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Measuring productivity in the healthcare sector: a bibliometric and content analysis

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Abstract

Background Productivity in the healthcare sector has evolved as an appealing research topic in the last few years. Despite the growing interest, the extant scientific literature mostly concentrates on methodologies rather than theoretical and practical insights. Although diverse methodologies provide valuable quantitative wisdom, their application is often misaligned with broader economic theories or healthcare purposes, limiting their contribution to advancing theoretical and practical understanding of efficiency and productivity in healthcare systems. In this respect, the current study endeavors to bridge the research gap concerning the lack of a comprehensive overview of productivity measurements in the healthcare sector.

Methods We investigate this concern through a bibliometric and content analysis of articles published on healthcare productivity measurement techniques in the Web of Science database between 2003 and 2023. We provide a quantitative and critical analysis of conceptualization, methods, findings, and implications of the selected published articles concerning productivity measurements in the healthcare sector.

Results Our research discovered that the sanitary crisis generated by COVID-19 boosted the publication of scientific papers on productivity measurements in healthcare, with Europe emerging as a leading region in publication output. Although Data Envelopment Analysis and the Malmquist Index monopolize the range of measurement techniques used to quantify productivity, current research highlights the requirement for alternative methodologies to grasp the multidimensionality of healthcare productivity, including its interaction with quality and technological progress.

Conclusions We raise awareness that future efforts should prioritize multidimensional and context-sensitive approaches to measuring healthcare productivity, balancing efficiency, technological progress, and quality of care. Policymakers should focus on designing context-specific policies tailored to regional challenges and promoting targeted research funding to explore underrepresented areas of healthcare services.

Keywords Productivity, Healthcare, Bibliometric analysis, Content analysis

JEL C10, I15, J24

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Introduction

Productivity in the healthcare sector has become an evolving research topic since the COVID-19 pandemic. Increased efficiency and better resource allocation are still considered potential solutions to the sector`s challenges, positively contributing to the healthcare system`s financial stability [1, 2] and increasing patient satisfaction [3, 4].

Despite the growing interest, productivity remains a challenging indicator to quantify and unify in a single definition or calculus method, raising countless controversies in numerous studies that have tried to pinpoint the ideal method to quantify and diagnose it [5, 6]. In this realm, Hollingsworth`s [7] scientific work emphasizes a potential research gap insufficiently debated in existing studies: the supply of healthcare productivity research papers increased significantly, while the demand did not follow the same pathway. The seminal work of Hollingsworth [8] debates the "have data– must analyze" concern about the need to deliver suitable policy implications for interested parties without being pressed by the data collection tools and novel mathematical techniques to quantify productivity in the healthcare system. This concern relies on over-interpreted data, which may lead to potentially inconsistent information with destructive effects [7]. In these circumstances, a survey of scientific studies on productivity measurements in the healthcare sector would enrich knowledge and grasp of the existing research gaps and concerns by providing valuable insights for policymakers that may attenuate the damaging effects of over-interpreted data.

As stated, the extant body of healthcare productivity studies concentrates more on methodologies than theoretical insights. Although these approaches provide valuable quantitative wisdom, their application often misaligns with broader economic theories or healthcare purposes, limiting their contribution to advancing theoretical and practical understanding of efficiency and productivity in healthcare systems. The present research objective is to tackle this underexplored area by rendering a structured and encompassing overview of productivity measurements in healthcare by combining methodological rigor with theoretical insights to provide a comprehensive understanding using a robust analytical approach: bibliometric and content analysis of articles published between 2003 and 2023 in the WoS database on healthcare productivity measurement methods.

Present research acknowledges a significant contribution to literature from multiple perspectives. Firstly, this study fills the research void by providing a holistic perspective of the productivity measurement sector. Secondly, the dual perspective of the bibliometric analysis performed through performance analysis and science mapping facilitates the summarization of the research metrics, highlighting the structural features of scientific research by quantifying and visualizing their configuration and interconnections. Thirdly, our research moves beyond existing studies by employing content analysis to systematically explore how productivity is conceptualized and measured within the healthcare sector, enabling the identification of key themes, research trends, and methodologies related to productivity measurement. Last, it provides valuable insights to healthcare policymakers by advancing practical and theoretical dimensions of healthcare productivity measurement.

In this respect, the rest of the paper is structured as follows: Section II describes the materials and methods used for the analysis. Section III presents the bibliometric and network analysis methods. Section IV discusses the results of the content analysis. Finally, findings, conclusions, and limitations are discussed in Section V.

Materials and methods

Data

To gather bibliometric data, we used the Thomson Reuters Web of Science (WoS) database because of multiple reasons. Compared with other scientific databases (e.g., Scopus, EBSCO, Google Scholar) that include a high number of publications, WoS is recognized as a foremost quality database in the academic environment, that encloses standardized and consistent articles [9] indexed by the International Scientific Indexing (ISI) [10]. Furthermore, the WoS scientific database delivers articles from various fields and thematic research areas, being reported as a relevant database for interdisciplinary literature reviews [11]. Also, the WoS database provides metadata like abstract, authors list, affiliation, number of citations, authors` country of origin, and references, which are necessary for a bibliometric analysis [12]. This feature does not apply to multiple available scientific databases.

Concerning the bibliometric analysis-based articles published in the social science area, numerous outstanding bibliometric studies rely only on one database, either WoS [13–16] or Scopus [17–19], to mitigate likely homogenization concerns driven by the consideration of multiple distinctive databases [20]. Besides, searching up on solely one database eliminates the expected bias generated by the utilization of multiple databases [21].

Additionally, our science mapping procedure relies on co-citation analysis that examines the references reported in the bibliography list of our considered sample articles. This aspect facilitates the exploration of additional publications from other databases, which may be overlooked during the standard articles search process.

Because of the aforementioned reasons, we advocate that the WoS database has more standardized and consistent records than other databases [9]. Consequently, we selected WoS for our research analysis.

Following this, we formulated the search query "productivity measured in healthcare" in the titles, abstracts, and keywords of the indexed articles. The search was carried out in January 2024. A preliminary investigation identified 1334 articles. We shortlisted only articles written in English. We decided to keep only journal articles that were double-blind peer-reviewed to ensure a high academic and scientific quality of our sample, so we excluded conference papers, review articles, and book chapters. Pursuing the procedure shown in Fig. 1, we considered 47 articles for our final database.

Methods

The research methodology considers two complementary approaches: bibliometric and content analysis.

Bibliometric analysis is intensively used to analyze productivity measurement, specifically referring to the medical sector [18, 22–24]. As mentioned, the bibliometric approach considers two research directions: performance analysis and science mapping [25]. The performance analysis investigates articles-related metrics, countries and regions` scientific production, authors` and institutions` performance, sources, and keywords analysis. Science mapping is accomplished through co-authorship, co-citation, and co-word analysis. The bibliometric analysis was performed using the *bibliometrix* package [26] and the *biblioshinny* web application - tools from the R software [27], version 4.4.1 for Windows.

Content analysis aims to systematically explore how productivity is conceptualized and measured within the healthcare sector. This approach involves reducing the large volume of data from the analyzed papers into manageable categories [28], enabling the identification

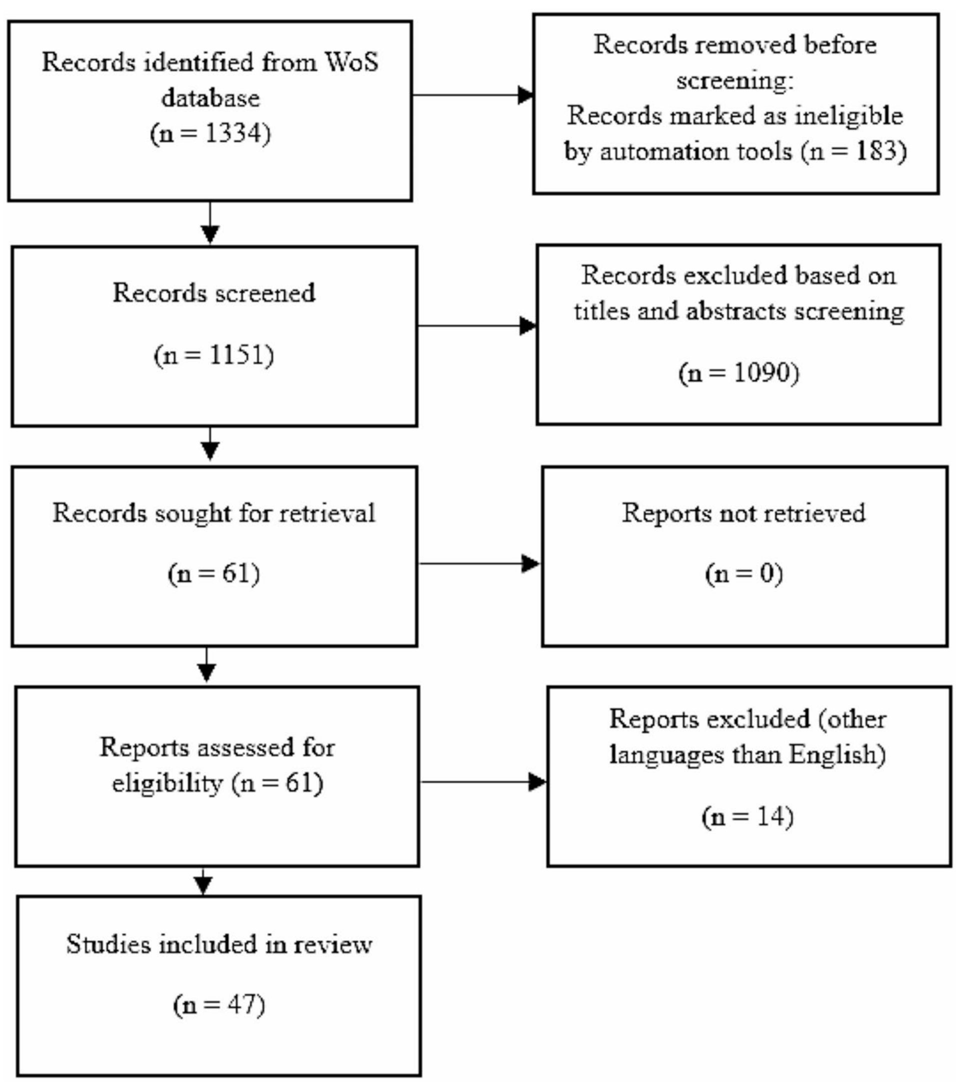

Fig. 1 Literature collection flow

Table 1 Descriptive statistics

Database	No. of articles	Time period	Document average age	No. of publishing sources	Average citation per article	Highest number of citations per article
WoS	47	2003–2023	8.4	38	29.43	478

