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Efficiency, Innovation, and Sustainability in Healthcare Systems

Edited by
Nikolaos Kontodimopoulos and Olatunde Aremu

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Article

Achieving Robust Medical Coding in DRGs Systems: Innovative Actions Adopted in Greece

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Abstract: The purpose of this study is to evaluate and illustrate the effectiveness of a specialized digital platform developed to improve the accuracy of medical coding during the full implementation of Greece's new DRG system, and to highlight innovative actions for achieving and/or improving accurate medical coding. Already grouped DRG cases recorded in the first DRG implementation year in the region of Crete were examined. A sample of 133,922 cases was analyzed and audited, through a process consisting of three stages: (i) digitalization, (ii) auditor training, and (iii) control and consultation. The results indicated that a significant proportion of DRG coding, with a length of stay exceeding one day, was reclassified into different DRG categories. This reclassification was primarily due to coding errors—such as the omission of secondary diagnoses, exclusion of necessary medical procedures, and the use of less specific codes—rather than mistakes in selecting the principal diagnosis. The study underscores the importance of medical coding control and consulting services. It demonstrates that targeted actions in these areas can significantly enhance the implementation of the DRG coding system. Accurate medical coding is crucial for transparent allocation of resources within hospitals, ensuring that hospital services and reimbursements are appropriately managed and allocated based on the true complexity and needs of patient cases.

Keywords: diagnostic-related group; coding; health systems; efficiency; activity-based funding; innovation; digital platform; artificial intelligence

1. Introduction

Optimizing funding for inpatient care has been crucial for the Greek healthcare system [1]. In 2011, Greece launched a new hospital reimbursement system, KEN, inspired by the DRG (Diagnosis-Related Groups) concept. The primary difference between the KEN and DRG systems is that KEN was based solely on the patient's main diagnosis, without considering the medical procedure. Furthermore, the KEN classification was conducted manually due to the absence of supporting software. Additionally, the costs associated with KEN were not systematically updated. Limitations arose due to the absence of (i) proper medical classifications suited for a case mix system, (ii) an automated DRG grouping tool, and (iii) a process for cost adjustments. These limitations resulted in the KEN system proving initially inadequate to provide fair and objective budget allocation among hospitals within the health system [2–4].

Established by 2014 legislation, the Greek DRG Institute, known as the National Center for Documentation and Costing of Hospital Services, hereinafter referred to as “KETEKY”, and initially known as ESAN S.A, is an independent, self-governing body with a core mission to implement a fair and transparent system for hospital service costing

and reimbursement. KETEKNY's central goal is to create an integrated system for scientifically based costing and compensation of hospital care in Greece. This approach aims at promoting an evidence-based healthcare system, ensuring that resources are allocated efficiently. KETEKNY initially signed a License Agreement with the German limited liability company InEK GmbH to secure the rights to implement a DRG system in Greece, modeled after the German system. Since then, the Greek DRG system has been updated in two major revisions in 2019 and 2021. KETEKNY, drawing on best practices from around the world, focuses on developing, implementing, monitoring, and updating a Diagnosis-Related Group (DRG) patient classification system.

In January 2021, KETEKNY selected the University General Hospital of Heraklion (PAGNI) to first implement the Greek DRG system due to its wide range of specialties and services. A Joint Ministerial Decision on 7 April 2021 authorized PAGNI to use the Greek DRG coding guidelines for all inpatient cases and update financial data. By 24 December 2021, the DRG system was extended to all hospitals in Crete. Following a further decision on 28 November 2022, hospitals in Macedonia and eight other locations across Greece adopted the system. Finally, the remaining public hospitals and three private entities (Papageorgiou General Hospital, Onassis Cardiac Surgery Center, and Santorini General Hospital) began using the Greek DRG system after a final decision on 21 December 2023.

The implementation of a DRG system in a country raise concerns about the accuracy of medical coding [5]. Medical coding is the conversion of health diagnoses, procedures, medical services, and equipment into internationally common alphanumeric codes. For this reason, it is necessary to check the medical coding in order to document the correctness of the entries and therefore of the data to be evaluated and used [6]. According to the WHO report (2012), the various causes of miscoding can be identified through an effective control mechanism. The causes for errors can be both unethical coding practices (which are the subject of a stronger audit process) and subjective errors in coding practices (which require more intensive training) [7].

The quality of hospital discharge data is crucial for accurate DRG case allocation, as it directly affects how cases are categorized [8]. DRG-based payment systems can potentially reduce the length of stay (LOS) [9], with technological advances like minimally invasive procedures contributing to faster recovery and discharge [10]. Effective implementation requires personnel training, adherence to quality standards, and clear guidelines [11]. Countries such as France have enhanced their DRG systems to better manage hospital activity and ensure appropriate care [12]. To improve hospital efficiency and fairness in payments, it is essential to leverage data for benchmarking, identify efficient providers, and share best practices [13]. Flexible governance and accurate patient classification are keys to the success of DRG-based funding and achieving policy goals [14].

The purpose of this study is to evaluate and illustrate the effectiveness of a specialized digital platform developed by KETEKNY to improve the accuracy of medical coding during the full implementation of Greece's new DRG system. The platform (Figure 1) was created in response to concerns about coding accuracy, which is crucial for the correct categorization of patient cases and the equitable allocation of hospital resources. By systematically capturing and analyzing medical information from patients' files in accordance with the Greek Coding Guidelines, the platform aims to identify and correct coding errors. Additionally, it serves as a comprehensive tool for enhancing medical coding practices by providing real-time auditing, enabling targeted training, and facilitating the implementation of new coding rules and guidelines. Through this study, the platform's role in ensuring accurate, reliable medical coding is assessed, offering insights into strategies that can be adopted to support DRG system integrity and healthcare quality.

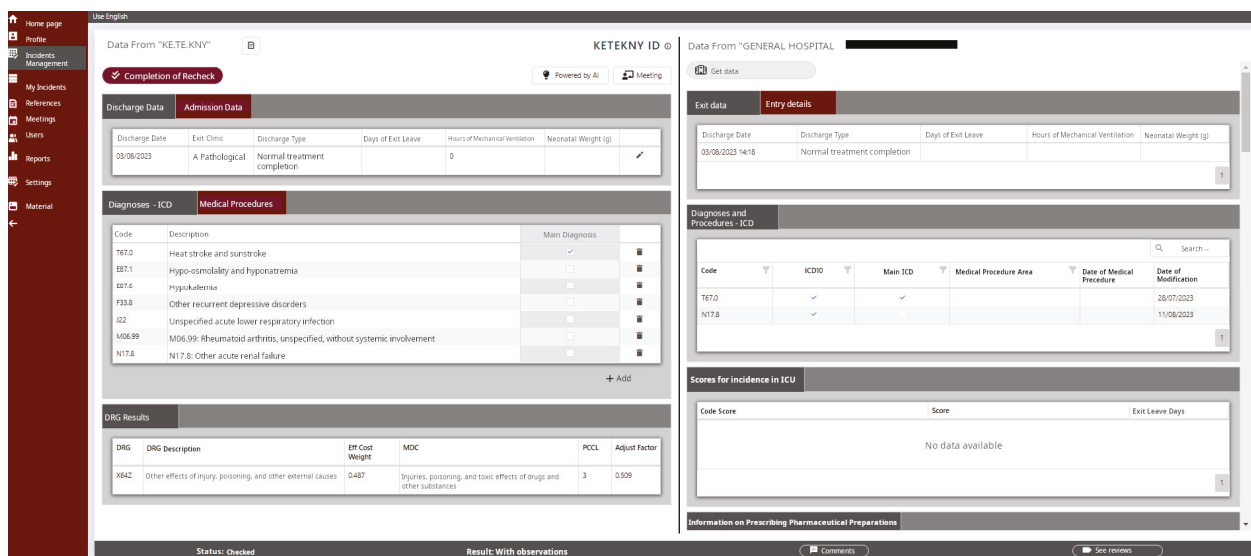


Figure 1. Print screen from the digital platform.

2. Materials and Methods

The implementation of the project included current situation analysis, assessment of needs, development of a platform, auditing, analysis of results, and training of healthcare professionals in the clinical coding of incidents by the DRG coding system.

2.1. Sampling and Audit Process

During the project, the already grouped DRG cases from the first year of implementation in the region of Crete were examined. Due to limited time available for conducting the audits, a sample was drawn and 133,922 cases, out of a total of 200,000, were analyzed and audited. The sample was randomly selected from all hospitals in the region for the first 12 months of the initial year of DRG system implementation. The sampling method used was stratified random sampling, ensuring that the same percentage of total random cases was chosen from each hospital. The audit process consisted of the following stages:

(i) Digitalization: The Greek DRG Institute developed a digital platform to support auditing, which resulted in the establishment and strengthening of medical coding control mechanisms. This intervention aimed to identify and address any discrepancies between the coding of a patient's medical record and the allocated DRG coding, based on the Greek Coding Guidelines. The platform boasts a highly sophisticated architecture. Data flows seamlessly directly from hospitals, and through secure connections, to KETEKNY's specialized Grouper software (version 1.0). On a single, user-friendly interface, the platform presents two key data sources: (i) data from the Grouper software, which analyzes and classifies hospital medical coding data collected directly from hospitals' coders, and (ii) individual patient medical files, which provide comprehensive patient information for a holistic view.

This consolidated view empowers auditors to efficiently conduct controls by having all relevant information readily available on a single screen. Furthermore, the platform offers a range of user-friendly functionalities surrounding this core function, including easy-to-use browsing menus for efficient navigation, the ability to make corrections and add notes for improved clarity, a feature to assign statuses to cases for better organization, and the option to schedule meetings with therapists or physicians for further clarifications.

These features streamline the auditing process and facilitate effective communication with medical personnel, all while maintaining the highest standards of data privacy. The platform is built on a foundation of data anonymization and strict adherence to GDPR regulations at all phases of the auditing process. During the transfer of data from the

hospital's patient files to the auditing platform, the patient's name and registration number are encrypted, ensuring that no one has access to this information.

(ii) Auditors training: A team of highly skilled auditors underwent specialized training in medical coding according to the DRG classification system, conducted by experts from the Greek DRG Institute.

