding the efficiency of providers as well.

Theoretical background

The next paragraphs present an overview of the theoretical background of the four papers composing the dissertation, in order to position their focus within previous research and theory. Readers are directed to the second chapter for a fine grained relevant theoretical backgrounds for each paper.

Evidence-based management

Evidence-based management (EBMgt) by definition refers to "the systematic application of the best available evidence to the evaluation of managerial strategies for improving the performance of health services organizations" as stated by Kovner and Rundall (2006, p. 6). The concurrence of using several databases together with evidence-based approaches in healthcare, encourages hospital managers as well as healthcare professionals to "the conscientious, explicit and judicious use of current best available evidence in making decisions relevant to the care of individual patients" (David L Sackett, William M C Rosenberg, J A Muir Gray, R Brian Haynes & Richardson 1996).

Recent developments have increased the promise and imperative of evidence-based practices assisting decision-making processes in management and policy fields as well (Morrell 2011). Vast growth in evaluative clinical sciences; advances in information technology (IT) (Afyouni et al. 2015; Fernández-Luque et al. 2015; Holzinger et al. 2016), and growing acceptance that evidence-based frameworks in social sciences such as management are helping to understand what works for service based sectors like healthcare and addressing policy challenges (Oliver et al. 2014; Omachonu 2010).

EBMgt in healthcare is a controversial area of investigation, satisfying the need of relying on significant data and sought to promote rigorous analysis of service programs and policy options in order to improve the quality of decision-making especially related to the higher level of organizations like hospital managers (Head 2010). Improving healthcare quality is one example of the application of evidence-based methods trying to decrease the gap between the theory and practice of healthcare management and economics in organizations like hospitals.

Important advances have been made in the healthcare management are promising the better dissemination of research findings to encourage managers and leaders of organizations to use advance and more robust evidence for decision making.

In the literature, there are studies which consider the importance of adoption of EBMgt by suggesting frameworks in facilitating the decision making processes and change management for managers, policy-makers, and professionals (Veillard et al. 2005; McAlearney et al. 2014; Jaana, Teitelbaum, et al. 2014; Nelson & Pilon 2015). EBMgt approaches are closely related to implementation of change management and knowledge transfer in hospitals targeting managers, physicians, nurse and IT leaders to base their decisions and activities on the basis of best evidence that should come from experience and previous practices. From the many decisions, one crucial decision is those affecting the overall effectiveness of services and quality of services provided for certain population which makes it coherently crucial as hospitals are subject to governmental and regulatory forces that drive change and improvements.

Performance measurement in hospitals

As mentioned earlier in the research context, performance measurement provides scholars and practitioners with an overview of the current and past state of organizations using different data sources and performing different analysis based on certain goals.

Performance measurement systems and approaches helping to promote continuous improvement processes among the service providers such as hospitals. Having a broad perspective of the use of performance measures for a hospital will concerns all kind of decision makers in healthcare, and will benefit citizens with valuable information to be used for choosing a hospital over another (Lingsma et al., 2009). Distribution of performance information allow patients or general physicians to compare hospitals/providers to select the best case for their treatment. This in return will motivate providers to improve performance to attract public recognition and demand (OECD Reviews of Health Care 2015).

Although the background on performance measurement is rich with studies trying to address quality of care improvements for hospital services, experts are still struggling on which are the most appropriate set of measures to evaluate and compare providers in regional or national level (Veillard et al. 2005; McCoy et al. 2016; Rouse et al. 2010). Measuring hospital performance indeed require different determinants from different lenses; political, clinical, or economical that could be for Research, service improvement, Referrer and patient choice, resource management, or accountability" (WHO Regional Office for Europe Health Evidence Network (HEN) 2003). From the political point of view, new national reports and programmed are insisting on the importance of the performance measurements for increasing safety, effectiveness, and efficiency and pushing providers to improve process and practices for a better outcome and keeps them accountable for the quality of health care (Pronovost & Lilford 2011).

This study was also inspired by the OECD Reviews of Health Care Quality in Italy (OECD2015 2015) as well. The findings from this review echo the need for regional performance assessments to overcome the differences in performance inside and between regions. Indicators like 30-day mortality and 30-day readmission for HF patients were highlighted for assessing the problem within regions. This underlines the need for regional performance evaluations while clarifying what makes the change and differ each local hospital from another. Additionally as marked in this report the role of other available data sources should be assessed and used for improvement strategies: *"A particular challenge will be to better use patient feedback and other sources of routine data to encourage health professionals to reflect on and improve their practice."*

Health administrative data

From the many sources of evidence and information in healthcare, one common source to track quality measures include Administrative Health Data that apart from the structure or ownership, each hospital is committed to routinely collect and report this data to the national/regional authorities. By definition, healthcare administrative databases are large repositories of data on healthcare systems that are routinely collected by healthcare providers and other institutions (e.g. civil registry). They provide a variety of already stored data with an ongoing collection process and they may contain information on hospitalisations, outpatient care, drug prescriptions, rehabilitation services, implanted end prostheses, psychiatric service, etc. Thus, the reason behind their collection is for reimbursements purposes (e.g., in the form of discharge abstracts).

Like the other data and evidence sources in healthcare available for performance evaluation, these datasets have advantages and shortcoming. One big advantage of using administrative data for performance evaluation include low collection cost, easy access, large samples, and coverage of the entire population over long observation periods in a real-world perspective without stringent patient selection common to clinical trials (Gutacker et al. 2015; Yampolskaya et al. 2004). On the other hand, compared with other clinical datasets such as registries or electronic medical records, they lack clinical data that might help to characterize the patients and their clinical history and thereby give greater potential for risk adjustment and risk prediction (Mazzali & Duca 2015).

While, considering only performance measurement through administrative data, many recent studies focused on the so-called 'hard clinical outcomes', such as patient survival, unscheduled hospital readmissions, and hospital length of stay, while different variables have been used based on the aim of each study (e.g., (Bottle et al. 2014; Eijkenaar & Van Vliet 2013)). Similar to Swaminathan's (2008) findings, we expect that monitoring yearly trends of observed performance out of expected ones may lead us to probabilities of having the same performance in next years (or not).

Contributions of the dissertation

This PhD dissertation contributes to the field of healthcare management and economics within hospitals and quality of care improvements incentives by bridging the gap between theory and practice. Based on the literature, in an international context one big source of evidence for decision making in healthcare is using already stored datasets that contain information from different levels of patients, wards and hospitals like administrative data. Inspired from the works done in many other high income and developed countries in Europe or across the world, the focus of this research was also on considering more variables when defining production process for hospitals and trying to highlight the importance of the organizational characteristics that managers could change for improvement purposes. Lombardy Region is also one of the best regions in Italy which is advanced in healthcare management and economics by overcoming many issues for improving the quality of care outcomes for citizens till today. When it comes to assessing the already efficient regions healthcare outcomes/outputs, using local data sources such as administrative health data have been used in this PhD research for certain population will empower its managerial potentials to focus on what makes the difference between different providers like hospitals in the same financial context. In this stage, the difference could be investigated in the details by considering that different wards inside of hospitals could have a different impact on the overall effectiveness and their performance could be assessed separately to inform manager's decisions when competing in achieving the excellence in their production processes.

During this PhD dissertation several quantitative data analytics and original models have been conducted with a focus on outcome-based quality indicators such as hospital mortality and readmission rates to test the impact of other external environmental factors related to each specific provider such as ownership or % of surgical DRGs on quality of hospital services. Considering the case mix of patient characteristics and their previous background help me focus on the processes of hospital care and service organisation (Laudicella et al. 2013) when measuring quality of care provided for the patients.

The empirical findings of this dissertation suggest several contributions to the field of healthcare management and economics. First, literature findings illustrate that hospital managers as well as professionals are the most users of EBMgt approaches that are mostly concerned with performance measurement and knowledge transfer within healthcare organization. It came out that the most investigated sources of evidence for managers and professionals are experts/peers opinions. On the contrary, the role of other data sources like electronic medical records and administrative databases were overlooked in the last decade.

Second, as found on the second paper analyses, considering the composite outcome does not improve the comprehension of the factors associated with mortality and readmissions yet hospitals were not achieving their potentials when considering 30-day unplanned readmissions for HF patients. This will highlight the sensitivity and importance of case of readmission rate for professionals and managers when evaluating quality of care. We included the ward of admission as covariate in our model, and the results suggest that patient pathways are highly important and effects on the outcome of patient.

The third paper findings approved the existence of hospital effect on performance over time and our original models tested and examined the use of hospital administrative data for performance measure and identification of new covariates when measuring hospital performance in matter of quality of care. Our results show the key role of managers within hospitals to improve quality of care by learning from previous data and effective management practices.

Performance of a hospital should be defined using both patients' and hospitals' characteristics together.

Similarly, the last analyses performed in the last paper approved that respecting to HF patients, the choice of the admission ward at the first hospitalization, the hospital mean length of stay (MLOS), hospital percentage of surgical DRGs, and hospitals structure were the most significant measures identified through analyses for explaining the outcomes of treatments.

Healthcare management scholars might consider the effect of these variables for future research and also for other pathologies. Respect to the policy makers, there are many reports debating the benefit of MLOS reduction plans to help hospitals manage their cost, while based on the driven finding of this work, such reduction decisions may harm the patient and affect their health outcome. In this view, hospital managers are responsible to manage this trade-off considering other impacts on patients' health. Expected advancements of knowledge are detailed in the followings.

Limitations and future directions

Although, the literature were mentioning using other RWD sources – rather than those used in this work – for providing evidence on individual's performance (e.g., wearables and social media), the development and exploit of what have been called as "smart data" were less relevant for my case (i.e., healthcare management and hospitals single services performance measurement), while instead they are more and more important for patient-centred healthcare solutions.

As like many other data sources, using administrative data for analyses have pros and cons that have been mentioned in details in papers. But in between, using these data needs access to the data, quality assurance, and skills for data management and making the results reliable to use. In my case the quality of data have been checked by the Lombardy Region and the all parts of data management and analyses were double checked with my colleagues who are expert on medical statistics in both management engineering and math departments. Additionally, this dissertation is conducted at the micro level, and focuses on the healthcare sector and from that on hospital single services provided for HF patients, therefore, the findings may be not immediately transferable to other industries. Therefore, future studies could investigate the same research questions perhaps in other service based industries like as education in order to prove the generalizability of our findings.

In particular, this thesis gets advantage of specific data source as administrative data which indeed includes a certain amount of information specially when dealing with hospital characteristics future analyses are needed in advancing these analyses as well as the longitudinal dataset by integrating different data sources including bigger variety of variables that can clear the effect of the hospital and managerial practices (e.g., human resources) on performance of hospitals in matter of the effectiveness and efficiency. Similarly, further qualitative research could value this work on the individual and/or group levels of decision makers such as hospital managers, senior physicians, and health regulators as demonstrated in the literature review, whom they are the target users of such a results driven from data analyses in healthcare. This will profit the work in order to explore hospital managers' and professionals' preferences and biases when dealing with evidence-based decision-making.

For the matter of the generalizability of this PhD dissertation, the results are driven from the specific data for the specific population over time and coherently it makes it hard to easily consider any expectation of achieving similar findings from other healthcare systems, since the effect of institutional arrangements did not consider in this thesis and hospitals were consider within the same payment and normative framework. Though, the concept and research questions used in these four papers could be generalized and used for other healthcare systems in matter or target users/decision makers. The research questions were consistent and inspired by the literature and were shaped when testing the data with different models. Likewise, statistical models performed in this work were identified through the relevant literature that includes variety of other predictive models and approaches like efficiency analyses and spatial econometrics analyses to also consider the effect of peer rivals on the performance while comparing the way each provider could be ranked and compared through time.

Conclusions

Despite the extant contributions from different disciplines – like as operations management, medical statistics, health economics and public management – in healthcare management literature concerning performance measurement evaluations and results, evidence on the effect of hospital characteristics affecting performance is incompatible. The current literature shows couple of main limitations. First, past studies gathered evidence through the use of single methods without testing the reproducibility of results through other methods or the different informative value for decision-makers at both institutional and organizational level. Second, past studies relied on partial datasets that limited researchers' capability to explore the different determinants of hospital performance, privileging traditional covariates about the patient and hospital characteristics. Data about hospital management practices have been widely overlooked or collected through episodic–neither integrated nor longitudinal–surveys administered to hospital managers.

In this respect, as presented earlier in Figure 2, this dissertation contributes to increase our knowledge on: i) Understanding the state of data as sources of evidence and kinds of managerial decisions/management practices that different groups of decision-makers use for their decision making, ii) understanding hospital effect on performance by identifying the determinants for effect on performance and finally, iii) examining the stability of 'hospital effect' over time.

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Chapter 2. Collection of papers

Paper Number 1: What Evidence on Evidence-Based Management?

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Afsaneh Roshanghalb collaborated as the correspond author in all parts of this literature review.

Structured Abstract

*Purpose_* This manuscript discusses the main findings gathered through a systematic literature review aimed at crystallizing the state of art about evidence-based management (EBMgt) in healthcare. This study narrows the main gaps in current understanding about the linkage between sources of evidence, categories of analysis and kinds of managerial decisions/management practices that different groups of decision-makers put in place. In fact, although EBMgt in healthcare has emerging as a fashionable research topic, little is still known about its actual implementation.

*Design_* Using the Scopus database as main source of evidence, we carried out a systematic literature review on EBMgt in healthcare. Inclusion and exclusion criteria have been crystallized and applied. Only empirical journal articles and past reviews have been included to consider only well-mature and robust studies. A theoretical framework based on a “process” perspective has been designed on these building blocks: inputs (sources of evidence), processes/tools (analyses on the sources of evidence), outcomes (the kind of the decision) and target users (decision-makers).

*Findings_* Applying inclusion/exclusion criteria, 30 past studies were selected. Of them, 10 studies were past literature reviews conducted between 2009 and 2014. Their main focus was discussing the previous definitions for EBMgt in healthcare, the main sources of evidence and their acceptance in hospitals. The remaining studies (n=20, 67%) were empirical; among them, the largest part (n=14, 70%) was informed by quantitative methodologies. The sources of evidence for EBMgt are: published studies, real world evidence and experts' opinions. Evidence is analysed through: literature reviews, data analysis of empirical studies, workshops with experts. Main kinds of decisions are: performance assessment of organization units, staff performance assessment, change management, organizational knowledge transfer and strategic planning.

*Originality/Value_* This study offers original insights on EBMgt in healthcare by adding to what we know from previous studies a "process" perspective that connects sources of evidence, types of analysis, kinds of decisions and groups of decision-makers. Our main findings are useful for academia as they consolidate what we know about EBMgt in healthcare and pave avenues for further research to consolidate this emerging discipline. They are also useful for practitioners, as hospital managers, who might be interested to design and implement EBMgt initiatives to improve hospital performance.

Keywords. Evidence-based Management; Healthcare Management; Decision-making; Systematic Literature Review

Background

The ongoing debate on whether and how evidence-based management practices should be developed and implemented in healthcare has been reinforced by the increasing availability of massive datasets from very heterogeneous sources coupled with an improved capacity to analyse them (Hopp et al., 2018). Scholars of healthcare management and decision management as well as policy-makers and healthcare professionals are investigating to what extent the consolidating bodies of knowledge and practices about Evidence-Based Management (EBMgt) are better informing and supporting how managerial decisions are taken in healthcare, echoing what has been achieved in medicine through the Evidence-Based Medicine (EBM) experience. With this respect, also a cursory review of the extant literature would show that past studies on EBMgt dealt with a wide spectrum of "evidence" sources. Evidence used to inform decision-making ranged from robust scientific evidence (Hamlin et al. 2011; Veillard et al. 2005; Francis-Smythe et al. 2013; Grundtvig et al. 2011; HakemZadeh & Baba 2016) to healthcare managers' expertise (Briggs & McBeath 2009; Francis-Smythe et al. 2013), from peer opinions (Fazaeli et al. 2014; Davies & Howell 2012; Schmalenberg et al. 2005) to local data sources

(Hornby & Perera 2002; Willmer 2007; Hamlin 2002; Beglinger 2006), also considering patients' preferences (Marschall-Kehrel & Spinks 2011; Slater et al. 2012).

This variety of sources well reflect the variety of decisions and judgements that healthcare professionals have to make day-to-day (Briner et al. 2009) that require different data and level of evidence. When these different sources of evidence are used inappropriately, poorer decisions are taken and poorer outcomes are achieved (Kovner 2014). Like as in medicine, robust scientific evidence should constitute the "backbone" for informing decision-making (Aron 2015); however, many decisions or managerial practices might require other sources of evidence, whose level of robustness is lower. With this respect, Jaana et al. (2014) claimed, in their scoping review, that past studies on EBMgt focused to healthcare professionals (physicians and nurses) as decision-makers, overlooking other relevant groups of decision-makers (e.g., hospital managers, policy-makers, etc.). In particular, further light is still needed to understand how different groups of decision-makers in healthcare apply EBMgt to their daily managerial practice and decision-making, with respect to the types of decisions, the sources of evidence and their investigation. This research direction would provide further elements to debate what (YOUNG 2002) called as the need to create a "management culture", that in healthcare is still a priority. In fact, while physicians are getting used to ground their clinical decisions to the best available evidence, hospital managers and policy makers are still far from this culture, preferring personal judgement and insights.