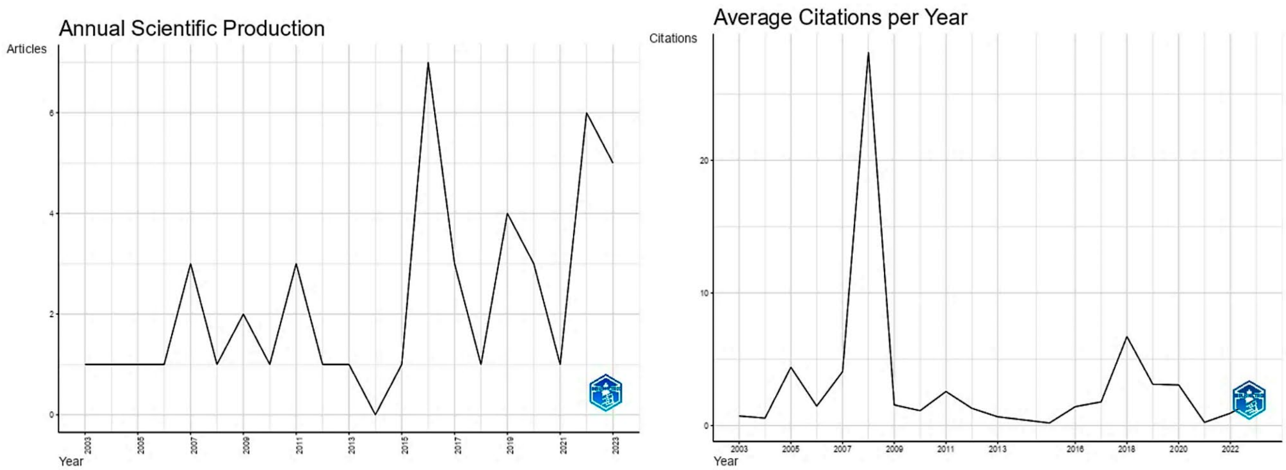

Fig. 2 Research progress between 2003–2023

of key themes, trends, and methodologies related to productivity measurement. To ensure consistency and rigor, a predefined coding framework is developed based on a preliminary review of the literature. The articles are coded according to the following categories: healthcare level productivity (e.g., system-wide productivity, specific departments productivity), research provenance (e.g., international cooperation, local expertise), tools and methods used in productivity measurement (e.g., Data Envelopment Analysis, Malmquist Index, etc.), external factors (e.g., economic crises, health policies, etc.), organizational and workforce impact (e.g., physicians roles, organizational practices, etc.) and healthcare quality (e.g., safe practices, quality objectives). Through this analysis, the study aims to identify commonly used productivity metrics in healthcare settings, examines the various methods employed for measuring productivity, and emphasizes research trends over time, such as shifts toward quality-based care and the increasing use of technology.

Bibliometric analysis

Performance analysis

Articles-related metrics

Our database comprises 47 articles published between 2003 and 2023 in 38 distinct scientific journals. Descriptive statistics are presented in Table 1. As can be seen, the mean number of authors per document is 4.04, and 29.79% of articles are published in international co-authorship. The documents` average age is 8.4, and the average number of citations per article is 29.43.

The highest number of published articles is in 2007 (14.89%). In that period, a survey related to primary care physicians and patients from six nations identified that even if the USA invests an important budget in healthcare, it performs lowest in quality, access, equity, and healthy lives, compared to analyzed countries [29]. These outcomes raised the question of efficient resource allocation at the international level, which may also be reflected in the number of studies published in that year.

Figure 2 presents research evolution year-wise, and concerning the period under consideration, we observe that over half of the articles (51.06%) were published in the last five years. Consequently, we deem that productivity measurements in the healthcare sector have become a topic of growing interest since the 2019 pandemic sanitary crisis. Regarding the number of citations, most were in 2008, 478 sources with a mean value per year of 28.12. Existing analyses of bibliometric research [30–32] have shown that published articles need at least two or three years to accumulate several citations that may be reliable for a bibliometric study. Therefore, it is not surprising to find a high number of citations in older articles.

Countries and regions scientific production

The scientific performance by regions considers the countries of authors` affiliations. Each country is counted only once, even if multiple authors from the same region authored the paper [14]. If a paper is in international collaboration, it is attributed to all the countries of its co-authors [33]. Europe is distinguished as a dominant region with 60 (42.25%) published papers, Sweden and the Netherlands, two countries that have actively engaged in reforms of the healthcare system in the last two decades [34–36], are the most productive countries. Important scientific production is encountered in North America, the United States counting 43 (30.28%) research articles. Subsequently, 25 (17.61%) articles are authored by Asian researchers. Minimal scientific production is reported in South America (4.93%), Australia (4.23%), and Africa (0.70%). Figure 3 presents the country`s scientific production.

Concerning the total citations, Australia achieves the most, 523 (37.82%), with an average article citation of 174.3, followed by North America with 335 citations (24.22%) and an average article citation of 23.9. The Netherlands is the most cited country in Europe, with 123 citations (8.89%) and an average article citation of 41. In Asia, China has the highest academic influence, with the greatest number of citations: 91 (6.58%).

Cross-country collaboration analysis reveals that most research partnerships were established by the United States (with Austria, China, Germany, Iran, Korea, and Malaysia), followed by Sweden, which cooperated with China, Egypt, Finland, and Norway. In the last decade, the collaboration between the USA and China in publications has strengthened because of China`s growing scientific and technological capabilities, such as advanced research and development investments and high academic rankings [37, 38]. Meanwhile, until 2012th was a period of intensified collaboration between South Korea and the USA, which declined in the last years because South Korea increased its partnerships with other Asian regions [37]. Figure 4 graphically presents the countries` collaboration world map, while Table 2 summarizes cross-country research partnerships.

Authors performance

In our sample of articles there are 183 distinct authors, with an average of 4.04 authors per document. Only two authors contribute with a single-authored document. Interestingly, most authors (96.72%) contribute with a single article on productivity measurement in healthcare topic, and only one author contributes with three articles.

Considering the number of research articles written by the most prolific authors, investigating productivity measurement in health seems to be a topic of occasional curiosity rather than a research specialization. According to their current affiliation, most productive authors belong to the American and European continents. Even if in Europe, Sweden and the Netherlands are the most productive countries in terms of number of published articles, no author from these countries emerged as a prolific

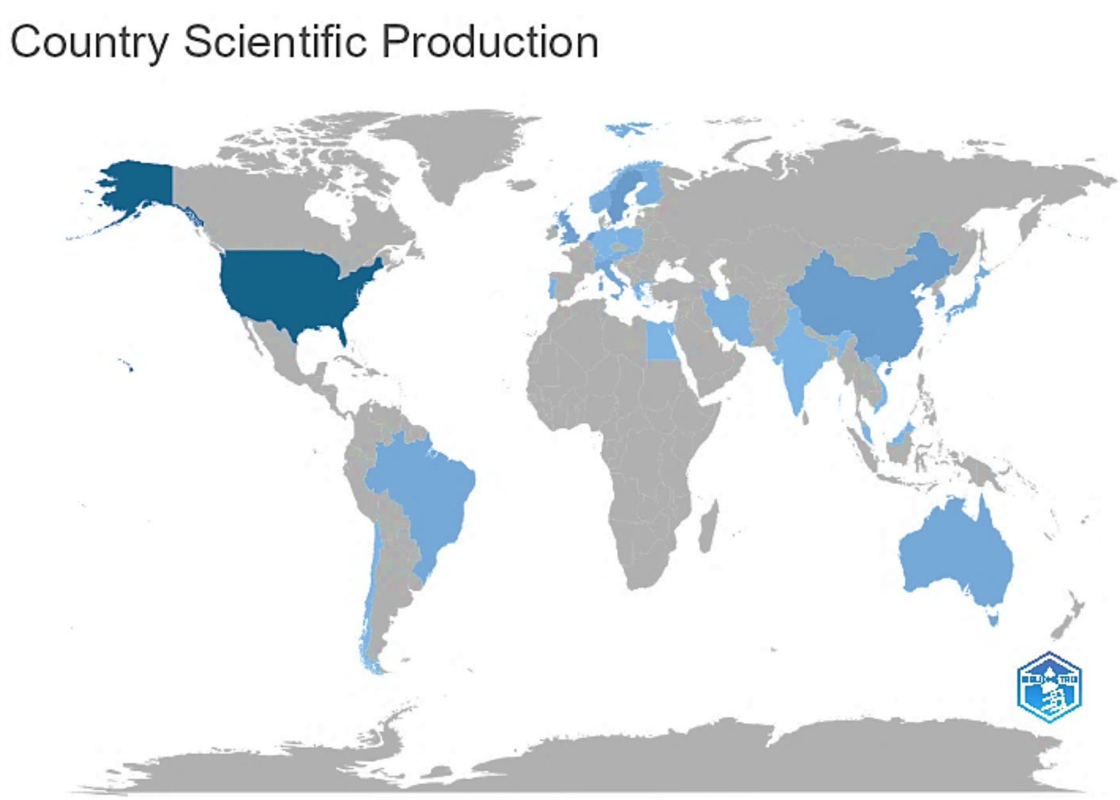

Fig. 3 Country scientific production

Fig. 4 Countries collaboration world map

Table 2 Cross-country collaboration

From	To
Brazil	Portugal
China	Egypt
	United Kingdom
Germany	Malaysia
Iran	Germany
	Malaysia
Italy	Switzerland
Korea	Vietnam
Netherlands	Chile
Sweden	China
	Egypt
	Finland
	Norway
United Kingdom	Australia
	Italy
USA	Austria
	China
	Germany
	Iran
	Korea
	Malaysia

author. Hollingsworth Bruce, professor of Health Economics at the Faculty of Health and Medicine, Lancaster University, comes out as the most prominent researcher with three articles and 497 citations. One of his articles [7], published in 2008th, which reviews published papers on frontier efficiency measurement in health care delivery, proves an impactful research in the domain, counting a total of 1042 citations at the end of 2023 on the Google Scholar platform. Chou Shin-Yi, Kittelsen Sverre A.C., Ford Eric W., Huerta Timothy, and Thompson Mark A. have each published two articles, but their number of citations is comparatively lower. Table 3 summarizes the author`s overall performance.

Institutions performance

A total of 108 academic organizations published papers in our sample data, 73.15% contributing with only one article. Productivity measurement in healthcare emerges as a topic of interest mainly in technical institutions. The most productive institution is Erasmus University Rotterdam from the Netherlands with ten published articles of which four are attributed distinctively to the Medical Faculty of Erasmus University Rotterdam. In the second position, based on the number of published papers, is Universidade de São Paulo from Brazil, with five papers.