(iii) Control and consultation: Performed by specialized auditors on a randomly selected sample of cases. The objectives of this process were to verify the accuracy of the classification of incidents in the DRG system and to ensure the completeness of the coding, in accordance with the information obtained from the patient's medical file. Additionally, the auditors assessed whether the coding adhered to the Greek Coding Guidelines. A key focus was to promptly address issues of under- and over-coding, which are recognized in the international literature and are mitigated through ongoing training for coders. These efforts were designed to enhance and streamline the process of medical recordkeeping, objectively showcase the work performed by each hospital, and promote fair resource allocation within the healthcare system.

The audit platform and the results of the provision of medical coding control and consulting services will be used for the correct implementation of the DRG system by ensuring the quality of medical coding and the documented distribution of available resources in hospitals. These implemented actions can include highly targeted training sessions, for example, focusing on the most frequent mistakes or errors. Additionally, interventions can be made that address both user experience and the medical file itself, potentially including the adoption of new, sophisticated rules or restrictions. Finally, prediction models can be adopted to suggest more accurate codes and schedule periodic controls.

2.2. Process Flow and Analysis

The flowchart in Figure 2 illustrates the flow of the total process. The initial step of the process is the auditing phase, where the auditors proceed with the medical file inspection to capture errors in the hospitals' coding. In the second stage, the analysis begins with descriptive statistics to identify the reasons why the errors occurred and determine the main causes. This stage identifies the areas that require further improvement. In the next step of reporting, detailed reports are prepared, followed by further big data analysis.

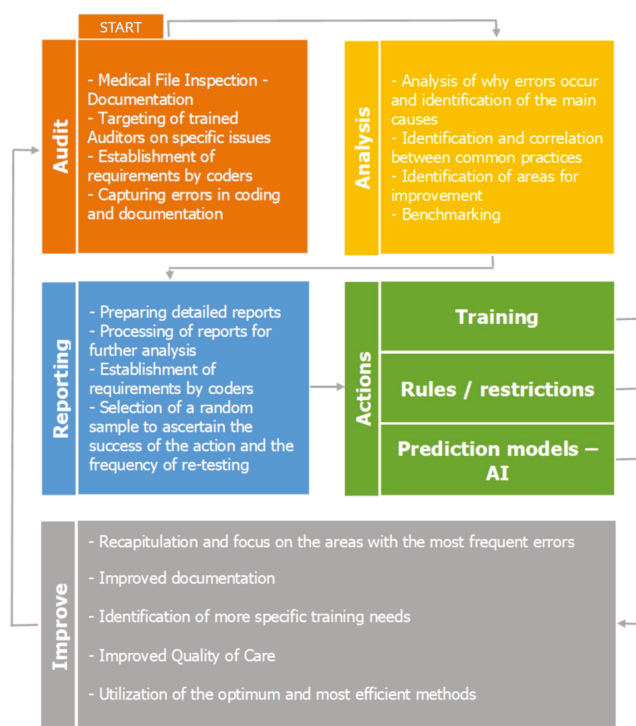


Figure 2. The flow of the total process.

This study used descriptive statistics to highlight the need for further analysis of cases with a length of stay (LoS) over one day. Crosstabulation and chi-squared tests confirmed a significant relationship between DRG cases with different LoS values. Additionally, the Kruskal–Wallis H test assessed how DRG changes affect hospital revenue, identifying significant differences among groups. The purpose of these methods was to identify significant patterns and impacts related to DRG coding changes, thereby guiding improvements in coding practices and hospital revenue management. The final stage is the action phase, where all analyses and validation of the data lead to the adoption of actions, categorized into three categories: training, rules and restrictions, and prediction models. All of these steps contribute to the improvement of coding, documentation, and quality of care, which is the final step before the process begins again with the auditing phase.

2.3. Final Reporting and Reassessment

The final report included a comprehensive analysis of the data obtained from the digital audit platform. The analysis was conducted in two phases: the main audit project phase and a second phase focused on rechecking a subset of the cases. This second phase aimed to oversee the auditors' work. Specifically, 10% of the previously audited cases were rechecked by KETEKNY to ascertain the success of the action and verify the auditors' accuracy.

2.4. Audit Results and Categorization

The audit results were analyzed and categorized within the digital audit platform. The findings were grouped into key categories: cases that were fully correct with no issues identified, cases requiring coding changes—such as incomplete or incorrect coding of diagnoses (including errors in primary or secondary diagnosis coding) or medical procedures—and cases with observations. The latter included issues like incomplete input documentation, incomplete files, insufficient coding documentation, missing practices, absent secondary diagnoses, missing information notes, missing medical procedures, and incomplete patient histories. Additional findings that did not fit into these categories were also noted.

3. Results

The results are presented in three distinct sections to enhance clarity.

3.1. Initial Audit Findings and Coding Accuracy

A complete analysis of a sample coded by the coders of the Hospitals of the Crete Healthcare Region indicated that 26.29% of the sample had no coding errors and was fully correct, 51.94% of the cases had observations, and 21.76% of the overall sample required coding changes in the initial phase of the audit (Figure 3). An interesting finding was that only 9022 out of the 133,922 analyzed and audited cases (6.7%) ultimately had their DRG code changed. The remaining cases (93.3%) had their original DRG codes unchanged. Of the cases changed, 13.91% remained within the same DRG group, but were assigned a code for more complex cases.

To identify discrepancies across various coding categories, the entire sample was re-analyzed. The results indicated that 6.61% of the cases had a different primary diagnosis, 27.63% had a different secondary diagnosis, 17.62% had a different medical procedure, and 0.75% had a different category regarding the pathological and surgical sector. Finally, 29.19% of the incidents reviewed were labeled as “Incomplete File”, whereas 30.70% had an absence of medical notice and practical surgery.

Regarding the rechecks phase, out of 46,762 rechecks reviewed by the project team's medical examiners, it was found that in 21.8% of the sample there were no findings and the coding was deemed correct, whereas 52.1% of the incidences resulted in observations, and 26.1% resulted in coding changes. Furthermore, 6.8% of the cases had a different primary diagnosis, 23.2% had a different secondary diagnosis, and 18.3% had a different medical

procedure. Finally, 32.47% of the incidents reviewed were labeled as “Incomplete File”, while 39.27% of the cases had an absence of medical notice and practical surgery.

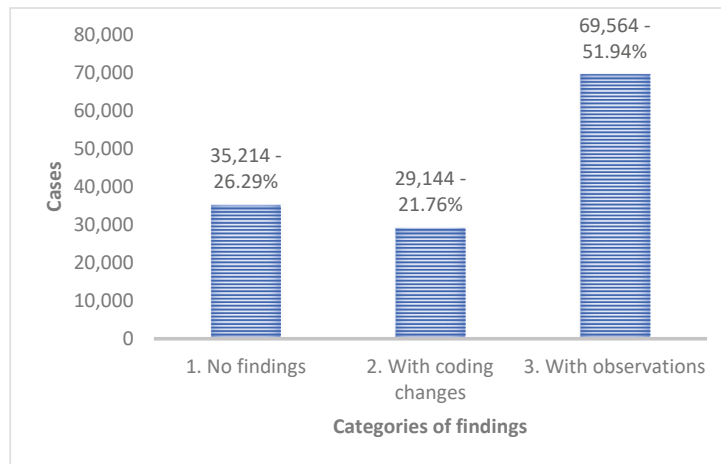


Figure 3. Audit results of all cases based on three main categories of findings.

3.2. Impact of Length of Stay on DRG Code Changes

However, the analysis excluded cases with a one-day LoS, which are typically less complex, simplifying medical coding for primary and secondary diagnoses and medical procedures. A second analysis was conducted for cases with a LoS longer than one day. Among these cases, which represent 41.82% (56,009) of the total sample, 19.26% had no coding errors, 37.75% had some observations requiring further investigation, and the remaining 42.99% required coding changes.

The analysis revealed that cases with a LoS exceeding one day were nearly twice as likely to require coding changes, compared to total cases, and three times more than the ones with LoS equal to one (Figure 4). The analysis revealed that 12.35% of DRG codes required changes. This is an important finding, as it represents a nearly two-fold increase compared to the overall case analysis. Among the changed codes, 16.72% remained within the same DRG group, possibly due to minor coding adjustments. More significantly, 90.92% of the DRGs which remained in the group resulted in upgrades to higher-valued DRGs, suggesting increased resource utilization or case complexity. The remaining 9.75% of changes involved downgrades to lower-valued DRGs, which may indicate coding errors that initially attributed a higher acuity level than was accurate.

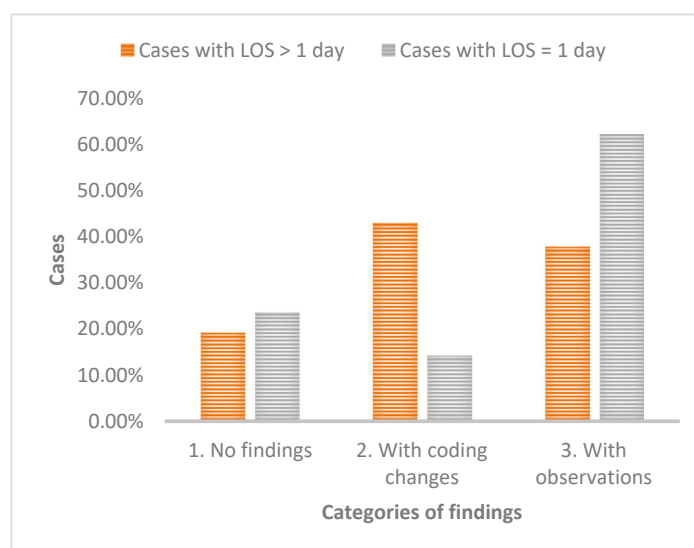


Figure 4. Percentage of status cases with LoS > 1 day vs. cases with LoS = 1.

A broader analysis of the results follows. An important finding is the presence of discrepancies in coding categories across cases in comparison with the total sample (Figure 5). Notably, 11.40% of cases had a different primary diagnosis, 19.26% had a different secondary diagnosis, and a substantial 26.54% involved a different medical procedure code. Interestingly, discrepancies within the pathological and surgical partition category were much lower at only 1.60%. The above finding highlights the importance of auditing the primary diagnosis and the medical procedure of the cases with LoS longer than one day.