Against this background – and coherently to the research need pointed out above – this study aims at crystallizing the state of art of EBMgt in healthcare from an original angle. Respect to past literature reviews on EBMgt in healthcare (e.g., Young 2002; Jaana et al., 2014; HakemZadeh and Baba 2016), this study will focus on the overlooked relationship between managerial decisions and sources of evidence, with specific reference to different groups of decision-makers. In this view, this study will adopt a process perspective that has been incorporated into a novel theoretical framework based on the Input-Process-Output (I-P-O) model (McGrath, 1964). The I-P-O framework has been recently taken as theoretical anchor for other studies in the field of management (e.g. Simsek, 2009; Ghezzi et al., 2017), because it can help to distinguish the main antecedents, mechanisms and outcomes of the process under investigation. By taking this perspective, we aim at shedding novel light on what is already known from past reviews. A theoretical framework that will connect groups of decision-makers, with types of managerial decisions and with different analyses to extract insights from source of evidence, will be crystallized as reference map to understand what evidence we have so far about EBMgt in healthcare. In this view, this study aims at paving avenues for further research, and thus focusing the attention of scholars of healthcare management and decision management to areas of research that have not been sufficiently investigated yet. Additionally, healthcare professionals and managers will gather a comprehensive view of EBMgt in healthcare and a reference framework that might help them designing and implementing evidence-based managerial practices.

Methods

Past studies on EBMgt in healthcare have been identified and selected through a systematic approach following the best practice of systematic literature reviews (Tranfield et al., 2003). In the followings, the search strategies that have been implemented, how past contributions have been selected and what data have been extracted to inform the literature review, will be detailed briefly.

Search strategies and contributions identification

The literature review was performed referring to Scopus as main source of past studies. This database covers extensively social sciences journals and is commonly used as reference source for systematic literature reviews (e.g., Cerchione and Esposito, 2016; Ghezzi et al., 2017). To limit the potential risk of overlooking relevant contributions, the same query has been run on ISI Web of Knowledge and Pubmed without founding additional contributions respect to those already identified through Scopus.

To increase the likelihood of a comprehensive exploration of past contributions dealing with "evidence based management" in healthcare, the query strategy has been left significantly open thus searching for "evidence based management" OR "evidence-based management" in titles, abstracts and key words. A time limitation has not been implemented, and data collection has been run in February 2018; in this regards, all articles collected in Scopus till February 2018 have been searched through the queries that have been pointed out above. With respect to the "type" of contribution, the searched has been restricted to "Article" and "Review" because of the very large number of past contributions about EBMgt (cf. in the followings). No "domain" limitation has been applied, accepting contributions ranging from medicine to management, from engineering to economics, etc. Only studies published in English have been selected. As result of this search strategy, 1,253 contributions have been identified for screening.

Study selection

Past studies identified through queries have been screened by the co-authors to select those in scope with this literature review. The high number of studies – even if larger than other studies – has been considered coherent to the purpose of the study – i.e., crystallizing the state of art with respect to how different groups of decision-makers in healthcare implement evidence-based management practices and inform decision-making – and co-authors' screening capacity. Inclusion and exclusion criteria have been agreed. Contributions were included when dealing with sources of evidence for EBMgt, with types of decisions and analysis, and groups of decision-makers. Contributions were excluded when neither empirical nor focused to healthcare. Screening has been carried out by two co-authors for each contribution to limit the risk of excluding relevant past studies or including studies that were out of scope; in case of opposite judgement, the two co-authors discussed their opinions to gather an agreed evaluation; when the co-authors remained on their previous opinions and an agreement could not be achieved, a third co-author reviewed the contribution to decide whether include or exclude it.

The first round of screening – coherently to the large number of contributions identified through the query strategies – dealt with titles and abstracts. Since titles could not provide the readers with enough confidence with the actual contribution of the article, co-authors agreed to be prudent at this stage of the screening process and to exclude only those studies that were evaluated as surely out of scope and to leave the final decision to the next stage based on abstract first and full text then.

The first screening based on title and keywords reduced the included contributions from 1,253 to 164 with the exclusion of 1,089 studies that have judged as out of scope from two reviewers. The remained records (n=164) were screened by at least two co-authors on the basis of their abstract. At this stage the exclusion criterion about the focus and the relevance for the healthcare context has been applied. Other 95 contributions have been excluded because they did not deal with EBMgt in healthcare (e.g. (Rudasill & Dole 2017). The remaining 69 contributions have been screened on the full text. After this stage, 39 studies have been excluded either because their findings and conclusions were not based on empirical data or the full text was not retrievable (Borba & Kliemann Neto 2008). After three rounds of screening, 30 past contributions have been selected and included in this literature review. The results at the different stages have been synthetized in the PRISMA chart (Hutton et al. 2015) in Figure 1.

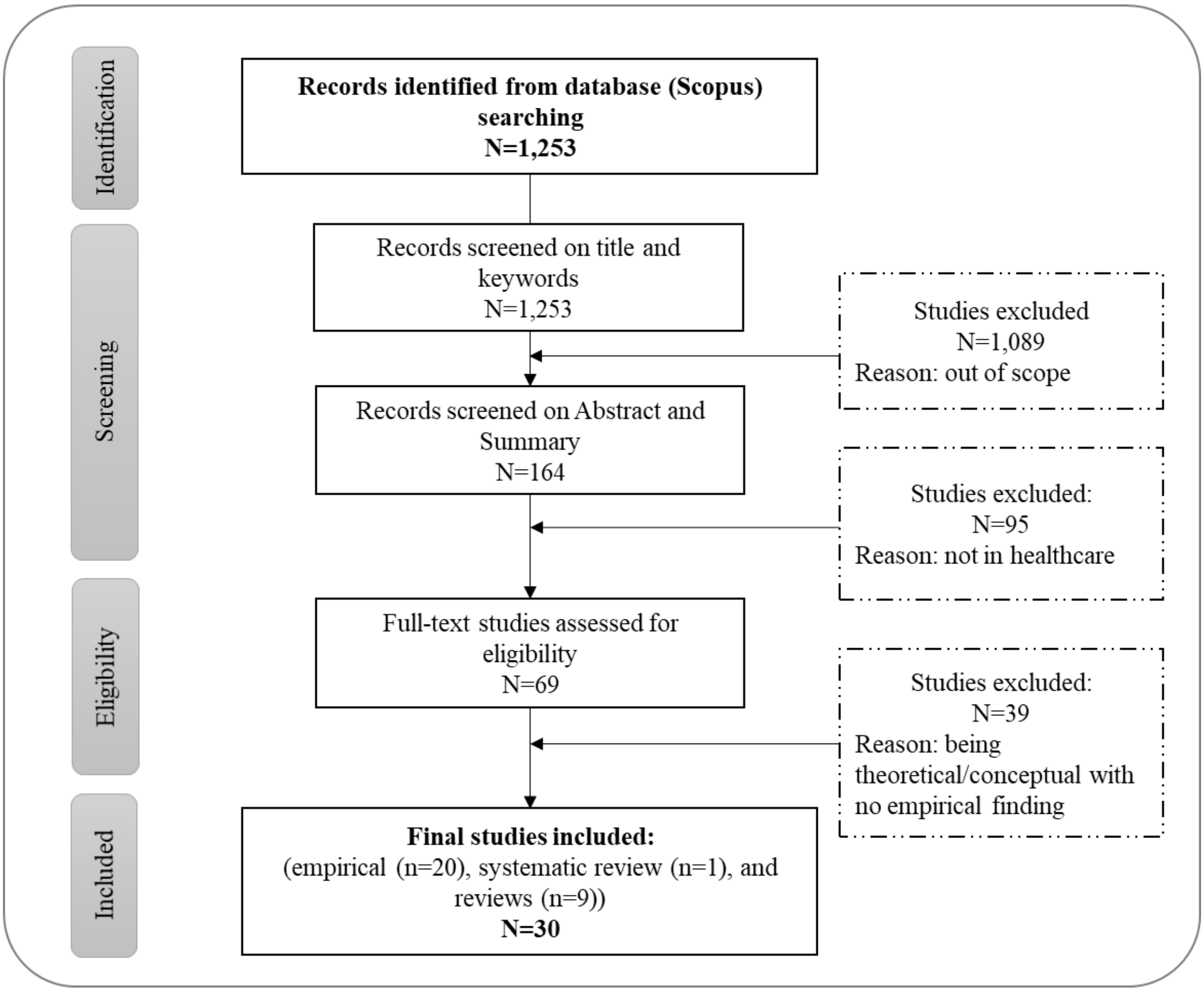

Figure 3.PRISMA Chart based on the inclusion, exclusion process from Scopus database.

Data extraction

As result of the screening, 30 contributions have been selected for grounding this literature review. Of them, 20 contributions are empirical studies, 9 are past reviews, and 1 systematic review. Selected contributions are listed in Table 1.

Table 1. List of selected contributions to inform the literature review.

#	*Type*	*Author(s)*	*Title*	*Journal*	*Year*
1	Review	Young SAMK.	Evidence-based management : a literature review	*Journal of Nursing Management*	2002
2	Review	Scott, IA	Determinants of Quality of In-Hospital Care for Patients with Acute Coronary Syndromes	*Disease Management and Health Outcomes*	2003
3	Review	Arndt M, Bigelow B	Evidence-based management in health care organizations: a cautionary note	*Health care management review*	2009
4	Review	DelliFraine JL, Langabeer JR 2nd, Nembhard IM.	Assessing the evidence of Six Sigma and Lean in the health care industry.	*Quality management in health care*	2010
5	Review	Marschall-Kehrel D, Spinks J	The Patient-Centric Approach: The Importance of Setting Realistic Treatment Goals.	*European Urology Supplements*	2011
6	Review	Hakemzadeh F, Baba V V. ,	Toward a theory of evidence based decision making	*Management Decision*	2012
7	Review	DelliFraine JL, Wang Z, McCaughey D, Langabeer JR 2nd, Erwin CO	The use of six sigma in health care management: are we using it to its full potential?	*Quality management in health care*	2013
8	Review	Rangachari P, Rissing P, Rethemeyer K	Awareness of evidence-based practices alone does not translate to implementation	*Quality management in health care*	2013
9	Review	Jaana M, Vartak S, Ward Mm	Evidence-Based Health Care Management : What Is the Research Evidence Available for Health Care Managers?	*Health Services Research and Practice*	2014
10	Systematic Review	Nicolay, C.R.; Purkayastha, S.; Greenhalgh, A., et al.	Systematic review of the application of quality improvement methodologies from the manufacturing industry to surgical healthcare	*British Journal of Surgery*	2012
11	Empirical Article	Veillard, J.; Champagne, F.; Klazinga, N., et al.	A performance assessment framework for hospitals: The WHO regional office for Europe PATH project	International Journal for Quality in Health Care	2005
12	Empirical Article	Willmer, M.	How nursing leadership and management interventions could facilitate the effective use of ICT by student nurses	Journal of Nursing Management	2007

#	*Type*	*Author(s)*	*Title*	*Journal*	*Year*
13	Empirical Article	Pritchard, R.D.; Harrell, M.M.; DiazGranados, D.; Guzman, M.J.	The Productivity Measurement and Enhancement System: A Meta-Analysis	Journal of Applied Psychology	2008
14	Empirical Article	McAlearney, A.S.; Garman, A.N.; Song, P.H., et al.	High-performance work systems in health care management, Part 2: Qualitative evidence from five case studies	Health Care Management Review	2011
15	Empirical Article	Grundtvig, M.; Gullestad, L.; Hole, T., et al.	Characteristics, implementation of evidence-based management and outcome in patients with chronic heart failure. Results from the Norwegian heart failure registry.	European Journal of Cardiovascular Nursing	2011
16	Empirical Article	Slater, H.; Davies, S.J.; Parsons, R., et al.	A policy-into-practice intervention to increase the uptake of evidence-based management of low back pain in primary care: A prospective cohort study	PLoS ONE	2012
17	Empirical Article	Davies, C.; Howell, D.	A qualitative study: Clinical decision making in low back pain	Physiotherapy Theory and Practice	2012
18	Empirical Article	Booker, L.D.; Bontis, N.; Serenko, A.	Evidence-Based Management and Academic Research Relevance	Knowledge and Process Management	2012
19	Empirical Article	FrÃ¸lich, A.	Identifying organisational principles and management practices important to the quality of health care services for chronic conditions.	Danish medical journal	2012
20	Empirical Article	Song, P.H.; Robbins, J.; Garman, A.N.; McAlearney, A.S.	High-performance work systems in health care, Part 3: The role of the business case	Health Care Management Review	2012
21	Empirical Article	Kramer, M.; Brewer, B.B.; Halfer, D., et al.	Changing our lens: Seeing the chaos of professional practice as complexity	Journal of Nursing Management	2013
22	Empirical Article	Francis-Smythe, J.; Robinson, L.; Ross, C.	The role of evidence in general managers' decision-making	Journal of General Management	2013
23	Empirical Article	Rangachari, P.; Madaio, M.; Rethemeyer, R.K, et al.	Role of communication content and frequency in enabling evidence-based practices	Quality Management in Health Care	2014

#	*Type*	*Author(s)*	*Title*	*Journal*	*Year*
24	Empirical Article	Jaana, M.; Teitelbaum, M.; Roffey, T.	It strategic planning in hospitals: From theory to practice	International Journal of Technology Assessment in Health Care	2014
25	Empirical Article	Fazaeli, S.; Ahmadi, M.; Rashidian, A.; Sadoughi, F.	A framework of a health system responsiveness assessment information system for Iran	Iranian Red Crescent Medical Journal	2014
26	Empirical Article	McAlearney, A.S.; Hefner, J.L.; Sieck, C., et al.	Evidence-based management of ambulatory electronic health record system implementation: An assessment of conceptual support and qualitative evidence	International Journal of Medical Informatics	2014
27	Empirical Article	Alavi, S.H.; Marzban, S.; Gholami, S.; et al.	How much is managers' awareness of evidence based decision making?	Biomedical and Pharmacology Journal	2015
28	Empirical Article	Nelson, K.E.; Pilon, B.	Managing organizational transitions: The chief nurse perspective	Nurse Leader	2015
29	Empirical Article	Bai, Y.; Gu, C.; Chen, Q.; Xiao, J.; Liu, D.; Tang, S.	The challenges that head nurses confront on financial management today: A qualitative study	International Journal of Nursing Sciences	2017
30	Empirical Article	Guo, R.; Berkshire, S.D.; Fulton, L.V., et al.	Use of evidence-based management in healthcare administration decision-making	Leadership in Health Services	2017

Co-authors have read the 30 selected papers and evidence from them have been extracted after having agreed a data extract form. Articles management has been supported through the use of the Mendeley software (version1.16.1). Data extraction has been informed by the design of a theoretical framework, based on an I-P-O approach, whose building blocks are: inputs (sources of evidence), processes/tools (types of analysis of sources of evidence), outcomes (types of decisions), and target users (decision-makers). Such framework allows to crystallize the state of art about EBMgt according to a “process” perspective.

The framework provides at least two main insights on what we know so far about EBMgt in healthcare. First, reading the framework as columns, four domains of analysis are pointed out: (i) the groups of decision-makers with respect to EBMgt in healthcare; (ii) the types of decisions that are taken within the EBMgt domain; (iii) the kinds of analysis that are run on the available evidence; and (iv) the sources of evidence. Second, reading the framework as rows (as shown by the example in Figure 2), the four domains are connected in logical chains, that, starting from the main groups of decision-makers, crystallize which decisions or management practices refer to them, based on which methods of analysis of the available evidence and on which are the sources of this evidence. This original framework is useful to, on the one hand, to crystallize what we know from past studies on EBMgt in healthcare, and, on the other hand, which are the most promising areas of further research.

Findings

As result of our screening, 10 past reviews published in the timespan 2002-2014 have been identified. Their main focus was discussing previous definitions of EBMgt in healthcare, the sources of evidence and the acceptance of evidence-based management practices in hospitals. Although the undoubtable relevance of these topics, they are out of scope with respect to main purpose of this literature review, i.e., providing a "process" view of what we know about EBMgt in healthcare. In this view, the studies included in these literature reviews have been screened through the inclusion and exclusion criteria applied to the Scopus database. After such process, no additional empirical studies on EBMgt in healthcare have been included in this review respect to those already identified through the search within the Scopus database. This result confirmed the relevance of these studies for grounding this literature review. In this regards, Table 2 offers a comprehensive overview about the information that is stored in the 20 papers on sources of evidence (inputs), analyses and tools (processes), managerial practices (outcomes) and groups of decision-makers.

In a nutshell, this picture emerges. The sources of evidence for EBMgt are: published studies, real world evidence and experts' opinion. Evidence is analysed through: literature reviews, data analysis of empirical studies, and workshops with experts. Decisions deal with: performance assessment of organization units, staff performance assessment, change management, organizational knowledge transfer and strategic planning.