Table 3 Authors overall performance

Author	First Publication Year	No. of articles	Total Citations	Current Affiliation	H-Index (in WoS)
Hollingsworth Bruce	2008	3	497	Lancaster University	24
Chou Shin-Yi	2016	2	33	Lehigh University	22
Ford Eric W.	2011	2	8	University of Alabama Birmingham	49
Huerta Timothy	2011	2	8	Ohio State University	24
Kittelsen Sverre A.C.	2017	2	17	Frisch Centre	14
Thompson Mark A.	2011	2	8	Augusta University	16

Table 4 Institutions performance

Rank	Organization	Country	No. of articles	QS Ranking*
1	Erasmus University Rotterdam	Netherlands	10	176
2	Universidade de São Paulo	Brazil	5	85
3	Texas Tech University	USA	4	801–850
4	Texas Tech University System	USA	4	-
5	Lehigh University	USA	3	548
6	Monash University	Australia	3	42
7	Oregon Health And Science University	USA	3	-
8	Scuola Superiore Sant`anna	Italy	3	-
9	Umea University	Sweden	3	465
10	University of North Carolina at Chapel Hill	USA	3	132

*QS Ranking– QS University Ranking 2024

According to the 2024 QS University ranking, only two institutions are in the top 100 positions. Moreover, just seven institutions out of ten are included in the QS World University Ranking 2024. Table 4 ranks the most productive academic institutions.

Sources analysis

The analyzed articles are published in 38 distinct publications, with 84.21% of scientific journals publishing only one paper. Health Policy is the leading journal concerning the number of published articles, while Health Economics records the highest number of citations, respectively 478. Table 5 presents a list of the first six journals in terms of publications and citation counts. As can be observed, most papers are published in journals from the medical field without any interdisciplinary approach.

Table 5 Contributing journals as per number of articles and citation counts

Journals as per number of articles		Journals as per number of citations	
Journal	**No. of articles**	**Journal**	**No. of citations**
Health Policy	4	Health Economics	478
BMC Health Services Research	3	Journal of Occupational and Environmental Medicine	134
BMJ Open	2	Pharmacoeconomics	88
INQUIRY: The Journal of Health Care Organization, Provision, and Financing	2	International Journal of Productivity and Performance Management	81
International Journal of Productivity and Performance Management	2	BMC Health Services Research	71
Social Science & Medicine	2	Journal of the Royal Society of Medicine	62

Keywords analysis

The keyword analysis reveals that the most frequently used keywords and their root keywords are relevant to measuring productivity in the healthcare field. "Productivity" emerges as the most used keyword (17 occurrence frequency). "Healthcare" appears in the second position concerning the most used keywords (10 occurrence frequency). On the third position is identified "data envelopment analysis" trigram (9 occurrence frequency), and it has two root keywords: "data envelopment analysis (DEA)" and "data envelopment analyses". The rest of the most used keywords and their root-keywords deal with: "efficiency", "cost", "quality" and "Malmquist productivity index". Figure 5 presents the word cloud of the most frequent keywords.

Science mapping

Co-authorship analysis

Co-authorship analysis allows research networks identification by considering the researchers` scientific background, research interest, and geographical residence. Our data conveys the existence of 15 clusters, as presented in Fig. 6.

The first cluster (in red) includes American researchers interested in healthcare and economic sciences. The second cluster (in blue) is geographically limited to the USA and is an interdisciplinary collaboration between scientists focusing on healthcare, health economics, productivity, networks, and econometric methods. The third cluster (in green) is also limited to the USA, the academic researchers being interested in the medical field.

The fourth cluster (in purple) comprises two authors from the public administration sector and is geographically limited to Brazil. The fifth cluster (in orange) is

Fig. 5 Keywords frequency

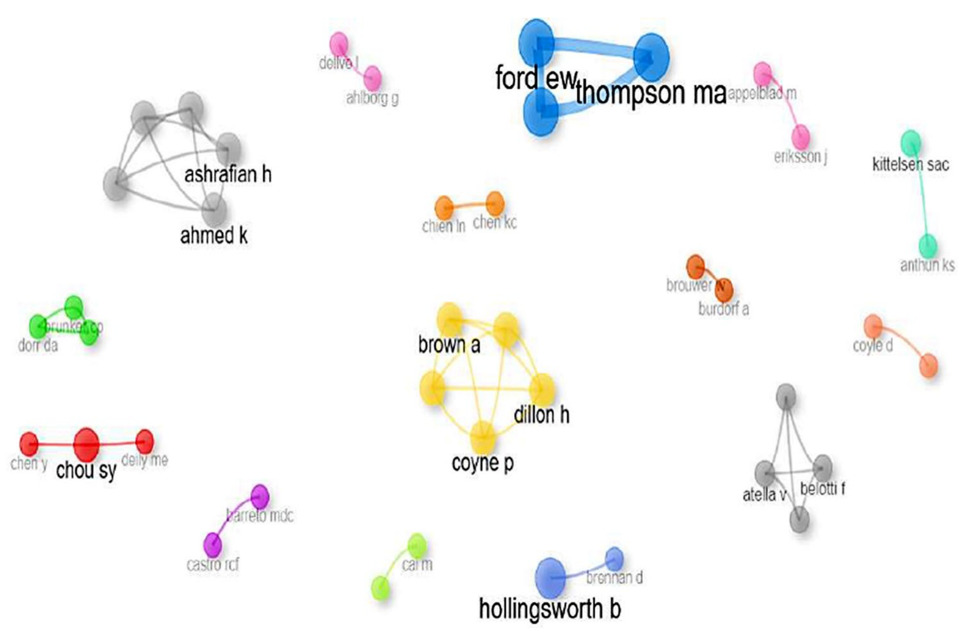

Fig. 6 Co-authorship clusters

limited to Taiwan and includes academics with a scientific focus on health care. The sixth cluster (in dark orange) includes academics with a Netherlands affiliation specialized in health, well-being, welfare, and behavioral economics. The seventh cluster (in light pink) includes authors from Sweden with an interest in medical sciences and cognitive neuroscience. The eighth cluster (in light grey) presents a collaboration between academics of Italian and British nationalities with scientific interest in econometrics, health economics, health performance, efficiency, and productivity. The ninth cluster (in mint green) is geographically limited to Norway and includes academics interested in healthcare services. The tenth cluster (in light orange) includes researchers with an interest in public policy and economic measurements from the United Kingdom. The eleventh cluster (in light blue) presents a collaboration between authors with British and Australian affiliations, interested in public health, health economics, and quality of life.

The twelfth cluster (in dark pink) is limited to Sweden, similar to the seventh cluster, and it includes academics with an interest in healthcare and occupational medicine. The thirteenth cluster (in light green) is limited to China and includes researchers interested in epidemiology and pandemics. The fourteenth cluster (in yellow) comprises only authors with a USA affiliation, specialized in palliative care and health system finance. The fifteenth cluster (in dark grey) is limited to the United Kingdom and includes academics specialized in medical sciences.

The fact that most clusters are formed by health care specialists supports the assumption that the interest is in identifying suitable policies to improve productivity in this sector. Therefore, the research interest does not intend to be mainly academic but an endeavor to pinpoint potential solutions to increase productivity.

Co-citation analysis

Co-citation emerges when two articles are cited by a third scientific paper [26]. This method emphasizes the intellectual design of a specific domain [39, 40] by promoting the identification of thematic clusters that incorporate network nodes, i.e., cited papers, and edges representing co-citation networks [41, 42]. Centrality indicator developed by [43] is used in this process by implementing two calculation methods: betweenness [44, 45] and closeness [46, 47].

Betweenness relates to the control that some authors manifest in the communication process of other counterparts and their capacity to restrict this process [48]. Closeness measures independence, that is the capacity to interact with counterparts without intermediaries [48].

The co-citation analysis was carried out with 50 nodes and walktrap as clustering algorithm [49]. The results exhibit a network with three significant and central nodes, as presented in Fig. 7: "farrell mj 1957" [50] (betweenness centrality = 265.789), "hollingsworth b 2008" [7] (betweenness centrality = 225.349) and "charnes a 1978" [51] (betweenness centrality = 216.983). The paper published in 1957 by [50] intends to identify a reliable measurement of productive efficiency. Hollingsworth`s academic research [7] provides a review of published papers on the measurement of productivity and efficiency in the healthcare sector. The 1978 paper authored by Charnes [51] is a very cited paper on a scalar estimate of the efficiency of not-for-profit entities.

The result of co-citation analysis identifies ten clusters, as presented in Fig. 7, of which four include only one paper. One of those studies analyses whether participation in the Taiwan Quality Indicator Project (TQIP) led to improvements in hospital quality and operational efficiency using DEA. Another paper explores the relationship between hospital ownership and operational efficiency in Taiwan using DEA and finds out that private hospitals generally operate more efficiently than public ones, a result that may reflect differences in case complexity or service focus rather than better management

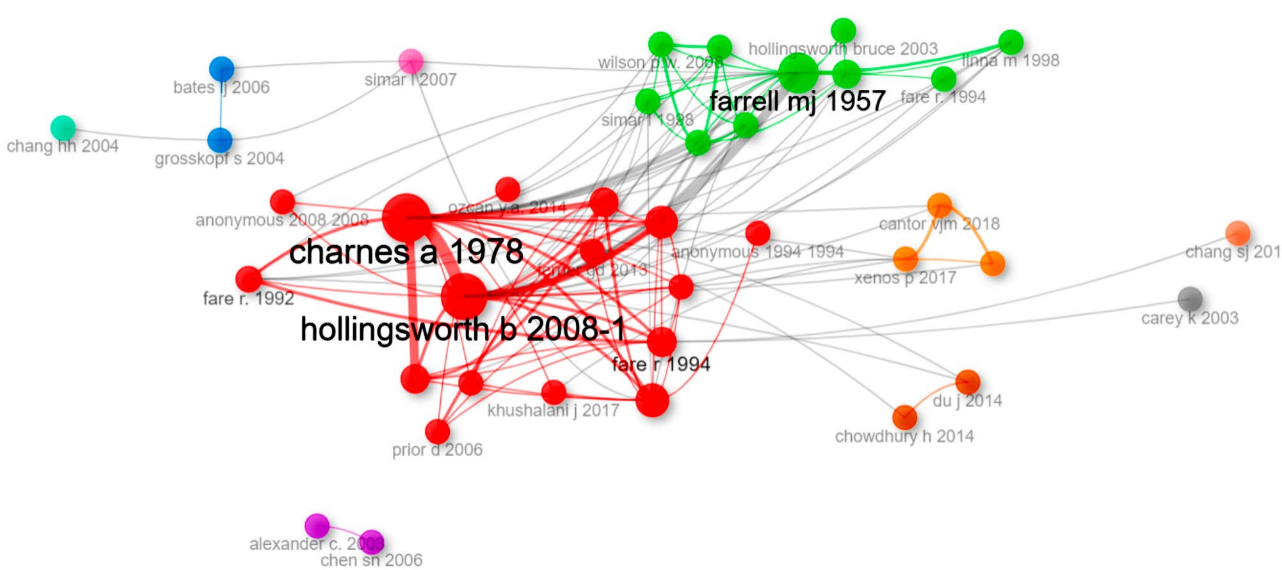

Fig. 7 Co-citation analysis of references

of private hospitals. Another research article tackles the methodological challenges of two-stage procedures for analyzing productive efficiency, proposing bootstrap methods that improve statistical inference and enhance estimation accuracy through Monte Carlo simulations, while one last study explores how strategic and structural characteristics impact the efficiency of U.S. hospital systems using stochastic frontier analysis.