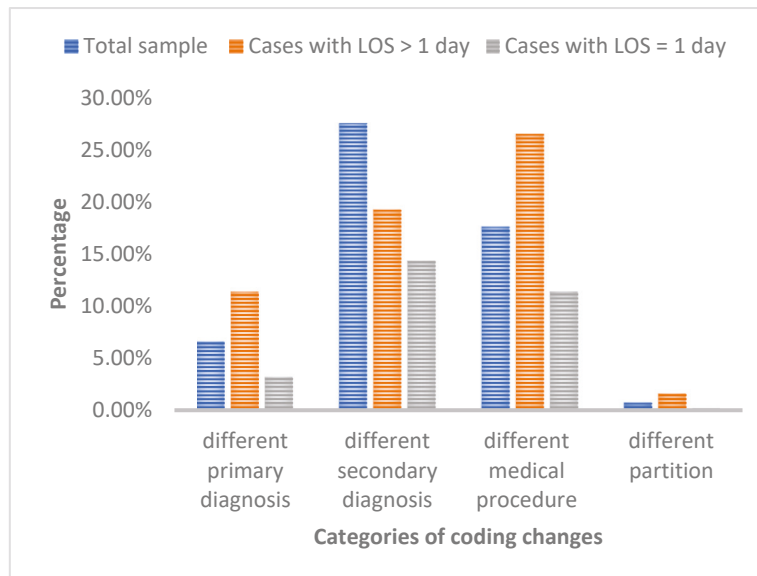


Figure 5. Percentage of status of total cases vs. cases with LoS > 1 day vs. cases with LoS = 1.

To assess whether there is a significant association between the need for DRG code changes and the duration of the patient stay in the hospital, we conducted a chi-square test of independence. Length of stay is a critical factor because it often indicates the complexity or severity of a patient's condition, which can influence the accuracy and appropriateness of the initial DRG coding. This relationship was further illustrated using crosstabulation to provide a visual representation of the frequency distribution of the two variables (Table 1).

Table 1. Crosstabulation—DRG change vs. LoS (% of total).

		Length of Stay		
		Cases with LoS > 1 Day	Cases with LoS = 1 Day	Total
DRG Change	No	36.7%	56.6%	93.3%
	Yes	5.2%	1.6%	6.7%
Total		41.8%	58.2%	100.0%

To test the hypothesis that LoS has a significant influence on medical coding, particularly leading to cases where DRG codes require changes, a Pearson chi-square test was conducted to assess the association between the LoS (categorized as one day versus more than one day) and the occurrence of a DRG code changes. The results (Table 2) revealed a chi-square value of 4824.574 ($p < 0.001$), implying a very strong likelihood that LoS influences the need for modifications in DRG coding. Specifically, when LoS extends beyond one day, the probability of requiring a DRG code change increases significantly.

Table 2. Chi-square tests for checking association of LoS = 1 and LoS > 1 regarding DRG code changes.

	Value	Df	Asymptotic Sig. (2-Sided)	Exact Sig. (2-Sided)	Exact Sig. (1-Sided)
Pearson Chi-Square	4824.574 ^a	1	0.000		
Continuity Correction ^b	4823.039	1	0.000		
Likelihood Ratio	4861.607	1	0.000		
Fisher's Exact Test				0.000	0.000
Linear-by-Linear Association	4824.537	1	0.000		
N of Valid Cases	133,922				

^a 0 cells (0.0%) have expected count less than 5. The minimum expected count is 3773.19; ^b Computed only for a 2 × 2 table.

3.3. Hospital-Specific Variations in DRG Code Reclassification

Building on the initial analysis, we extended our investigation to explore how the relationship between a LoS exceeding one day and the frequency of DRG code changes varies across different hospitals. By doing so, we aimed to understand whether this relationship is consistent across various healthcare institutions or if there are notable differences that could indicate hospital-specific factors influencing DRG coding practices. Table 3 presents the results of this analysis, which involved comparing the incidence of DRG code changes for patients with a LoS exceeding one day across multiple hospitals.

Table 3. Crosstabulation—hospital vs. DRG change (% of total).

		DRG Change		
		No	Yes	Total
Hospital	Hospital 3	21.2%	3.5%	24.7%
	Hospital 2	15.2%	1.9%	17.2%
	Hospital 4	2.3%	0.2%	2.5%
	Hospital 5	2.5%	0.1%	2.6%
	Hospital 6	6.2%	0.7%	6.8%
	Hospital 1	2.9%	0.4%	3.4%
	Hospital 7	0.5%	0.0%	0.6%
	Hospital 8	36.8%	5.5%	42.2%
Total		87.7%	12.3%	100.0%

The analysis concludes that there is a statistically significant association between hospitals and the frequency of DRG code changes, as demonstrated in Table 4. This finding indicates that the likelihood of DRG code modifications is not uniform across all hospitals, but rather varies significantly from one institution to another.

Table 4. Chi-square tests for checking the association.

	Value	df	Asymptotic Sig. (2-Sided)
Pearson Chi-Square	227.591 ^a	7	<0.001
Likelihood Ratio	270.451	7	<0.001
N of Valid Cases	56,009		

^a 0 cells (0.0%) have expected count less than 5. The minimum expected count is 39.14.

Results also indicated that a significant proportion of DRGs were reclassified by the auditors into different DRGs, with most being recoded to higher-cost-weighted DRGs. This reclassification could lead to a substantial increase in hospital revenue. To investigate how hospital revenue was affected, we examined whether the DRG assignment after the audit improved or worsened revenue to the same extent for all hospitals. The ordinal DRG change data (unchanged, improved, worsened) was categorized for each hospital and compared using non-parametric tests.

The Kruskal–Wallis H test revealed a statistically significant difference ($\chi^2(2) = 40.005$, $p < 0.001$) in how DRG changes impacted revenue across hospitals. The mean rank scores were as follows: Hospital 1 (28,021.35), Hospital 2 (27,907.02), Hospital 3 (28,114.06), Hospital 4 (27,869.66), Hospital 5 (27,723.48), Hospital 6 (27,817.84), Hospital 7 (27,532.99), and Hospital 8 (28,041.62). Since the null hypothesis of the Kruskal–Wallis test was rejected, indicating an overall difference, Dunn’s test for non-parametric pairwise multiple comparisons was conducted to identify which hospitals have statistically different outcomes in revenue change (results are illustrated on Figure 6). This could imply that certain hospitals might need to adjust their coding practices or audit procedures to optimize revenue, or that there are systemic differences in how patient care is coded across hospitals.

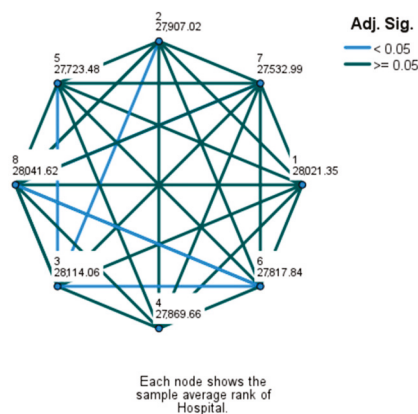


Figure 6. Pairwise comparisons of hospitals.

In cases where the length of stay (LoS) exceeded one day, the primary errors were linked to various coding issues, such as the omission of secondary diagnoses and medical procedures that should have been documented, as well as the use of overly general codes. Analyzing and comparing cases with an extended LoS highlights the importance of targeted analysis and actions tailored to different patient segments, as the results can vary significantly when viewed from different perspectives. Beyond LoS, further analysis could be conducted by hospital, clinic, major diagnostic category, admission type, and other relevant factors to gain a deeper understanding of these discrepancies.

4. Discussion

The findings from this study underscore the importance of considering LoS when evaluating the accuracy of DRG coding, as longer hospital stays often reflect more complex or severe cases, which may not be adequately captured by the initial DRG code assignment. The analysis also revealed that while some hospitals exhibit a strong correlation between extended LoS and subsequent DRG code changes, others show a weaker or even negligible association. These differences suggest that factors such as hospital size, available resources, coding procedures, and the complexity of cases managed by the hospital could influence the likelihood of DRG code revisions. For instance, larger hospitals or those handling more complex cases may have more stringent auditing processes, leading to a higher incidence of DRG code changes for longer stays [15]. Overall, this highlights the importance of considering institutional variability when evaluating DRG coding practices. Understanding

these differences can help in developing tailored strategies for improving coding accuracy and consistency across various healthcare settings.

The provision of medical coding control and consulting services can be instrumental in the proper implementation of the DRG classification system, by fostering accurate medical coding and ensuring transparent allocation of resources within hospitals. The main actions that can be regulated and adopted for the proper implementation of the DRG system might include correct and complete entry of all medical data into the electronic medical record to ultimately retrieve correct information, as well as correct coding of all necessary medical information. By classifying patients into DRGs based on their condition, hospitals can improve the accuracy of medical records and ensure they are receiving appropriate reimbursement, ultimately leading to higher quality healthcare [16].

In Greece, the DRG system has been connected to the majority of public hospitals' digital patient files. This, in itself, is an opportunity for the coding software to be further developed to do more than suggest codes or prevent coder errors through pre-programmed rules and edits based on official coding manuals. It can also be developed to check the assigned diagnosis and procedure codes for accuracy [5]. Initial rules and restrictions have been implemented, such as preventing coders from making errors based on age/sex, and prohibiting assistance in the coding process using “balloons” (which likely refer to prompts or suggestions). It can also be further developed to identify potential coding errors. This could involve a coding and validation process that checks for missing codes or incorrect code combinations.

Additionally, by applying coding logic, the software could highlight cases where a certain procedure would not typically be performed for a specific diagnosis, prompting the coder to review the case in real-time. A coding system like this could be implemented by checking the medical materials used during a hospitalization and the invasive medical procedures performed. For example, if medical materials are used, but no corresponding medical procedure is coded, the software would prevent the case submission until the medical procedure is documented. Furthermore, analyzing the data can lead to more sophisticated methods for adding value to coding quality. This includes filtering data, adding rules and improving the user experience of medical data records. For instance, adding DRG information to the home page of medical records can provide a solid foundation for both a comprehensive evaluation of DRG effectiveness and improvements in overall medical quality [17].

Our results suggest variation in DRG code modifications across hospitals. We did not investigate specific factors such as coding practices, resources, patient demographics, or case complexity, although the literature indicates that these factors often influence DRG code modifications [18,19]. Hospitals with robust auditing and coding processes tend to have more frequent code adjustments, whereas those with fewer resources show fewer changes. This underscores the need for tailored interventions to enhance DRG coding accuracy at the hospital level. Customizing actions—such as improving training, auditing, and resource allocation—can ensure accurate DRG coding, leading to better reimbursement and healthcare quality.