Table 2. Information stored in the empirical papers (n=20) included in the literature review

#	Study Title. Country, Year.	Authors	Inputs (Sources of Evidence)	Processes/Tools (Analyses on the Sources of Evidence)	Outputs (The Kind of the Decision)	Target Users (Decision Makers)
1	A performance assessment framework for hospitals: The WHO regional office for Europe PATH project. Europe, 2005.	Veillard, J.; Champagne, F.; Klazinga, N., et al.	Personal/Experts experiences	Literature search Conducting a Survey with key informants	**Organizational performance Assessment;** Identification of dimensions	Policy-makers
2	How nursing leadership and management interventions could facilitate the effective use of ICT by student nurses. UK, 2007.	Willmer, M.	Personal/Experts experiences	Conducting interviews with nurses mentors/managers	**Change management Implementation;** Development of Information and Communications Technology skills	Clinicians; student nurses
3	The Productivity Measurement and Enhancement System: A Meta-Analysis. USA, 2008.	Pritchard, R.D.; Harrell, M.M.; diazgranados, D.; Guzman, M.J.	Peer opinion	Gathering internal group feedback reports	**Staff performance Assessment;** Reducing role ambiguity and role conflict	Researchers

#	Study Title. Country, Year.	Authors	Inputs (Sources of Evidence)	Processes/Tools (Analyses on the Sources of Evidence)	Outputs (The Kind of the Decision)	Target Users (Decision Makers)
4	High-performance work systems in health care management, Part 2: Qualitative evidence from five case studies. USA, 2011.	Mcalearney, A.S.; Garman, A.N.; Song, P.H., et al.	Peer opinion	Literature search Conducting a series of interviews with key informants	**Organizational performance Assessment;** Identification of links between HPWPs and employee outcomes to system- and organization-level outcomes.	Managers
5	Characteristics, implementation of evidence-based management and outcome in patients with chronic heart failure. Results from the Norwegian heart failure registry. Norway, 2011	Grundtvig, M.; Gullestad, L.; Hole, T., et al.	Local population based data sources	Analysing patient data	**Staff performance Assessment;** Measuring hospitalization, morbidity and mortality rates	Clinicians
6	A policy-into-practice intervention to increase the uptake of evidence-based	Slater, H.; Davies, S.J.; Parsons, R., et al.	Personal/Experts experiences Peer opinion	Measuring self-report measures records for conducting an interdisciplinary evidence-based framework	**Staff performance Assessment;** Self-management strategies were recommended more	Clinicians; primary care physicians (PCPs)

#	**Study Title. Country, Year.**	**Authors**	**Inputs (Sources of Evidence)**	**Processes/Tools (Analyses on the Sources of Evidence)**	**Outputs (The Kind of the Decision)**	**Target Users (Decision Makers)**
	management of low back pain in primary care: A prospective cohort study. Western Australia, 2012.				frequently post-intervention”	
7	A qualitative study: Clinical decision making in low back pain. USA, 2012.	Davies, C.; Howell, D.	Personal/Experts’ experiences Experts preferences	Investigating the decision-making process PTs use when managing patients with LBP by conducting interviews	**Identification of best practices;** preferred classification systems were identified	Clinicians; physical therapists (PT)
8	Evidence-Based Management and Academic Research Relevance. Canada, 2012.	Booker, L.D.; Bontis, N.; Serenko, A.	Experts preferences	Investigating the distribution of knowledge about advances in interviewees’ field of expertise	**Organizational knowledge translation;** having efficient market intermediaries in the form of knowledge translation mechanisms	Managers
9	Identifying organisational principles and management practices important to the quality of health care services for	Frã¸lich, A.	Local population based data sources	Analysing patient data	**Organizational performance Assessment;** promoting continuity of care and quality of health care services	Managers

#	**Study Title. Country, Year.**	**Authors**	**Inputs (Sources of Evidence)**	**Processes/Tools (Analyses on the Sources of Evidence)**	**Outputs (The Kind of the Decision)**	**Target Users (Decision Makers)**
	chronic conditions. USA, 2012.					
10	High-performance work systems in health care, Part 3: The role of the business case. USA, 2012.	Song, P.H.; Robbins, J.; Garman, A.N.; mcalearney, A.S.	Personal/Experts experiences Experts preferences	Investigating the business case for HPWPs in U.S. health care organizations by conducting interviews	**Organizational strategic planning;** Shape understanding about organizations' perspectives of the business case for HPWP investment	Managers
11	Changing our lens: Seeing the chaos of professional practice as complexity. USA, 2013.	Kramer, M.; Brewer, B.B.; Halfer, D., et al.	Personal/Experts experiences	Testing an evidence-based management practice in an organization	**Organizational performance Assessment;** Managing multiple patients with simultaneous complex needs	Clinicians; nurses
12	The role of evidence in general managers' decision-making. UK, 2013.	Francis-Smythe, J.; Robinson, L.; Ross, C.	Personal/Experts' experiences Peer Opinions	Testing an evidence-based management practice in an organization	**Organizational knowledge translation;** Managers get able to enhance their business practice by utilising more sources of evidence	Managers

#	Study Title. Country, Year.	Authors	Inputs (Sources of Evidence)	Processes/Tools (Analyses on the Sources of Evidence)	Outputs (The Kind of the Decision)	Target Users (Decision Makers)
13	Role of communication content and frequency in enabling evidence-based practices. USA, 2014.	Rangachari, P.; Madaio, M.; Rethemeyer, R.K, et al.	Local population based data sources	Conducting a prospective study	**Organizational knowledge translation;** Providing communication content and frequency associated with collective learning and culture change	Clinicians; physicians and nurses, Managers
14	IT strategic planning in hospitals: From theory to practice. Canada, 2014.	Jaana, M.; Teitelbaum, M.; Roffey, T.	Scientific literature Personal/Experts experiences	Running expertise workshops and conducting qualitative analyses	**Organizational strategic planning;** IT strategic planning for mobile and remote access to patients' information, and implementation of an integrated EMR.	IT leaders Managers
15	A framework of a health system responsiveness assessment information system for Iran. Iran, 2014.	Fazaeli, S.; Ahmadi, M.; Rashidian, A.; Sadoughi, F.	Personal/Experts experiences Expertise preferences	Conducting qualitative analyses	**Organizational performance Assessment;** Providing recommendations and developing a framework	Managers

#	Study Title. Country, Year.	Authors	Inputs (Sources of Evidence)	Processes/Tools (Analyses on the Sources of Evidence)	Outputs (The Kind of the Decision)	Target Users (Decision Makers)
16	Evidence-based management of ambulatory electronic health record system implementation: An assessment of conceptual support and qualitative evidence. USA, 2014.	Mcalearney, A.S.; Hefner, J.L.; Sieck, C., et al.	Personal/Experts experiences Peer opinion	Synthesizing best practices for managing ambulatory EHR system implementation in healthcare organizations by conducting interviews	**Organizational strategic planning;** implementing Plan-Do-Study-Act (PDSA) quality improvement (QI) mode	Managers
17	How much is managers' awareness of evidence based decision making? Iran, 2015	Alavi, S.H.; Marzban, S.; Gholami, S.; et al.	Personal/Experts experiences Scientific literature	Determining the level of manager's awareness of evidence based decision making by implementing a Cross-sectional study	**Organizational knowledge translation;** Raising the efficiency of management in healthcare organizations	Managers
18	Managing organizational transitions: The chief nurse perspective. USA, 2015.	Nelson, K.E.; Pilon, B.	Scientific literature Personal/Experts experiences Peer opinion	Implementing a proposed organizational transition framework	**Change management Implementation;** The organizational transition framework was successful although the different hospital and leaders characteristics	Clinicians; nurse leaders

#	Study Title. Country, Year.	Authors	Inputs (Sources of Evidence)	Processes/Tools (Analyses on the Sources of Evidence)	Outputs (The Kind of the Decision)	Target Users (Decision Makers)
19	The challenges that head nurses confront on financial management today: A qualitative study. China, 2017.	Bai, Y.; Gu, C.; Chen, Q.; Xiao, J.; Liu, D.; Tang, S.	Peer opinion Personal/Experts experiences	Identifying the financial management practice challenges in the organization by conducting group interviews	**Change management Implementation;** The decision on implementing a cooperative management model, evidence-based management training, and data-driven tools to improving the financial management capacity of nurse managers	Clinicians; head nurses/ nurse managers
20	Use of evidence-based management in healthcare administration decision-making. USA, 2017.	Guo, R.; Berkshire, S.D.; Fulton, L.V., et al.	Peer opinion	Conducting a cross-sectional study to collect the opinion of managers	**Organizational knowledge translation;** The decision on managers priority setting of using evidence sources for consulting daily and weekly for decision-making	Managers

Going more in-depth, two main groups of decision-makers are targeted by articles about EBMgt in healthcare. They are hospital professionals (mainly physicians and nurses) (n=8, 40%) and hospital managers (n=10, 50%). Other groups of decision-makers such as policy-makers and researchers have been targeted by just one study respectively. With respect to hospital professionals, management practices that should be evidence-based deal mainly with change management initiatives (n=3, 38%) and the assessment of either individual (i.e., of hospital professionals) or organizational performance (within audit or benchmarking programs).

In either cases, expert or peer opinion is the most used source of evidence to inform decision-making. Evidence extracted from electronic medical records or local databases lack far behind. Literature reviews and evidence extracted from journal articles is cited in a limited number of studies. This finding shows that while physicians and nurses are used to refer to this source of evidence – according to the well-established Evidence-Based Medicine discipline – for health related issues and decision-making, they refer to evidence with lower robustness – i.e., expert opinions – when dealing with managerial practices. Being the source of evidence mainly qualitative, the types of analysis or tools used to extract "value" from the sources of evidence are those that are typically utilised for qualitative data, such as interviews, focus groups and meetings.

With respect to hospital managers, the picture has both differences and similarities. Management practices that should inform by evidence deal mainly with organizational knowledge translation (n=5, 50%), performance assessment of organizational units (n=3, 30%), and organizational strategic planning (n=3, 30%). As for hospital professionals, the most used source of evidence refers to experts' opinion (n=7, 70%). Data from electronic medical records and hospital databases (n=2, 20%) and articles from the extant literature (n=1, 10%) are used in a limited number of cases. In particular, databases are used mainly with respect to the assessment of organizational units. Again, the methods used to extract evidence from these sources are mainly qualitative and grounded on interviews and interactions with peers and experts. Summarizing, in a nutshell, what has emerged from the literature is synthetized in Figure 2, that shows the "process" view of the state of art about EBMgt in healthcare based on an Input-Process-Outcome framework. In particular, the arrows that connect the building blocks of the framework show two examples of the investigated logical connections among groups of decision-makers (managers in the specific example), types of managerial decisions/practices, types of analysis and tools used to extract value from the sources of evidence, and sources of data.

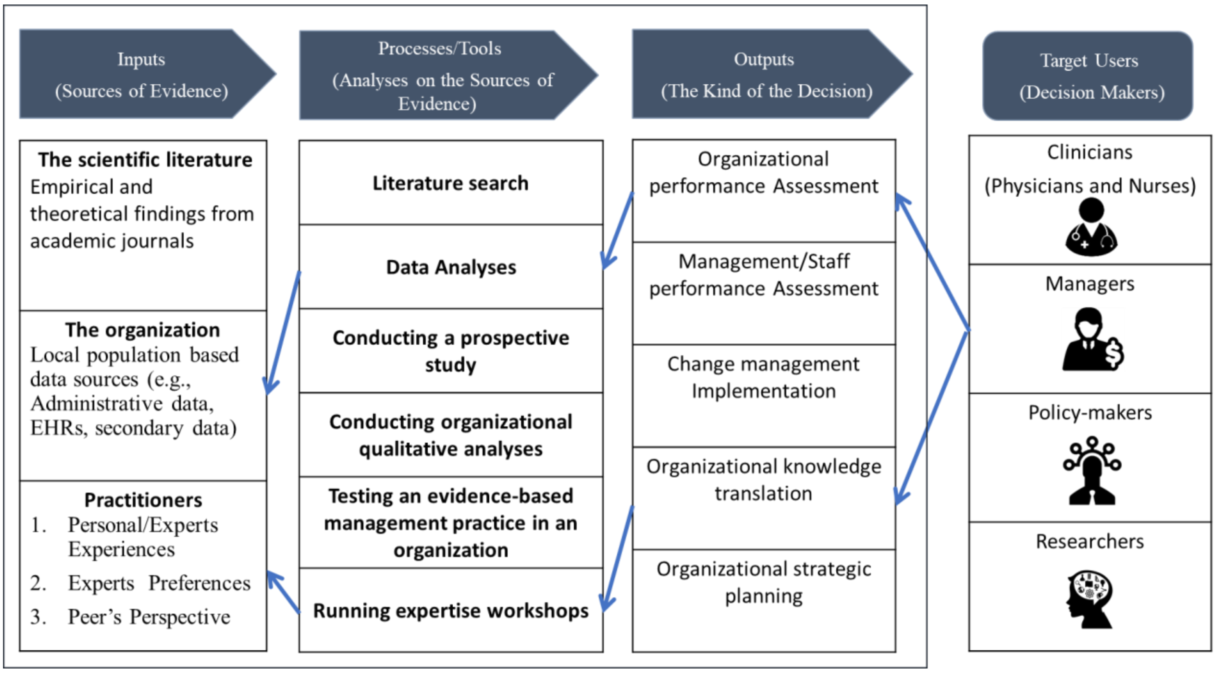

Figure 4. The "process" view of EBMgt in healthcare based on an Input-Process-Outcome framework (the blue arrows show an example of the logical connections among the building blocks of the framework)

Discussion and conclusions

This study aimed at crystallizing the state of art of EBMgt in healthcare through the novel angle of a "process" view. Past reviews focused mainly to the comparison of different definitions and scopes of EBMgt in healthcare pointing out the need of better formalization of this research field. Despite the undoubted value of this debate, this study takes a step ahead by systematizing the main findings from past researches within an Inputs-Processes-Outcomes framework that allows to materialize the logical connections among various groups of decision-makers, types of managerial decisions/practices, types of analysis and tools to extract value from different sources of evidence, and the available sources of evidence (Figure 2).

In the light of the results emerged from the literature review, three main issues are worth of discussion. First, EBMgt deals mainly with two groups of decision-makers: hospital managers and professionals. On the one hand, this result clarifies that EBMgt should not be limited to managers but should include all professionals that in healthcare are in charge of taking managerial decisions and execute practices of management. Head physicians combine professional and managerial responsibilities, and because of that they should translate those they have learned about Evidence-Based Medicine (EBM) to tasks and issues that deal with management. On the other hand, other relevant groups of decision-makers have been largely overlooked. This is the case of policy-makers. Even if the last years have seen the diffusion of narratives about evidence-based policy-making, this is not what emerged from this study. This difference might be due to the choice of including in this literature review only studies with an empirical grounding. Evidence-based policy-making is still far from consolidated practices and tools that have been investigated through quantitative analyses. What we know and what is expected for the next years are mainly based on expert opinions and positioning papers. In this view, more efforts should be paid by scholars of decision making and healthcare management to pave quantitatively the avenue of evidence-based decision-making.

Second, the most investigated sources of evidence are opinions of experts and peers. This result is in contrast with the emphasis paid to electronic medical records and administrative databases in the last decade. On the one hand, these sources of evidence collect data that are not salient for management-related decisions. For instance, the actual capability to explain the performance variance for a sample of hospitals in terms of different management practices is very limited through administrative health data. These datasets do not collect exhaustive information about the organizational determinants of hospital performance and thus hospital managers are forced to explore other sources of evidence, such as opinions of experts and peers or qualitative surveys. On the other hand, hospital managers might not have enough confidence and skills to make sense of quantitative sources of evidence such as administrative data. Results from this systematic literature review show that hospital managers and hospital professionals have similar behaviours in term of sources of evidence for management-related decisions, although physicians are used to ground clinical decisions on sources with a higher degree of robustness and generalizability. In this view, further research should be carried out to investigate the attitude of different groups of decision-makers to ground their management practice to innovative sources of evidence.

Third, the development of a theoretical framework anchored in an Inputs-Processes-Outcomes model has shown that current research on EBMgt in healthcare needs a different angle to take a step ahead and overcome the impasse that has characterized the last decade. The authors argue that the debate about what “evidence” is or should be in healthcare is sterile where not connected with the specific group of decision-makers, the specific group of management practices or managerial decisions, the specific group of analytic techniques and the specific sources of evidence. In this view, Figure 2 offers interesting insights to both academicians and practitioners. Researchers should pay additional efforts to complete such picture. In fact, the picture is the result of what has been found so far in past studies and is not the result of theoretical arguments. For instance, other groups of decision-makers might be included (e.g., patients and advocacy groups) as well as other sources of evidence (e.g., real world data and social media). Additionally, the logical connections among the building blocks should be discussed in-depth and crystallized. Practitioners, vice versa, might benefit from this picture in terms of improved awareness of the scope and complexity of EBMgt in healthcare and improved capability to develop best practices that connects sources of evidence with analytic techniques and with groups of management practices. By leveraging on such framework, the set-up of benchlearning initiatives would be easier and more focused.

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Paper Number 2: Mortality and Readmissions for Heart Failure Patients: Insights on the Composite Outcome.

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**Afsaneh Roshanghalb collaborated as the correspond author in all parts of this study.*

Abstract

Background: Controlling the quality of care through readmissions and mortality for Heart failure (HF) patients is still a national priority for healthcare politicians in developed countries. In this study, using administrative data about hospital discharge forms (HDFs), emergency departments (EDs) access and vital statistics, we test new covariates for predicting mortality and readmissions of patients hospitalized for Heart Failure (HF) and discuss the use of combined outcome as an alternative.

