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What is the difference between specialisation and diversity in hospitals? Investigating their relationship with efficiency

Ginevra Giuliani *, Simone Gitto

Department of Information Engineering and Mathematics, University of Siena, Via Roma 56, 53100, Siena, Italy

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ABSTRACT

The relationship between hospital specialisation and efficiency is crucial for managing hospital services. We discuss hospital specialisation as a specific instance of the more general concept of diversity and the conceptual opposite of variety. Unlike prior studies that focus on specialisation measures without a theoretical background, we employ the Blau Index, based on the concept of variety, enabling us to assess diversification's impact on efficiency.

We apply the non-parametric meta-frontier approach to a sample of Italian hospitals from 2000 to 2019 in a two-stage analysis. In the first phase, we employ Data Envelopment Analysis (DEA) to evaluate healthcare efficiency. In the second phase, we use bootstrap truncated regression to explore the impact of hospital specialisation and various organisational factors on efficiency.

Our findings challenge the prevailing assumption that specialisation leads to higher efficiency, showing instead that hospitals with greater diversification tend to perform better. Hospital managers and regional decision makers can leverage this insight to make informed strategic decisions regarding strategic planning for service delivery.

1. Introduction

Over the past several decades, the slow and steady increase of healthcare costs above the average inflation rate has become an increasingly complex problem to manage in developed countries. This significant increase - driven by a growing older population, new medical innovations, and increased incidence of chronic illness - is placing unsustainable strain on national health systems. It is becoming increasingly difficult for many countries to uphold high-quality care without jeopardising financial stability. High healthcare costs also widen the gap in access to medical services, particularly for lower-income individuals who may encounter financial barriers to receiving high-quality care [1].

Emerging medical technologies offer the potential for substantial improvements in quality but are almost always associated with increased costs. Driven by these escalating tensions, several nations are undertaking comprehensive healthcare reforms. Consequently, these reforms to reduce costs and improve efficiency and equity of access to care typically involve the introduction of outcome-based payment systems, vertical integration between healthcare and social sectors, and digital technologies that strengthen information systems and coordinate services. For example, Italy has undergone significant health system reforms to alleviate the pressure of rising costs on public debt and budget deficits [2]. Much research has focused on measuring hospital efficiency and assessing the impacts of healthcare reforms, managerial decisions, and environmental factors [2–4].

This research stream contributes to a growing understanding of how efficiency can be boosted and how it shapes healthcare systems [5]. Numerous studies have examined the determinants of hospital efficiency across different countries, including work by Ferreira et al. [6,7], Lee et al. [8], Marques and Carvalho [9], Kohl et al. [10], and Afonso et al. [11,12]. In particular, recent studies have analysed hospital efficiency in different contexts, including the effects of external shocks such as the COVID-19 pandemic. For instance, Vara et al. [13] and Nunes and Ferreira [14] examined the efficiency of Portuguese public hospitals before and during the outbreak, highlighting how crisis periods can alter hospital performance and resource allocation.

Improving hospital efficiency means enhancing the capacity to provide quality patient care with existing resources like staff, equipment, and funds. This leads to waste reduction and decreased wait times and, therefore, better patient outcomes. Hospital management can improve

* Corresponding author.
E-mail addresses: ginevra.giuliani2@unisi.it (G. Giuliani), simone.gitto@unisi.it (S. Gitto).

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efficiency in different ways: reorganising healthcare and administrative processes, introducing new technologies and optimising the resources or changing the output mix, i.e., changing the hospital's focus (specialisation) [5,8,15,16].

The concept of specialisation, long recognised as a key performance driver, has deep roots in economic theory. The idea that specialisation can increase the efficiency change component of productivity has been generally acknowledged since Adam Smith's groundbreaking work on the division of labour [17]. Taylor [18] expanded on this concept by arguing that work should be assigned according to each person's unique skill set to increase organisational performance. While Smith [17] and Taylor [18] focused on individual specialisation, particularly in specific activities, March and Simon [19] expanded on this concept by distinguishing between individual and organisational specialisation. Clark and Huckman [20] demonstrated that these approaches are not mutually exclusive and can be effectively integrated within organisational structures. As we will be discussed further in the next section, in the context of hospitals, specialisation can be measured using input quantities (such as the number of departments or specialities provided by the hospital) or output quantities (such as the number of patients in each category).

The interplay between hospital specialisation and efficiency is crucial for managing healthcare services effectively. Specialised hospitals often deliver higher-quality care, better patient outcomes, and lower complication rates than less specialised facilities [21]. Hospitals specialising in treating specific conditions are more likely to deliver efficient and effective care [22]. On the other hand, facilities offering a broader range of services can take advantage of economies of scope, minimising the time patients spend navigating multiple appointments and enabling shared use of resources across various departments [23]. Economies of scope arise when the joint production of various services leads to cost savings, as inputs can be shared to produce similar outputs. Additionally, synergies from complementary services can enhance efficiency in diversified hospitals [6].

The efficiency and specialisation of healthcare systems have been widely researched [3,8,15,24–26].

However, we believe that hospital specialisation is a complex notion that has not always been fully conceptualised. Consequently, there are still significant gaps in understanding the implications of various specialisation metrics on hospital efficiency. This research area holds substantial potential to impact hospital management practices and improve performance outcomes, making it a compelling focus for future investigation.

While the methodology for measuring specialisation in the hospital context has matured and been widely applied to efficiency, there are still notable gaps in the literature. Previous works focused on singular components of specialisation or used proxy measures that may not capture the multiple effects of specialisation on hospital efficiency. A more integrated approach is needed to understand how these various specialisation measurements are interconnected and what their direct impact on hospital efficiency and patient outcomes.

Building on the foundations laid by previous research, our study seeks to develop and theoretically define more appropriate measures of hospital specialisation. We will then use specialisation indices to evaluate the efficiency of Italian hospitals. Our analysis involves a two-stage Data Envelopment Analysis (DEA) approach. In the first stage, we will assess the technical efficiency of Italian hospitals from 2000 to 2019 using DEA. In the second stage, we will conduct a truncated regression analysis to investigate the relationship between efficiency, specialisation, and other exogenous factors using the bootstrapping procedure developed by Simar and Wilson [27]. This approach enables the precise assessment of certain forms of specialisation, as well as other parameters, on hospital efficiency.

2. Background

2.1. Literature

A hospital's specialisation is not a directly observable variable; consequently, it is difficult to assess and comprehend. The literature identifies four main characteristics for assessing a hospital's degree of specialisation [26]. The first approach examines single-service hospitals, defining specialisation as the exclusive provision of a specific type of care [28,29]. The second method uses observable variables - such as the proportion of surgical patients, case-mix index, availability of high-technology services, and the presence of board-certified physicians - to construct a latent variable representing specialisation [30]. The third approach interprets specialisation based on the number of hospital departments and the range of services offered [31]. The fourth and most widely used method involves analysing hospital patient data, categorised by diagnosis, to quantify specialisation levels [26]. It is noteworthy that these four approaches conceptualise specialisation based on both input and output quantities.