Deep learning and artificial intelligence techniques can be employed to develop accurate DRG prediction models that identify primary and secondary diagnoses and medical procedures. This platform is a crucial part of the data analysis framework for DRG prediction. It uses deep supervised learning to evaluate the database's quality and completeness, and ensures the creation of labeled datasets for both training and testing. These models use a loss function to measure accuracy and adjust their weights to minimize errors [20,21]. Research indicates that deep learning models can achieve high accuracy in predicting primary diagnoses for DRGs. Implementing such an automated DRG coding system could reduce incorrect coding, potentially increase hospital revenue, improve resource allocation, and enhance overall hospital performance [22,23].

Another important action that can be adopted is the organization of post-audit training of coders (physicians) who must know what findings were made, be aware of miscoding,

and adhere to the rules of DRG coding. KETEKNY has already organized the first presentation of this finding and plans to further adapt it. In the Greek DRG system, physicians currently handle the coding of cases. While this allows them to describe each incident in greater detail and more consistently, surveys indicate that many hospitals are hesitant to transition entirely to specialist coders [24]. Customized and targeted training is suggested, with material that is enriched by the results of the audits with coding quality [25]. These trainings can be highly targeted and adaptive to small-group training when necessary. Sometimes post-test training is effective at a large-group level, but sometimes it still needs to be one-on-one to maximize effectiveness.

A notable limitation of this study, which should be taken into consideration, was the scarcity of healthcare professionals with specialized expertise in code auditing, which posed a significant challenge during the auditing process. Additionally, since the hospitals were in the early stages of DRG system implementation, their coding practices were less mature. This necessitated increased guidance and support for hospital staff, resulting in a greater effort and time investment than initially anticipated.

5. Conclusions

This project aims to establish a foundation for future initiatives, including a permanent sample control process through the KETEKNY platform. It will involve selecting cases from all Greek hospitals based on various criteria to ensure accurate hospitalization data recording in medical files and the Grouper system, aligning cases with the correct DRG. A proposed strategy is to adjust audit frequency based on past performance. Hospitals with better coding records would face fewer audits, while those with poorer performance would be audited more often. This approach could encourage competition and improvement among hospitals. Additionally, there is an increasing need for specialized solutions tailored to individual hospitals.

The more specialized and unique the hospital's spatial and organizational characteristics, the greater the need for the implementation of custom tools. Currently, the KETEKNY platform connects directly with hospitals' electronic patient files. It complies with GDPR regulations and aims to extend this direct connection to the rest of the Greek healthcare regions. The concurrent implementation of all the above actions, along with the recent assignment of responsibility for the Gr-DRG system to an independent, self-governing body, can achieve a clear strategic objective: optimal resource allocation among all hospital care providers in Greece, both in the public and private sectors. This approach would also support the establishment of clear standards and practical guidelines, with the necessary legal and policy support.

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Article

Efficiency of Primary Health Services in the Greek Public Sector: Evidence from Bootstrapped DEA/FDH Estimators

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Abstract: Strengthening primary healthcare (PHC) is vital for enhancing efficiency and improving access, clinical outcomes, and population well-being. The World Health Organization emphasizes the role of effective PHC in reducing healthcare costs and boosting productivity. With growing healthcare demands and limited resources, efficient management is critical. **Background/Objectives:** Building on this point, this study aimed to evaluate the efficiency of PHC units across Greece, focusing on Health Centers (HCs) and Local Health Units (ToMYs). The objective was to assess their efficiency levels and identify factors contributing to observed inefficiencies. This study explores a novel research area by being the first to assess the efficiency of restructured primary healthcare facilities in Greece, utilizing 2019 data—the first year operational data became available for the newly established ToMY facilities following recent healthcare reforms. **Methods:** We applied a comprehensive suite of non-parametric methods, including Data Envelopment Analysis (DEA) under variable, constant, increasing, and decreasing returns to scale (VRS, CRS, IRS/NDRS, DRS/NIRS) assumptions, along with the Free Disposal Hull (FDH) model, all oriented toward output maximization. Efficiency scores were refined using bootstrapping to calculate 95% confidence intervals, and efficient units were ranked via the super-efficiency model. Outliers were identified and removed through the data cloud algorithm. For the first time at this scale, the final sample included the vast majority of PHC facilities in Greece—234 Health Centers and 94 Local Health Units—with inputs categorized into three human resource types: medical, nursing/paramedical, and administrative/other staff. Outputs encompassed scheduled visits, emergency visits, and pharmaceutical prescription visits. This diverse and comprehensive application of DEA methods represents a novel approach to evaluating PHC efficiency in Greece, with potential relevance to broader healthcare contexts. **Results:** The analysis revealed significant inefficiencies and differences in technical efficiency between HCs and ToMYs. HCs could nearly double their outputs (VRS score: 1.92), while ToMYs could increase theirs by 58% (VRS score: 1.58). Scale efficiency scores were closer, with HCs slightly more aligned with their optimal scale (1.17 vs. 1.20 for ToMYs). **Conclusions:** There is significant potential to improve efficiency in PHC, with variations depending on unit characteristics and regional differences. This evaluation provides a foundation for policymakers to identify areas for improvement and enhance the overall performance of healthcare services in Greece.

Keywords: primary healthcare (PHC); efficiency; data envelopment analysis (DEA); free disposal hull (FDH); super-efficiency; bootstrap; Greek public sector

1. Introduction

As stated in the Astana Declaration, primary healthcare (PHC) is the cornerstone of health systems, essential for achieving universal health coverage and meeting the health-related Sustainable Development Goals of the United Nations [1]. According to the

World Health Organization [2], PHC aims to ensure the highest possible level of health and well-being for society based on people's needs and encompasses a wide range of services, from information and prevention to treatment and rehabilitation. Strengthening PHC services is a vital investment to improve health equity, access, clinical outcomes, and population well-being while reducing healthcare and social costs and enhancing population productivity [3].

Sufficient funding and the reinforcement of PHC are crucial objectives for health systems as they play key roles in enhancing healthcare efficiency, service quality, resource utilization, and equitable access for all citizens. Historically, PHC in Greece has been marked by a lack of centralized planning and comprehensive policies, leading to fragmented healthcare services; understaffing of specialized personnel; significant shortages in diagnostic equipment, especially in rural areas; limited community-based prevention and health promotion services; poor coordination with secondary care; and high levels of public dissatisfaction [4–7].

The absence of mandatory referral (gatekeeping) mechanisms from primary to secondary care and the failure to establish a functional connection between PHC services and hospital care result in systemic inefficiencies, further contributing to public dissatisfaction [7]. In 2010, during the economic crisis, PHC became a target for reforms as part of the economic adjustment program. The reforms aimed to reduce and rationalize costs while improving efficiency and effectiveness [8–11].

Law 3918/2011 [12] established the National Organization for the Provision of Health Services (EOPYY) by merging primary social security funds (IKA, OGA, OAEE, OPAD). Law 4238/2014 [13] introduced the National Primary Care Network (PEDY), which integrated IKA's PHC services into the National Health System (ESY), transforming EOPYY into a healthcare purchaser, and, additionally, all public PHC facilities were placed under the jurisdiction of the Regional Health Authorities (RHA/YPE) [8,14,15]. Later, Law 4486/2017 [16] renamed PEDY Health Units as Health Centers and established Local Health Units (ToMYs) as decentralized branches of these Health Centers, aiming to provide holistic, efficient, and patient-centered care tailored to the population's needs.

Currently, in Greece, primary healthcare (PHC) services in the public sector are provided through structures of the Greek National Health System (ESY), including Health Centers (HCs) and their affiliated Regional Medical Offices, Multipurpose Regional Medical Offices, Specialized Regional Medical Offices, Local Medical Offices, Local Health Units (ToMYs), and outpatient clinics in hospitals [17].

Between 2010 and 2019, there was a 24.5% decrease in medical personnel and a 29.5% reduction in non-medical personnel in Health Centers, contrasted by a 26.6% increase in nursing personnel [17,18]. Ambulatory care expenditures decreased by 41.68%, with public spending down by 21.03% and private spending down by 52.25%, reflecting declining disposable incomes [19–22]. Despite these reductions, private expenditures still constituted a larger share than public spending.

As healthcare needs grow and resources remain constrained, efficient management becomes crucial. Modern methods for assessing the efficiency of PHC units, such as Data Envelopment Analysis (DEA), offer valuable tools for policymakers. DEA is a non-parametric method widely used to evaluate the efficiency of healthcare units, including hospitals and PHC facilities [23–33].

1.1. Related Studies

In Greece, studies utilizing Data Envelopment Analysis (DEA) have primarily focused on evaluating the efficiency of primary health facilities, namely, the NHS's Health Centers (HCs) and IKA's healthcare centers. [4,34–37]. One early study [35] analyzed 133 of the 242 IKA's healthcare centers, which, at that time, served as the primary public health insurance provider. The analysis employed output data from 1998 (including patient visits and laboratory tests) and staffing data from September 1999. The results were categorized by the population served, with groups defined as up to 10,000, 10,000–25,000,

25,000–50,000, and over 50,000. The findings indicated that units equipped with technological resources for laboratory and radiological examinations demonstrated higher efficiency. Moreover, mid-sized units performed better than larger or smaller units. IKA HCs serving populations between 10,000 and 50,000 individuals were notably efficient, with none in the 25,001–50,000 range scoring below 50% efficiency.

Another study [4] evaluated the efficiency of 194 primary healthcare facilities using data from 2004, which included 103 NHS Health Centers (HCs), representing 67.9% of the total, and 91 IKA healthcare centers, representing 57.8% of the total. The facilities were categorized by the population served into three groups: small (<15,000), medium (15,000–30,000), and large (>30,000). Additionally, they were classified by location as urban/semi-urban or remote/island-based. The results showed that IKA healthcare centers were generally more efficient than NHS Health Centers (84.9% vs. 70.1%). Smaller units outperformed medium and large ones (84.2%, 72.4%, and 74.3%, respectively), and remote/island units were more efficient than urban centers (81.1% vs. 75.7%). In terms of scale efficiency, IKA units again outperformed NHS units (89.7% vs. 85.9%), with large and urban units showing higher efficiency scores (96.3% and 91.9%, respectively) than medium/small and remote units (90.9%–75.9% and 75.3%). These findings suggested a potential influence of facility size, location, and administrative affiliation on primary healthcare efficiency.