Methods: Logistic models, with stepwise selection method, were estimated on 70% of the sample and validated on the remaining 30% to evaluate 30-day mortality, 30-day readmissions, and the combined outcome. We followed an extraction method for any-cause mortality and unplanned readmission within 30 days after incident HF hospitalization. Data on patient hospitalization and previous history were extracted by HDFs and ED dataset.

Results: our principal findings demonstrates models discriminant ability is consistent with literature both for mortality (AUC=0.7388, CI (0.7297-0.7480)) and readmissions (AUC=0.5777, CI (0.5615-0.5939)). Additionally, the discriminant ability of the composite outcome model is satisfactory (AUC=0.6749, CI (0.6660-0.6839)).

Conclusion: Hospitalization characteristics and patient history introduced in the models don't improve their discriminant ability. The composite outcome prediction is led more by mortality than readmission, without improvements for the comprehension of the readmission phenomenon.

Keywords. Administrative data, Mortality, Readmission, Heart Failure.

Background

Heart Failure (HF) is a common cardiovascular condition in the aging population of the most developed Countries (Bottle et al. 2014; Murtaugh et al. 2017; Teryl K. Nuckols 2015; Go et al. 2014; McLean & Mariell Jessup 2013). These patients are a priority for both healthcare regulators and professionals and despite the significant technological advancements experienced in the last years (Teryl K. Nuckols 2015), when admitted in hospital, they show a high risk of 30-day mortality (Vaartjes et al. 2010; Teryl K. Nuckols 2015) as well as a high probability of incurring in multiple unplanned 30-day readmissions (Chiang et al. 2011; Gu et al. 2009; Au et al. 2012; Keenan et al. 2008). The establishment since October 2012 by the Center for Medicare and Medicaid Services (CMS) of the Hospital Readmissions Reduction Program (HRRP) that creates financial penalties for hospitals with higher-than-expected 30-day risk-adjusted readmission rates for adults age 65+ (Teryl K. Nuckols 2015) crystallizes the relevance and urgency to improve such situation through the implementation of effective, evidence-based improvement strategies (Gu et al. 2009; Murtaugh et al. 2017). In this regard, as suggested in the literature (Maier et al. 2016), administrative data/claims (Bottle et al. 2018) linked with vital statistics datasets offer population-based, already-collected, and enough complemented and reliable evidence to investigate 30-day mortality and 30-day unplanned readmission (Bottle, Sanders, et al. 2013).

A literature review carried out by Ross et al. (2008) (Ross et al. 2008) concluded that the use of administrative data for predicting patient readmissions is a promising avenue for evidence-based policy-making while has open challenges to cope with. In fact, patient demographic and clinical characteristics significantly associated with readmissions vary among past studies. This review showed that comparing past studies none of patient characteristics is a consistent predictor of 30-day readmissions. Otherwise, considering 30-day mortality after hospitalization for HF the discriminant ability of statistical models has been found higher than that of readmissions, even if they considered similar predicting variables.

Based on these findings, we could argue that mortality and readmissions are predicted by different factors – or that other variables affect the probability of being readmitted. This could lead to the conclusion that 30-day mortality and unplanned 30-day readmissions should be investigated separately because they are part of different stories and thus of different improvement strategies. Even if this focus had the undoubted value of allowing the researchers to go more in-depth and thus improving the predictive ability of their models (e.g., (Lim et al. 2015)), in this manuscript we argue that there is also the need for academicians, healthcare regulators and professionals to consider that mortality and readmissions are competing outcomes (Jong et al. 2003; Huynh et al. 2015; Ross et al. 2008; Au et al. 2012) because patients who will die outside the hospital will not generate readmissions. From a theoretical perspective, it is thus critical to understand the specific contribution of each of the two outcomes to the combined one.

This was one of the main goal of a three-year strategic research project promoted by the Health Directorate of the Lombardy Region (Northern Italy) with respect to the comprehension and improvement of the care provided to HF patients. As for many developed Countries, the 9.5 million residents of the Region are aging and, although a reduction of the incidence of the HF condition over the last decade (Frigerio et al. 2017) 30-day mortality and 30-day unplanned multiple readmissions still are issues that require intervention.

Within this research project, we studied the effect of patient's characteristics, previous history, and in-hospital treatment in predicting the risk of mortality, readmission and the combined outcome. This study has been informed by administrative data routinely collected by hospitals. In particular, we used the regional datasets of HDFs, ED services, and vital statistics, all linked at the patient level. Data have been treated as confidential and citizens' privacy has been guaranteed according to the regional guidelines for the use of these data.

This manuscript has a twofold contribution to the extant literature on the prediction of 30-day mortality and 30-day unplanned readmissions for HF patients. First, our study improves past models by evaluating the significance of variables related to patient's previous history and treatment during the hospitalization. Moreover, it explores the effect of patients died shortly after discharge without being readmitted in hospital, because of their terminal condition, by excluding those who died within 10 days from discharge. In fact, they might have the characteristics of patient in critical condition without the expected outcome of readmission. Second, we compared and discuss the model on the combined outcome with the models focused to death and readmissions. By doing so, we aim at contributing also to healthcare regulators and professionals, who are struggling to improve care for HF patients while saving costs for the long-term sustainability of care delivery (Teryl K. Nuckols 2015).

Methods

Context

The Lombardy Region (Northern Italy) offers tax-based care (with limited out-of-pocket contributions) to 9.5 million inhabitants (France et al. 2005). Almost all hospitals in the Region deliver care on behalf of the Regional Healthcare System and pass through a formal accreditation procedure. Because of that, hospitals have to compulsory submit period information to the regional administration to receive reimbursement for the care services that have been delivered (Cavalieri et al. 2013).

This impressive, systematic flow of data has fed the Regional administrative health database and currently stores reliable and consistent information for more than fifteen years about the whole population of the Lombardy Region. These data have been recently opened to approve studies with the aim of unfolding the informative value stored in them and informing evidence-based improvement strategies.

Within this context, the Health Directorate promoted the 3-year strategic research project about HF patients, funded by the National Ministry of Health as pilot experimentation for advancing the practice of evidence-based policy-making through administrative data. The choice of HF patients as piloting exercise grounds in the relevance of this cardiovascular condition concerning incidence of new cases (3.13 per 1,000 adult inhabitants/year in 2012), annual HF hospitalizations (53,830 in 2012), in-hospital mortality (9.4% in 2012), and expenditure for the Regional Healthcare System (about 2.6 billion in 2002-2011, with a mean of 235 M€ per year).

Data

The main informative source for this study is administrative data. We obtained data on hospital discharge forms and ED accesses from 2000 to 2012 for all Lombardy Region patients who have been hospitalized for HF in this period. The Regional data owner linked these data at the patient level with the vital statistics, making available for the researchers the date of death for those patients who died before December 31st, 2012. This information was essential to evaluate mortality outside the hospital. Hospital discharge forms contain information about patient characteristics (e.g., sex and age) and hospital admissions (e.g., date of admission, date of discharge, principal diagnosis and comorbidities (secondary diagnoses, procedures, admission ward, etc.). Diagnoses and procedures within the hospital discharge forms are coded using the International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9-CM).

Hospitalizations for HF were identified using the ICD-9-CM codes as recommended by the Agency for Healthcare Research and Quality (AHRQ) in their quality indicator of intra-hospital mortality due to HF (AHRQ 2015) and by the CMS in their risk adjustment model for capitation payments and in particular the category HCC80 (CMS-HCC80, version 12) (Pope et al. 2011). The codes were searched in every diagnosis position of the hospital discharge forms.

To study mortality and readmissions, we considered incident hospitalizations for HF – i.e. the first hospitalization for HF of any Lombardy Region resident in the temporal window 2010 to 2012 occurred in any hospital located in the Region. A hospitalization for HF was defined as the incident one for the patient if there was a previous period of at least five years free from other HF hospitalizations.

Considering the hospitalizations for any cause from 2000 to 2012, we evaluated:

- Hospital re-admissions for any cause after the incident HF hospitalization;
- The number of hospital admissions in the 6-month period before the incident HF hospitalization;
- The comorbidities affecting the patient at the incident hospitalization.

With respect to comorbidities, we referred to the method proposed by Gagne et al. (2011) (Gagne et al. 2011). Because not all comorbidities are specified in the secondary diagnoses in the discharge forms – especially when they have not been treated during the hospitalization – Sharabiani, Aylin, and Bottle (2012) (Sharabiani et al. 2012; Mazzali et al. 2016) suggested searching for comorbidities also in the previous hospitalizations (look-back period). Thus, we considered a look-back period of one year before the incident HF; when a chronic comorbidity was detected, it was considered affecting the patient in the subsequent hospitalizations, regardless it was actually present or not in the hospital discharge form. Additionally, using data on ED services from 2000 to 2012, we determined the number of patients accesses to ED for any cause in a six-month period before the incident HF hospitalization.

Outcomes

We considered three different outcomes: mortality within 30 days from the incident hospitalization, unplanned readmissions in the same period, and the combined outcome of mortality or readmission. Mortality was evaluated considering intra-hospital and out of hospital mortality for all causes, using the regional vital statistics. Readmissions were defined as non-programmed hospitalizations for any cause within 30 days after the incident HF admission. A hospitalization was not considered a readmission if the patient was transferred from another hospital, if it was planned and if it occurred more than 30 days after the incident hospitalization. To evaluate readmissions, we excluded patients who died during the incident admission or within 10 days from discharge. The last choice was made to exclude patients who decided to spend his/her last life days at home rather than in hospital. Finally, for the combined outcome, we considered the occurrence of at least one between 30-day mortality and 30-day unplanned readmission.

Statistical models

The choice of the explanatory variables for estimating mortality and readmission was based on past contributions (Jong et al. 2003; Au et al. 2012; Wallmann et al. 2013; Gagne et al. 2011) as well as on the available data. We considered the following variables: age, sex, in-hospital length of stay, number of admissions and of ED accesses for any cause in the six-month period before the incident HF event, the type of admission ward, the process of care and comorbidities. The variable "admission ward" has two levels to distinguish between patients directly admitted in a Cardiology ward from patients admitted in other wards. This variable is assumed as a proxy of the correct placement of the patient. The process of care (Wallmann et al. 2013) was obtained categorizing the procedures occurred during the hospitalization according to the Procedures-Classes-Tools proposed by the AHRQ (AHRQ 2015).

Procedures have been divided in: minor diagnostic, minor therapeutic, major diagnostic, and major therapeutic. We considered the process of care as a binary variable presence of any major therapeutic procedure vs. other procedures or none procedure at all. Finally, we considered the following comorbidities, evaluated through the algorithm by Gagne (Gagne et al. 2011): metastatic cancer, renal failure, hemiplegia, any tumor, cardiac arrhythmias, chronic pulmonary disease, coagulopathy, complicated diabetes, deficiency anemia, fluid and electrolyte disorders, peripheral vascular disorder, psychosis, pulmonary circulation disorders, and hypertension.

The effect of patient characteristics on mortality and/or readmission was evaluated using a multivariable logistic model. We estimated the predictive model using a random sample of about 70% of our dataset and validated on the remaining 30%. Covariates of the outcome were selected through a stepwise selection method. We included in the model only variables with a minimum p-value of 0.20; then then p-value required to remain in the model was 0.05. We calculated the Area Under the Curve (AUC) for all the models to evaluate their discriminant ability. The threshold to maximize the Youden index (i.e., sensitivity + specificity - 1) was evaluated for all the models (Wallmann et al. 2013) as well as the associated sensitivity (SE), specificity (SP), positive and negative predictive values (PPV and NPV respectively) were evaluated. Data management and statistical analysis were performed using SAS 9.4.

Results

Descriptive analysis

The number of incident hospitalizations for HF from January 2010 to November 2012 was 73,802. We considered incident hospitalizations until November to leave at least 30 days free to control for 30-day mortality and 30-day readmissions. The number of patients died within 30 days from discharge was 9,801 (13.3%); 6,293 of them actually died during the hospitalization. After the exclusion of patients died during the hospitalization or within 10 days from discharge, 65,953 hospitalizations could generate non-programmed readmission. The total number of non-programmed 30-day readmissions was 4,460 (6.8%); while the number of patient experiencing the composite outcome was 14,264 out of 73,802 (19.1%). The characteristics of patients at the incident hospitalization are shown in Table 1 with respect to the whole sample (2nd column) and the readmission sample (3rd column). The characteristics of patients died during hospitalization or within 10 days are also provided in Table 1 (4th and 5th columns). Patients died within 10 days are older and have a higher percentage of tumor and metastatic cancer than patients considered for readmission. They share similar characteristics with patients died in hospital except for the presence of chronic pulmonary diseases, tumor and metastatic cancer. Therefore, the idea that those patients are facing a terminal condition appears almost adequate.

Table 3. Patient characteristics at the incident HF hospitalization: mortality and readmission samples; patients died during the hospitalization and within 10 days have been excluded from the readmission sample.

Patient characteristics	**Sample for mortality (73,802)**	**Sample for readmissions (65,953)**	**In-hospital deaths (6,293)**	**Patients died within 10 days (1,556)**
Women (n, %)	38,271 (51.9)	33,950 (51.5)	3,492 (55.5)	829 (53.3)
Age (years)				
Mean (std. dev.)	78.0 (11.6)	77.3 (11.7)	83.7 (9.2)	84.0 (9.0)
Median (IQR)	80 (72-86)	80 (72.85)	85 (80-89)	85 (79-90)
In-hospital length of stay (days)				
Mean (std. dev.)	10.8 (8.1)	10.8 (7.7)	9.6 (10.4)	14.3 (10.9)
Median (IQR)	9 (6-14)	9 (6-14)	6 (2-13)	12 (7-18)
Patient admitted in a Cardiologic ward (n, %)	18,345 (24.9)	17,735 (26.9)	482 (7.7)	128 (8.23)
Major therapeutic procedures (n, %)	5,721 (7.8)	5,428 (8.23)	249 (3.4)	44 (2.8)
Number of ED accesses in the previous six months (n, %)				
0	53,729 (72.8)	48,223 (73.1)	4,419 (70.2)	1,087 (69.9)
1	14,554 (19.7)	12,922 (19.6)	1,303 (20.7)	329 (21.1)
2+	5,519 (7.5)	4,808 (7.3)	571 (9.7)	140 (9.0)
Number of hospitalizations in the previous six months (n, %)				
0	57,986 (78.6)	52,500 (79.6)	4,447 (70.7)	1,039 (66.8)
1	11,976 (16.2)	10,286 (15.6)	1,325 (21.1)	365 (23.5)
2+	3,840 (5.2)	3,167 (4.8)	521 (8.3)	152 (9.8)

In-hospital deaths	6293 (8.5)	N.A.	6,293 (100.0)	N.A.
Cardiac arrhythmias (n, %)	23,149 (31.5)	21143 (32.1)	1520 (24.5)	486 (31.6)
Hypertension (n, %)	13,024 (17.7)	12,150 (18.5)	677 (10.9)	197 (12.8)
Chronic pulmonary disease (n, %)	12,247 (16.7)	11,110 (16.9)	857 (13.8)	280 (18.2)
Renal failure (n, %)	8,415 (11.4)	7,332 (11.4)	844 (13.6)	239 (15.5)
Deficiency anemias (n, %)	3,925 (5.3)	3,446 (5.2)	367 (5.9)	112 (7.3)
Any tumor (n, %)	3,997 (5.4)	3,139 (4.8)	630 (10.2)	228 (14.8)
Pulmonary circulation disorders (n, %)	3,049 (4.1)	2,870 (4.4)	131 (2.1)	48 (3.1)
Peripheral vascular disorder (n, %)	2,906 (4.0)	2,582 (3.9)	258 (4.2)	66 (4.3)
Complicated diabetes (n, %)	2,219 (3.0)	2,033 (3.1)	148 (2.4)	38 (2.5)
Fluid and electrolyte disorders (n, %)	2,141 (2.9)	1,657 (2.5)	386 (6.2)	98 (6.4)
Metastatic cancer (n, %)	1,269 (1.7)	860 (1.3)	288 (4.7)	121 (7.9)
Hemiplegia (n, %)	467 (0.6)	369 (0.6)	82 (1.3)	16 (1.0)
Psychosis (n, %)	383 (0.5)	348 (0.5)	29 (0.5)	6 (0.4)
Coagulopathy (n, %)	308 (0.4)	240 (0.4)	53 (0.9)	15 (1.0)

Results about 30-day mortality

Results of the logistic regression on 30-day mortality are presented in Table 2. Patients with metastatic cancer or any tumor present higher risk of mortality when compared with other patients. Other comorbidities found associated with a higher risk of death are fluid and electrolytes disorders, coagulopathy, and hemiplegia. We found hypertension associated with a lower risk of death, confirming literature (Gagne et al. 2011). As they argued, hypertension should not be interpreted as a protective factor, but as the "signal" of other factors that are inversely correlated with mortality (e.g., physicians might have explicitly coded hypertension only for those patients without other more severe comorbidities, thus "signaling" healthier individuals). Other comorbidities, such as arrhythmia, chronic pulmonary diseases, and pulmonary circulatory diseases are also associated with a lower risk of death. This counterintuitive result could be explained considering that such comorbidities are likely to be associated with other heart diseases, and that these patients are treated with adequate cardiac therapies that act as protecting factors for the risk of death.