The Information Theory Index (ITI), first presented by Lee et al. [8], aligns with the fourth approach described above, which is the most commonly used. To evaluate hospital specialisation, this index compares the percentages of patients in various diagnostic categories with the average percentages observed in a regional or national setting. Conversely, a hospital with a similar distribution of patients is considered less specialised. A highly specialised hospital will have a patient distribution that differs significantly from the national or regional average. A hospital with a high ITI is considered specialised due to its distinctiveness, even though it does not always exhibit a concentrated mix of diagnosis categories [26].

Lee et al. [8] used DEA to assess hospital efficiency in Korea. According to their findings, internal hospital characteristics, such as resource management and organisational structure, had a more significant impact on specialisation than external market considerations. Although this study emphasises the significance of internal factors in shaping specialisation, it might overlook broader general market dynamics and how their effect on hospital efficiency.

Park et al. [15] further investigated hospital specialisation's effects on efficiency using the Information Theory Index (ITI) and the Internal Herfindahl Index (IHI). They reported a positive relationship between specialisation and efficiency, with ITI reflecting a hospital's Diagnostic Related Group (DRG) share and IHI assessing the concentration of services offered. Despite these findings, these indices may fail to capture the complexities of specialisation in large, multi-disciplinary hospitals catering to a broader spectrum of services and patient needs.

In 2009, Daidone and D'Amico [3] introduced the Gini coefficient as a measure of specialisation, focusing on how uniformly a hospital's patient population is distributed across diagnostic categories. This approach highlights distribution uniformity but does not directly measure how specialisation impacts hospital efficiency. For example, while a hospital might have a uniform distribution of patients, this does not necessarily correlate with the efficiency of care delivery. Using a stochastic frontier approach, they examined the correlation between specialisation and technological efficiency. They found a positive relationship between specialisation and efficiency, although higher capitalisation, often seen in private healthcare systems, was negatively correlated with efficiency. This suggests that while specialisation might enhance operational efficiency, increased capital investment does not always translate into better efficiency, especially in private sector settings.

Karmann and Roesel [24] investigated the effects of regional policy on hospital efficiency and specialisation throughout Germany. Their methodology, which evaluated specialisation across hospital departments using the normalised Gini index, showed significant variations among states and a decrease in specialisation over time. Their study highlights the impact of policy interventions on hospital efficiency and suggests that some policies could enhance specialisation and efficiency.

Zwanziger et al. [25] proposed alternative metrics such as the case-mix specialised measures of difference and the Herfindahl-Hirschman Index (HHI). The case-mix specialised measures evaluate how much a hospital's patient mix deviates from a predefined baseline. In contrast, the HHI quantifies the concentration of patient groups by summing the squares of the proportions of patients in each treatment group without direct baseline comparisons. These metrics offer insights into how patient distributions are concentrated but may not adequately address the dynamic and evolving nature of patient distributions and treatment diversity across different hospitals.

Lindlbauer and Schreyögg [26] critically evaluated existing specialisation measures and advocated for indices based on patient volumes rather than proportions. They introduced Category Medical Specialisation (CMS) and Inner-Category Medical Specialisation (ICMS) to address the shortcomings of proportion-based measures, especially in large hospitals with diverse service offerings. Their research found that larger hospitals exhibited different specialisation trends, with CMS and ICMS initially declining and then increasing as hospitals grew. This finding highlights the importance of precise definitions and specialisation measures.

While previous studies have examined hospital specialisation using various metrics, our research advances the literature in several key aspects. First, we conceptualise hospital specialisation, as a specific instance of the broader concept of diversity, and more specifically, as a case of variety. Second, diverging from approaches that utilise concentration-based indices like ITI or HHI, we employ the Blau Index, a metric rooted in diversity theory. This diversity-based metric provides a more nuanced interpretation of hospital service distribution, allowing us to assess the impact of diversification on efficiency. Third, we apply both a single-frontier and a meta-frontier approach to account for technological heterogeneity. By doing so, we evaluate whether efficiency trends persist when considering different levels of technological development.

By integrating these methodological advancements, our study addresses a critical gap in the literature and provides novel insights into how diversification can enhance hospital efficiency, particularly in the context of ongoing healthcare system reforms.

2.2. Linking hospital specialisation and diversity

Hospital specialisation is a complex concept that spans the literature of organisational and management studies, encompassing various facets of diversity and heterogeneity. Organisational research has mainly focused on specific forms of team or structural diversity and their impact on performance, innovation and outcomes [32].

In this context, specialisation emerges as a key area of study, often viewed as the inverse of diversity. It is defined by the homogeneity within organisational units, such as hospital departments. This relationship is significant in healthcare, where the trade-off between specialisation (e.g., performing one specific kind of surgery) and diversity (e.g., many kinds of medical services) can affect both patient care and organisational challenges.

Hospital specialisation can be analysed using the same metrics traditionally applied to measure diversity, but with a focus on the inverse relationship. For instance, a hospital highly specialised in a particular medical field, such as oncology, would exhibit low variety, as most of its departments or services would be concentrated in that area, and the diversity of roles, skills, or tasks is reduced as members or units focus on a narrow set of functions. Specialisation can lead to significant advantages, such as increased efficiency, improved patient outcomes in specific areas, and enhanced expertise within specialised departments [15]. Hospitals might produce at lower costs because their staff builds expertise, and care is better organised. However, potential drawbacks include the risk of reduced flexibility, limited service offerings, and potential challenges in addressing a broad spectrum of patient needs. Furthermore, highly specialised hospitals might face higher costs associated with attracting more complex patients within specific diagnosis-related groups or maintaining specialised, expensive equipment [32].

Conversely, a hospital offering various medical services would exhibit more variety and typically provides a broad spectrum of healthcare services. A varied hospital has the potential to enable cross-speciality collaboration, enhance patient-centricity across diverse needs, and provide integrated and comprehensive treatment. Nonetheless, regarding a trade-off, this diversity may entail reduced depth of specialisation in certain areas and challenges in ensuring consistent quality across all services [33].

Hospital leaders can use this framework as a guide to inform strategic decisions about where the organisation is focusing its efforts and investments. For example, if a hospital finds itself operating within a niche market surrounded by other specialised providers. In that case, the need to expand their service lines may serve as a way to market and draw new patient populations. On the other hand, focusing on fewer, highly specialised medical services may prove to be a competitive advantage in specific areas. Using diversity metrics to measure specialisation gives hospital managers a quantitative measure of where their organisation sits in the landscape. This creates an opportunity to use data to guide decisions that are more aligned with organisational strategy and patient needs.