Considering the rest of the clusters, the largest is the first one (colored in red), which consists of 16 papers concentrated on measuring and analyzing efficiency within the healthcare sector using DEA. Several articles emphasize the importance of considering quality alongside efficiency, and many involve cross-national or cross-institutional comparisons, particularly among OECD nations, to benchmark performance and identify best practices.

The second largest cluster is the third one (colored in green), which contains ten articles that utilize non-parametric methods to assess efficiency. Several emphasize the critical role of advanced statistical techniques, such as bootstrapping, in improving the reliability and robustness of efficiency measurements. A few examine how technical progress and innovation influence efficiency changes over time, especially in industrialized economies. One article focuses on developing software tools to support the practical application of efficiency analysis methods.

The third cluster comprises three papers (colored in orange) that discuss the efficiency of public health in the period 2008–2016 in some European regions. The rest of the clusters are composed of two academic research papers, out of which one cluster (colored in blue) comprises papers that use DEA approach to measure the efficiencies of US hospitals. In contrast, another cluster (colored in purple) concentrates on the impact of this financial reform on hospital productivity. The last cluster (dark orange) comprises papers that analyze productivity, efficiency, and technological changes in hospital services.

Co-word analysis

Co-word analysis describes a technique meant to explore the co-appearance of essential notions in the keywords, abstracts, and titles, assuming that concepts that appear repeatedly together reveal thematic connections [25]. This procedure enables the visualization of conceptual clusters [41].

We realized a thematic map by plotting the bigram terms from the paper abstracts into four quadrants considering centrality and rank scores. Centrality relates to the interaction between networks and estimates the significance of a concept in a specific area. Density measures the group inner strength and determines the level of development of a subject [52, 53]. The frequency of the notions and the number of related documents determine cluster size.

Thematic map categorizes thematic clusters into motor themes, niche themes, emerging/declining themes, and basic themes [52]. Figure 8 presents graphically the results of the co-word analysis.

The motor themes cluster includes well-developed notions in the analyzed domain [52]. In our analysis, the motor themes quadrant comprises multiple clusters. The most prominent ones are "data envelopment"

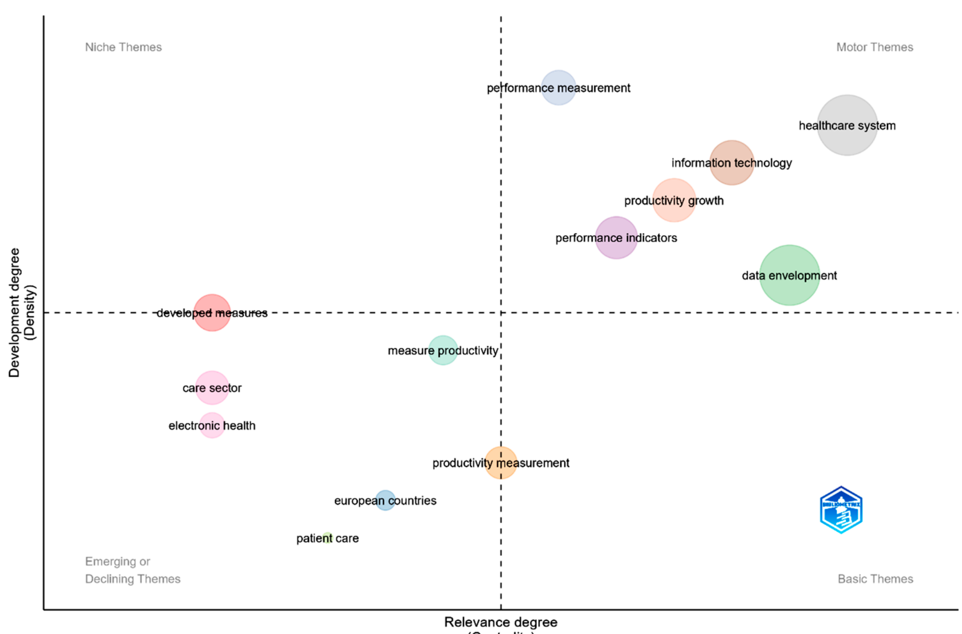

Fig. 8 Social structure: co-word analysis

(density = 90.402, centrality = 14.671) and “healthcare system” (density = 137.164, centrality = 23.413), followed by “information technology” (density = 135.606, centrality = 10.472) and “performance indicators” (density = 97.222, centrality = 4.778).

The niche themes group considers technical and marginal notions in the overall field [52]. “Developed measures” cluster (density = 89.286, centrality = 0.500) is at the border between niche and emerging or declining themes.

The emerging or declining themes cluster assumes topics characterized by low density and centrality [52]. The most prominent clusters are “measure productivity” (density = 87.500, centrality = 2.667), “care sector” (density = 83.333, centrality = 0.500) and “electronic health” (density = 83.333, centrality = 0.500).

The basic themes quadrant considers topics characterized by high density and centrality [52]. These topics are important to the research domain but appear undeveloped. “Productivity measurement” (density = 137.500, centrality = 3.708) cluster is at the border between emerging or declining themes and basic themes.

Co-word analysis reveals no niche themes debated in the investigated articles. Lacking specific notions or detailed conceptualization, the bigram terms from the paper abstracts appear to describe generic concepts.

Beyond the descriptive statistics that we gathered through the bibliometric analysis, we witness that even if most of the papers were in partnership between healthcare specialists, productivity as a research subject seems to be more a topic of occasional inquisitiveness rather than a research specialization, an aspect verified by the number of articles written on this topic by the investigated authors and also by the general notions analyzed through their research.

However, our bibliometric analysis alone does not allow us to determine whether any conclusive theoretical and empirical implications emerge from these studies. For an overall picture, we refer to a structured content analysis in the following section.

Content analysis

To complement the bibliometric analysis of the scientific papers included in our study, this section presents a content analysis to understand better how different aspects of healthcare productivity are explored in the analyzed literature. We examine not only the themes they address within the context of healthcare productivity and whether the definitions of productivity across the studies are consistent or conflicting but also the specific healthcare departments where productivity was measured. Additionally, we consider the authors` country of origin in terms of the healthcare system they studied.

Regarding the focus of the analyzed papers within the healthcare sector, 32 papers examine productivity across the entire healthcare system. The emphasis on system-wide productivity likely reflects a predominant interest in examining broader factors that influence efficiency and performance across the healthcare sector. Additionally, data availability at the level of the entire healthcare system may be more extensive compared to that from individual units or departments. In contrast, two papers specifically concentrate on surgical departments [54, 55], and another two focus on emergency departments [56, 57]. The remaining studies target various specialized areas, including orthopedic departments [58], traditional Chinese medicine [59], palliative care [60], rehabilitation [61], maternity care [62], dental care [38], teaching hospitals [63], and Veterans Affairs [64] departments. The limited focus on specific departments suggests that these areas may be underexplored in terms of productivity analysis, highlighting the need for further research in these specialized fields. This distribution indicates a potential need for more balanced research efforts that not only address broad systemic issues but also investigate individual departments, which may present distinct productivity challenges and opportunities. Such targeted research could provide unique insights that broader, system-wide analyses may fail to capture.

Next, understanding the provenience of authors in relation to the countries where studies are conducted can reveal the extent of international cooperation, the influence of local expertise, and the potential for cross-cultural exchange in addressing specific healthcare challenges. In 27 of the analyzed papers, the authors are from the same country where the study was conducted. In the papers focusing on multicountry studies (11 out of 47), the authors are from one of the countries included in the research. In the remaining articles, there is a collaboration between authors from the host country and those from other countries. The fact that over 57% of the articles feature authors from the same country where the study was conducted suggests a strong reliance on local expertise and a deep understanding of the specific healthcare context. This local focus likely results in research that is closely aligned with the unique needs and challenges of that country or region. On the other hand, the remaining articles underscore the importance of cross-cultural exchange, where the collaboration of authors from different countries facilitates the sharing of ideas, methods, and perspectives. This international collaboration is crucial for enhancing both the quality and the broader impact of the research. Three of the analyzed papers discuss healthcare productivity during the COVID-19 pandemic, yet none of the authors are from China. While China was the initial epicenter of the pandemic, these studies emphasize the global impact of COVID-19 on healthcare systems across different regions, highlighting the universal challenges posed by the pandemic and the varied responses of healthcare systems worldwide.

The provenance of authors plays a crucial role in the context of healthcare productivity bibliometric analysis, because this provenance often reflects the specific focus of an author, which aligns with the priorities and context of the region or culture in which the author resides. In our research, we observe that productivity is consistently tied to resource optimization and accessibility, regardless of whether the country is classified as low-, middle-, or high-income. However, when authors originate from high-income countries, such as the United States [54, 65, 66], Taiwan [67], or Sweden [58], their work frequently emphasizes resource optimization and accessibility also through technological advancements (e.g., electronic health records and other innovative technologies).

Moreover, while all studies prioritize cost-efficiency and procedural throughput, certain regional and cultural differences emerge. For instance, studies from Greece place a significant emphasis on patient satisfaction [68] and employee satisfaction [69]. Similarly, a focus on employee satisfaction is observed in a study from Sweden [70]. These findings underscore the importance of considering the regional and cultural context of authors in bibliometric analyses, as such considerations can reveal distinct healthcare priorities and inform tailored strategies to enhance productivity across diverse settings.

An important part of this content analysis involves grouping the papers by the themes they address within the context of healthcare productivity, allowing us to better understand the directions in which the authors have developed this concept. The analysis reveals that the papers explore healthcare productivity through specific tools and models used for productivity measurement, economic and external factors influencing productivity, the role of information technology, organizational and workforce factors, and the impact of healthcare quality. Each of these relationships is briefly discussed below.

Regarding the specific tools and models used in productivity measurement, several studies employ standard DEA [71, 72], along with variations of it, such as hybrid DEA combined with game theory [73], bootstrapping DEA [59, 74], or window-DEA [75], which address specific challenges related to healthcare system productivity. In essence, DEA focuses on assessing the efficiency of units by comparing them to the best performers.

Another significant portion of the analyzed papers measures healthcare productivity using the Malmquist Index [58, 65, 67, 68, 76–80], which is also a DEA technique that evaluates changes in productivity over time, incorporating both technical efficiency and technological progress or innovation [77]. The remaining studies use various statistical methods, including different regression models, standard productivity formulas (e.g., bed utilization rate), or combinations of DEA, Stochastic Frontier Analysis, and the Malmquist Index. The number of papers by the statistical method used to measure healthcare productivity is presented in Table 6.