A separate study [36] assessed the efficiency of 152 NHS Health Centers using data from 2005. The findings indicated that 61 centers (39%) were technically efficient. Regarding scale efficiency, 96 centers (62.7%) demonstrated increasing returns to scale, while 15 (9.8%) exhibited decreasing returns. The results indicated that larger and urban Health Centers performed more effectively, whereas smaller and rural Health Centers faced scale inefficiencies.

A recent study [34] evaluated the efficiency of 42 Health Centers within the sixth Regional Health Authority, using data from 2010. The average efficiency scores were 0.57 for overall technical efficiency (TE), 0.67 for pure technical efficiency (PTE), and 0.87 for scale efficiency (SE). Only two Health Centers reached full technical efficiency, while nine achieved full pure technical efficiency and five attained full-scale efficiency. The study identified technical inefficiency as the primary source of overall inefficiency, suggesting that these Health Centers could potentially increase output by an average of 33% without additional resources by optimizing current production capacities.

Given these past findings, it is essential to reassess the current efficiency level of Greece's primary healthcare (PHC) structures to evaluate resource utilization, identify inefficiencies, assess recent reforms, examine regional variations, and inform new policy recommendations.

1.2. Application Context

This study, based on 2019 data, offers the only post-crisis, pre-COVID-19 efficiency assessment of Health Centers (HCs) and Local Health Units (ToMYs) in Greece. The year 2019 is significant as it marks the first time operational data became available for the newly established ToMY facilities. Additionally, the number of HCs increased substantially following Law 4486/2017, which reclassified PEDY Health Units as Health Centers and established the ToMY units. The significance of this research is underscored by the ongoing healthcare reforms aimed at implementing a new national health map, with a primary focus on strengthening the PHC sector to reduce pressure on overburdened secondary facilities, conserve resources, and enhance the quality and accessibility of healthcare services.

Identifying the potential for output expansion, specifically the additional capacity for service delivery that Health Centers (HCs) and ToMYs could provide, is a significant goal of this study. This research is the first to quantify the “additional capacity” of the country's primary healthcare structures using existing resources, employing a comparative evaluation approach.

To our knowledge, this is the only study that (a) includes the largest sample of Health Centers to date, covering over 75% of all centers with full geographic distribution across the country; (b) represents the first analysis of ToMY structures, examining nearly all units; and (c) uses the most recent data. This study's methodological innovation extends beyond a conventional, naïve application of DEA models, employing a suite of methods to address the inherent limitations of basic DEA applications. This extensive methodological framework provides a detailed presentation of each method's theoretical underpinnings and implications, equipping managers and policymakers with a deeper understanding of these analytical techniques.

This study addresses potential biases by identifying and excluding outliers and applying the bootstrap method to assess the robustness of results at specific statistical significance levels. Additionally, the super-efficiency method is used to classify efficient units and identify those with unique production profiles that warrant closer examination, while the Free Disposal Hull (FDH) model highlights indisputable benchmark units that outperform others across all dimensions. Furthermore, this study is the first to report results across regions stratified by levels of urbanization, using both Eurostat [38,39] and FAO [40] typologies, and by geographical area as defined by the administrative boundaries of the seven Health Regional Authorities (RHAs/YPE) in the Greek health system.

Key motivations for this approach include (a) assessing efficiency at the national level as well as within distinct geographic areas to determine the potential for additional services within the current resource framework, which could alleviate pressure on secondary care facilities, and (b) identifying individual efficiency scores for targeted interventions at the unit level.

The remainder of this paper is structured as follows: Section 2 details the methods and provides a brief overview of the theoretical background of the techniques employed to measure efficiency, including the software tools used, data selection process, model specification, DEA application, and urbanization and administrative classification levels chosen. Section 3 presents the results of the analysis; Section 4 discusses the findings, limitations, and policy implications; and, finally, Section 5 concludes with a summary and recommendations.

2. Materials and Methods

2.1. Methods

This research used cross-sectional data from 2019 to assess the relative efficiency of primary healthcare facilities in Greece. This study applied Data Envelopment Analysis (DEA) to benchmark Health Centers (HCs) and Local Health Units (ToMYs) based on resource utilization and service outputs. The non-parametric Data Envelopment Analysis (DEA) method was employed based on the assumptions of the constant returns to scale (CRS), variable returns to scale (VRS), increasing returns to scale (IRS/NDRS), and decreasing returns to scale (DRS/NIRS) models, as well as the Free Disposal Hull (FDH) model, all of them oriented toward output maximization. Efficiency scores were adjusted using a bootstrap technique to derive 95% confidence intervals. A suitable bootstrap method was also utilized to determine the type of global returns to scale for the underlying technology. Comparative evaluation and ranking of the efficient units were performed using the super-efficiency model. Additionally, the results were presented as aggregated scores (weighted averages) across various geographical areas and the seven Regional Health Authorities (RHAs/YPE) in the country and statistically analyzed to identify any significant differences.

2.1.1. Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a non-parametric method introduced by Charnes et al. in 1978 [41]. It utilizes linear programming to benchmark the efficiency of a group of similar production units, known as decision-making units (DMUs). These DMUs use a common set of inputs to produce a common set of outputs. The evaluation is relative, meaning that units showing no potential for improved efficiency are assigned a score of

1, indicating 100% efficiency. For all other units, a score below or above 100% is assigned. This score reflects, for each unit, the percentage by which inputs must be reduced (while maintaining current output levels) or the percentage by which outputs must be increased (while maintaining current input levels) to achieve 100% efficiency. In the former case, the efficiency is input-oriented, and, in the latter, it is output-oriented.

In geometric terms, each production unit can be represented as a point within the input–output space. Units with the same output levels can be compared based on their distance from the origin if they are positioned along the same radial direction in the input space. The unit closest to the origin is the most efficient, receiving an efficiency score of 1 (or 100%), while units farther from the origin are less efficient, with scores below 100%. This efficiency score is calculated as the ratio of the distance of the most efficient unit to the origin compared to that of the less efficient unit. Similarly, for units with the same input levels along the same radial direction in the output space, the unit farthest from the origin is deemed the most efficient, also receiving a score of 1. In this case, units closer to the origin have efficiency scores exceeding 100%. This score is determined by the ratio of the efficient unit’s distance from the origin to that of each less efficient unit. The assessment of efficiency mentioned above relies on what is known as the Farrell measure of efficiency [42].

However, this method can only be applied when there are at least two units along the same radial direction in the input or output space, sharing identical input or output levels. Only then is it possible to compare their distances and calculate efficiency scores. However, in practice, given that samples under evaluation consist of only a limited, discrete number of production units, it is highly improbable that units will align perfectly along the same radial direction in the input or output space, considering the infinite number of possible directions. To enable meaningful comparisons, it becomes necessary to determine the most efficient point along each radial direction.

This can be achieved by applying certain assumptions that allow transitioning from the discrete set of production possibilities in the sample to a complete (dense) set. From this full set, the most efficient operating point for each radial direction is identified. Geometrically, this corresponds to defining the feasible production possibilities region and, consequently, its outer boundary, known as the efficiency or best-practice frontier, which separates feasible from infeasible production possibilities. The points on this frontier represent the most efficient units. The intersection of this surface with the radial directions of the units being evaluated identifies the benchmarks, against which the efficiency scores of other units can be measured. The assumptions that are typically made include the assumption of the free disposability of inputs and outputs, the convexity of the production possibility set, and the type, if any, of prevailing returns to scale (non-increasing, non-decreasing, or constant). The construction of the production possibility set P under the aforementioned assumptions is derived mathematically as follows [43,44]:

Consider a set of n decision-making units (DMUs), where each unit p utilizes varying amounts of different m inputs

$$x_{1p}, x_{2p}, \dots, x_{mp}$$

and produces varying amounts of the total of s outputs

$$y_{1p}, y_{2p}, \dots, y_{sp}$$

where inputs and outputs are considered non-negative, without all being zero (i.e., at least one input and at least one output are strictly positive numbers) [45]:

$$x_{ip} \geq 0, y_{jp} \geq 0 \quad \forall i, j, p$$

$$\sum_{i=1}^m x_{ip} > 0, \sum_{j=1}^s y_{jp} > 0$$

Each such decision-making unit p is called an activity and will henceforth be generally denoted by the pair (x, y) or the pair (x_r, y_r) (when there is a need to refer to the specific index r that indicates a particular DMU).

Starting from the set of the n total units mentioned above, for which the corresponding n productive activities are (empirically) known

$$(x_r, y_r), (r = 1, 2, \dots, n) \quad (1)$$

a more comprehensive set of feasible production possibilities is constructed by incorporating all additional production possibilities derived from one or more of the following assumptions:

- Assumption of Free Disposability of Inputs and Outputs: If an activity (x, y) belongs to P , then any activity (x', y') with $x' \geq x$ and $y' \leq y$ will also belong to P .
- Assumption of Convexity of Set P : Any weighted average of activities in P also belongs to P

$$(x, y) \in P, (x', y') \in P \Rightarrow \lambda(x, y) + (1 - \lambda)(x', y') \in P, \lambda \in [0, 1] \quad (2)$$

- Assumption of the Type of Returns to Scale: If an activity (x, y) belongs to P then the activity $(\lambda x, \lambda y) = \lambda(x, y)$ also belongs to P , where

- i. $\lambda \in (0, 1]$ under the assumption of non-increasing returns to scale (NIRS)
- ii. $\lambda \in [1, +\infty)$ under the assumption of non-decreasing returns to scale (NDRS)
- iii. $\lambda \in (0, +\infty)$ under the assumption of constant returns to scale (CRS)

Based on these assumptions, the production possibility set P is given by the following construct:

$$P^{PPS} = \left\{ (x, y) \in \mathbb{R}_+^m \times \mathbb{R}_+^s \mid \exists \lambda_r \in \Lambda(PPS) : x \geq \sum_{r=1}^n \lambda_r x_r, y \leq \sum_{r=1}^n \lambda_r y_r \right\} \quad (3)$$

where PPS values are given by

$$PPS \in \{CRS, NIRS, NDRS, VRS, FDH\}$$

and the sets $\Lambda(PPS)$ are defined according to the specifications provided in Table 1 below:

Table 1. Production possibility set (PPS) assumptions and constraints for different DEA and FDH models. Summary of assumptions and structural constraints for each PPS .