2.3. The different categories of diversity

In their seminal paper, Harrison and Klein [34] presented a comprehensive framework for understanding organisational diversity. According to them, organisational diversity can be conceptualised through three distinct types of differences among members: separation, variety, and disparity, which are the three aspects of differences among members in an organisation.

i. Separation.

Separation refers to differences in position and opinion among organisational members. It represents horizontal diversities, representing differences in values, beliefs, or attitudes. This type of diversity is often measured using the Mean Euclidean distance or the Standard Deviation, which indicates the extent to which members differ in position or opinion. For example, in a hospital setting, separation could be reflected in differing medical philosophies or treatment approaches among departments.

ii. Variety.

Variety refers to differences in the knowledge, skills, and backgrounds individuals bring to an organisation. It reflects the individuals' knowledge, educational backgrounds, and fields of specialisation, thus contributing diverse perspectives and capabilities to the organisation. Variety is measured using the Teachman/Entropy Index or the Blau Index. The Blau Index, for instance, measures categorical diversity by calculating the probability that two randomly selected group members belonging to different categories. The range of medical specialities or services offered by a hospital exemplifies variety, indicating the breadth of its expertise.

iii. Disparity.

Disparity represents the vertical concentration of valued resources, such as power, status, or compensation. It measures the degree to which members of an organisation have unequal access to such valued resources. Disparity is typically quantified using the Coefficient of Variation or Gini Index, which measure the inequality of resource distribution. In hospitals, disparity might manifest in the internal hierarchy, where certain physicians or groups possess greater power, control over resources, or higher remuneration.

Applying this framework, organisational diversity within a hospital context can be understood through the distinct characteristics of its different units or departments. We conceptualise specialisation as a form of organisational variety, where departments within a hospital differ qualitatively by the medical disciplines they represent. The distribution of patients across these departments serves as an indicator of this variety.

Conceptualising specialisation as variety allows us to measure it using indices sensitive to the breadth of categories, such as the Blau Index. This measurement (variety) is inversely related to the level of specialisation; a higher variety score indicates a wider range of medical fields represented within the hospital. Unlike separation (reflecting differences in opinion, values, or goals) or disparity (reflecting inequality in resources), variety focuses on the breadth of categorical differences in knowledge and skills within the organisation. Employing the Blau Index allows for the quantification of this variety, thereby inversely reflecting the degree of hospital specialisation [34,35].

A low Blau index signifies high specialisation, indicating that the hospital concentrates its activities within a limited number of service categories. Conversely, a high Blau Index suggests greater diversity (i.e., lower specialisation), reflecting a wider range of services and potentially indicating that patients interact with multiple departments.

3. Methodology

The literature identifies two primary methods for measuring healthcare efficiency: Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) [36,37]. These techniques differ in their underlying methodologies and assumptions, as Jacobs et al. [38] noted. Our study employs the DEA approach because it allows for the determination of the efficiency frontier without requiring a predefined functional form for cost minimisation or profit maximisation. This flexibility is a crucial advantage of DEA over SFA, which often necessitates specific assumptions about the production function.

Our study employs a two-step procedure to analyse the impact of regulatory changes on the technical efficiency of Italian hospitals. In the first stage, we calculate each hospital's technical efficiency from 2000 to 2019 using the DEA method.

In the second stage, we investigate the factors influencing hospital efficiency using a bootstrap truncated regression. This regression allows us to estimate the effect of specific organisational variables on efficiency scores while controlling for other relevant factors included in the model.

3.1. Blau index

Blau's index was first introduced to measure species variety in ecosystems and has since become a widely used metric for assessing diversity in organisational studies [39]. According to Harrison and Klein [34], the formula is:

$$BLAU_i = 1 - \sum p_{ij}^2 \qquad [1]$$

where p_{ij} is the ratio of discharges times CMI of a given department j in hospital i to the total discharges times CMI of a given hospital. Blau's index ranges from 0 to $\frac{J-1}{J}$, where J is the maximum number of departments. The index reaches its maximum value when members are evenly distributed across all categories, a concept referred to as "evenness" or "relative abundance" in ecological terms [40]. Statistically, Blau's index reflects the probability that two randomly selected group members belong to different categories [34].

In the context of hospital specialisation, when Blau's index value is close to 0, it indicates a highly specialised hospital concentrating its activity in few departments. In contrast, a value near the maximum suggests a highly diversified hospital distributing its activity across a broad range of departments. This indicator also allows us to assess and quantify the degree of specialisation and diversity within hospitals. This allows for a quantitative analysis of how diversity (as the inverse of specialisation) relates to hospital efficiency and potentially patient outcomes.

3.2. First stage: DEA

In the first stage of our analysis, we employ the DEA approach to measure the efficiency of healthcare services [41–43]. We follow the literature [2,16,44,45] and adopt an output-oriented model. This model is particularly suited to the management of public services in many countries, where the objective is often to maximise the services provided within a given budget constraint. In an output-oriented DEA model, particularly under the Variable Returns to Scale (VRS) assumption, we calculate an efficiency score $\widehat{D}_{it}$ for each decision-making unit (DMU) i ($i = 1, 2, \ldots, n$) at time t ($i = 1, 2, \ldots, T$). The efficiency score is derived by solving the following linear program:

$$\begin{aligned} &\widehat{\theta}_{it} = [\widehat{D}_{it}]^{-1} = max_{\theta\lambda}\theta \\ &s.t. \quad x_{it} \geq X_t\lambda \\ &\theta y_{it} \leq Y_t\lambda \quad i = 1, 2\ldots, n; \quad t = 1, 2, \ldots, T \\ &1'\lambda = 1 \\ &\lambda \geq 0 \end{aligned} \qquad [2]$$

In this model, $\widehat{\theta}_{it}$ and $\widehat{D}_{it}$ represent the Farrell [46] and Shepard [47] distance functions, respectively. Here, n is the number of DMUs, and t denotes the time period. Y_t is an sxn matrix of s outputs, and X_t is an rxn matrix of r inputs. The vector λ is an nx1 vector of weights used to obtain a convex combination between inputs and outputs, and $1'$ is a vector of ones. The VRS assumption is important because it allows for the evaluation of a hospital's efficiency independently of its operating scale [26,38]. This is particularly relevant in the healthcare sector, where the relationship between inputs and outputs may not be proportional as the size of the hospital varies. Under the VRS assumption, both a small, specialised hospital and a large, general hospital can be efficient while operating at different scales.