Table 6 The number of studies by the statistical method used to measure healthcare productivity

Statistical Method	Frequency
Malmquist Index	16
Data Envelopment Analysis (DEA)	14
Regression analyses	5
Stochastic Frontier Analysis (SFA)	4
Other methods developed/applied by authors	15

Each method has unique strengths and limitations. Regression analysis is powerful for estimating effects and predicting outcomes but does not benchmark relative efficiency. DEA excels in efficiency evaluation by comparing multiple decision-making units (DMUs), but it is sensitive to outliers. Malmquist Index complements DEA by capturing productivity dynamics, distinguishing between technological and efficiency changes, but requires consistent longitudinal data. These differences make the choice of method context-dependent, with regression analysis being suitable for outcomes prediction, DEA for static efficiency benchmarking, and the Malmquist Index for time-series performance evaluation. Each method serves distinct purposes, and their combined use (e.g., as seen in [65, 73]) can provide more comprehensive insights into healthcare productivity and efficiency.

Through these measurement tools, the authors highlight the potential of models such as DEA and the Malmquist Index to generate practical implications in real-world healthcare settings. Below, we discuss some of the most significant practical steps suggested by studies included in our database, which can be implemented in healthcare systems to enhance productivity and efficiency. As highlighted in previous research [71], DEA is widely utilized to analyze efficiency, identify factors influencing efficiency, and assess efficiency trends over time. Building on these insights, the findings suggest that policymakers can leverage DEA methodologies to evaluate efficiency before and after specific events, such as the COVID-19 pandemic. Furthermore, employing advanced DEA models, such as network DEA or Metafrontier DEA, can provide healthcare managers with a more detailed understanding of efficiency across various levels of the healthcare system. Additionally, integrating DEA with complementary methodologies, such as SFA or game theory, could yield actionable insights to enhance decision-making in resource allocation and healthcare management. Using DEA in their study, some researchers [73] identify that inefficient healthcare centers could improve their performance by emulating the decisions and practices of reference (efficient) units identified through the

DEA model. Furthermore, the DEA model demonstrates its capability to recommend specific adjustments, such as changes in population coverage or personnel allocation, to achieve better performance. Similarly, the study conducted in 2022 [81] reveals critical insights for policymakers designing healthcare system reforms, particularly those involving price negotiations or competitive mechanisms. For instance, reforms expanding “free price negotiations” may unintentionally incentivize hospitals to prioritize high-volume, lower-cost services, potentially compromising efficiency in teaching hospitals or those delivering complex care. The study also suggests that hospitals with larger volumes and diverse case mixes tend to exhibit lower efficiency. However, it identifies an optimal hospital size (200–400 beds) that achieves a balance for higher efficiency.

In the European Union, DEA and the Malmquist Index have been applied to compare efficiency and productivity among member states. Some authors [82] argue that investing resources in healthcare infrastructure - such as constructing new hospitals, upgrading existing facilities, and acquiring advanced medical equipment - can promote a positive shift in the technological frontier. Furthermore, addressing healthcare productivity within the EU requires policies focused on retaining skilled healthcare professionals. This can be achieved by improving salaries and working conditions to reduce the outflow of medical staff, while also providing opportunities for professional growth. The same study underscores the importance of strengthening data collection and analysis by investing in the creation of unified, high-quality datasets at the EU level. These datasets should include critical indicators such as human capital and healthcare quality metrics, which are often unavailable or inconsistent across countries. For instance, the study was unable to evaluate patient satisfaction and the quality of healthcare facilities due to the lack of unified data across all EU member states.

A study on the productivity of township hospitals [74], emphasizes the benefits of collaboration across different levels of healthcare. Partnerships between townships, county, and tertiary hospitals can enhance resource sharing, expertise exchange, and technology utilization, thereby reducing inefficiencies and fostering a more integrated healthcare delivery system. Such collaborations could also address regional disparities by targeting the specific needs of underperforming hospitals in rural and resource-constrained areas. Although most of the studies involve DEA or Malmquist Index to assess healthcare productivity, these tools also have some context-specific challenges. Both DEA and Malmquist Index typically assume a uniform availability of resources across decision-making units. However, significant disparities exist influenced by infrastructure limitations, workforce shortages, or inadequate funding [51]. Moreover, variations in healthcare system structures (i.e., public vs. private, centralized vs. decentralized) can have a profound influence on productivity measurement and these models can fail to fully capture the differences leading to skewed interpretations [7].

Beyond the tools and methods used to measure productivity, a part of the analyzed papers explores how various economic and external factors influence the productivity of healthcare institutions or systems. Economic crises [54, 68, 83, 84], such as the Great Recession [80] and the COVID-19 pandemic, had significant impacts on healthcare productivity, primarily due to resource constraints, financial pressures, and increased patient volumes. It was observed that while budget reductions during economic crises initially improved efficiency, they eventually led to long-term technological regression and a decline in quality [68]. To mitigate such effects, adopting balanced cost-cutting strategies that protect essential technology investments and allocate funds for sustaining technological advancements is critical for maintaining healthcare productivity. Economic crises also drive notable shifts in healthcare systems. During the 2008th financial crisis, Greece experienced a socioeconomic downturn that severely affected public health and wellbeing, with significant repercussions for healthcare productivity [85]. Similarly, the COVID-19 pandemic placed an enormous economic burden on healthcare systems. In Italy, one of the first European countries hit, operational costs soared as hospitalization expenses rose with the complexity of care required [86]. The pandemic also triggered widespread burnout and mental health challenges among healthcare workers, resulting in higher absenteeism, staff turnover, and diminished productivity [87]. Additionally, while the rapid adoption of telemedicine during the pandemic provided long-term productivity benefits, it incurred significant initial costs and was hindered by steep learning curves [88]. Additionally, health managers and policymakers must give considerable attention to the ethical concerns associated with telemedicine implementation, such as data privacy risks, inequitable access, and challenges faced by underserved populations. Privacy concerns involve ensuring proper data protection, encryption, and obtaining informed consent, while access disparities arise from inadequate internet infrastructure, gaps in digital literacy, and affordability issues, necessitating targeted policy measures and technological assistance. To address these challenges, healthcare policymakers and managers should focus on balanced cost-cutting measures that protect critical technology investments and prevent long-term productivity declines. Strategies such as the strategic adoption of technologies, workforce training, mental health support for healthcare workers, efficient resource allocation, and proactive technological preparedness are essential for maintaining productivity during crises, as demonstrated by the COVID-19 pandemic and the 2008th financial downturn.

Another part of the studied articles focuses on national health policies, including variations in funding mechanisms and regulatory frameworks [78, 89], compensation models, and benchmarking practices [60], as well as variations in economic integration within the EU, such as varying levels of funding and cross-border cooperation [82], that play critical roles in shaping healthcare productivity outcomes. Additionally, hospital size and case mix are found to influence productivity, with larger hospitals generally expected to benefit from economies of scale, while specialized hospitals face distinct productivity challenges due to differences in patient types and treatment procedures [79].

Technological advancements and information technology are key drivers of productivity in healthcare. Advancements in surgical techniques and standardized healthcare policies have boosted productivity, particularly in procedures like total hip arthroplasty [58]. Similarly, investments in health information technology (HIT) are linked to improved hospital productivity and financial performance, especially when effectively integrated with hospital operations [66]. A group of researchers [65] emphasize the importance of selecting HIT vendors that align with hospital needs, as this significantly influences total factor productivity (TFP). Another study [62] noted that while adopting EHRs may initially reduce physician productivity due to learning curves, long-term integration into clinical workflows can enhance productivity and patient outcomes.

Research conducted by [74] underscores the impact of declining technological capabilities on productivity, suggesting that upgrading medical equipment, integrating EHRs, and providing technical training can drive TFP change. Innovative technologies like EHRs, telemedicine, and artificial intelligence (AI) have further advanced healthcare productivity. For instance, the implementation of EHRs in U.S. hospitals improved accessibility, accuracy, and care coordination by reducing administrative burdens and enhancing clinical decision-making [90]. Telemedicine adoption by the Veterans Health Administration reduced interhospital transfers from 3.46 to 1.99%, streamlining care delivery [91]. At Moorfield`s Eye Hospital, AI systems achieved over 94% accuracy in recommending patient referrals, matching expert clinician performance, and increasing diagnostic efficiency [92]. In summary, adopting and effectively integrating advanced healthcare technologies, along with training staff in their use, is critical for driving productivity gains and improving patient outcomes.

Another part of the analysed papers highlights the impact of organizational and workforce factors on healthcare productivity [57]. debate the idea that dedicated teams, particularly in emergency departments, have been shown to significantly enhance productivity by improving communication, team cohesion, and more efficient resource utilization. Similarly, the organization of physician roles and the provision of adequate administrative support are critical for maximizing productivity in healthcare settings, as highlighted in a study on Veterans Affairs medical centers [64]. In primary care, the adoption of multi-condition care management programs has been found to increase productivity by streamlining care processes and reducing redundancies [93]. Moreover, effective organizational practices within surgical departments, such as optimized scheduling and resource allocation, play a crucial role in enhancing productivity by minimizing downtime and increasing the throughput of procedures [55]. However, the relationship between workforce incentives and productivity is complex; while high work attendance driven by strong incentives can lead to immediate productivity gains, it may also result in long-term negative consequences such as burnout, ultimately affecting overall productivity [94].

The final aspect explored in some of the analyzed papers is the interrelation between healthcare quality and productivity, which is notably complex and context-dependent [95]. examine this relationship in the dialysis industry, demonstrating that both high productivity and quality can be achieved through efficient resource management and technological advancements [76]. investigate the impact of implementing safe practices in hospitals, finding that such practices can enhance TFP by reducing errors and improving operational efficiency, which in turn positively affects quality [77]. analyze the effects of participating in the Medicare Shared Savings Accountable Care Organizational Program, revealing that aligning financial incentives with quality objectives leads to simultaneous improvements in both productivity and quality. However, in environments such as nursing homes and dental practices, it is crucial to carefully balance productivity with quality to ensure that efficiency gains do not compromise care standards [96, 97].

In terms of the definitions that can be found in the analyzed papers with respect to healthcare productivity, it can be said that they are largely complementary, with most sharing a common foundation in the efficiency and effectiveness of resource utilization to achieve high-quality healthcare services. The variations mainly arise from the different contexts in which productivity is being assessed, which enriches the overall understanding rather than contradicting it. Each definition adds a layer of specificity that addresses different aspects of healthcare productivity, making the overall concept more comprehensive.