Scaling	Free Disposability	Convexity	Returns to Scale
$\Lambda(CRS) = \{\lambda_r \in \mathbb{R}_+ \mid \sum_{r=1}^n \lambda_r > 0\}$	•	•	• (CRS)
$\Lambda(NIRS) = \{\lambda_r \in \mathbb{R}_+ \mid \sum_{r=1}^n \lambda_r \leq 1\}$	•	•	• (NIRS)
$\Lambda(NDRS) = \{\lambda_r \in \mathbb{R}_+ \mid \sum_{r=1}^n \lambda_r \geq 1\}$	•	•	• (NDRS)
$\Lambda(VRS) = \{\lambda_r \in \mathbb{R}_+ \mid \sum_{r=1}^n \lambda_r = 1\}$	•	•	-
$\Lambda(FDH) = \{\lambda_r \in \mathbb{N}_+ \mid \sum_{r=1}^n \lambda_r = 1\}$	•	-	-

The input-oriented (-IO) efficiency of unit p is calculated by solving the next linear programming problem

$$TE_p^{PPS-IO} = \min \left\{ \theta_p : \theta_p x_p \geq \sum_{r=1}^n \lambda_{r(p)} x_r, y_p \leq \sum_{r=1}^n \lambda_{r(p)} y_r, \lambda_{r(p)} \in \Lambda(PPS) \right\} \quad (4)$$

whereas the output-oriented efficiency (-OO) is derived respectively by the following problem:

$$TE_p^{PPS-OO} = \max \left\{ \Phi_p : x_p \geq \sum_{r=1}^n \lambda_{r(p)} x_r, y_p \Phi_p \leq \sum_{r=1}^n \lambda_{r(p)} y_r, \lambda_{r(p)} \in \Lambda(PPS) \right\} \quad (5)$$

The assumptions listed in the first three rows of Table 1 correspond to the three DEA models, each defined by their assumption regarding returns to scale: DEA-CRS (constant returns to scale), DEA-NIRS (non-increasing returns to scale), and DEA-NDRS (non-decreasing returns to scale). The model in the fourth row is known as DEA-VRS (variable returns to scale), while the final row represents the FDH (Free Disposal Hull) model. For completeness of terminology, CRS and VRS are also referred to as CCR and BCC [46], with their scores representing overall efficiency and pure technical efficiency, respectively.

2.1.2. Free Disposal Hull (FDH)

The key distinction between FDH and DEA models lies in their assumptions about the production possibility set. In the FDH model [47], the sole assumption is the free disposal of inputs and outputs, meaning that the production possibility set is determined strictly by the actual production activities of the units being evaluated. Consequently, FDH benchmarking is based on comparison with a specific, existing unit rather than a theoretical production activity created from a linear combination of other units. In contrast, DEA benchmarks against a composite unit formed by aggregating portions of multiple existing units.

This characteristic is reflected in the set of possible values, denoted by $\Lambda(\text{FDH})$. Consequently, the only permissible linear combinations used for benchmarking in the FDH model are those involving a single existing unit with a coefficient of unity. This is because only in this manner does the condition $\{\lambda_r \in \mathbb{N}_+ | \sum_{r=1}^n \lambda_r = 1\}$ hold.

From a managerial perspective, it is important to note that the identification of a set of dominant production units through the presentation of actual implemented production activities that are demonstrably more efficient lends credibility to the inefficiency scores, which often lack such substantiation when reference is made to an abstract frontier [48].

It should also be noted that, specifically for FDH, the calculation of efficiency can be performed analytically, making it unnecessary to solve the linear programming problem. Specifically, the FDH efficiency score of unit p , with an input orientation (-IO) or output orientation (-OO), can be calculated by solving the following simple minimax problems [44]:

$$TE_p^{\text{FDH-IO}} = \min_{r: y_r \geq y_p} \max_{i=1,2,\dots,m} \frac{x_{ir}}{x_{ip}} \quad (6)$$

$$TE_p^{\text{FDH-OO}} = \max_{r: x_r \leq x_p} \min_{j=1,2,\dots,s} \frac{y_{jr}}{y_{jp}} \quad (7)$$

2.1.3. Peer Units

By solving the above linear programming problems for each unit p , the (input or output oriented) efficiency score, (θ_p) or (Φ_p) , is calculated along with the weighting factors $\lambda_{r(p)}$, which form a linear combination of fully efficient units [44].

$$\left(\sum_{r=1}^n \lambda_{r(p)} x_r, \sum_{r=1}^n \lambda_{r(p)} y_r \right) \quad (8)$$

This linearly combined activity corresponds to the most efficient point against which, if present, the evaluated unit p would ultimately be compared. In other words, this is the point on the efficient frontier where the production point under evaluation is radially projected. In this context, the units of the sample that have been assigned positive weighting factors are referred to as the “peer units” of unit p :

$$\text{Peer Units of } p = \left\{ (x_r, y_r), r \in \{1, 2, \dots, n\} \mid \lambda_{r(p)} > 0 \right\} \quad (9)$$

2.1.4. Super Efficiency

A limitation of the DEA evaluation method is that all units forming the efficiency frontier receive a score of 1, making it difficult to rank efficient units. To differentiate between them, the super-efficiency model, introduced by Andersen and Petersen [49], calculates how much a unit can “underperform” while still remaining efficient. This margin is based on either the maximum possible increase in inputs or decrease in outputs until the unit’s score reaches 1. Larger margins indicate greater relative efficiency.

In the super-efficiency model, each unit is excluded from the efficiency frontier calculation. If efficient, the unit’s removal shifts its position, resulting in a score either greater or less than 1. This score allows for the ranking of efficient units based on their distance from the frontier. In output-oriented models, a score below 1 means that the unit can produce more output than other efficient units, with larger deviations indicating higher super-efficiency [49–51].

Therefore, the super-efficiency DEA model enhances traditional DEA by ranking efficient units, detecting outliers, identifying untapped potential, and providing more accurate benchmarks for improvement. It offers decision-makers detailed insights into both the robustness and the vulnerabilities of their units, helping them optimize resource allocation, improve operational efficiency, and set more effective performance targets for both efficient and inefficient units.

To compute super-efficiency scores, the two linear programming problems, as well as the sets $\Lambda(\text{CRS})$, $\Lambda(\text{NIRS})$, $\Lambda(\text{NDRS})$, and $\Lambda(\text{VRS})$, are reformulated, with the sole modification being the exclusion of the unit being evaluated, denoted as p . Practically, this means that in all summations where the index r ranges from $r = 1$ to $r = n$, the value corresponding to the evaluated unit p is excluded ($r \neq p$).

$$\sum_{r=1}^n (\dots) \rightarrow \sum_{\substack{r=1 \\ r \neq p}}^n (\dots) \quad (10)$$

2.1.5. Weighted Average Efficiency Score

When assessing the efficiency of production units, it is often valuable to consider not only the individual efficiency scores but also the overall efficiency of all units, represented by a comprehensive score for an average representative unit. Using a simple arithmetic mean of the individual efficiency scores can be misleading [52] and, therefore, a weighted mean is recommended. For an output-oriented model with a sample of n units using s outputs, the weighted mean is calculated as follows:

$$\overline{TE}_{avg}^{PPS-OO} = \sum_{p=1}^n w_p TE_p^{PPS-OO} \quad (11)$$

where the weighting w_p of each unit p is calculated as

$$w_p = \frac{1}{s} \left(\frac{y_{1p}}{\sum_{r=1}^n \{y_{1r}\}} + \frac{y_{2p}}{\sum_{r=1}^n \{y_{2r}\}} + \dots + \frac{y_{sp}}{\sum_{r=1}^n \{y_{sr}\}} \right) = \frac{1}{s} \sum_{j=1}^s \frac{y_{jp}}{\sum_{r=1}^n \{y_{jr}\}} \quad (12)$$

$$p = 1, 2, \dots, n$$

2.1.6. Outliers

Outliers are observations that deviate substantially from the majority of observations in a sample dataset, either being much higher or lower than typical values, often falling outside the “expected range” of the data. These anomalies may result from natural variability, measurement errors, or rare occurrences and can significantly influence the accuracy of models, particularly in the context of Data Envelopment Analysis (DEA), where they can distort efficiency estimates and skew results. Outliers in a DEA dataset can significantly distort the construction of the corresponding best-practice frontier, which, in turn, can

heavily influence the efficiency scores of certain units. As such, it is crucial to identify and remove these outliers. Although there are several methods for detecting outliers in non-parametric frontier models, no single method can identify all outliers under any circumstances. For this reason, it is often recommended to use multiple methods when analyzing data. In this study, the data cloud method, as outlined by Wilson [53], was chosen as the primary approach for detecting outliers. This method assesses the geometric volume D formed by the DMUs and analyzes how sensitive this volume is to changes when subsets of DMUs—such as individual units, pairs, or triplets—are excluded from the dataset. A group of r DMUs are considered potentially outlying if their removal results in a significant change in the volume.

2.1.7. Returns to Scale Assumption

In this study, the method proposed by Simar and Wilson [54] was utilized to identify the appropriate returns to scale type. This approach, which employs bootstrapping, consists of two sequential tests. The first test (test 1) evaluates the null hypothesis that the production function has globally constant returns to scale (CRS) against the alternative hypothesis that the technology exhibits globally variable returns to scale (VRS):

Test 1: [H_0 : technology is globally CRS] versus [H_1 : technology is VRS].

If H_0 is rejected, the second test is conducted. Test 2 assesses whether the technology displays globally non-increasing returns to scale (NIRS) compared to the alternative of globally VRS:

Test 2: [H'_0 : technology is globally NIRS] versus [H'_1 : technology is VRS].

If both H_0 and H'_0 are rejected, this indicates that the underlying technology demonstrates globally variable returns to scale (VRS). Among the various test statistics available for these tests, the following ratios of sums (across all units) were chosen for application:

$$ts_1 = \frac{\sum_{i=1}^n TE_i^{CRS}}{\sum_{i=1}^n TE_i^{VRS}}, \quad ts_2 = \frac{\sum_{i=1}^n TE_i^{NIRS}}{\sum_{i=1}^n TE_i^{VRS}} \quad (13)$$

These two statistics can be interpreted as representing the ratios of the average distances from CRS to VRS frontiers (for test 1) and from NIRS to VRS frontiers (for test 2).