The inefficiency measure $\widehat{\theta}_{it}$ always assumes a value equal to or greater than one, indicating how much a DMU could proportionally expand its outputs while still consuming the same level of inputs. Conversely, $\widehat{D}_{it}$, is an efficiency measure that ranges between zero and one. DMUs with an efficiency score of one are considered fully efficient, as they operate on the "best practice frontier", meaning their outputs cannot be increased without a proportional input increase.

This approach allows us to identify which hospitals are operating efficiently and which are not, providing a clear benchmark for productivity improvement.

3.3. Second stage: bootstrap truncated regression

In the second stage of our analysis, we employ a bootstrap truncated regression model, following the methodology proposed by Simar and Wilson [27], to evaluate how a set of exogenous variables influences healthcare efficiency. The regression model is specified as follows:

$$\widehat{\theta}_{it} = z_{it}\beta + \varepsilon_{it} \quad i = 1, 2, \ldots, n; \;\; t = 1, 2, \ldots, T \qquad [3]$$

In this equation, z_{it} represents a set of explanatory variables for each unit i at time t, and ε_{it} is a normally distributed error term with a mean of 0 and a standard deviation of σ, truncated from below at $1 - z_{it}\beta$.

As Simar and Wilson [27] suggested, we adopt a double bootstrap approach for estimating and inferring the parameters of the truncated regression model. This approach is crucial as it corrects for the bias inherent in the estimated DEA scores and addresses the complex correlation structure, allowing for valid statistical inference on the coefficients β. In particular, we apply Algorithm #2 using 1000 and 2000 bootstrap replications to estimate the truncated regression model and obtain valid confidence intervals for the coefficients β.

This two-stage approach has been implemented using the FEAR statistical package incorporated into R software. FEAR is a purpose-built package for conducting efficiency and productivity analysis. Its functionalities, such as implementing DEA and other related statistical methods, ensure the credibility and consistency of the analysis [48].

In this way, we can use this evidence to identify more accurately the determinants, including hospital size and general environmental factors, of hospital technical efficiency.

3.4. Meta-frontier approach

Initially, we conducted the DEA analysis using a single frontier, assuming a homogeneous technology across all hospitals and over the entire time period. However, to account for potential technological differences over time, we also applied a meta-frontier approach over the 20-year period.

Unlike the standard DEA model, which evaluates efficiency against a single best-practice frontier, the meta-frontier approach first constructs separate frontiers for each year and then integrates them into a higher-level frontier encompassing all period-specific frontiers [49]. This methodology provides a more refined perspective on efficiency by recognising shifts in technology over time [50,51].

This approach has been widely applied across various sectors, including healthcare, to assess efficiency while accounting for technological disparities. For instance, See et al. [52] employed a Dynamic Network DEA (DNDEA) model with a non-convex meta-frontier to evaluate hospital pharmacy services in Malaysia. Their study compared specialist and non-specialist hospitals to identify differences in technological efficiency. Guo et al. [53] analysed healthcare efficiency in China using a meta-frontier approach combined with a non-radial directional distance function. Their study considered regional heterogeneity and non-radial slacks, offering a more comprehensive efficiency evaluation.

4. Data

The data for this analysis were sourced from the Italian Ministry of Health, covering the period from 2000 to 2019. This dataset enables a comprehensive assessment of hospital efficiency across Italy over two decades.

Our analysis focuses on the efficiency scores of Italian hospitals through a unit-level analysis, applying a bootstrap truncated regression to evaluate how various factors influence efficiency. This methodological approach aligns with the standard practices in existing healthcare efficiency research [54–56]. In the dataset are present four different hospital types, distinguished by management form: Hospital Enterprises (Aziende Ospedaliere, AOs), Teaching Hospitals (Ospedali Universitari, THs), Directly Managed Hospitals (Ospedali a Gestione Diretta, OGDs), and Institutes for Scientific Research and Treatment (Istituti di Ricovero e Cura a Carattere Scientifico, IRCCSs). For an in-depth understanding of these types within the Italian healthcare system, see Ferrè et al. [57]. Table 1 provides an overview of the number of hospitals included in the analysis for each year. The fluctuations in the number of hospitals across the years reflect structural changes in the healthcare system, including hospital closures or mergers.

Table 1
Number of hospitals per year.

YEAR	Number of hospitals
2000	387
2001	409
2002	413
2003	423
2004	391
2005	407
2006	415
2007	429
2008	418
2009	406
2010	396
2011	373
2012	368
2013	358
2014	343
2015	334
2016	320
2017	254
2018	256
2019	271

4.1. Input-output data

We carefully cleaned the dataset before calculating the efficiency scores by removing observations with missing values and outliers. We applied minimum thresholds to filter out hospitals with implausibly low or potentially erroneous input and output values, ensuring that only relevant data were analysed.

The analysis incorporates five input variables: the number of physicians, nurses, other employees, outpatient beds, and inpatient beds. These variables are commonly used in previous studies on hospital efficiency [2,58–60]. These inputs are quantified as follows: the number of salaried physicians, the number of nurses, other employees (calculated as the total number of staff minus physicians and nurses), and the number of beds (differentiated between outpatient and inpatient). Outpatient beds account for day hospital and day surgery capacities, while inpatient beds refer to those available for overnight stays. The number of beds is a proxy for capital, a common practice in hospital efficiency studies [2,61,62]. This proxy is commonly adopted due to the difficulty in obtaining standardised capital value data across hospitals and over time.

We include the number of inpatients, outpatients, and surgical procedures, as output variables, initially measured in physical quantities. Since not all inpatients require the same level of care, we adjust the output measures (number of inpatients and surgical procedures) using the Case Mix Index (CMI), which accounts for the complexity and intensity of the treatments provided. This adjustment ensures a more accurate reflection of hospital productivity, as it weighs output quantities by the intensity of care [62,63].

Table 2 summarises the descriptive statistics (mean, median, standard deviation, minimum, maximum) for the input and output variables used in the efficiency analysis, providing an overview of their distribution and variability.

The data are right-skewed, as evidenced by the values presented in Table 2. This skewness supports our decision to use a DEA nonparametric estimator, as Wilson and Carey [64] recommended. Parametric methods can be sensitive to violations of distributional assumptions (such as the normality of errors) and may require data transformations or the adoption of more complex models to handle such asymmetries. DEA, being a non-parametric method, does not make restrictive assumptions about the data distribution.

4.2. Second-stage data

A substantial body of literature has provided extensive evidence on the factors influencing hospital efficiency, including organisational and managerial variables [2,16,65]. These factors are directly considered in the second stage of the analysis.

This analysis regresses the calculated inefficiency scores against several explanatory variables: the Blau index (measuring specialisation), capital intensity, hospital size, dependence on the ASL (Local Health

Table 2
Descriptive statistics of input and output variables.