In terms of the common foundation these articles put on defining healthcare productivity, most of them agree that productivity in healthcare is primarily about how efficiently resources (inputs such as staff, equipment, and finances) are converted into healthcare services (outputs). This efficiency is often measured using ratios of outputs to inputs, such as DEA. Another consensus of the articles highlights the fact that productivity should not only focus on the quantity of outputs but also on the quality of care provided [57, 66–68, 82, 95]. The inclusion of factors such as patient outcomes, the effectiveness of treatments, and adherence to clinical guidelines is common across many definitions. In addition to the commonly accepted perspectives on healthcare productivity, the analyzed articles also present complementary views that expand on the traditional definition. Some definitions incorporate the role of innovation and technological advancements in enhancing productivity, emphasizing the dynamic nature of optimizing inputs over time [58, 62, 65, 66], while others emphasize the role of workforce factors, such as absenteeism, presenteeism, and health conditions, which affect productivity from a human resource perspective [56, 64, 94, 98–101]. In addition to direct healthcare outputs, some definitions include the achievement of societal goals, organizational effectiveness, and strategic objectives as part of productivity [61, 65, 101, 102]. Additionally, a few definitions also address the productivity of research activities in healthcare, focusing on the impact of academic contributions and the effectiveness of research in driving clinical practice improvements [63, 103, 104].

To sum up, productivity in healthcare is a multifaceted concept that varies based on the context in which it is applied. Definitions often range from basic efficiency measures, such as the ratio of outputs (e.g., healthcare services) to inputs (e.g., resources), to more complex frameworks that incorporate quality, innovation, and organizational health. For instance, in resource-constrained settings, efficiency-focused definitions are crucial for optimizing the use of limited resources, while in well-resourced systems, productivity measures often include quality and patient outcomes. Furthermore, productivity definitions must align with key healthcare goals, such as improving population health, enhancing patient experiences, and ensuring cost efficiency. Definitions that incorporate quality indicators, such as clinical outcomes or patient satisfaction, directly support the goal of delivering value-based care. Input-output efficiency measures, on the other hand, are essential for achieving cost-effective resource utilization, especially in systems facing financial constraints. Additionally, broader definitions that address innovation and workforce satisfaction contribute to long-term sustainability. Aligning productivity with healthcare goals ensures that evaluations not only measure efficiency but also reflect the broader mission of improving health outcomes and maintaining high-quality care.

The studies collectively highlight the complexity of measuring productivity in healthcare, showing that it is shaped by a combination of efficiency, technological advancements, and quality improvements. The predominant use of the Malmquist Index and DEA in these methodologies reflects a focus on tracking changes in technical efficiency and technology over time. Over extended periods, healthcare systems generally show modest productivity gains. For instance [79], reported a steady annual productivity increase of 1.5% over 16 years, while [58] found variations in productivity, with an overall annual growth of 1.4%. Additionally, measuring healthcare productivity is multifaceted, requiring a balance between efficiency improvements and technological or quality changes, as demonstrated by studies from [68, 76, 77, 79, 82]. A nuanced approach is necessary to account for both inputs and outputs since different combinations of these factors can lead to varying productivity outcomes, as shown in studies by [54, 79].

Implications, conclusions and future research

Concluding remarks

This paper aims to bridge the gap in healthcare productivity research by combining methodological rigor with theoretical insights to provide a comprehensive understanding of productivity measurement in the sector.

Through bibliometric and content analysis of 47 articles published between 2003 and 2023 in the WoS database, the study evaluates the methodologies employed and their theoretical implications, delivering actionable insights for researchers and policymakers. The bibliometric analysis underlines that the procedure of assessing scientific research remains a challenging aspect. Through bibliometric study, we observed that over half of the analyzed articles were published in the last five years, reflecting the growing interest in healthcare productivity since the COVID-19 pandemic, a trend also highlighted in a published bibliometric analysis [71]. Europe emerges as a leading region in publication output, followed by the United States, which contributes significantly to international research partnerships. In contrast [71], identifies China as the leading country whose healthcare systems are most frequently assessed for productivity.

The dominance of non-parametric techniques, particularly DEA and the Malmquist Index, in productivity measurement reflects their adaptability and utility in evaluating system-wide efficiency and changes over time. These findings align closely with the results presented in both [7] and [71] research. However, our findings also highlight the need for alternative methodologies that capture the multidimensionality of healthcare productivity, including its interplay with quality and technological progress. The significance of local expertise in addressing regional healthcare challenges is clear; however, fostering international collaborations is essential for sharing best practices and enriching the global discourse on healthcare productivity. For instance [71], noted a strong focus on evaluating the productivity of Asian healthcare systems in scientific literature. This trend may be attributed to the growing emphasis in Asian countries on understanding the efficiency of their healthcare systems. Additionally, efficiency studies are often more actively conducted in developing countries experiencing rising demand for public healthcare services. The insights gained from such studies can provide valuable support to middle- and low-income countries, helping them adopt best practices to improve the efficiency of their healthcare systems. Future efforts should prioritize the development of dynamic, multidimensional frameworks that integrate efficiency, quality of care, and technological advancements while accounting for the unique characteristics and operational scales of healthcare systems. Moreover, integrating these methods can offer a more holistic view of healthcare performance. For instance [65], combined the Malmquist Index with logistic regression to study HIT adoption`s impact on productivity, while [73] innovatively merged DEA with game theory to enhance resource allocation. These approaches illustrate the value of leveraging the complementary strengths of these tools to provide actionable insights for improving healthcare systems.

Key factors influencing healthcare productivity include economic crises, policy variations, hospital size, and case mix. Technological advancements like electronic health records and optimized workflows improve efficiency, while aligning financial incentives with quality objectives enhances care outcomes. This study emphasizes the importance of multidimensional and context-sensitive approaches to measuring healthcare productivity, balancing efficiency, technological progress, and quality of care.

To address the complexities of healthcare productivity, policymakers should focus on designing context-specific policies tailored to regional challenges and promoting targeted research funding to explore underrepresented areas of healthcare services. They should also prioritize the long-term monitoring of productivity trends to foster continuous improvement, while integrating advanced health information technologies can enhance efficiency. A very good example in this direction is Atrium Health [105], a nonprofit health system and part of Advocate Health, which created the hospital-at-home concept to manage hospital capacity during the COVID-19 pandemic. The Atrium Health Hospital at Home (AH-HaH) program allows patients to receive care in the comfort of their own homes through a remote monitoring kit (including pulse oximeters, blood pressure monitors, and tablets for virtual consultations) integrated with Atrium Health`s electronic health records to track health data. The program also includes daily virtual meetings with a multidisciplinary care team and twice-daily in-home visits from paramedics. Following the pandemic, the program expanded due to the region`s aging population with chronic health conditions and ongoing health inequities. It now serves patients with both chronic (e.g., diabetes) and acute (e.g., deep vein thrombosis) conditions that can be safely monitored at home. The AH-HaH program helped reduce hospital readmissions and administrative workload, while optimizing scheduling. Additionally, the program has supported over 8,400 patients in the Charlotte region of North Carolina and saved nearly 30,000 bed days since March 2020. Additionally, workforce optimization through training, workload management, and incentives can improve team cohesion and efficiency, ensuring sustainable productivity gains across healthcare systems. This recommendation is also suggested by a research conducted on hospitals in Shandong [106], eastern China, which found that monetary incentives positively correlate with job performance, demonstrating that financial rewards contribute to employee motivation. Effective leadership, coupled with well-structured incentives, fosters a supportive work environment, leading to higher job satisfaction and commitment. Furthermore, proper workload management through strategic allocation of supervisors ensures that employees are not overwhelmed, thereby improving productivity and service quality. For researchers, international collaboration is vital for sharing the best practices and methodologies, while productivity measurement models must include quality indicators to safeguard care standards. Moreover, researchers are encouraged to adopt innovative methodologies for more robust and comprehensive analyses.

Limitations and future research

Although this study significantly contributes to the knowledge of healthcare productivity measurements, it has a few limitations.

This study assesses only the WoS database for listing articles corresponding to our research criteria. A forthcoming perspective will consider comparing the bibliometric and content outcomes of WoS and Scopus databases for a more comprehensive perspective. Another constraint is the analysis of gray literature. Though potentially delivering fruitful insights (perhaps with lower quality than articles published in referred scientific journals), besides co-citation analysis, it was not included in a deeper investigation because of the lack of bibliometric information.

Thirdly, bibliometric indicators are considered a good proxy of a scientific paper`s impact. Usually, a highly cited paper represents a vote of confidence, allowing researchers to quantify the effect of a study in a scientific domain. However, we cannot admit that a highly cited paper is influential in a specific field. In this regard, citation as a bibliometric metric helps in measuring the effect of one article on the authors of other articles. No evidence allows us to settle that a highly cited paper improved hospitals` productivity, patient condition, or satisfaction.

Finally, our analysis concentrates on bibliometric and content analysis, disregarding thematic analysis, which goes beyond counting frequencies and trends, by focusing on deeper patterns of meanings that emerge from the investigated articles. Forthcoming study will also enforce a thematic analysis.

All in all, our analysis emphasizes the necessity for a multidimensional and dynamic approach to measuring healthcare productivity, and further investigation will be oriented in this direction.

Author contributions
Conceptualization, I.-A.P.; methodology, I.-A.P.; software, I.-A.P; formal analysis, I.-A.P.; writing—original draft preparation, I.-A.P and A.B.; writing—review and editing, I.-A.P and A.B. All authors reviewed the manuscript.

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Competing interests
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References