2.1.8. Scale Efficiency: Most Productive Scale Size (MPSS)

The Most Productive Scale Size (MPSS) is defined [55] as a production possibility $(x_0, y_0) \in P$ whose average productivity of its input–output mix is maximized. At the MPSS, the average output is at its peak, and any deviation from this point of operation results in reduced average output. Formally, $(x_0, y_0) \in P$ is an MPSS for its input and output mix if, and only if, for all $(\alpha x_0, \beta y_0) \in P \Rightarrow \alpha \geq \beta$

The loss from not operating at the MPSS is quantified by scale efficiency (SE), which is calculated as

$$SE = \frac{TE^{CRS}}{TE^{VRS}} \quad (14)$$

The relationship between MPSS and scale efficiency is captured by the following proposition: A production is an MPSS for its input and output mix if, and only if, $TE^{VRS} = 1$ and $SE = 1$. Therefore, if (x_0, y_0) is an MPSS, then constant returns to scale prevail at (x_0, y_0) .

The Most Productive Scale Size (MPSS) is the point where constant returns to scale prevail, and it reflects how close a unit is to achieving its optimal scale of operation. Units with increasing returns to scale (IRS) fall before the MPSS, while those with decreasing returns to scale (DRS) come after it on the efficiency frontier. It is important to note, however, that the MPSS is specific to the particular input and output mix being evaluated.

2.1.9. Bootstrap

A notable criticism of DEA is its underlying assumption that the entire distance of a DMU from the efficiency frontier is attributed solely to inefficiency. In practice, this distance also captures noise, as input and output data are typically prone to errors. Since DEA uses non-statistical linear programming methods, it cannot evaluate the accuracy of the efficiency estimates. Additionally, the estimated production technology is only a partial representation of the true, unknown technology, meaning that DEA efficiency scores tend to be higher than the actual values. This inherent upward bias in DEA scores is a structural issue. To mitigate this problem, Simar and Wilson [56,57] proposed a bootstrap-based methodology that helps assess the statistical properties of DEA estimators. In this study, their bootstrapping method was applied to compute bias-corrected efficiency scores and provide estimates of their confidence intervals.

Figure 1 presents the methodological workflow for the efficiency analysis, including outlier detection, returns-to-scale testing, DEA with various scale assumptions, super-efficiency, FDH, statistical validation via bootstrap, and statistical inference using Kruskal–Wallis tests.

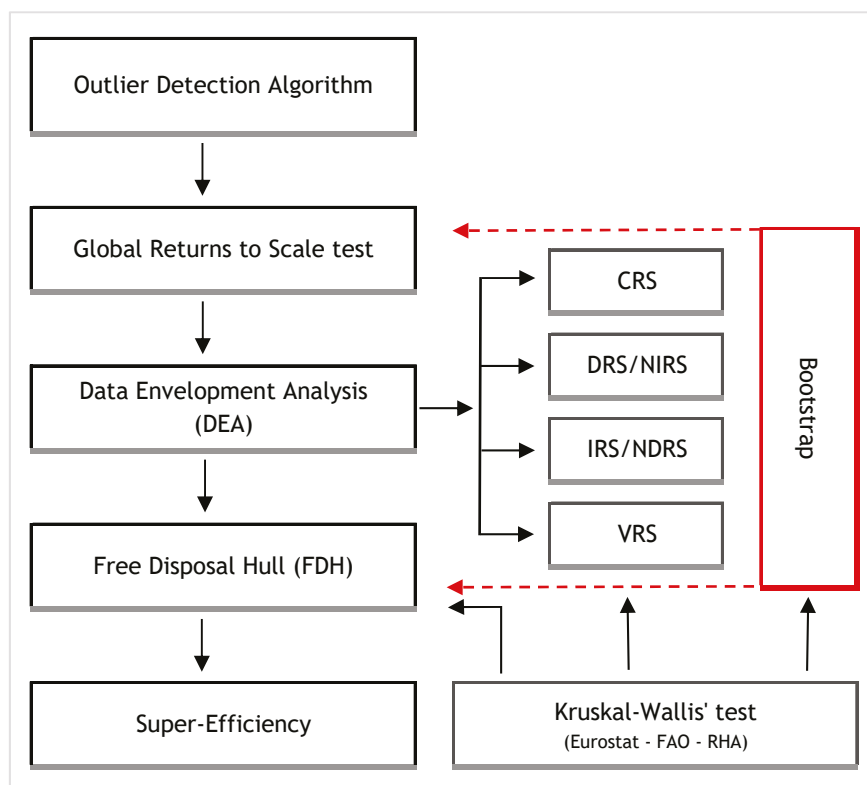


Figure 1. Workflow of methods used for efficiency analysis.

2.2. Software Tools

For this study, existing software applications were used to solve specific models (EMS, DEA SOLVER, R packages—“Benchmarking” and “FEAR”) and SPSS 29.0 (IBM Corp., Armonk, NY, USA) for statistical tests. Additionally, custom Excel routines were developed where needed.

2.3. Data and Model Specification

2.3.1. Sample

The study sample comprised Health Centers and ToMYs from 2019. Primary data were sourced from the Ministry of Health (following a formal request) for all facilities, totaling 307 Health Centers and 117 ToMYs nationwide. Facilities with incomplete input/output

data (66 Health Centers and 17 ToMYs) were excluded, resulting in a sample of 241 Health Centers and 100 ToMYs, representing 78.5% and 85.5% of the total units, respectively.

The data were then examined through distribution analysis and pairwise correlations, as illustrated in the scatter plot matrix in Figure 2. A preliminary review of these plots revealed the presence of outlier units, which, as discussed extensively in a later section, were excluded from the analysis to ensure that the remaining data were representative and robust for subsequent analysis. Using an appropriate outlier detection algorithm, 7 Health Centers and 6 ToMYs were identified and removed, resulting in a final sample of 234 Health Centers and 94 ToMYs, representing 76.2% and 80.3% of the original totals, respectively. These sample sizes were considered more than satisfactory, offering both comprehensive and current data coverage with extensive geographic representation across all regions of the country.

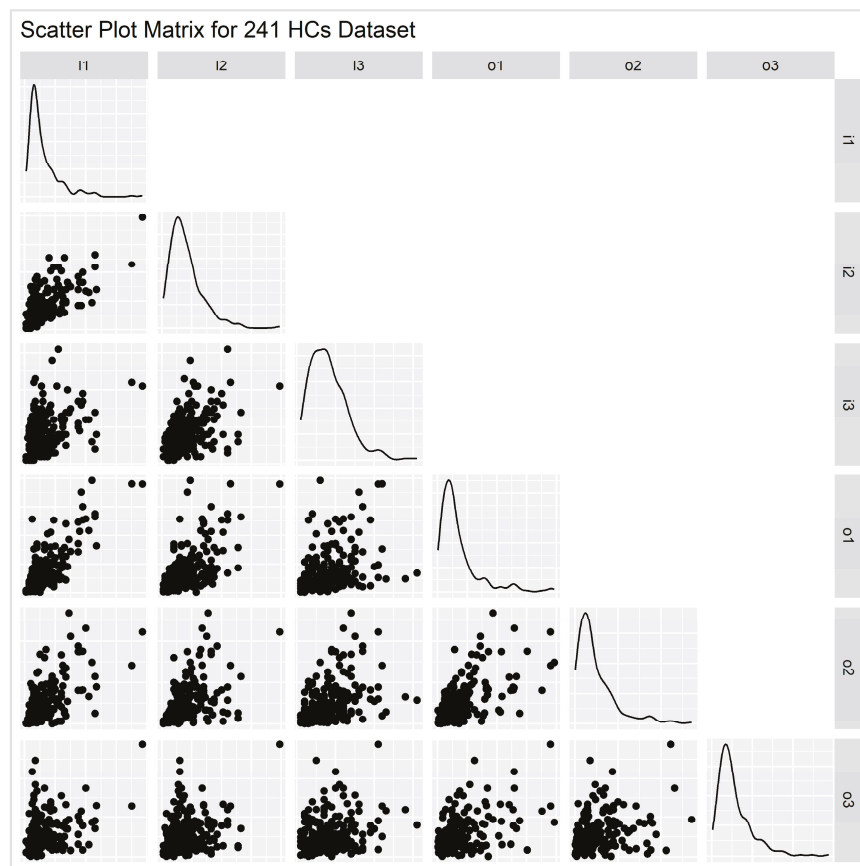


Figure 2. Scatter plot matrix of the three inputs and three outputs for the 241 HCs dataset. Pairwise relationships (in the off-diagonal plots) and individual variable distributions (on the main diagonal) are shown. Inputs: (i1) number of medical staff, (i2) number of nursing and paramedical staff, (i3) number of administrative and other staff. Outputs: (o1) number of scheduled patient visits, (o2) number of emergency patient visits, (o3) number of patient visits for obtaining pharmaceutical prescriptions.

The flowchart in Figure 3 outlines the steps to derive the final sample sizes for Health Centers (HCs) and Local Health Units (ToMYs), beginning with the initial dataset of 424 units. Units were excluded due to missing input/output data, and additional outliers were removed, resulting in a final sample of 234 HCs and 94 ToMYs.

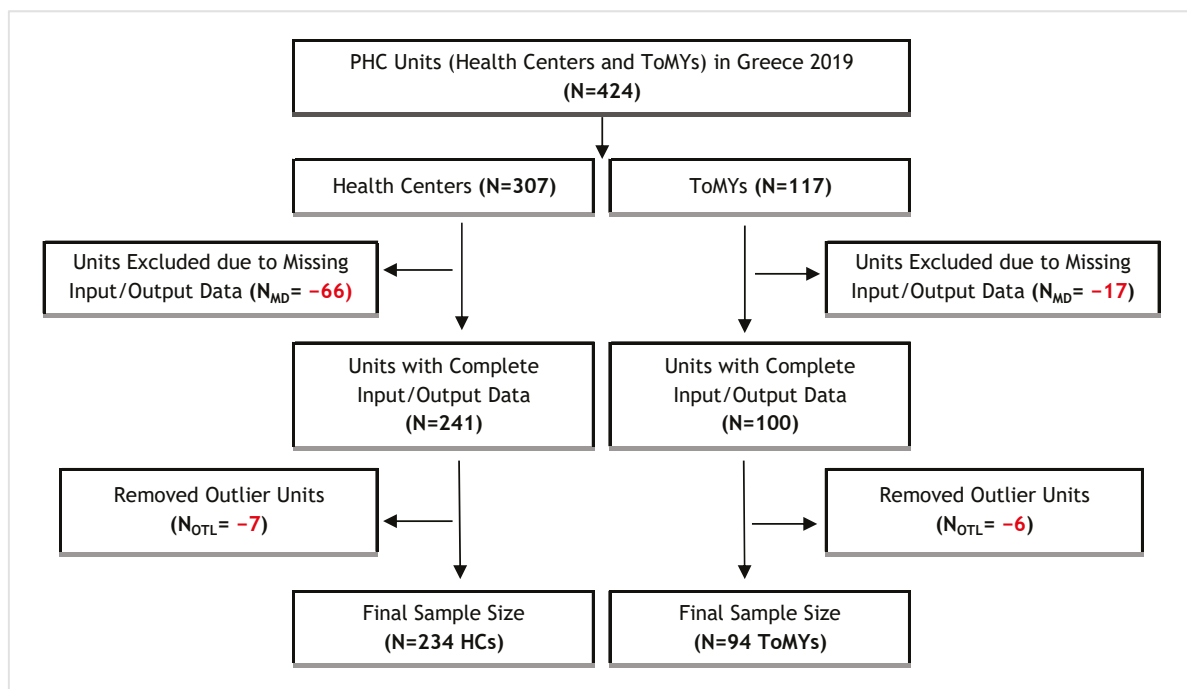


Figure 3. Data selection process for primary healthcare (PHC) units (Health Centers and ToMYs) in Greece, 2019.