	Min	Median	Mean	Std. Dev.	Max
Inputs					
Number of Physicians	31	168	237.8	205.62	1622
Number of Nurses	35	380	559.3	491.76	3784
Number of Other Employees	22	279	469.2	502.23	4652
Number of Inpatient Beds	20	288	392.2	327.84	2453
Number of Outpatient Beds	11	30	45.25	41.22	348
Outputs					
Number of Inpatients * CMI	140.2	10,842.7	14,954.8	13,298.93	91,589.4
Number of Outpatients	2	1247	1877	2249.53	46,827
Number of Surgical Procedures * CMI	3.84	12,021.94	19,874.02	22,956.8	227,128.75

Authority), regional organisational model dummies, regional reimbursement system dummies, a year trend, and population.

- **Blau Index**: The Blau index is calculated by considering the number of discharges in each hospital department relative to the total number of discharges in the facility (proportions), each weighted by its case mix index (CMI).
- **Capital Intensity**: The ratio of the number of ordinary inpatient beds to the number of physicians in each hospital. This metric indicates how resources are allocated between physical capacity (beds) and labour (medical staff) [24]. A higher capital intensity could imply that a hospital is focused on expanding its physical capacity relative to its medical workforce, which may influence its ability to manage patient volumes efficiently. However, this may also lead to inefficiencies if the medical staff is not proportionally increased to handle the demand, potentially affecting the hospital's overall efficiency.
- **Hospital Size**: Hospital size is based on the total number of beds available in each facility, including those for day hospitals, day surgeries, and inpatient care. This represents the hospital's overall capacity [24].
- **Dependence on ASL**: A dummy variable coded 1 if the hospital is directly managed by the ASL, and 0 if it is an independent entity (AO, TH, IRCCS). This variable indicates whether each hospital operates as an independent public entity (including research and teaching hospitals) or is directly managed by an ASL. Independent hospitals, directly accountable to regional governments, generally enjoy greater operational flexibility. On the other hand, hospitals managed by an ASL are subject to regional regulations and centralised management, which could impose additional constraints.
- **Organisational Models**: Each Italian region has adopted one of three health organisation systems: the ASL-centred, the Region-centred, and the Purchaser-provider split templates [2]. In the ASL-centred model, ASLs can contract with public and private providers. The Region-centred model limits ASL autonomy, with regional governments directly financing providers based on their activities. The Purchaser-provider split model, used in the Lombardy region, separates the roles of purchaser and provider, with ASLs acting solely as purchasers.

Two dummy variables are used, indicating Purchaser-provider split and Region-centred models, respectively, with the ASL-centred model serving as the reference category.

- **Reimbursement System**: The Italian healthcare financing system operates as a closed-end system [2,66], allowing for regional variations in reimbursement for medical services. According to Lo Scalzo et al. [67], three different regional compensation schemes can be identified:
  i. **Cost-adjusted**: The region adjusts tariffs for various categories of hospitals based on service configuration while still applying national Diagnosis-Related Group (DRG) weights.
  ii. **Analytic**: Costs are standardised to determine the average cost of care for a specific ailment, applied to a sample group of regional hospitals.
  iii. **National**: The national DRG cost table is applied, with variations allowed for different types of hospitals, such as public versus private or teaching versus non-teaching hospitals.

Two dummy variables indicate the Analytic and Cost-adjusted systems, respectively, with the National system (based on national Diagnosis-Related Group - DRG - tariffs, potentially with adjustments) serving as the reference category.

- Year Trend: The year trend variable captures the passage of time throughout the study period. By assigning a sequential numeric value to each year, this variable helps control for potential time-based effects and identify overall trends in efficiency over time.
- Population: This variable represents the population of each province where the hospital is located, with data sourced from the ISTAT (National Statistical Institute) website.

Table 3 provides an overview of the organisational models and reimbursement systems adopted by the different Italian regions. It highlights the diversity in regional healthcare governance and distinguishes between three main organisational models: region-centred, ASL-centred, and purchaser-provider. The table also classifies the reimbursement systems used across regions, which include national, analytic, and cost-adjusted schemes. This classification underscores the heterogeneity in healthcare management across Italy, reflecting variations in regional autonomy, financial structures, and policy priorities that may influence healthcare efficiency and service delivery.

Table 4 provides an overview of the explanatory variables used in the

Table 3
Regional characteristics.

Region	Organisational Model	Reimbursement System
Abruzzo	Region-centred	National
Basilicata	ASL-centred	National
Calabria	ASL-centred	National
Campania	Region-centred	National
Emilia-Romagna	ASL-centred	Analytic
Friuli-Venezia Giulia	Region-centred	National
Lazio	ASL-centred	Analytic
Liguria	Region-centred	National
Lombardia	Purchaser-provider	Analytic
Marche	ASL-centred	National
Molise	Region-centred	National
Piemonte	ASL-centred	Cost adjusted
Prov. Auton. Bolzano	ASL-centred	National
Prov. Auton. Trento	ASL-centred	National
Puglia	ASL-centred	National
Sardegna	ASL-centred	National
Sicilia	Region-centred	Cost adjusted
Toscana	ASL-centred	Analytic
Umbria	ASL-centred	Analytic
Valle d'Aosta	ASL-centred	National
Veneto	ASL-centred	Analytic

Table 4
Second-stage variable definition.

Variable	Definition
Blau_Index	Blau Index for hospital discharges
Capital_intensity	Ratio between ordinary inpatient beds and physicians
Hospital_size	Total number of beds in the structure
Dummy_Dip	Dummy variable for the type of structure dependent on ASL
Dummy_model_PP	Organisational model: PP = Purchaser-provider split template
Dummy_model_RC	Organisational model: RC = Region-centred template
Dummy_reimb_A	Reimbursement system: A = Analytic system
Dummy_reimb_C	Reimbursement system: C = Cost-adjusted system
Year_trend	Sequential numeric value to each year
Population	Population of each province

regression model, highlighting the hospitals' key structural, organisational, and financial characteristics. These variables allow for a more comprehensive analysis of the factors influencing inefficiency levels.

5. Results

5.1. DEA scores

Fig. 1 below illustrates the trend of average meta-frontier inefficiency scores for healthcare facilities from 2000 to 2019, distinguishing between facilities dependent on the Local Health Authority (ASL) (dummy_Dip = 1, solid line) and independent facilities (dummy_Dip = 0, dashed line).