Table 4. Results of the logistic model on 30-day mortality, unplanned readmissions, and mortality or unplanned readmissions using a stepwise selection method. In grey, the covariates associated with the composite outcome.

30-days	**Mortality**				**Readmission**				**Mortality OR Readmission**			
Effect	**OR**	**95% CL**		**p**	**OR**	**95% CL**		**p**	**OR**	**95% CL**		**p**
Sex (M vs F)	0.850	0.804	0.899	<.0001					0.925	0.882	0.970	0.0013
Age (years)	1.075	1.072	1.079	<.0001	0.993	0.990	0.997	<.0001	1.039	1.037	1.042	<.0001
Number of ED accesses in the previous six months	1.047	1.012	1.083	0.0088					1.032	1.002	1.062	0.0332
Number of hospitalizations in the previous six months	1.424	1.367	1.483	<.0001	1.241	1.181	1.306	<.0001	1.335	1.289	1.383	<.0001
In-hospital length of stay					1.015	1.010	1.019	<.0001	1.004	1.002	1.007	0.0020
Patient admitted in cardiac ward (Yes vs No)	0.400	0.366	0.438	<.0001	0.769	0.700	0.845	<.0001	0.515	0.482	0.550	<.0001
Major therapeutic procedure (Yes vs No)	0.809	0.703	0.930	0.0030	1.225	1.075	1.396	0.0023				
Metastatic cancer (Yes vs No)	3.608	3.070	4.241	<.0001	1.367	1.045	1.790	0.0227	2.893	2.484	3.370	<.0001
Renal diseases (Yes vs No)					1.139	1.020	1.272	0.0207	1.085	1.013	1.161	0.0203
Hemiplegia (Yes vs No)	2.348	1.786	3.085	<.0001	1.506	1.024	2.214	0.0375	1.851	1.452	2.360	<.0001
Any tumor (Yes vs No)	1.748	1.571	1.946	<.0001					1.515	1.377	1.666	<.0001
Arrhythmia (Yes vs No)	0.743	0.700	0.790	<.0001					0.807	0.767	0.848	<.0001

30-days	**Mortality**				**Readmission**				**Mortality OR Readmission**			
Effect	**OR**	**95% CL**		**p**	**OR**	**95% CL**		**p**	**OR**	**95% CL**		**p**
Chronic pulmonary disease (Yes vs No)	0.790	0.730	0.854	<.0001	1.168	1.064	1.283	0.0011	0.880	0.827	0.935	<.0001
Coagulopathy (Yes vs No)	2.452	1.766	3.404	<.0001					1.567	1.167	2.103	0.0028
Anemia (Yes vs No)	0.807	0.720	0.904	0.0002	1.166	1.004	1.353	0.0445				
Psychosis (Yes vs No)					1.597	1.075	2.373	0.0205				
Fluid and electrolyte disorders (Yes vs No)	1.753	1.547	1.988	<.0001					1.533	1.368	1.717	<.0001
Pulmonary circulatory diseases (Yes vs No)	0.687	0.575	0.822	<.0001								
Hypertension (Yes vs No)	0.556	0.512	0.604	<.0001	1.103	1.006	1.210	0.0371	0.712	0.668	0.760	<.0001

The number of previous admissions and of ED accesses have been found positively associated with the risk of death. Patients admitted in Cardiologic wards and undergoing major procedures are associated with lower probability of 30-day mortality. The discriminant ability of the model is quite good (AUC = 0.7504; Confidence Interval (CI) = (0.7446-0.7562)) for the training set and is confirmed for the validation set (AUC = 0.7388, CI = (0.7297-0.7480, see Table 3). The Youden index estimated on the validation set is associated with SE = 0.66, SP = 0.69, PPV = 0.24, and NPV = 0.93 (see Table 3 for CI).

Table 5. Performance of the model applying the Youden index as threshold on the three outcomes in the validation set.

30-days	**AUC (CI)**	**Youden index (p)**	**SE (CI)**	**SP (CI)**	**PPV (CI)**	**NPV (CI)**
Mortality	0.7388 (0.7297-0.7480)	0.35 (0.15)	0.66 (0.64 - 0.68)	0.69 (0.68 - 0.69)	0.24 (0.23 – 0.25)	0.93 (0.926 – 0.934)
Readmissions	0.5777 (0.5615-0.5939)	0.12 (0.07)	0.44 (0.41 – 0.48)	0.68 (0.67 – 0.69)	0.09 (0.08 – 0.10)	0.94 (0.939 - 0.947)
Mortality or readmission	0.6749 (0.6660-0.6839)	0.25 (0.20)	0.63 (0.62 – 0.65)	0.62 (0.61 – 0.62)	0.28 (0.27 – 0.29)	0.88 (0.871 – 0.882)

AUC = Area Under the Curve; SE = Sensitivity; SP = Specificity; PPV = Positive Predictive Value; NPV = Negative Predictive Value; CI = Confidence Interval.

Results on 30-day unplanned readmissions

Among variables reflecting in-hospital treatment, the hospital length of stay and the presence of major procedures have been found positively associated with a higher risk of readmission (see Table 2). Admittance in a Cardiologic ward has a protective effect for readmission (as found also for mortality). As for patient history, only the number of previous admissions is positively associated with readmissions. The comorbidities significantly associated with readmission are reported in Table 2; unlike what found for mortality, all of them are risk factors for 30-day unplanned readmissions. The discriminant ability of the model on the training set is very poor (AUC = 0.5902; CI = (0.5798-0.6006) and is confirmed in the validation set (AUC =

0.5777; CI = (0.5615-0.5939), see Table 3). The Youden index, evaluated in the validation set, is associated with SE = 0.44, SP = 0.68, PPV = 0.09, and NPV = 0.94.

Results on the combined outcome (mortality or unplanned readmissions)

All the variables associated with mortality are also associated with the combined outcome, except for major therapeutic procedures; anemia and pulmonary circulatory diseases (see Table 2). They preserve the same type of association, either positive or negative, they have with mortality even when it is in contrast with their effect on readmission (age, chronic pulmonary diseases, and hypertension) or when they have not any significant effect on readmission (sex, number of previous hospitalizations, tumor, arrhythmia, coagulopathy, and fluid and electrolyte disorders). Major therapeutic procedures and anemia have opposite effects on mortality and readmissions, but the association is not particularly strong for both the outcomes (see Table 2). Length of stay and renal diseases are the only variables significantly predicting the combined outcome; which were associated with readmissions but not with mortality (see Table 2). The discriminant ability of the model on the training set is fair (AUC = 0.6788; CI = (0.6730-0 6847)) and it is confirmed in the validation set (AUC = 0.6749; CI = (0.6660-0.6839); see Table 3). The Youden index, evaluated in the validation set, is associated with SE = 0.63, SP = 0.62; PPV = 0.28, and NPV = 0.88 (see Table 3).

Discussion

The discriminant ability of the two models on 30-day mortality and 30-day unplanned readmissions is similar to those shown in past studies (Gu et al. 2009; Au et al. 2012; Wallmann et al. 2013). Predicting readmissions because of demographic and clinical characteristics of the patient is the main avenue while not being a trivial exercise (Ross et al. 2008). In this regard, administrative data suffer for the lack of detailed clinical information that improve the prediction ability of models. To improve the discriminant ability of our models, we introduced covariates on patient’s history and treatment during hospitalization. Among them, the number of previous hospitalizations and the admission ward have been found associated with mortality, readmissions, and with the combination of them. Previous study on the HF patient outcome (Jong et al. 2003) found that better outcomes could be achieved when cardiologists take the lead during the hospitalization.

Although the Lombardy Region administrative data do not store this information, we included in our study the admission ward as a proxy of the correct placement of the patient and of the physicians in charge of her hospitalization. The risk reduction associated with the admission to a Cardiologic ward suggests the importance of in-hospital patient pathways, even if we cannot exclude the effect of a non-completely controlled bias for patients' clinical condition.

Our results show that the introduction of new covariates on patient history and in-hospital treatment and the exclusion of patients died within 10 days from discharge do not clearly improve the discriminant ability of the model on readmission, which remains similar to those reported in past studies (Au et al. 2012; Wallmann et al. 2013). Previous studies (Wallmann et al. 2013) developed a model to predict readmissions for all cardiac diseases, with a fair discriminant ability (AUC = 0.64). It is worth to be noting that while they evaluated readmissions on a specific subset of hospitalizations (in MDC-5; i.e. diseases of the circulatory system), we implemented a broader definition of HF and considered readmissions for all causes.

The model on the combined outcome has fair performance, between those for mortality and readmissions. Out of 15 variables associated with the combined outcome, 13 were also associated with mortality. Half of the variables affecting the combined outcome also affect both mortality and readmissions. Additionally, they always had for the combined outcome the same effects shown on mortality, even if in contrast with the effects on readmission (in particular for age, chronic pulmonary diseases and hypertension). However, their effect on the combined outcome is softened with respect to that on mortality. Six of the variables affecting the combined outcome were associated with mortality but not with readmissions.

Conclusion

As result of our analyses, the composite outcome has been found to offer a weaker clinical meaning; additionally, its prediction seems to be more related with prediction of death rather than readmission, also given the limited predictive ability of the model on readmissions. As consequence, we argue that considering the composite outcome does not improve the comprehension of the factors associated with mortality and readmissions. Recent research showed that hospitals in the Lombardy Region are more in control – in term of actual vs. risk-adjusted predicted results – for 30-day mortality than 30-day unplanned readmissions for HF patients. In this view, healthcare regulators and professionals urge further research to understand the "readmission phenomenon" in order to deliver better care and saving costs (Teryl K. Nuckols

2015) as well as improving public health surveillance systems to provide better information about the prevalence of chronic conditions (Raisa Deber & Schwartz 2016).

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Paper Number 3: Multi-level models for heart failure patients' 30-day mortality and re-admission rates: the relation between patient and hospital factors in administrative data.

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Afsaneh Roshanghalb collaborated as the correspond author in all parts of this study.

Abstract

Background: This study aims at gathering evidence about the relation between 30-day mortality and 30-day unplanned readmission and patient and hospital factors. In particular, the focus is on the role played by hospital-level factors.

Methods: A multi-level logistic model that combines patient- and hospital-level covariates has been developed to better disentangle the role played by the two groups of covariates. Hospital outliers in term of best/worst performers have been identified through the creation of funnel plots by comparing expected cases vs. observed cases. Covariates have been selected coherently to past literature. Data comes from the hospital discharge forms for Heart Failure patients in the Lombardy Region (Northern Italy). Considering incident cases for HF in the timespan 2010-2012, 78,907 records for adult patients from 117 hospitals have been collected after quality checks.

Results: Our results show that 30-day mortality and 30-day unplanned readmissions are explained by hospital-level covariates, paving the way for the design and implementation of evidence-based improvement strategies. While the percentage of surgical DRG and the hospital type are significant for mortality, the mean length of stay is significant for unplanned readmission, showing that mortality and readmission rates might be improved through different strategies.

Conclusions: Our results confirm that hospital-level covariates do affect quality of care, and that 30-day mortality and 30-day unplanned readmission are affected by different managerial choices. This confirms that hospitals should be accountable for their "added value" to quality of care.

Keywords: Quality of Care, Hospital Care Performance, Administrative Data, Heart Failure, Mortality, Readmission

Background

Hospitals show differences in terms of quality of care (McConnell et al. 2013). Past research has investigated extensively how to implement risk-adjustments based on inputs, case-mix or other patients' characteristics to limit potential biases when benchmarking hospital performance (Wallmann et al. 2013). Despite the undoubted value of these contributions, three intertwined limitations still puzzle our understanding of how to provide regulators and hospital managers with evidence-based guidelines about how to improve quality of care. First, past contributions underemphasized the role of management practices, privileging patients-related covariates (Au et al. 2012; Wallmann et al. 2013) or hospital resources (Hakkinen et al. 2013). Recent studies–for a review refer to (Lega et al. 2013)–claim that management practices affect hospital quality of care. Grounding on this emerging evidence, Lega et al. (2013) argued that "empirical efforts of researchers must extend our understanding of the relationship between management practices and performance" (pg. S50). Second, past studies that investigated the relationship between management practices and quality of care proved it through either self-reported surveys or expert opinion. In this view, regulators and hospital managers pointed out that current evidence about the existence of this relationship is not enough robust as studies on hospital performance based on administrative data (e.g., Bottle, Sanders, et al. 2013; Murdoch & Detsky 2013; Cook & Collins 2015)–even if limited to patient-related covariates. Regulators and hospital managers need more conclusive evidence about which managerial practices affect the quality of care to implement improvement strategies (Park et al., 2014). Third, 30-day mortality and 30-day unplanned readmission are competing outcomes (Di Tano et al. 2015). While the mainstream approach is to analyze them as a single outcome (Au et al. 2012), an increasing number of scholars (Krumholz et al. 2006; Wallmann et al. 2013) analyzed them separately to better understand what explains different quality of care and the role played by different managerial alternatives (Bonow 2008).

With this study, we aim at narrowing these limitations and shedding new light on the role that management practices might have to determine the quality of care. We developed and empirically tested, through administrative data, an original hierarchical logistic model that combines individual-level covariates about patients' characteristics with hospital-level ones about management practices to gather more robust evidence about the role that management practices play. Data comes from the hospital discharge abstracts for Heart Failure (HF) patients in the Lombardy Region (Northern Italy). As indicators of hospital quality of care, we considered the well-established measures of quality of treatment on short-term outcomes for Heart Failure (HF) patients (Bottle, Middleton, et al. 2013; Bonow 2008): 30-day mortality and 30-day unplanned readmission. A significant body of evidence shows that HF patients have a high risk of mortality (Frigerio et al. 2017; Krumholz et al. 2006) and a high probability of incurring multiple urgent admissions (Au et al. 2012; Keenan et al. 2008; Robertson et al., 2012). These indicators can be measured reliably through administrative data (Bottle, Sanders, et al. 2013). Finally, since reimbursement is based on tariffs that are independent of hospital performance, treatment costs have not been considered in this study.

Methods

Measurement of Quality of Care

In this study, we refer to 30-day mortality as the number of deaths for any cause within 30 days after the incident HF admission and 30-day unplanned readmission as the number of non-programmed hospitalizations for any cause within 30 days after the incident HF admission. With incident admission, we mean for any patient the first ever admission in a hospital for HF. While 30-day mortality was measured considering intra-hospital and out–of–hospital mortality for all causes, using the Lombardy Region's registries about deaths; 30-day unplanned readmissions were measured excluding the cases of a patient being transferred from one hospital to another, planned readmissions, and readmissions occurred more than 30 days after discharge. Additionally, patients died during the incident admission or within 7 days from discharge were excluded to evaluate non-programmed readmissions. The latter choice was made to exclude patients who have decided, for personal reasons, to die at home rather than in hospital. Finally, hospitals located outside the Lombardy Region or with less than 100 HF hospitalizations were excluded.

Data

Our analysis was based on administrative data from hospital discharge abstracts and death statistics with respect to the Lombardy Region. Data from death statistics allowed us to evaluate mortality outside the hospital. Other data (e.g., the percentage of surgical DRGs) were collected from regional reports on hospitals' activity. In Lombardy, hospital discharge abstracts contain information on patient characteristics (e.g., sex and age) and hospital admission (e.g., date of admission, date of discharge, principal diagnosis and comorbidities (from secondary diagnoses), procedures, admission ward, etc.).

Our study focused on Heart Failure (HF) to identify the most relevant covariates recommended by past studies. HF is the leading cause of hospitalization for citizens 65+ in all the most developed Countries (Joynt et al. 2011) that absorbs significant financial resources. Although the focus of our study is HF patients, we claim that our methods to generate evidence–by means of hierarchical logistic regressions and funnel plots–are generalizable to other typologies of patients as well as to other Regions/Countries that collect administrative data. Respectively, we considered incident hospitalizations for HF–i.e. the first hospitalization for HF–since 2010 to 2012 occurred in hospitals located in the Lombardy Region limited to patients who are residents in the same Region. Hospitalizations for HF were identified according to the ICD-9-CM codes proposed by the Agency for Healthcare Research and Quality in their quality indicator of intra-hospital mortality due to HF (AHRQ, 2015) and those proposed by the Center for Medicare and Medicaid Services (CMS) in their risk adjustment model for capitation payments. In particular, as recommended by (Pope et al. 2011), the category HCC80 have been used consecutively (CMS-HCC80, version 12th). The codes were searched in any diagnosis position (up to six) of the hospital discharge abstracts. A hospitalization for HF was defined as the incident one for the patient if there was a previous period of at least five years without other hospitalizations due to HF. Respectively, extracting these data we were able to evaluate 1) Hospital re-admissions for any cause after the incident HF hospitalization, 2) Number of admissions occurred for any cause within the 6 months before the incident HF hospitalization, and 3) Patients' comorbidities at the incident hospitalization, using the algorithm proposed by (Gagne et al. 2011). With respect to this point, we followed the recommendations by (Sharabiani et al. 2012) and thus we searched for codes of comorbidities in the previous hospitalizations of the patient. We adopted look-back period one year before the incident HF; when chronic comorbidities were detected, they were assumed affecting the patient also in the subsequent hospitalizations.