1. Gong C, Kang H. Resource allocation efficiency of urban medical and health financial expenditure under the background of employees' health. RMHP. 2023;16:1059–74.
2. Alshehri A, Balkhi B, Gleeson G, Atassi E. Efficiency and resource allocation in government hospitals in Saudi Arabi: A casemix index approach. Healthcare. 2023;11:2513.
3. Ferreira DC, Vieira I, Pedro MI, Caldas P, Varela M. Patient satisfaction with healthcare services and the techniques used for its assessment: A systematic literature review and a bibliometric analysis. Healthcare. 2023;11:639.
4. Yinusa A, Faezipour M. Optimizing healthcare delivery: A model for staffing, patient assignment, and resource allocation. ASI. 2023;6:78.
5. McEvoy VR. Why metrics overload is bad medicine. Mo Med. 2015;112:32–3.
6. Nabilou B, Yusefzadeh H, Rezapour A, Ebadi Fard Azar F, Salem Safi P, Sarabi Asiabar A, et al. The productivity and its barriers in public hospitals: case study of Iran. Med J Islam Repub Iran. 2016;30:316.
7. Hollingsworth B. The measurement of efficiency and productivity of health care delivery. Health economics. 111 river St, Hoboken 07030– 5774. Nj Usa: Wiley; 2008. pp. 1107–28.
8. Hollingsworth B. Non-parametric and parametric applications measuring efficiency in health care. Health Care Manag Sci. 2003;6:203–18.
9. Falagas ME, Pitsouni EI, Malietzis GA, Pappas G. Comparison of pubmed, Scopus, web of science, and Google scholar: strengths and weaknesses. FASEB J. 2008;22:338–42.
10. Yong-Hak J. Web of science. Thomson Reuters. 2013; Available from: http://wokinfo.com/media/pdf/WoSFS_08_7050.pdf
11. Fetscherin M, Usunier J. Corporate branding: an interdisciplinary literature review. Melewar TC, editor. European Journal of Marketing. 2012;46:733–53.
12. Gaviria-Marin M, Merigó JM, Baier-Fuentes H. Knowledge management: A global examination based on bibliometric analysis. Technol Forecast Soc Chang. 2019;140:194–220.
13. Araújo AG, Pereira Carneiro AM, Palha RP. Sustainable construction management: A systematic review of the literature with meta-analysis. J Clean Prod. 2020;256:120350.
14. Shashi, Centobelli P, Cerchione R, Mittal A. Managing sustainability in luxury industry to pursue circular economy strategies. Business strategy and the environment. 111 river St, Hoboken 07030– 5774. Nj USA: WILEY; 2021. pp. 432–62.
15. Tan H, Mong GR, Wong SL, Wong KY, Sheng DDCV, Nyakuma BB, et al. Airborne microplastic/nanoplastic research: a comprehensive web of science (WoS) data-driven bibliometric analysis. Environ Sci Pollut Res. 2023;31:109–26.
16. Azizan A, Ahmed W, Razak AHA. Sensing health: a bibliometric analysis of wearable sensors in healthcare. Health Technol. 2024;14:15–34.
17. Maral M. A bibliometric analysis of global research on education in the Scopus database, 2013–2022. GKMC [Internet]. 2024 [cited 2025 Jan 17]; Available from: https://www.emerald.com/insight/content/doi/https://doi.org/10.1108/GKMC-01-2024-0039/full/html
18. Senthil R, Anand T, Somala CS, Saravanan KM. Bibliometric analysis of artificial intelligence in healthcare research: trends and future directions. Future Healthc J. 2024;100182.
19. Banerjee A, Roy K, Gramatica P. A bibliometric analysis of the Cheminformatics/QSAR literature (2000–2023) for predictive modeling in data science using the SCOPUS database. Mol Divers [Internet]. 2024 [cited 2025 Jan 17]; Available from: https://link.springer.com/https://doi.org/10.1007/s11030-024-11056-8
20. Mariani M, Borghi M. Industry 4.0: A bibliometric review of its managerial intellectual structure and potential evolution in the service industries. Technol Forecast Soc Chang. 2019;149:119752.
21. Dwivedi YK, Venkitachalam K, Sharif AM, Al-Karaghouli W, Weerakkody V. Research trends in knowledge management: analyzing the past and predicting the future. Inform Syst Manage. 2011;28:43–56.
22. Wang Z, Nguyen BH, Zelenyuk V. Performance analysis of hospitals in Australia and its peers: a systematic and critical review. J Prod Anal. 2024;62:139–73.
23. Manoj Kumar L, George RJ. A. Bibliometric analysis for medical research. Indian J Psychol Med. 2023;45:277–82.
24. Nepomuceno TCC, Piubello Orsini L, De Carvalho VDH, Poleto T, Leardini C. The core of healthcare efficiency: A comprehensive bibliometric review on frontier analysis of hospitals. Healthcare. 2022;10:1316.
25. Donthu N, Kumar S, Mukherjee D, Pandey N, Lim WM. How to conduct a bibliometric analysis: an overview and guidelines. J Bus Res. 2021;133:285–96.
26. Aria M, Cuccurullo C. Bibliometrix: an R-tool for comprehensive science mapping analysis. J Informetrics. 2017;11:959–75.
27. R Core Team. R: A language and environment for statistical computing [Internet]. Vienna, Austria. 2023. Available from: https://www.R-project.org/
28. Bengtsson M. How to plan and perform a qualitative study using content analysis. NursingPlus Open. 2016;2:8–14.
29. Davis K, Schoen C, Schoenbaum SC, Doty MM, Holmgren AL, Kriss JL, et al. Mirror, mirror on the wall: an international update on the comparative performance of American health care. The Commonwealth Fund; 2007.
30. Abramo G, Cicero T, D'Angelo CA. Assessing the varying level of impact measurement accuracy as a function of the citation window length. J Informetrics. 2011;5:659–67.
31. Wang J. Citation time window choice for research impact evaluation. Scientometrics. 2013;94:851–72.
32. Belter CW. Bibliometric indicators: opportunities and limits. J Med Libr Assoc. 2015;103:219–21.
33. K-Synth. Frequently Asked Questions [Internet]. 2023. Available from: https://www.bibliometrix.org/home/index.php/faq
34. Ham C, Brommels M. Health care reform in the Netherlands, Sweden, and the united Kingdom. Health Aff. 1994;13:106–19.
35. Schut E, Sorbe S, Høj. Health Care Reform and Long-Term Care in the Netherlands [Internet]. 2013 Jan. Report No.: 1010. Available from: https://www.oecd

.org/en/publications/health-care-reform-and-long-term-care-in-the-netherlands_5k4dlw04vx0n-en.html
36. Hunter DJ, Bengoa R. Meeting the challenge of health system transformation in European countries. Policy Soc. 2023;42:14–27.
37. Schneider B, Alexander J, Thomas P, Publications Output. U.S. Trends and International Comparisons. National Science Board Science & Engineering Indicators 2024 [Internet]. 2023; Available from: https://ncses.nsf.gov/pubs/nsb202333/international-collaboration-and-citations
38. Lee JJ, Haupt JP. Winners and losers in US-China scientific research collaborations. High Educ. 2020;80:57–74.
39. Osareh F, Bibliometrics. Citation Analysis and Co-Citation Analysis: A Review of Literature I. Libri [Internet]. 1996 [cited 2023 Jul 18];46. Available from: https://www.degruyter.com/document/doi/https://doi.org/10.1515/libr.1996.46.3.149/html
40. Small H. Co-citation in the scientific literature: A new measure of the relationship between two documents. J Am Soc Inf Sci. 1973;24:265–9.
41. Fusco F, Marsilio M, Guglielmetti C. Co-production in health policy and management: a comprehensive bibliometric review. BMC Health Serv Res. 2020;20:504.
42. Trujillo CM, Long TM. Document co-citation analysis to enhance transdisciplinary research. Sci Adv. 2018;4:e1701130.
43. Freeman LC. Centrality in social networks conceptual clarification. Social Networks. 1978;1:215–39.
44. Freeman LC. A set of measures of centrality based on betweenness. Sociometry. 1977;40:35.
45. Anthonisse JM. The rush in a directed graph. Stichting Mathematisch Centrum. 1971.
46. Bavelas A. A mathematical model for group structures. Appl Anthropol. 1948;7:16–30.
47. Beauchamp MA. An improved index of centrality. Syst Res. 1965;10:161–3.
48. Muñoz-Muñoz AM, Mirón-Valdivieso MD. Analysis of collaboration and co-citation networks between researchers studying violence involving women. Inform Res. 2017;22.
49. Lancichinetti A, Fortunato S. Community detection algorithms: a comparative analysis. 2009 [cited 2024 Jul 12]; Available from: https://arxiv.org/abs/0908.1062
50. Farrell MJ. The measurement of productive efficiency. J Royal Stat Soc Ser (General). 1957;120:253.
51. Charnes A, Cooper WW, Rhodes E. Measuring the efficiency of decision-making units. Eur J Oper Res. 1978;2:429–44.
52. Cobo MJ, López-Herrera AG, Herrera-Viedma E, Herrera F. An approach for detecting, quantifying, and visualizing the evolution of a research field: A practical application to the fuzzy sets theory field. J Informetrics. 2011;5:146–66.
53. Cobo MJ, Martínez MA, Gutiérrez-Salcedo M, Fujita H, Herrera-Viedma E. 25years at Knowledge-Based systems: A bibliometric analysis. Knowl Based Syst. 2015;80:3–13.
54. Nakata Y, Watanabe Y, Ozaki A. Productivity change of surgeons during the coronavirus disease 2019 pandemic in Japan. Inquiry-The journal of health care organization provision and financing. 2455 ™ ler Rd, thousand Oaks, Ca 91320. Usa: SAGE Publications Inc; 2022.
55. Eriksson J, Fowler P, Appelblad M, Lindholm L, Sund M. Productivity in relation to organization of a surgical department: a retrospective observational study. BMC Surgery. Campus, 4 Crinan St, London N1 9xw, England: Bmc; 2022.
56. Gillespie GL, Gates DM, Succop P. Psychometrics of the healthcare productivity survey. Advanced emergency nursing journal. Two commerce Sq, 2001 market St, Philadelphia, Pa 19103. Usa: Lippincott Williams & Wilkins; 2010. pp. 258–71.
57. Ramos P, Paiva JA. Dedication increases productivity: an analysis of the implementation of a dedicated medical team in the emergency department. International Journal of Emergency Medicine. Campus, 4 Crinan St, London N1 9xw, England: BMC; 2017.
58. Goude F, Garellick G, Kittelsen SAC, Nemes S, Rehnberg C. The productivity development of total hip arthroplasty in Sweden: a multiple registry-based longitudinal study using the Malmquist productivity index. BMJ OPEN. British med assoc house, Tavistock square, London Wc1h 9jr. England: BMJ Publishing Group; 2019.
59. Liu X, Jia C, Cheng J, Wang X, Wang Q, Li H. Measuring productivity and relative efficiency of public tertiary traditional Chinese medicine hospitals in Hubei, China. Inquiry-The journal of health care organization provision and financing. 2455 ™ ler Rd. Thousand Oaks, Ca 91320 Usa: SAGE Publications Inc; 2023.
60. Mayer AM, Dahlin C, Seidenschmidt L, Dillon H, Brown A, Crawford T, et al. Palliative care: A survey of program benchmarking for productivity and compensation. Am J Hospice Palliat Med. 2022;39:1298–303.
61. van der Geer E, van Tuijl HFJM, Rutte CG. Performance management in healthcare: performance indicator development, task uncertainty, and types of performance indicators. Soc Sci Med. 2009;69:1523–30.
62. Meyerhoefer CD, Deily ME, Sherer SA, Chou S-Y, Peng L, Sheinberg M, et al. The consequences of electronic health record adoption for physician productivity and birth outcomes. Ilr review. 2455 ™ ler Rd, thousand Oaks, Ca 91320 Usa. Sage Publications Inc; 2016. pp. 860–89.
63. Horenberg F, Lungu DA, Nuti S. Measuring research in the big data era: the evolution of performance measurement systems in the Italian teaching hospitals. Health policy. Elsevier House,: ELSEVIER Ireland LTD;; 2020. pp. 1387–94. Brookvale Plaza, East Park Shannon, Co, Clare, 00000, Ireland.
64. Coleman D, Moran E, Serfilippi D, Mulinski P, Rosenthal R, Gordon B, et al. Measuring physicians' productivity in a veterans affairs medical center. Academic medicine. 210 S 13th St, Philadelphia, Pa 19107 USA. Hanley & Belfus Inc; 2003. pp. 682–9.
65. Ford EW, Huerta TR, Menachemi N, Thompson MA, Yu F. Health information technology vendor selection strategies and total factor productivity. Health Care Management Review. Two Commerce Sq, 2001 Market St, Philadelphia, Pa 19103 USA: Lippincott Williams & Wilkins; 2013. P. 177–87.
66. Wang T, Wang Y, McLeod A. Do health information technology investments impact hospital financial performance and productivity? Int J Acc Inform Syst. 2018;28:1–13.
67. Chen K-C, Chien L-N, Hsu Y-H, Yu M-M. Metafrontier frameworks for studying hospital productivity growth and quality changes. Int J Qual Health Care. 2016;28:650–6.
68. Mitropoulos P. A metafrontier Global Malmquist framework for hospitals productivity and quality measurement: Evidence from the Greek economic recession. Euro Journal on Decision Processes. Radarweg 29, 1043 Nx Amsterdam, Netherlands: ELSEVIER; 2022.
69. Paleologou V, Kontodimopoulos N, Stamouli A, Aletras V, Niakas D. Developing and testing an instrument for identifying performance incentives in the Greek health care sector. BMC HEALTH services research. England: BMC; 2006. Campus, 4 Crinan St, London N1 9xw,.
70. Dellve L, Hadzibajramovic E, Ahlborg G Jr. Work attendance among healthcare workers: prevalence, incentives, and long-term consequences for health and performance. J Adv Nurs. 2011;67:1918–29.
71. Jung S, Son J, Kim C, Chung K. St Alban-Anlage 66, Ch-4052 BASEL. Switzerland: MDPI;: Processes; 2023. Efficiency Measurement Using Data Envelopment Analysis (DEA) in Public Healthcare: Research Trends from 2017 to 2022.
72. Dohmen P, van Ineveld M, Markus A, van der Hagen L, van de Klundert J. Does competition improve hospital performance: a DEA based evaluation from the Netherlands. European Journal of Health Economics. One New York Plaza, Suite 4600, New York, Ny, United States: SPRINGER; 2023. pp. 999–1017.
73. Zare H, Tavana M, Mardani A, Masoudian S, Saraji MK. A hybrid data envelopment analysis and game theory model for performance measurement in healthcare. Health Care Management Science. One New York Plaza, Suite 4600, New York, Ny, United States: SPRINGER; 2019. pp. 475–88.
74. Cheng Z, Cai M, Tao H, He Z, Lin X, Lin H, et al. Efficiency and productivity measurement of rural Township hospitals in China: a bootstrapping data envelopment analysis. BMJ OPEN. British med assoc house, Tavistock square, London Wc1h 9jr. England: BMJ Publishing Group; 2016.
75. Miszczynska K, Miszczynski PM. Measuring the efficiency of the healthcare sector in Poland - a window-DEA evaluation. International journal of productivity and performance management. Howard house, wagon lane, Bingley Bd16 1wa. W Yorkshire, England: Emerald Group Publishing Ltd; 2022. pp. 2743–70.
76. Huerta TR, Thompson MA, Ford EW. The role of safe practices in hospitals' total factor productivity. Journal Of Healthcare Leadership. Po Box 300-008, Albany, Auckland 0752, New Zealand: Dove Medical Press Ltd; 2011. pp. 1–7.
77. Highfill T, Ozcan Y, Productivity, quality of hospitals that joined the Medicare Shared Savings Accountable Care Organization Program. International journal of healthcare management. 2–4 park square, Milton park, Abingdon Ox14 4rn, oxon. England: Routledge Journals, Taylor & Francis Ltd; 2016. pp. 210–7.
78. Kim Y, Oh D, Kang M. Productivity changes in OECD healthcare systems: bias-corrected Malmquist productivity approach. International Journal of Health Planning and Management. 111 River St, Hoboken 07030– 5774, NJ USA: WILEY; 2016. pp. 537–53.
79. Anthun KS, Kittelsen SAC, Magnussen J. Productivity growth, case mix and optimal size of hospitals. A 16-year study of the Norwegian hospital sector.