- ➢ 2000–2005 Period: Both categories experienced an increase in average inefficiency, with ASL-dependent facilities reaching a higher peak than independent ones.
- ➢ 2006–2010 Period: A sharp increase in inefficiency is observed for ASL-dependent facilities, peaking between 2007 and 2009. Meanwhile, independent facilities show a slightly decreasing trend.
- ➢ 2010–2015 Period: The inefficiency of ASL-dependent facilities declines significantly, while independent facilities continue a more gradual reduction.
- ➢ 2016–2019 Period: The inefficiency of independent facilities remains lower than that of ASL-dependent ones but shows a slight increase in 2018. Conversely, ASL-dependent facilities exhibit a more unstable trend, with a renewed rise in inefficiency in the last years of the period analysed.

Overall, ASL-dependent facilities (solid line) exhibit greater inefficiency than independent ones. This may suggest that independent facilities have greater managerial flexibility or face fewer bureaucratic constraints than those under ASL control.

The period between 2005 and 2010 appears to be critical for ASL-dependent facilities. Inefficiency rose significantly during this period, followed by a subsequent decline. This could be linked to healthcare reforms or changes in funding and management practices in public facilities.

In recent years, from 2016 to 2019, both categories showed signs of instability in inefficiency trends, suggesting that external factors might be affecting the healthcare system as a whole.

5.2. Regression results

In the regression model, the dependent variable is the inefficiency score derived from DEA. These inefficiency scores indicate how much a hospital deviates from the efficiency frontier, where a higher score reflects greater inefficiency. In this context, a negative coefficient for a variable suggests that an increase in this variable is associated with a decrease in inefficiency, thereby improving efficiency. Conversely, if a coefficient is positive, it implies that an increase in this variable corresponds to increased inefficiency. The statistical significance of these coefficients is assessed using significance levels (p-values) derived from the bootstrap procedure (indicated by asterisks in Tables 5–8).

Tables 5 and 6 present the results of the regression analyses conducted to examine the factors influencing hospital inefficiency. Table 5 reports the regression results using a single frontier approach, which assumes a homogeneous technology across all hospitals. Table 6 extends this analysis by applying the meta-frontier approach, which accounts for technological differences over time.

The "Blau_Index" variable has been utilised to express the measure of hospital discharges in terms of diversity. The higher the value, the greater the diversity of the types of treatment/services the hospital provides; the lower the value, the greater the hospital's specialisation, which means fewer service offerings. The negative coefficient associated with the Blau Index indicates that greater service diversification reduces inefficiency, ultimately improving the hospital's efficiency. One possible explanation for this result is the efficient distribution of the shared pool of resources across different hospital departments, allowing them to respond effectively to diverse patient demands. Hospitals that offer a

Table 5
Regression results with a single frontier.

	Estimate	Sig.
Intercept	2.885	***
Blau_Index	−1.380	***
Capital_intensity	-7.450×10^{-2}	***
Hospital_size	-7.098×10^{-4}	***
Dummy_Dip	0.240	***
Dummy_model_PP	0.318	***
Dummy_model_RC	−0.233	***
Dummy_reimb_A	−0.208	***
Dummy_reimb_C	0.163	***
Year_trend	-1.785×10^{-2}	***
Population	3.708×10^{-8}	***

Notes: ***,** and * denote statistical significance at the 1 %, 5 % and 10 % levels, respectively.

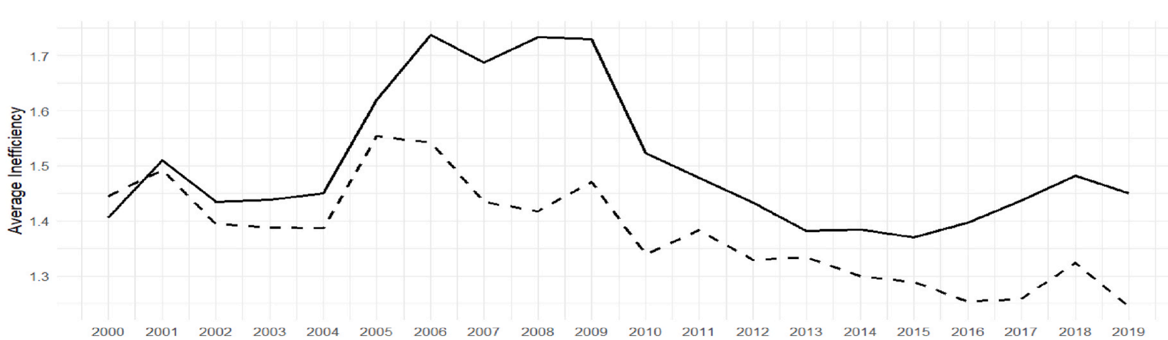

Fig. 1. Comparison of healthcare facility inefficiency: ASL-Dependent (solid line) vs. Independent (dashed line).

Table 6
Regression results with meta frontier.

	Estimate	Sig.
Intercept	3.573	***
Blau_Index	−2.088	***
Capital_intensity	6.511×10^{-2}	***
Hospital_size	-8.932×10^{-4}	***
Dummy_Dip	0.307	***
Dummy_model_PP	0.215	***
Dummy_model_RC	−0.167	***
Dummy_reimb_A	−0.166	***
Dummy_reimb_C	0.119	***
Year_trend	2.489×10^{-2}	***
Population	3.535×10^{-8}	***

Notes: ***,** and * denote statistical significance at the 1 %, 5 % and 10 % levels, respectively.

broader range of services may also benefit from greater resource flexibility and improved resource utilisation, as interdisciplinary teams can facilitate functional economies of scale and scope [68]. These hospitals may be better equipped to avoid underutilisation of capacity, distribute fixed costs more efficiently, and enhance staff productivity by integrating specialists across multiple disciplines.

The Blau Index retains a negative coefficient across both models, reinforcing the idea that greater diversification in hospital services contributes to increased efficiency. However, the coefficient is smaller in the meta-frontier model, suggesting that while diversification remains beneficial, the effect is slightly weaker when accounting for technological differences.

These findings contradict those of Park et al. [15], who found a positive correlation between hospital specialisation and efficiency in Korea. Their argument was that specialised hospitals operate more efficiently by focusing on core services and concentrating both tangible and human resources on specific activities, thus improving operational performance. Similarly, Daidone and D'Amico [3] found a positive relationship between specialisation and efficiency. However, their analysis was limited to hospitals in the Lazio region and employed the Gini Index, which conceptualises specialisation as disparity rather than diversity (see section 2.3). This divergence in findings underscores the complexity of the relationship between hospital diversity and efficiency. While their results support that narrowing hospital services can foster efficiency, suggesting that hospitals focusing on fewer services tend to be more technically efficient, our findings suggest otherwise. In line with Colombi et al. [4], we argue that service diversification can improve hospital efficiency, notably by realising economies of scope. Colombi et al. [4] distinguish between transient and persistent inefficiency and find that generalist hospitals, those offering a broader range of services, are more efficient in the short run. They attribute this advantage to the joint use of inputs and shared infrastructures across departments, which enhances resource coordination, capacity utilisation, and cost distribution. Interdisciplinary collaboration and complementary services further support functional synergies, enabling hospitals to manage complex patient needs more effectively.