Statistical Models

Our research strategy combined two-level hierarchical logistic regressions and funnel plots to identify hospitals with divergent performance (outliers) and isolate management practices (i.e., covariates at the hospital-level) that explain the differences between best and worst performers. Funnel plots were used to visualize outlier hospitals for both mortality and readmission and have been built on the ratio between the number of observed and the expected number of deaths (or readmissions), as stated in the formula (1):

$$Y = \frac{\sum_{i=1}^{n_j} y_{ij}^{obs}}{\sum_{i=1}^{n_j} \widehat{p_{ij}}} = \frac{O_j}{E_j} \tag{1}$$

where y_{ij}^{obs} is the observed outcome for patient 'i' treated in the hospital 'j', n_j is the number of patients treated in hospital 'j' and $p_{ij}$is the corresponding expected value for patient 'i' treated in hospital 'j'. The expected value was evaluated through a regression model and is described as follow. The upper and lower control limits, defined as 90% and 95% confidence intervals, were calculated as recommended by (Ieva & Paganoni 2015) in absence of over-dispersion (according to our data) and were used to identify outlier hospitals. To estimate correctly the expected values of mortality and readmissions, we developed a multilevel logistic regression model, adjusting for different characteristics of patients and hospitals (Diez-Roux 2000). Therefore, we introduced covariates at the patient- (first level of our hierarchical model) and hospital-level (second level of our model) to take into account possible heterogeneity in patients' or hospitals' management practices. The explanatory variables for estimating mortality and readmission, at both levels, have been selected based on past contributions (Gruneir et al. 2011; Au et al. 2012; Sasaki et al. 2013; Wallmann et al. 2013) and available data. As recommended for hierarchical models, we started testing the "null" model and evaluating the Interclass Correlation Coefficient (ICC). Then, we introduced the first level (i.e. about patients) variables and subsequently the second level (i.e. about hospitals) variables. Variables were included in our final statistical model through a backward selection method. Patient-level variables are age, sex, length of stay (LOS), comorbidities weight, number of admissions in the previous six months and type of admission ward. The latter variable had three levels to distinguish patients directly admitted in cardiologic wards, in Intensive Care Units or in other wards. We assumed this variable as a proxy for the correct placement of the patient at hospital admission.

The investigation of management practices through administrative data required the identification of those covariates that are included in the discharge forms and can be assumed as a proxy for managerial practices. The limitations–as well as the opportunities–of this approach compared to traditional surveys or expert opinion elicitation will be discussed in the "Limitations" section. We considered these variables: number of inpatient cases, average LOS, the percentage of surgical DRGs, type of hospital, attractiveness from local Health Districts (HDs) others than where the hospital is located, attractiveness from other Italian Regions or from abroad. At the time of this study, in the Lombardy Region, there were 15 HDs, including hospitals and outpatient services providers. The number of admissions, being related to the volume of patients, is a proxy of the hospital relevance and size; this characteristic is also explained by the attractiveness of patients from other HDs, other Regions and abroad. The percentage of surgical DRGs characterizes hospitals as it represents synthetically the frequency of the surgical procedures carried out by a hospital. The typology of a hospital–we considered three types: non-research public hospitals, non-research private hospitals, research hospitals (both public and private)– may echo different types of governance and processes. Data management and statistical analysis were performed using SAS 9.4.

Results

Considering the timespan 2010-2012, 78,907 residents in the Lombardy Region and aged at least 18 were hospitalized for HF for the first time. Applying the exclusion criteria described in the 'Methods' section, we identified 72,083 patients admitted to 117 hospitals eligible for evaluating mortality and 60,771 patients admitted to 116 hospitals at risk for unplanned 30-day readmissions. Regarding 30-day mortality ratio, out of 72,083 patients, 9,480 (13.15%) died within 30 days from the incident event. The ICC of the 'null' model is 4.85%, confirming the hierarchical structure of data. All patient-related variables (first level variables in our model) were correlated significantly with the outcome; therefore, all of them were included in our final model. Among the hospital-related variables second level variables in our model), only some of them were correlated significantly to the outcome; they were the percentage of surgical DRGs and the type of hospital (non-research public hospitals/non-research private hospitals/research hospitals). All the other second-level variables were removed from our final model with the backward selection method. Parameter estimates and odds ratios (ORs) for fixed effects in the definitive model are in Table 1.

Table 6. Hierarchical logistic model for 30-day mortality.

Variable	**Estimate**	**Standard Error**	**P-value**	**Odds Ratio**	**95% Confidence**
Intercept	-2.12	.08	<.0001	-	-
Age	.07	.001	<.0001	1.070	1.067-1.073
Sex (*male vs. female*)	-.15	.02	<.0001	1.166	1.112-1.223
Length of Stay	-.003	.001	.0299	.997	.994-1.000
Comorbidity weight	.17	.008	<.0001	1.190	1.172-1.209
Number of previous admissions	.28	.02	<.0001	1.323	1.281-1.367
% of surgical DRGs*	.01	.002	.0003	1.007	1.003-1.011
Admission ward					
• *IC or CIC vs. cardiac**	-1.06	.04	<.0001	3.108	2.801-3.448
• *Other vs. cardiac*	.07	.04	<.0001	2.890	2.655-3.145
Type of structure					
• *Research hospitals vs. non-research public hospitals*	.29	.09	<.0001	.624	.485-.803
• *Non-research private hospitals vs. non-research hospitals*	-.18	.14	<.0001	.746	.626-.889

Except two, all covariates have a positive association with 30-day mortality. Results are reported in terms of Odd Ratios and confidence intervals (CI). As expected, age (OR=1.070; CI (1.067-1.073)) and comorbidity weight (OR=1.190; CI (1.172-1.209)) positively affect the probability of death. The number of previous admissions, as a proxy of patient worsening condition, is also positively related to the probability of death (OR=1.323; CI (1.281-1.367)). Being male increases the risk of death (OR=1.323; CI (1.112-1.223)). The type of admission ward shows a strong association with 30-day mortality. As expected, patients admitted in Intensive Care Units show higher probabilities of death than those admitted in cardiac wards (OR=3.108; CI (2.801-3.448)); being admitted to non-cardiac wards is strongly associated to higher mortality than being admitted in cardiac wards (OR=2.890; CI (2.655-3.145)).

As “protective” factor, i.e. covariates associated with lower probability of death, the LOS indicates that the longer the stay the lower the probability of death (OR=0.997; CI (0.994-1.000)). However, although the significant p-value, the confidence interval suggests a moderate effect. At last, only the percentage of surgical DRGs–as variable at the hospital level–is positively associated with mortality (OR=1.007; CI (1.003-1.011)). Admissions in research hospitals and non-research private hospitals are associated with a lower mortality than in non-research public hospitals (respectively OR=0.624; CI (0.485-0.803) and OR=0.746; CI (0.626-0.889)). Finally, we calculated the total observed mortality for each hospital and we evaluated the expected deaths of patients admitted to the hospital to define the observed/expected ratio and to build the funnel plot, as shown in Figure 1.

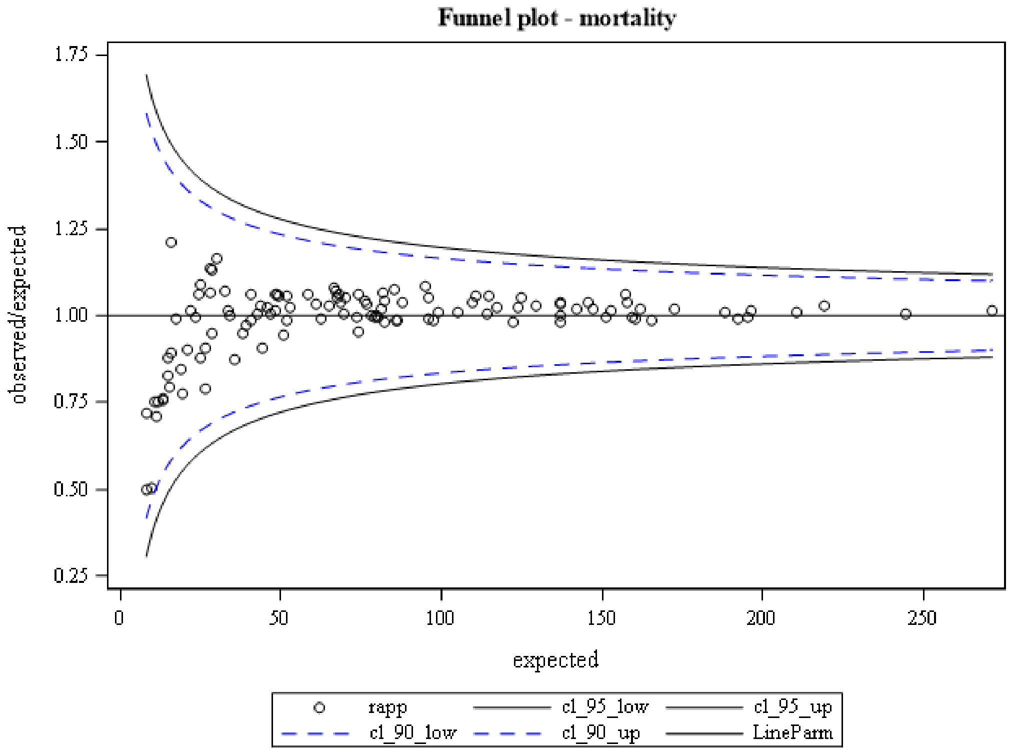

Figure 5. Funnel plot for mortality of the 117 hospitals studied (dots); 90% (dashed line) and 95% (continuous line) confidence limits

The funnel plot on 30-day mortality shows that all 117 hospitals are ‘in-control’ because none of them is over the upper limit (worst performers) or below the lower limit (best performers). This happens also considering the less restrictive 90% confidence interval. In addition, hospitals that manage a smaller number of HF patients (left side of the funnel plot) do not show performance that is over the upper limit.

Respecting to 30-day unplanned readmission ratio, out of 60,771 patients, 5,363 (8.82%) were readmitted within 30-days from the discharge of the incident hospitalization. The ICC of the ‘null’ model is 0.66%; such value is quite low. However, the ratio between the estimated variance (0.022) associated with the random effect, i.e. hospitals, and the associated standard error (0.007) is greater than 1.96 and, therefore, significantly different from zero. This suggests that a multilevel model has to be preferred (Alexandrescu et al. 2011). Unlike what we found for mortality, the effect of patients’ sex was not significant (p=0.1757) and this variable was therefore removed from the model. Among the second-level explanatory variables, the hospital average LOS was the only one with a significant effect (p<.0001) on readmissions and was therefore included in the final model. Parameter estimates and odds ratios for fixed effects in the definitive model are in Table 2. As expected, except for hospital mean LOS, all the other covariates had a positive association with the probability of readmission. As it happened for mortality, age (OR=1.011; CI (1.009-1.014)) and comorbidity weight (OR=1.094; CI (1.072-1.117)) are associated with higher probability of readmission. The number of previous admissions was also associated with an increased probability of readmission (OR=1.272; CI (1.221-1.325)).

As for mortality, this variable is a proxy of the worsening condition of the patient, who has needed several hospitalizations. The effect of the admission ward on readmissions was similar to what we found about mortality but with a weaker effect. Being admitted to an ICU (OR=1.510; CI (1.358-1.679)) or in other wards (OR=1.378; CI (1.272-1.493)) implies an increased probability of subsequent readmission compared to being admitted in a cardiac ward. Contrary to mortality, longer hospitalizations are associated with a higher probability of readmission (OR=1.023; CI (1.019-1.026)). Therefore, as for mortality, the association is probably due to the worse condition of patients admitted for prolonged periods. At hospital-level, only the average LOS shows a significant effect on readmission. In particular, hospitals with lower mean duration of hospitalization expose patients to a higher probability of readmission (OR=0.961; CI (0.945-0.977)).

Table 7. Hierarchical logistic model for 30-day readmissions.

Variable	**Estimate**	**Standard Error**	**P-value**	**Odds Ratio**	**95% Confidence**
Intercept	-2.33	.02	<.0001	-	-
Age	.01	.001	<.0001	1.011	1.009-1.014
Length of Stay	.02	.002	<.0001	1.023	1.019-1.026
Comorbidity weight	.09	.01	<.0001	1.094	1.072-1.117
Number of previous admissions	.24	.02	<.0001	1.272	1.221-1.325
Admission ward					
• *IC or CIC vs. cardiac**	-.32	.04	<.0001	1.510	1.358-1.679
• *Other vs. cardiac*	-.02	.05	<.0001	1.378	1.272-1.493
Hospital mean length of stay	-.04	.01	<.0001	.961	.945-.977

*IC= Intensive Care, CIC= Cardiac Intensive Care

As done for mortality, we calculated for each hospital the number of observed and expected readmissions to define the observed/expected ratio and build the funnel plot, as shown in Figure 2.

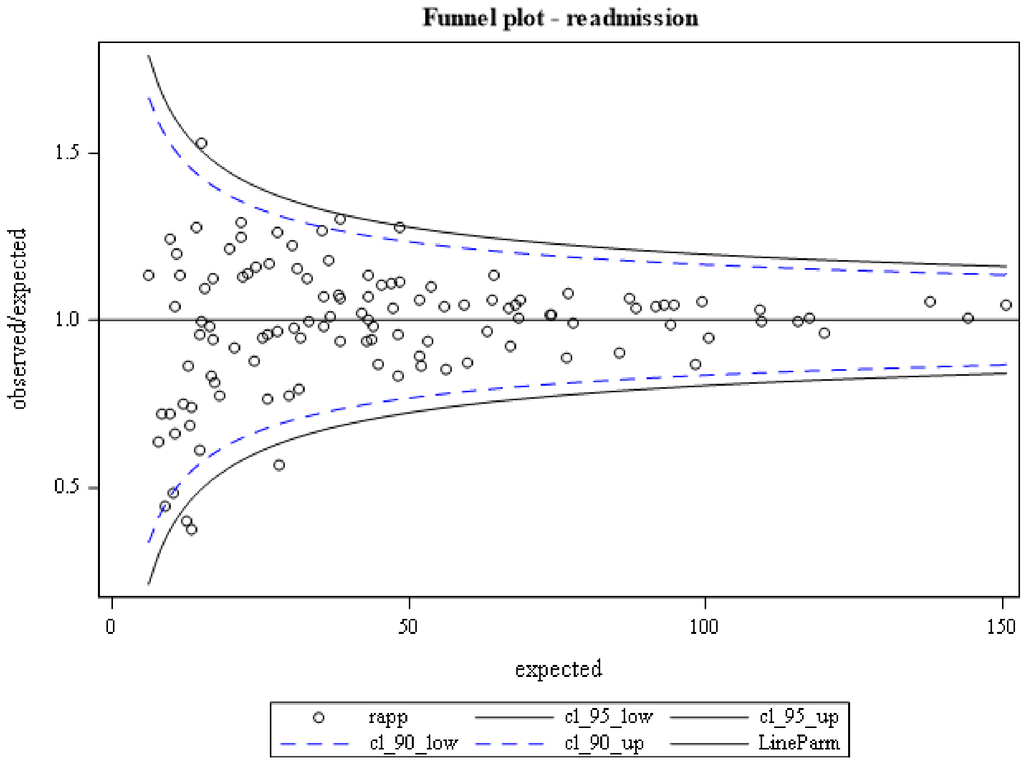

Figure 6. Funnel plot for readmission of 116 hospitals studied (dots) with 90% (dashed line) and 95% (continuous line) confidence limits

Considering the 95% confidence interval, four hospitals were located outside the control limits: among them, three hospitals were below the lower limit (best performers) and one hospital was over the upper limit (worst performers). If we consider the 90% confidence interval, eight hospitals are found as 'outliers': while five hospitals perform better than all the others do yet, three of them can be identified as worst performers.

Mortality vs. Readmission

Table 3 shows our results in terms of variables (both at the individual- and at the hospital-level) that have been confirmed to affect 30-day mortality and 30-day readmissions. These results are relevant for our discussion because, as claimed by (Keenan et al. 2008), the two performance indicators explain individually different dimensions of the "quality of care" but if analyzed together they allow understanding the potential trade-offs between these concurrent outcomes.

Table 8. Results for mortality vs. readmission.

<table>
<tr><td></td><td>Variables</td><td>30-day Mortality</td><td>30-day Readmission</td></tr>
<tr><td rowspan="6">Individual-level variables</td><td>Age</td><td>+</td><td>+</td></tr>
<tr><td>Sex (male vs female)</td><td>+</td><td></td></tr>
<tr><td>Length of Stay</td><td>(-)</td><td>+</td></tr>
<tr><td>Comorbidity Weight</td><td>+</td><td>+</td></tr>
<tr><td>Number of Previous Admissions</td><td>+</td><td>+</td></tr>
<tr><td>Ward Admission</td><td>+</td><td>+</td></tr>
<tr><td rowspan="6">Hospital-level variables</td><td>Mean Number of Admissions</td><td></td><td></td></tr>
<tr><td>Mean Length Of Stay (LOS)</td><td></td><td>(-)</td></tr>
<tr><td>% Surgical Hospitalizations</td><td>+</td><td></td></tr>
<tr><td>Type of Hospital</td><td>+</td><td></td></tr>
<tr><td>% Patients from other Local Health Agencies</td><td></td><td></td></tr>
<tr><td>% Patients from other Regions</td><td></td><td></td></tr>
</table>

Focusing on patient-related variables, our results show that age, the weight of comorbidities and number of previous admissions are significantly associated with an increased probability of 30-day mortality or 30-day unplanned readmission. These variables all-together capture the severity of the disease and the complexity of the clinical case that hospital professional have to cope with. Type of ward at the entrance shows a similar effect on both mortality and readmission, even if with a higher effect on mortality rather than on readmission.