Health policy. Elsevier House,: ELSEVIER Ireland LTD;; 2017. pp. 418–25. Brookvale Plaza, East Park Shannon, Co, Clare, 00000, Ireland.
80. Chen Y, Wang J, Zhu J, Sherman HD, Chou S-Y. How the Great Recession affects performance: a case of Pennsylvania hospitals using DEA. Annals Of Operations Research. Van Godewijckstraat 30, 3311 Gz Dordrecht, Netherlands: SPRINGER; 2019. pp. 77–99.
81. Dohmen P, van Ineveld M, Markus A, van der Hagen L, van de Klundert J. Does competition improve hospital performance: a DEA based evaluation from the Netherlands. Eur J Health Econ. 2023;24:999–1017.
82. Lacko R, Hajduova Z, Bakalar T, Pavolova H. Efficiency and Productivity Differences in Healthcare Systems: The Case of the European Union. International Journal Of Environmental Research And Public Health. St Alban-Anlage 66, Ch-4052 Basel, Switzerland: MDPI; 2023.
83. Coyle D, Dreesbeimdiek K, Manley A, Productivity. Uk healthcare during and after the Covid-19 pandemic. National Institute economic review. Edinburgh Bldg, Shaftesbury Rd, Cb2 8ru Cambridge. England: Cambridge Univ; 2021. pp. 90–116.
84. Pourmahmoud J, Bagheri N. Uncertain Malmquist productivity index: An application to evaluate healthcare systems during COVID-19 pandemic. Socio-Economic Planning Sciences. Ste 800, 230 Park Ave, New York, Ny 10169 USA: ELSEVIER Science Inc; 2023.
85. Stylianidis S, Souliotis K. The impact of the long-lasting socioeconomic crisis in Greece. BJPsych Int. 2019;16:16–8.
86. Foglia E, Ferrario L, Schettini F, Pagani MB, Dalla Bona M, Porazzi E. COVID-19 and hospital management costs: the Italian experience. BMC Health Serv Res. 2022;22:991.
87. Shanafelt T, Ripp J, Trockel M. Understanding and addressing sources of anxiety among health care professionals during the COVID-19 pandemic. JAMA. 2020;323:2133.
88. Mehrotra A, Chernew M, Linetsky D, Hatch H, Cutler D, What Impact Has. COVID-19 Had on Outpatient Visits? [Internet]. Commonwealth Fund; 2020 [cited 2025 Jan 24]. Available from: https://www.commonwealthfund.org/publications/2020/apr/impact-covid-19-outpatient-visits
89. Atella V, Belotti F, Bojke C, Castelli A, Grasic K, Kopinska J, et al. How health policy shapes healthcare sector productivity? Evidence from Italy and UK. Health policy. Ireland: ELSEVIER Ireland LTD;: Elsevier House,; 2019. pp. 27–36. Brookvale Plaza, East Park Shannon, Co, Clare, 00000.
90. Modi S, Feldman SS. The value of electronic health records since the health information technology for economic and clinical health act: systematic review. JMIR Med Inf. 2022;10:e37283.
91. Fortis S, Sarrazin MV, Beck BF, Panos RJ, Reisinger HS. ICU telemedicine reduces interhospital ICU transfers in the veterans health administration. Chest. 2018;154:69–76.
92. NHS Foundation Trust. Moorfields and DeepMind Health research partnership latest update. 2018.
93. Dorr DA, Wilcox A, McConnell KJ, Burns L, Brunker CP. Productivity enhancement for primary care providers using multicondition care management. American Journal of Managed Care. 241 Forsgate Dr, Ste 102, Jamesburg, Nj 08831 USA: Amer Med Publishing, M W C Company; 2007. pp. 22–8.
94. Dellve L, Hadzibajramovic E, Ahlborg G Jr. Work attendance among healthcare workers: prevalence, incentives, and long-term consequences for health and performance. Journal Of Advanced Nursing. Commerce Place, 350 Main St, Malden 02148, Ma USA: WILEY-BLACKWELL; 2011. pp. 1918–29.
95. Grieco PLE, Mcdevitt RC. Productivity and quality in health care: evidence from the Dialysis industry. Review of economic studies. Great Clarendon St, Oxford Ox2 6dp. England: OXFORD UNIV; 2017. pp. 1071–105.
96. Gutacker N, Harris A, Brennan D, Hollingsworth B. The determinants of dentists' productivity and the measurement of output. Soc Sci Med. 2015;124:76–84.
97. Filippini M, Masiero G, Santarossa M. Productivity change and efficiency in the Swiss nursing home industry. Applied economics. 2–4 park square, Milton park, Abingdon Ox14 4rn, oxon. England: ROUTLEDGE Journals, Taylor & Francis LTD; 2022. pp. 2837–50.
98. Koopmanschap M, Burdorf A, Jacob K, Meerding W, Brouwer W, Severens H. Measuring productivity changes in economic evaluation - Setting the research agenda. Pharmacoeconomics. 41 centorian Dr, private bag 65901, Mairangi Bay, Auckland 10. New Zealand: Adis International Ltd; 2005. pp. 47–54.
99. Loeppke R, Taitel M, Richling D, Parry T, Kessler RC, Hymel P, et al. Health and productivity as a business strategy. Journal of occupational and environmental medicine. Two commerce Sq, 2001 market St, Philadelphia, Pa 19103. Usa: Lippincott Williams & Wilkins; 2007. pp. 712–21.
100. Kamarainen VJ, Peltokorpi A, Torkki P, Tallbacka K. Measuring healthcare productivity - from unit to system level. International journal of health care quality assurance. Howard house, wagon lane, Bingley Bd16 1wa. W Yorkshire, England: Emerald Group Publishing Ltd; 2016. pp. 288–99.
101. Levesque J-F, Sutherland K. Combining patient, clinical and system perspectives in assessing performance in healthcare: an integrated measurement framework. BMC Health Services Research. Campus, 4 Crinan St, London N1 9xw, England: BMC; 2020.
102. Purbey S, Mukherjee K, Bhar C. Performance measurement system for healthcare processes. International journal of productivity and performance management. Howard house, wagon lane, Bingley Bd16 1wa. W Yorkshire, England: Emerald Group Publishing Ltd; 2007. pp. 241–51.
103. Tess BH, Furuie SS, Figueiredo Castro RC, Cavarette Barreto M do, Cuce Nobre C. MR. Assessing the Scientific Research Productivity of a Brazilian Healthcare Institution: A Case Study At The Heart Institute Of Sao Paulo, Brazil. Clinics. Fac Medicina, Univ Sao Paulo, Sao Paulo, Sp 00000, Brazil: Hospital Clinicas, Univ Sao Paulo; 2009. pp. 571–6.
104. Patel VM, Ashrafian H, Ahmed K, Arora S, Jiwan S, Nicholson JK, et al. How has healthcare research performance been assessed? A systematic review. J R Soc Med. 2011;104:251–61.
105. American Medical Association. Future of Health case Studies: Atrium Health [Internet]. 2024 [cited 2025 Feb 19]. Available from: https://www.ama-assn.org/system/files/future-health-case-study-atrium-health.pdf
106. Liu W, Liu Y. The impact of incentives on job performance, business cycle, and population health in emerging economies. Front Public Health. 2022;9:778101.

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