The conflicting conclusions in the literature may reflect important contextual differences, such as regional healthcare system organisation or study period, but also stem from the use of different conceptualisations and measures of specialisation. While the Gini Index captures concentration (disparity), the Blau Index reflects categorical spread (variety). Therefore, whether specialisation is interpreted as reduced heterogeneity or focused expertise can substantially affect the observed relationship with efficiency. Based on the Blau Index, our findings highlight the advantages of diversification in enhancing hospital performance, especially in systems that promote service integration and flexible resource use.

The comparison between Table 5 (single frontier) and Table 6 (meta-frontier) reveals a significant shift in the sign of the Capital Intensity coefficient. In the single-frontier model, the positive coefficient suggests that a higher ratio of hospital beds to physicians contributes positively to inefficiency. This result can be interpreted in the context of the well-documented shortage of medical personnel in Italy: having a relatively higher number of physicians hospital beds might enable hospitals to manage patients more effectively. In this scenario, efficiency improves due to a greater inpatient capacity, which partially offsets the shortage of healthcare professionals. However, the coefficient turns negative in the meta-frontier model, which accounts for different technological levels during the time. This indicates that when structural and technological differences between regional healthcare systems are considered, a higher number of beds per physician may increase efficiency. This result could reflect suboptimal resource allocation: some hospitals may have excess beds, with inefficiencies due to an unbalanced distribution of medical staff, leading to bottlenecks in patient management and inefficient use of available resources.

Furthermore, this difference in sign suggests that the relationship between capital intensity and efficiency is not uniform but context-dependent. While a higher number of hospital beds may seem beneficial at an aggregate level, a more detailed analysis that differentiates between regions and technological efficiency levels reveals that poor resource management can lead to inefficiencies.

Hospital Size maintains a negative coefficient in both models, supporting the idea that larger hospitals are more efficient. Such effectiveness can be explained by the partial connection to the Blau Index (the correlation between these variables is 0.37), as with an increase in bed numbers, the number of departments also generally increases, which widens the range of services available and both economies of scale and scope. However, the effect size is slightly reduced in the meta-frontier model, indicating that economies of scale may be less pronounced when technological heterogeneity is considered.

The negative impact on efficiency for ASL dependency indicates that hospitals directly managed by ASLs, which may have less organisational autonomy and decision-making power regarding resource allocation, tend to be less efficient. This could be due to the constraints imposed by ASL management structures, which limit the ability of these hospitals to respond flexibly to changing demands or optimise resource use.

About the Organisational Models, the positive coefficient for the Purchaser-provider split template (Dummy_model_PP) suggests that hospitals operating under this model, such as those in Lombardy, are associated with higher inefficiency scores compared to the baseline (likely the ASL-centred model). The research reveals that the Purchaser-provider split model probably does not contribute as much to reducing inefficiencies as De Nicola et al. [69] suggested, stressing that the Lombardy model is efficient owing to the moderate level of decentralisation.

In contrast, the coefficient of the Region-centred template (Dummy_model_RC) is negative; thus, hospitals experience fewer losses under this model than the ASL-centred model. This shows that the Region–centred model, where the regional government pays the providers of services on behalf of patients and clinics and restricts ASL autonomy, has advantages in promoting hospital efficiency on average. The centralised control and coordination of healthcare services in the territory, also reducing ASL activities, seems to contribute to efficient hospital management. Note that this result is complementary to the dummy of ASL dependency, as the former is related to the status of each hospital, while the Region-centred template refers to the regional organisational model.

The analysis of reimbursement systems reveals that the Analytic system (Dummy_reimb_A) is associated with lower inefficiency scores, suggesting it more effectively promotes hospital efficiency than the baseline National DRG system. Conversely, the Cost-adjusted system (Dummy_reimb_C) has different impacts, which signify inefficiencies being less effectively managed. This comparison helps reinforce the argument that the Analytical system is better at optimally allocating resources and improving hospital output.

The Year Trend variable changes sign between the two models, which has important implications for understanding long-term efficiency trends in the Italian hospital system. In the single-frontier model, the positive coefficient of the Year Trend suggests that inefficiencies have increased over time. This could be attributed to multiple factors, including evolving healthcare policies, management challenges, and structural inefficiencies that have accumulated over the years. Additionally, increasing healthcare system demands, resource constraints and workforce shortages may have contributed to a gradual decline in operational efficiency. However, in the meta-frontier model, the Year Trend coefficient becomes negative. This change in sign suggests that hospitals are getting closer to their respective efficiency frontiers over time when different frontiers by year are considered. In other words, although inefficiencies are rising when assessed against a single benchmark, hospitals are improving their efficiency relative to the best possible performance within their specific technological and operational environments. This shift in perspective highlights the importance of distinguishing between absolute efficiency trends (single frontier) and efficiency relative to available resources and technology (meta-frontier).

Finally, the Population variable has a positive and statistically significant coefficient, suggesting that hospitals operating in more densely populated provinces tend to be less efficient. This result could be linked to higher patient demand, congestion, and resource strain in these areas.

These results offer valuable insights for policymakers, suggesting that promoting diversification within hospitals may be a viable strategy for enhancing overall efficiency in the healthcare system.

5.3. Robustness set

In this section, we repeated the analysis of the previous section using the ITI, a commonly used index in the literature for hospital specialisation, as a robustness check [24]. Note that ITI is the inverse measure of Blau. A higher value of the Blau index indicates more diversification, while a higher ITI suggests greater specialisation. ITI is defined as [26]:

$$ITI_i = \sum_j p_{ij}\, ln\left(\frac{p_{ij}}{\theta_j}\right) \qquad [4]$$

where p_{ij} is the proportion of patients discharged times CMI in diagnosis category j in hospital i, and $\theta_j > 0$ is the national average of the patients discharged times CMI in each diagnosis category j. The ITI measures the degree to which hospitals are unusual compared to a typical baseline hospital.

The regression results using the ITI index (Tables 7 and 8) provide further support for our main finding. The ITI index, measuring specialisation, shows a positive coefficient in both models. Since the dependent variable is inefficiency, this indicates that higher specialisation (higher ITI) is associated with higher inefficiency, consistent with the Blau index results where higher diversification (higher Blau) was associated with lower inefficiency. A comparison between the single frontier model (Table 7) and the meta-frontier model (Table 8) reveals key differences in the estimated coefficients. In both models, the ITI index remains statistically significant and positively associated with inefficiency, reinforcing the idea that diversification enhances performance. However, its effect is less pronounced in the meta-frontier model, where the coefficient decreases from 0.472 in the single frontier to 0.305. This suggests that while efficiency gains from diversification persist, they may be influenced by technological heterogeneity, reflecting differences in hospital capabilities and structural constraints.