According to our results, being admitted in non-cardiac wards increases the risk of death and readmission. This is an interesting result because, despite it is a patient-level variable, the type of ward at admission can be associated with the organizational procedures and patient pathways put in place in the specific hospital. The same considerations can be done for the patient's LOS, whose duration is determined by a combination of patients' characteristics and hospital choices. However, LOS has an opposite effect on the two indicators. While a longer LOS is associated with a lower probability of 30-day death, a longer LOS is associated with a higher probability of unplanned readmission.

Moving to the hospital-level variables, mortality and readmission have been found associated with different variables. On the one hand, higher readmission rates are associated with lower mean hospital LOS. This indicates that, after controlling for hospital case-mix and patients' characteristics, hospital policies on LOS affect the probability of subsequent unplanned hospitalizations. This result is significant for both hospital managers and policy-makers who, while deciding for reducing LOS to save costs, might fail to see the future costs due to unplanned re-hospitalizations. On the other hand, higher percentages of surgical DRGs are associated with higher probability of death. This association captures, on the one hand, that surgery has higher risks rather than other kinds of treatments, and, on the other hand, that the hospital is accepting patients with more complex conditions. In this regard, it is worth to note once again that administrative data do not include detailed clinical information. Finally, the type of hospital has an impact on mortality. Public, non-research hospitals show higher mortality and readmission rates than private, non-research hospitals and research hospitals (private and public) does.

Discussion

Our results show management practices affect hospital quality of care despite patients' peculiar characteristics. In this view, the discussion will deal with two main issues. First, we will discuss the role played by management practices and their implication for theory advancement and practice improvement. Second, we will discuss administrative database as a source of evidence for grounding decision-making and the implementation of performance improvement strategies.

Our results show that hospital managers have the opportunity to improve quality of care by adopting effective management practices being a performance not driven just by patients' characteristics. Leveraging on different configurations of governance, processes, and practices, hospital managers can actually improve quality of care. With respect to HF patients, the "isolation" of this effect on performance refers to four practices: the choice of the admission ward at the first hospitalization (intensive care unit vs. cardiac unit vs. non-cardiac unit), the average LOS, the percentage of surgical DRGs, and the type of hospital (research vs. private, non-research vs. public, non-research).

These results suggest two directions of discussion. First, the former three variables echo hospital managers and professionals' capability to organize clinical pathways that are effective and safe. The choice of the ward at admission is mainly led by clinical motivations; however, it can be affected by the existence of skills and protocols that guarantee a correct triage of patients and the identification of the adequate treatment for them. Leaving the patients wandering through different wards has the twofold effect of decreasing the quality of care–and thus increasing the probability of death or readmission–and absorbing more costs for ineffective–when not harmful–care. Similar reasoning deals with the choice of the adequate LOS. Reducing the average LOS while might contribute to increase the hospital profitability in both the short-term (because reimbursements are decided based on tariffs regardless of the days actually spent by the patients in the hospital) and the mid/long-term (because of repeated hospitalizations), could harm the patient. In this view, hospital managers and professionals have the responsibility to manage this trade-off balancing ethics and sustainability over time.

Similar implications can be argued with respect to the percentage of surgical DRGs. On the one hand, surgery is characterized by superior risks rather than other treatments and thus professionals should define appropriate protocols to select those patients who might actually benefit from this risk-increasing procedure. On the other hand, surgery treatments should be concentrated in specialized hospitals that, by performing a significant number of surgical procedures per year, would develop superior skills to minimize the risk of death or side effects.

Second, the significance of the type of hospital points out the relevance of innovation and change. Research hospitals, regardless of their ownership, have been found to outperform the others. Their continuous tension to innovation, improvement, and learning paves the way for the systematic updating of governance configurations and clinical pathways, aligning them to best available evidence. Considering non-research hospitals, private hospitals have been found to outperform public ones. Because we are not fully able with administrative data to control for patients' clinical condition, part of the explanation might be related, as found in previous studies (Berta et al. 2010), to the fact that private hospitals are more likely to select patients with a lower case-mix (i.e., treated patients have a better general condition and facilitate the achievement of positive performance). Another explanation grounds on the superior capability of private hospitals to design and implement changes aimed at improving performance; in particular, private hospitals implement such changes rapidly and with limited resistance from healthcare professionals.

The second issue is the role that administrative data might play in helping policy-makers and hospital managers and professionals to isolate the effect that management practices play in shaping the quality of care and generate reliable evidence to support decision-making and improvement strategies. Our multilevel statistical model allowed us to identify those hospitals achieving "out of control" performance in terms of 30-day mortality or readmissions and, more than this, to disentangle explanatory patient-related variables from hospital-related ones. Our results, despite the specific case of HF patients, confirmed that administrative data are a valuable source of evidence to benchmarking hospital performance and provide decision-makers at different levels with relevant and reliable insights about performance and their determinants. Our results should encourage policy-makers and hospital managers to crystallize best practices and virtuous behaviors from best performers to translate them to the poor performers (Dover & Schopflocher 2011). Although the value stored in administrative data, particular attention should be paid to the interpretation of the results. The main concern is the lack of detailed clinical information, which could better guide researchers in unfolding the specific characteristics of the treated patients and avoid biases in the comparison.

Additionally, the weight of comorbidities and of case-mix could provide first-hand information about the clinical status of patients, but more detailed clinical information is necessary to risk-adjust the performance achieved by different hospitals. For instance, the correlation between the LOS and 30-day mortality could be biased by fact that some hospitals treat more complex patients who actually die after the very first days because of their severe conditions that did not leave possibilities to professionals. We controlled for age, sex, previous admissions, comorbidities score etc. but these factors, the only available in administrative datasets, could not be enough to capture all the variance connected to the severity of the clinical condition of patients.

In this regards, two actions should be taken to improve the richness of the available data. On the one hand, administrative data should be complemented with clinical information stored in clinical registries and hospital medical records. On the other hand, different administrative data should be integrated to provide researchers with all available information. For instance, administrative data from discharge abstracts should be complemented with data from the Emergency Departments and about drug prescriptions.

Despite the limitations described above, our results show that the combination of multilevel statistical models and funnel plots offers policy-makers and regulators the opportunity to monitor and control the performance achieved by the regional healthcare system with respect to different pathologies. For instance, the fact that there are not outliers for 30-day mortality means that the system as a whole is achieving satisfying performance and guarantees patients about the safeness and effectiveness of the services received. In this regard, further research should monitor such results with a longitudinal perspective aimed at understanding if (i) the delivery system is improving as a whole; (ii) specific improvement strategies (e.g., the sharing of best practices, the design of more severe accreditation parameters, the increased frequency of audits and inspections, etc.) are or not producing the expected benefits; and (iii) hospitals have or not the capability to improve performance over time, understanding both the time required to change and improve (thus testing our argument that private hospitals are faster in implementing change and in reacting to poor performance) as well as the factors that might facilitate/inhibit such changes.

Conclusions

This study offers original insights on the use of administrative data to investigate the effect that management practices have on the quality of care. Administrative data can provide policy-makers and hospital managers with the opportunity to design evidence-based improvement strategies by understanding the management practices that explain the difference, in terms of quality of care, between best and worst performers. By applying hierarchical statistical models, researchers can manage the nested structure of these data to compare significant performance such as 30-day mortality and readmission. In this regard, funnel plots offer an evidence-grounded identification of “out of control” hospitals and an easy-to-get interpretation of results also to those decision-makers who might not familiar with sophisticated statistical analyses (Ieva & Paganoni 2015).

The identification of variables significantly associated with death and readmission as well as of characteristics that differentiate best vs. worst performers. This identification offers original and evidence-based insights to further the discussion about patient pathways within and outside the hospital, hospitals’ policies on LOS, the implications of public vs. private ownership and of research vs. non-research orientation, volumes of treated cases and the need of minimum scales of activities. Coherently, we expect administrative data will receive an increasing interest from scholars of health services research as well as from policy-makers and practitioners, aimed at implementing improvement strategies by unfolding the evidence stored in routinely collected data (Taylor et al., 2015).

Despite the contributions offered, our results must be interpreted under the light of the limitations of our study, that pave the way for further research. First, our analysis dealt with HF patients treated in Lombardy Region hospitals. Although we argue that our approach could be generalized to other pathologies and other Countries that have access to administrative data, further research should confirm or disconfirm such claim. Second, the information available in administrative data to characterized hospitals is limited to the variables explored in our analysis. Other variables that might be explanatory of different variables such as senior managers’ and senior physicians’ leadership styles, technological excellence, tension to innovation measured by publication impact factors or patents were not easily available and thus overlooked in this study. Further research should collect such information from other accessible sources (e.g., hospitals’ website, official documents, etc.) to extend our comprehension.Regulators should evaluate the systematic collection of this data from hospitals to enable longitudinal studies.

Third, the patient hospitalized for HF may be transferred from a hospital to another one to receive treatment or procedures unavailable in the previous one. The 30-day mortality and re-admission rates developed in the model assigns the responsibility for results to hospitals in which patients were originally admitted. This approach places in the hands of the sending hospital responsibility to transfer patients appropriately, establishing properly timing and health facility. If the receiving hospital is not able to provide high-quality care, then the first hospital should consider other options (Krumholz et al. 2006). However, a future development could be done attributing the outcome to all the hospitals that treated the patient, in the perspective of sharing responsibilities on the patient outcome. Fourth, further analysis should take a longitudinal approach to gather evidence about the capability of the system and of each hospital in the system to improve.

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Paper Number 4: Stability over time of the "hospital effect" on 30-day readmissions: Evidence from administrative data.

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Abstract

This study investigates the stability over time of the "hospital effect" (i.e., covariates at the hospital level) on 30-day unplanned readmissions. Using 78,907 heart failure adult records from 117 hospitals in the Lombardy Region (Northern Italy) over three years (2010-2012), we analysed and compared hospital performance in term of 30-day unplanned readmissions to gather evidence about the stability of the hospital effect. Best/worst providers were identified through a multi-level model that combines both patient and hospital covariates in each year. Our results confirm that even if hospital covariates (and the connected managerial choices) affect 30-day unplanned readmissions, their effect, contrary to expectations, is not stable in the short-term (three years).

Keywords_ Hospital Effect, Hospital Performance, Administrative Data, Readmission, Heart Failure.

Introduction

During recent years there has been an increasing interest to translate the concepts and tools of Evidence-Based Medicine (EBM) to Management with the declared purpose of informing decision-making and selecting those improvement strategies that actually proved to work (Rn et al. 2006; Wright et al. 2016; Morrell 2015; Arndt & Bigelow 2009). Real world data – in particular, administrative data gathered from hospital discharge forms – have the potential to make this ‘dream come true’ through the analysis of massive quantities of data about patients’ (Groves et al. 2013) and hospitals’ behaviors and performance. In this regard, the benchmarking of hospital performance has attracted a growing interest in the last years. Even a cursory review of past research would reveal an extremely rich body of literature that has been developing (e.g., (Berta et al. 2013; Shams et al. 2015; Valdmanis et al. 2016; Choi et al. 2015; Ieva & Paganoni 2015)) around hospital performance and how hospitals could implement improvement strategies learning from the ‘best in class’. Policy-makers, hospital managers, health professionals, scholars of healthcare management, operations analysis, public administration etc. paid significant efforts to define and explain what has been called as the ‘hospital effect’ on performance (e.g., 30-day unscheduled readmission, 30-day mortality, average length of hospital stay (Tiemann et al. 2012; Büchner et al. 2016; Czypionka et al. 2014)).

In this manuscript, with ‘hospital effect’ we refer to the assumption that hospital managers and professionals can affect positively (or negatively) hospital performance through the adoption (or not) of management practices, clinical and administrative processes, reward systems, technologies, etc. Coherently to this line of argument, we argue that hospital performance are not driven exclusively by the individual characteristics of patients who have been admitted and treated, but that, when dealing with similar cohorts of patients, hospitals can organize themselves to achieve superior performance in terms of effectiveness, safeness, and efficiency.

Because of that, the identification of those organization-level factors and the proportion of their effect, which explain the ‘hospital effect’ on performance would constitute paramount value for policy-makers, hospital managers, and professionals and, not least, for patients and communities.

In fact, evidence about what makes the hospital work (or do not work) would inform the design and implementation of effective policy initiatives – as well as improvement strategies – aimed at not only narrowing the gap between the best and the worst performers (Cadarette & Wong 2015; Kohn 2013; Kiivet et al. 2013; Roos et al. 2004) but also reducing variation in the performance distribution in general perspective.

Additionally, the knowledge of those factors would improve both the quality and reliability of the endless number of public or private reports that benchmarking hospitals through multi-criteria data aim at recommending hospitals to patients/citizens (Williams et al. 2016; Dehmer et al. 2016). Although these reports seem to go in the direction of what citizens are experiencing for other services – restaurants, hotels, apartments, etc. – past research (Paruolo 2013) has already warned about the production of unreliable hospital rankings. But this line of reasoning makes sense only in case that 'hospital effects' prove to remain stable over time and that hospitals' capabilities to achieve superior performance in the past will guarantee the achievement of superior performance at least in the next future. In this regard, despite the undoubtable contribution of past research about hospital efficiency (e.g., (Bastian et al. 2016; Scippacercola & Sepe 2016; Jayaram & Xu 2016)) to pave our understanding of the 'hospital effect' on performance, two main limitations still puzzle it. On the one hand, past analyses relied on aggregate data at the hospital-level (Smith et al. 2008; Sulku 2012; Capkun et al. 2012; Berger et al. 2014; Kiivet et al. 2013) overlooking the information stored in data at the patient-level (e.g., comorbidities scores, age, sex, organization unit for the first admission, etc.). On the other hand, few attempts in literature discussed on the persistency of the performance over time (Swaminathan et al. 2008), thus leaving the floor open to criticisms to rankings and to the dissemination of evidence about hospital performance to citizens [20].

This study aims at narrowing these limitations by taking advantage of the opportunities offered by administrative data as their value for performance measurement is increasingly recognized (despite its limitations) during the last decade.

By administrative data, we mean data that are routinely collected by hospitals – as well as by other healthcare providers – to document their activities and get reimbursed by the payers (Mazzali & Duca 2015; Groene et al. 2014). By combining the individual-level data (e.g., age, sex, comorbidities) contained in the hospital discharge abstracts with hospital-level data (e.g., hospital characteristics, patients treated, percentage of surgical DRG (Diagnostic Related Groups)) available from public reports, it is possible to inform hierarchical statistical models that can help to disentangle the 'hospital effect' on performance from the effect due to patients' characteristics.

Leveraging our access to administrative data, this study aims at investigating the stability of the 'hospital effect' on performance over time. This will help to go far beyond current hospital rankings that do not take into enough consideration the stability of the 'hospital effect' over time.

Prior Research

Efforts on performance measurements are not a new but there is a growing interest using real-world data in healthcare to extract 'meaningful patterns in the data' (Yang et al. 2014). Considering which variables make the change and is there any trend during time of their effect on organization (i.e., hospital) performance is finding momentum.

Administrative data are one of the biggest sources of real-world data which based on the country and authority of the data hold information regarding the patient, ward, and hospital.

In Italy, the National Healthcare System (Servizio Sanitario Nazionale) was established and decentralized at regional and local levels in 1978. Regional administrations have the authority of maintaining and distributing the health administrative data for research purposes.

The stored datasets may contain information on hospital discharge abstracts, ambulatory care services and drug prescriptions (Mazzali & Duca 2015). The data have recently been used for a variety of purposes: examples are epidemiological studies (Yébenes et al. 2017; Roos et al. 2003), outcomes evaluation (Sun & Van Ryzin 2012), identification of risk factors (Shahian et al. 2012), drug adverse events detection (Solberg et al. 2004), and hospital performance evaluation (Roberts et al. 2015; Silva Portela et al. 2016).

Advantages of using administrative data for performance assessments include low collection cost, easy access, large samples, and coverage of the entire population over long observation periods in a real-world perspective without stringent patient selection common to clinical trials (Gutacker et al. 2015; Yampolskaya et al. 2004). On the other hand, compared with other clinical datasets such as registries or electronic medical records, they lack clinical data that might help to characterize the patients and their clinical history and thereby give greater potential for risk adjustment and risk prediction (Mazzali & Duca 2015).

Considering only performance measurement through administrative data, many recent studies focused on the so-called 'hard clinical outcomes', such as patient survival, unscheduled hospital readmissions, and hospital length of stay, while different variables have been used based on the aim of each study (e.g., (Bottle et al. 2014; Eijkenaar & Van Vliet 2013)). Similar to Swaminathan's (2008) findings, we expect that monitoring yearly trends of observed performance out of expected ones may lead us to probabilities of having the same performance in next years (or not).

This study aims at addressing two main literature gaps using administrative heath data. As discussed earlier, none of the previous studies in relevant literature focused on answering the debate about the stability of the hospital performance in terms of less readmission, during time. However, it is been proved that the hospitals should be evaluate considering their own performance changes over time (Gu et al. 2009).

Respectively, we asked three main research questions: (I) How big is the ‘hospital effect’ on performance. (II) Which are the determinants of the ‘hospital effect’ in each year? (III) Is the ‘hospital effect’ on performance stable over time? Scholars of healthcare management, operations analysis, public administration, etc. could review past studies and ground future studies considering administrative data to investigate the ‘hospital effect’ on performance. This will help to go far beyond hospital rankings in terms of efficiency. Regulators, hospital managers, and professionals could ground their policies and/or improvement strategies on evidence that is more robust and promote the actual translation of good managerial practices and processes from best to worst performers.

Methods

Study Setting and Design

This study takes advantage of the project “Utilization of Regional Health Service databases for evaluating epidemiology, short- and medium-term outcome, and process indexes in patients hospitalized for heart failure”, funded by the Ministry of Health and promoted by the Lombardy Region (Northern Italy). The main aim of the project was to evaluate epidemiology, short- and medium-term outcomes and process indexes in patients hospitalized for Heart-Failure (HF), using administrative healthcare databases. The choice of HF patients echoes the warnings by the World Health Organization (WHO) in their Cause-of-Death Statistics reports about the fact that cardiovascular diseases remained the first cause of mortality in the most developed or high-income countries for overall two decades (WHO Fact sheet N°310 2014). Additionally, new policies – e.g., Hospital Readmissions Reduction Program (HRRP) – and penalties for hospitals are being adjusted focusing on HF cases (Fonarow et al. 2017) urging assessing care performance for limiting readmissions cases in order to improve quality while managing the cost.

Data and patient cohort

In this study we used administrative data provided by Lombardy Region for the above-mentioned project for HF patients. We used three years (2010-2012) of discharge abstracts provided us with relevant information on patient characteristics (e.g., sex and age) and hospital admissions (e.g., date of admission and discharge, principal diagnosis, comorbidities and procedures). The data contains hospital discharge abstracts, drug prescriptions, and outpatient care information. Diagnosis information is recorded using the International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9-CM) (Anon n.d.). Based on clinical similarities and resource absorption, hospital discharge abstracts are also classified into one of the Diagnosis Related Groups (DRGs). We selected HF hospitalizations focusing on Major Diagnostic Category (MDC) 01, 04, 05 and 11 (Mazzali et al. 2016) and using the ICD-9-CM codes together to include those disease outcome pairs most relevant to heart failure. Only patients aged 18 or over were included.

Based on unique encrypted patient identification code, there comes the possibility to combine the original data with regional administration reports on hospitals activity too. This enabled us to gather and combine further information regarding our sample; information like 'percentage of surgical DRGs' and 'number of cases treated by hospitals' were considered, using regional reports at hospital level, to consider the size of activity and level of specializations.

Next, we focused on incident cases. Using HF data there are some considerations to make such as summarizing information about admissions that may occur in different hospitals and stored in different records. In addition, admissions of the same patient that are very close to each other in time may be connected to the same episode of care for heart failure.

To overcome these two limitations, two admissions were considered as a single episode of care if their distance was less or equal to 1 day (defined as the number of days between the end of the first admission and the beginning of the second one). To do this, a period of five years free of HF hospitalization was considered to identify incident cases. Finally, hospitals located outside the Lombardy Region or with less than 100 HF hospitalizations in three years were excluded from our analysis.

Outcome measures

We used 30-day unscheduled readmission as a well-established measure of quality of care on short-term outcomes for HF patients (Kohn et al. 2014; Joynt et al. 2011; Bhatia et al. 2014). With 30-day unscheduled readmission we refer to the total number of unscheduled hospitalizations for any cause within 30 days after the incident HF admission with exclusion of patients who died within 7 days from discharge. By incident admission, we refer to the first ever admission for any patient in any hospital for HF. This simplifies the admission trajectory and acknowledges the fact that the first admission for HF represents an important milestone in disease progression.

Statistical Analysis

Using SAS statistical software (SAS 9.4 TS Level 1M3) our analysis on the data started with combining the two-level hierarchical logistic regression models and funnel plots to identify 'out of control' (i.e., outlier) hospitals and to track their trend in terms of their performance improvement/worsening. We created a multilevel logistic model in each year to combine both patients' and hospitals' characteristics and making it coherent to the hierarchical nature of our data. In fact, one of our expectation is that similar outcomes will be observed for patients treated in the same hospital. Furthermore, we used funnel plots as a method for displaying outliers as suggested in literature for having 'disaggregated outcomes at provider level' (Mayer et al. 2011), and less biased in labelling outliers. We considered outliers as those hospitals that differ from others in terms of ratios between observed readmission cases out of expected ones. Thus, the result could provide triggers to convert leads to main decision makers, who are in charge of healthcare planning to set up their improvement strategies in line with understanding the causes of these occurrences year by year and assessing the reason behind their stability.

First, based on Ene et.al. 2015 (Ene et al. 2015), we developed an unconditional/null model (with no predictors) to calculate "the intra-class correlation coefficient (ICC)" while estimating how much of the variation in the probability of readmission has been taken into account by each hospital. Second, using patient and hospital covariates as fixed effects, our first and second models were analysed respectively. The choice of the explanatory variables have been made on the basis of the literature contribution and the availability of the data [31-32].

Patient-level variables are: age, sex, type of admission ward ('Main place of care') (Society & Heart 2013), length of stay (LOS), co-morbidities score, and number of hospitalizations within the previous six months. Hospital-level variables are: number of ordinary hospitalizations, mean length of hospital stay for HF patients, percentage of surgical DRG (level of hospital specialization), and type of hospital (ownership and research status). We also were interested to know about the effect on performance if the hospital doing selections on the patients based on the place of care as result we included two other variables as 'number of admissions from other local healthcare agencies', and 'number of admissions from other Italian Regions or abroad'.

The choice of including the hospital-level variables were in line with understanding if different hospital characteristics could shape the effectiveness of each hospital in terms of reducing 30-day unscheduled readmissions. Finally yet importantly, variables were included in our final statistical model through a backward selection method (Jen et al. 2011) by excluding those variables that were not significant (using P>0.05 cut-off). In each year the final model with significant variables have been used to shape the creation of funnel plots. The identification of best and worst performers was based on the ratio of expected cases of readmissions vs. observed cases ones, as stated in the formula (1):

$$Y = \frac{\sum_{i=1}^{n_j} y_{ij}^{obs}}{\sum_{i=1}^{n_j} \widehat{p_{ij}}} = \frac{O_j}{E_j} \tag{1}$$

Where y_{ij}^{obs} is the observed outcome for patient 'i' treated in the hospital 'j', n_j is the number of patients treated in hospital 'j' and $\widehat{p_{ij}}$ is the corresponding expected value for patient 'i' treated in hospital 'j'. The expected value is evaluated through the multi-level regression model previously explained (Ieva & Paganoni 2015). Based on Spiegelhalter (2005) (Spiegelhalter 2005), by assuming approximate normal distribution, the upper and lower control limits were defined as 90% and 95% confidence intervals, and were used to identify outlier hospitals for readmission in three years (Figure 1).

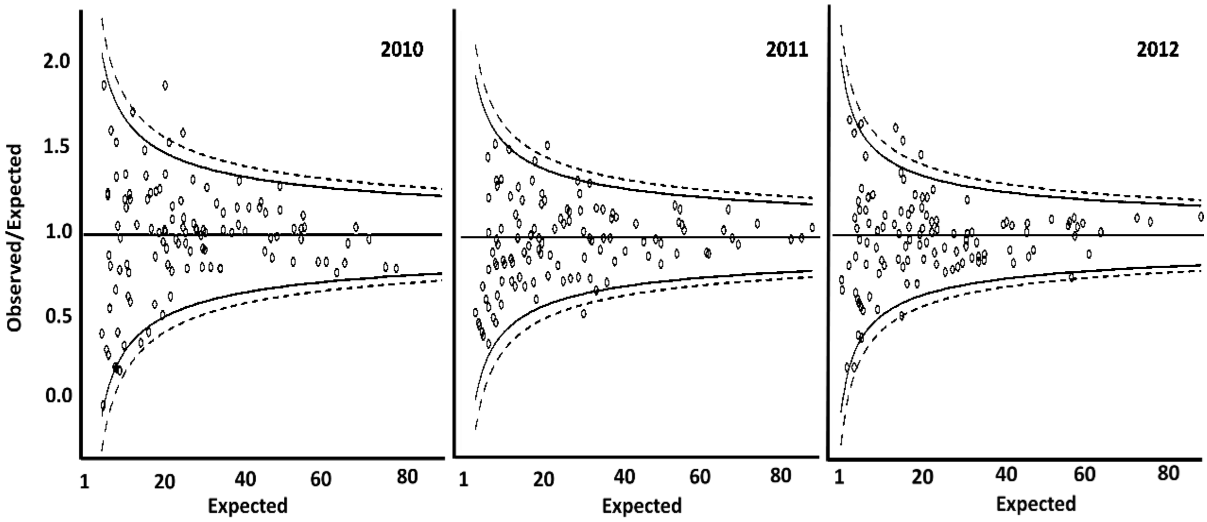

Figure 7. The 30-day unscheduled readmission ratio funnel plots in 2010, 2011, and 2012 with band limits at 95% and 90 %. The horizontal solid black line is the target limit (Y=1).

Additionally, to monitor changes of readmission during three years, we considered the vertical distance between hospital performance ratios and band limits from observed cases (x vector), reflecting the variability of hospital rates. To this end, using formula (2), the position of all hospitals in the funnel was captured in each year and focusing on those that were out of control, it could be used to compare their positions on the following years to see the trends.

$$\text{Distance} = \left[Y - (x \pm (z\_(\tfrac{1-\alpha}{2})) \times \sqrt{1/E_j}\,)\right] \times \sqrt{E_j} \quad (2)$$

Where Y is the ratio of observed out of expected cases in formula (1), x is the point that we aim to measure the distance from i.e. the target limit, the upper control limit, or the lower control limit into the funnels, $z\_(\frac{1-\alpha}{2})$ is the quantile of order of a normal standard distribution. Furthermore, the target is having the exact amount of observed cases as we expected (i.e. $\theta = 1$) with E_j number of expected cases, so that, in our case $z_{0.025} = -1.96$ and$z_{0.049} = -1.65$. In this study, we decided to consider the distance from both band limits and target limit together to distinguish the points that are placed above the target limit from those placed distinguish those points that are above or below at the same distance from it. After calculating the distance for each hospital in 2010, 2011, and 2012, we categorized them in three groups of being "best, worse, or in control" performers. To this, based on the sign and the value of the distance from target and control limits outliers identified as best/worst performers.

For example, if the hospital performance indicator came out to be greater than target and greater than upper band limit, then the point is positioned at the top of upper band limit namely as 'worst performer with high rate of readmission'. As result of our statistical analysis, we created the funnel plots showing the positioning of all hospitals in year 2010, 2011, and 2012 respectively with particular emphasis on outliers in terms of 30-day unscheduled readmissions.

Results

In 116 hospitals, 78,907 HF patients aged at least 18 and residents in Lombardy Region were included in our analysis. We created the funnel plots for the years 2010, 2011, and 2012 respectively, showing the positioning of all hospitals with particular emphasis on outliers in terms of 30-day unscheduled readmissions. In this regard, our data show that 30-day unscheduled readmissions are explained by different variables. Our results identified as significant only the mean length of stay from hospital-level variables in common in three models (see Table 1. for details), and it excluded the sex variable from the patient-level ones.

Table 9. Type III tests of fixed effects for 30-day unscheduled readmission in 2010, 2011, and 2012.

	Effects	2010			2011			2012		
		ß value	P value	OR for 95% CI	ß value	P value	OR for 95% CI	ß value	P value	OR for 95% CI
Patient level covariates	Number of Admissions in the previous six months	0.244	<.0001	1.277 (1.193-1.367)	0.256	<.0001	1.293 (1.204-1.389)	0.221	0.0001	1.248 (1.161-1.342)
	Index of all comorbidities	0.088	<.0001	1.093 (1.056-1.131)	0.087	<.0001	1.092 (1.054-1.131)	0.094	<.0001	1.099 (1.060-1.139)
	Length of stay for patient	0.022	<.0001	1.023 (1.018-1.028)	0.022	<.0001	1.023 (1.017-1.028)	0.021	<.0001	1.021 (1.016-1.027)
	Sex M vs F	-	-	-	-	-	-	-	-	-
	Age	0.013	<.0001	1.014 (1.009-1.019)	0.010	<.0001	1.011 (1.006-1.016)	0.009	<.0001	1.010 (1.005-1.014)
	Admission ward • From ICU vs Cardiologic ward	-0.241	0.0003	1.370 (1.144-1.641)	-0.364	<.0001	1.690 (1.408-2.029)	-0.351	<.0001	1.497 (1.246-1.798)
	• From all other vs Cardiologic ward	0.073	0.0003	1.273 (1.116-1.451)	0.160	<.0001	1.440 (1.251-1.657)	0.051	<.0001	1.421 (1.238-1.632)
Hospital	Number of HF patients treated in each hospital	-	-	-	-	-	-	-	-	-
	Mean length of hospital stay	0.037	0.0050	0.964 (0.939-0.989)	0.037	0.0075	0.964 (0.938-0.990)	0.0421	0.0026	0.959 (0.933-0.985)

	Percentage of surgical DRG	-	-	-	-	-	-	-	-	-
	Cases transformed from other Regional centres	-	-	-	-	-	-	-	-	-
	Cases transformed from other Local centres	-	-	-	-	-	-	-	-	-
	Type of structure (research status)	-	-	-	-	-	-	-	-	-
	Type of structure ownership (public/private)	-	-	-	-	-	-	-	-	-

Within our timespan (2010 until 2012), from 116 hospitals, 58% changed their position year-by-year inside the funnel (i.e. 27% had temporal improvement and 30% had temporal worsening from 2010 until 2012), while 15% improved their situation to the Best and 27% worsened it to the Worst. Finally, regarding only outlier hospitals, some of them showed a trend of improving or worsening over time, but still their structural characteristics were not explaining any differences in three years.

Discussion and Conclusions

This study offers original insights to further the debate about the use of administrative data to measure hospital performance and drive improvements. Administrative data offers the opportunity to crystallize the ‘hospital effect’ and point-out the hospital-level variables that have/have not affect their own performance. Considering heart failure disease, it is important to compare and monitor hospitals based of their unscheduled readmission outcome. Hospital managers need to know where and what changes need to be done in order to improve performance and the quality of care while reducing the cost of care.

Thus, from the political point of view, it is important to know how the regional and local system is operating in real world. One way is to learn from the superior performers based on available evidence for translating the change into others. In our case, including both patient and hospital-level variables enabled us to present a micro-foundation of performance measurement through multilevel models. By doing outlier detection, not an efficiency analyses, we put a further step from benchmarking hospitals by measuring hospital improvements or worsening over time trying to show the real situation of hospitals through three years. Having significant hospital-level covariates in explaining the variance of performance confirms past researches about the existence of a ‘hospital effect’ on performance. As shown in Table 1, our data showed that apart from patient characteristics, hospital characteristics have an effect (ß value) on performance too. In particular, our results pointed out the mean length of stay as the only significant covariate from the batch of hospital-level variables (see Table 1. for details). This finding has two main implications.

Covariate is widely intertwined with managerial choices. First, while reducing the average length of stay might contribute to increase hospital profitability in the short-term (because reimbursements are decided based on tariffs regardless of the days actually spent by the patients in the hospital) and the mid/long-term (because of repeated hospitalizations), it could harm the patient. In this view, hospital managers and professionals have the responsibility to manage this trade-off balancing ethics and sustainability over time. Second, in our model, the "hospital effect" is not fully captured by our set of explanatory variables. One suggestion here for future steps is to expand the model with more hospital specific variables; examples are technology equipment, human resources costs, total reimbursement per each case of HF, etc. This means that hospital discharge forms alone are not enough to gather evidence about how managerial and professional choices drive hospital performance, and this dataset should be complemented with data coming from other sources. This need is reinforced by the fact the trend showed by the 116 hospitals over three years was not fully captured by the variables included in our model. In fact, regarding outlier hospitals, some of them showed a trend of improving or worsening over time, but still their structural characteristics were not explaining any differences in three years. These results echo the need for further evaluation of bigger time span datasets for readmission rate as in the short-term the improvement is led by hospital managers' capability to implement change.

Having limited number of outliers in our model, suggests that the hospital-based care is mostly safe and effective but it also necessitates more improvements for those that are operating less than their expected standards. In this regard, scholars of operations management in healthcare should take advantage of administrative data to further explore which variables cause differences between best and worst performers. Best practices and managerial choices in place in best performers must be translated to the worst performers to inform change while improving the situation for the worst ones to the first. Administrative data offer large amount of 'real-world' data; however, they proved to be not enough to fully explain performance evolution in the short-term. In this regard, further research should take into account wider periods (at least ten years) or integrate administrative data with clinical registries or surveys to hospital managers.

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