This result indicates that greater diversification (or lower specialisation) is associated with higher efficiency, reinforcing the interpretation that, under the analysed conditions, diversification is preferable for achieving more efficient outcomes.

Since Blau and ITI indices are expressed in different units of measurement, a direct comparison of their raw values is not meaningful. To address this, we use the coefficient of variation (CV), a standardised statistical measure that normalises differences in scale and allows for a more accurate assessment of variability. The CV represents the ratio of the standard deviation to the mean, providing insight into the relative dispersion of values within each index. A higher CV indicates greater variability, meaning that the data points are more spread out relative to the mean, while a lower CV suggests that values are more concentrated around the average.

Table 9 presents the descriptive statistics for both indices, including their mean, standard deviation, and coefficient of variation (CV). The Blau index exhibits a mean value of 0.845 with a standard deviation of 0.124, leading to a CV of 0.147. This relatively low CV suggests that the distribution of the Blau index is more stable, with values clustering closely around the mean. In contrast, the ITI index has a much lower mean of 0.039 but a substantially higher standard deviation of 0.499, resulting in a CV of 12.795. The markedly higher CV indicates that the ITI index values are far more dispersed, reflecting significant heterogeneity in diversification levels across hospitals. These findings suggest that the Blau index provides a more consistent and stable measure of diversification, making it potentially more reliable for comparative analysis [26].

Table 7
Regression results with a single frontier.

	Estimate	Sig.
Intercept	1.631	***
ITI_Index	0.472	***
Capital_intensity	0.108	***
Hospital_size	-8.868×10^{-4}	***
Dummy_Dip	0.325	***
Dummy_model_PP	0.199	***
Dummy_model_RC	−0.169	***
Dummy_reimb_A	−0.101	***
Dummy_reimb_C	0.139	***
Year_trend	2.829×10^{-2}	***
Population	2.397×10^{-8}	**

Notes: ***,** and * denote statistical significance at the 1 %, 5 % and 10 % levels, respectively.

Table 8
Regression results with meta frontier.

	Estimate	Sig.
Intercept	1.574	***
ITI_Index	0.305	***
Capital_intensity	-3.758×10^{-2}	*
Hospital_size	-7.140×10^{-4}	***
Dummy_Dip	0.250	***
Dummy_model_PP	0.311	***
Dummy_model_RC	−0.242	***
Dummy_reimb_A	−0.170	***
Dummy_reimb_C	0.185	***
Year_trend	-1.544×10^{-2}	***
Population	3.377×10^{-8}	**

Notes: ***,** and * denote statistical significance at the 1 %, 5 % and 10 % levels, respectively.

Table 9
Descriptive statistics of blau and ITI indices.

	Blau index	ITI index
Standard deviation	0.124	0.499
Mean	0.845	0.039
Coefficient of variation	0.147	12.795

6. Conclusions

This study provided an in-depth analysis of hospital efficiency in the Italian healthcare system, focusing on how various structural, organisational and administrative variables influence efficiency scores derived from the DEA model. The regression analysis revealed several key findings regarding diversity and efficiency.

Regarding theoretical implications, this study presented and applied a coherent theoretical framework to analyse and measure the hospital's specialisation. In particular, we conceptualised the specialisation as the inverse of variety, measuring it using the Blau index. Our findings, based on the Blau Index, which measures service diversity, indicate that hospitals exhibiting greater diversity (i.e., lower specialisation) tend to be more efficient. This suggests that diversity in service provision may allow hospitals to coordinate resources better, adapt to different patient needs, share common resources and improve overall efficiency. However, this finding contrasts with some literature linking specialisation with higher efficiency, highlighting the complexity and contextual nature of the relationship between efficiency and diversification.

A potential limitation relates to the categorisation used for measuring diversity. While this study employed the Blau Index based on CMI-weighted discharges across hospital departments, utilising alternative classifications (e.g., Major Diagnostic Categories, specific service lines) could potentially influence the results and warrants further investigation.

Regarding managerial implications, our findings suggest potential strategies for management and policy formulation practices to improve healthcare and related outcomes. Focusing on the Italian healthcare system, our findings contribute to the research that highlights the importance of strategic diversification over specialisation in enhancing hospital performance. This result is particularly relevant for hospital managers, ASL, and regional decision makers as it suggests potential efficiency benefits associated with larger, more diversified hospitals compared to smaller, highly specialised ones. Hospital managers might consider the potential benefits of strategic service diversification, while regional decision-makers could evaluate policies supporting the development of larger, diversified healthcare providers or facilitating efficient mergers, where appropriate, considering local context.

A further limitation of our study is that we have not included in our analysis information about healthcare costs, such as expenses for operating activities, physicians, nurses and other hospital employees. Further research should examine the robustness of findings, also considering different production and cost efficiency models.

Finally, a significant limitation of the current work is related to the importance of considering the quality of care and its connection with efficiency and specialisation. Our work focuses on efficiency, but several works have underlined that exploring cost savings without considering the quality of care implies that focusing solely on technical or cost efficiency might lead to improvements that compromise care effectiveness or patient outcomes [6]. Therefore, further studies incorporating specific quality indicators relevant to the Italian context are needed to investigate the complex interplay between quality of care, efficiency, and specialisation/diversification.

CRediT authorship contribution statement

Ginevra Giuliani: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Simone Gitto:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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Data availability

Data will be made available on request.

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Simone Gitto, PhD, is an Associate Professor of Business and Management Engineering at the University of Siena (Italy). He teaches Economics and Organisation, Managerial Economics. Previously, he held academic positions at the University of Udine, University of Rome Tor Vergata, and Clemson University. His main research interests include: management engineering, digital transformation, healthcare management, efficiency, productivity and economic growth, forecasting methods and air transport management. His research has been published in international refereed journals, including *British Journal of Management, International Journal of Production Economics, Journal of Productivity Analysis, Management Decision, Socio-Economic Planning Science, and Transportation Research Part A*.

Ginevra Giuliani is a PhD student in Information Engineering and Science at the University of Siena (Italy), focusing on healthcare management. She holds a Master's degree in Engineering Management, earning top honours with a thesis on hospital efficiency and productivity, and a Bachelor's in Management Engineering. Her academic involvement includes teaching managerial and organisational courses, departmental tutoring, and representing PhD students. She has contributed to several research projects. Skilled in digital tools, her research interests encompass healthcare innovation, digital transformation, and economic efficiency analysis in health systems.