2.3.2. Inputs–Outputs

As evidenced in the pertinent literature, the appropriate selection of inputs and outputs is of paramount importance for ensuring the validity and reliability of results when utilizing Data Envelopment Analysis for benchmarking purposes.

Measuring efficiency in primary healthcare (PHC) is particularly challenging due to its holistic role, providing long-term, continuous support to individuals and families [32]. Unlike hospitals, where admissions and discharges create defined boundaries, PHC operates as an open, community-based system with fluid and often indefinite service parameters, complicating economic modeling [58]. Due to limited data on long-term health outcomes, researchers frequently adopt “activity-oriented” models, using metrics such as counts of visits or consultations, vaccinations, prescriptions, minor surgeries undertaken, referrals, and so on as proxies for output [33,59]. In Greece, assessing PHC efficiency is further complicated by variability in service delivery and the absence of a standardized framework. Greek PHC services vary widely, with little consensus on standardized definitions for resources, procedures, or outputs [34]. Different stakeholders often hold conflicting views on what constitutes effective care, while ambiguity in targets and resource definitions further complicates efficiency assessments. Consequently, input and output selection for benchmarking Greek PHC must be meticulously adapted to capture this variability and complexity.

In this study, the inputs selected for benchmarking Greek PHC facilities included (i1) medical staff, (i2) nursing and paramedical staff, and (i3) administrative and other support staff, each representing a distinct component of healthcare resources. The outputs measured were (o1) scheduled patient visits, (o2) emergency patient visits, and (o3) pharmaceutical prescription visits, capturing key activities and service demands. This selection aimed to provide a robust and contextually relevant measure of efficiency, mindful of the unique complexities and operational variability inherent in Greek primary healthcare.

The selected variables in this study were deemed to sufficiently represent the production process of PHC services and were consistent with those employed in similar studies [4,33–36,59–62], as shown in Table 2.

Table 2. Cross-reference of PHC DEA efficiency analysis studies utilizing specified input–output variables, including data sources and relevant literature references.

Inputs			Outputs			Ref.
i1	i2	i3	o1	o2	o3	
•	•	•				[59]
•	•		•	•		[61]
•	•				•	[60]
•	•	•	•	•		[4]
•	•					[62]
•	•	•	•	•		[36]
•	•		•	•	•	[34]
•	•	•		•	•	[33] *
•	•	•				[35]
Data Sources						
MoH	MoH	MoH	MoH	MoH	MoH	

Note: (i1) No. of medical staff, (i2) no. of nursing and paramedical staff, (i3) no. of administrative and other staff, (o1) no. of scheduled patient visits, (o2) no. of emergency patient visits, (o3) no. of patient visits for obtaining pharmaceutical prescriptions. (*) Systematic review article, MoH = Ministry of Health.

2.3.3. Discriminatory Power

With respect to discriminatory power, this study fully satisfied the empirical rule for sample adequacy in DEA. According to this rule of thumb [63], the number of decision-making units (DMUs) should exceed either three times the sum of inputs and outputs or twice their product. With three inputs and three outputs, the minimum threshold is 18 DMUs ($3 \times (3 + 3) = 18$, $2 \times (3 \times 3) = 18$). The samples analyzed—241 Health Centers (HCs) and 94 Local Health Units (ToMYs)—exceeded this requirement by factors of 13 and 5.4, respectively, providing the DEA model with sufficient discriminatory power to avoid result distortion and minimize the likelihood of misclassifying inefficient units as efficient.

To rank fully efficient units, the super-efficiency model was applied [49] as an indirect method of enhancing the discriminatory capability of standard DEA. Although Principal Component Analysis (PCA) could potentially reduce the number of variables—and thereby decrease the number of units deemed efficient, enhancing discrimination [64]—this approach was not selected for several reasons. First, it was essential to retain all relevant variables to capture the unique contributions of each. The three selected input variables represented distinct components of human resources, each included in disaggregated form due to their complementary yet fundamentally different roles. Second, even after reducing the number of fully efficient units, a subset of efficient units would still require relative ranking. Third, and most importantly, PCA+DEA has inherent limitations: PCA often produces both positive and negative component values, which are incompatible with DEA's requirement for non-negative data. A workaround—adding the absolute value of the minimum component plus one to each value [65]—would require the DEA models to be translation-invariant. However, this condition was not met by the CRS model, and in the output-oriented VRS model, translation-invariance applied only to the input side [66]. Consequently, in this study, PCA could only be applied to reduce the input dimensions by one, as the cumulative variance of the first two principal components accounted for 86.9% of the total. This reduction would have altered the input space while leaving the output space unchanged, complicating meaningful interpretation and, most importantly, limiting comparability with standard (non-PCA-based) DEA models from other studies, whether past or future.

Moreover, our results, presented in the next section, reveal substantial inefficiencies across DMUs, with mean efficiency scores indicating room for improvement. Given these findings, further refinement to increase discriminative power is unnecessary at this stage. Such adjustments may become relevant in future analyses, once the primary inefficiencies have been addressed.

2.3.4. Orientation

In terms of selecting between input minimization (reflecting a financial perspective) or output maximization (reflecting a social perspective), an output-oriented approach was chosen to identify potential areas for improvement, given the well-documented challenges of resource scarcity and the increasing demand for primary health services. In this context, it is crucial to evaluate current service levels relative to the available inputs. Recent years have seen a focus on strengthening primary care services for prevention and health promotion at the community level, with the goal of progressively developing an integrated healthcare model. Thus, assessing the capacity to expand service provision within the existing network of Health Centers (HCs) and Local Health Units (ToMYs) is essential for any future system redesign. Moreover, it is widely acknowledged that these healthcare units inherently aim to maximize population coverage, with a significant portion of their activities focusing on health promotion, disease prevention, and control. The objective, therefore, is to serve a larger proportion of the population with the available resources, rather than maintaining the same output levels with fewer resources [34,59,61,62,67–71].

2.4. Classification by Urbanization Levels

Most of the results for the Health Centers (HCs) will be presented based on urbanization levels, classified according to both Eurostat [38,39] and FAO [40] typologies, as well as their distribution across Regional Health Authorities (RHAs), whereas the results for the Local Health Units (ToMYs) will be shown solely according to their division among the RHAs.

Eurostat and FAO both classify urbanization levels into three categories, but with different criteria. Eurostat categorizes regions with over 1500 inhabitants per square kilometer as urban ('1'), those with 300–1500 inhabitants per square kilometer as intermediate ('2'), and those with fewer than 300 inhabitants per square kilometer as rural ('3'). FAO classifies urban areas as settlements with over 5000 people, peri-urban areas as those with 1000 to 5000 people, and rural areas as having fewer than 1000 people, typically focused on agriculture. Both classifications aim to analyze population distribution and inform planning and development strategies.

3. Results

3.1. Input–Output Summary Statistics

Descriptive statistics of the input and output variables for Health Centers (HCs) and Local Health Centers (ToMYs) that were included in the final sample are presented in Table 3. For HCs, which included 234 units, the mean values indicated that the average HC employs 11.4 medical staff, 15.7 nursing/paramedical staff, and 8.2 administrative personnel. In terms of outputs, the average HC manages 15,992.4 scheduled visits, 9255.6 emergency visits, and 10,409.4 prescription-related visits. The high standard deviations across inputs and outputs suggested significant variation among HCs, with larger centers vastly outstripping smaller ones. For instance, while the median number of scheduled visits was 11,917, the maximum reached a notable 75,381 visits, indicating the presence of some very large centers. This was further evidenced by the range values, with scheduled visits varying by as much as 75,040 across different HCs. The percentage distribution of inputs and outputs across regions, categorized by Eurostat's classification ('1', '2', '3') and FAO's classification (rural, p[eri]-urban, urban), as well as by Regional Health Authorities (RHA 1–7), are depicted in Figure 4.

Table 3. Descriptive statistics for input and output variables of Health Centers (HCs) and ToMYs.

Entity	Statistic	Inputs			Outputs		
		i1	i2	i3	o1	o2	o3
HCs (N = 234)							
	Mean	11.4	15.7	8.2	15,992.4	9255.6	10,409.4
	St Dev	8.7	10.0	4.9	13,975.1	8845.2	7185.5
	Median	8.0	13.5	7.5	11,917.0	6333.0	8529.5
	Min	1	1	1	341	75	364
	Max	47	53	31	75,381	54,156	36,929
	Range	46	52	30	75,040	54,081	36,565
	Sum	2665	3675	1908	3,742,211	2,165,821	2,435,798
ToMYs (N = 94)							
	Mean	2.6	3.1	2.5	4944.7	1025.9	2860.5
	St Dev	1.2	0.9	0.7	3123.5	845.2	2019.9
	Median	3.0	3.0	3.0	4491.0	786.0	2419.0
	Min	1	1	1	465	12	109
	Max	5	5	5	14,161	3812	8737
	Range	4	4	4	13,696	3800	8628
	Sum	242	293	234	464,801	96,438	268,890

Note: (i1) No. of medical staff, (i2) no. of nursing and paramedical staff, (i3) no. of administrative and other staff, (o1) no. of scheduled patient visits, (o2) no. of emergency patient visits, (o3) no. of patient visits for obtaining pharmaceutical prescriptions.

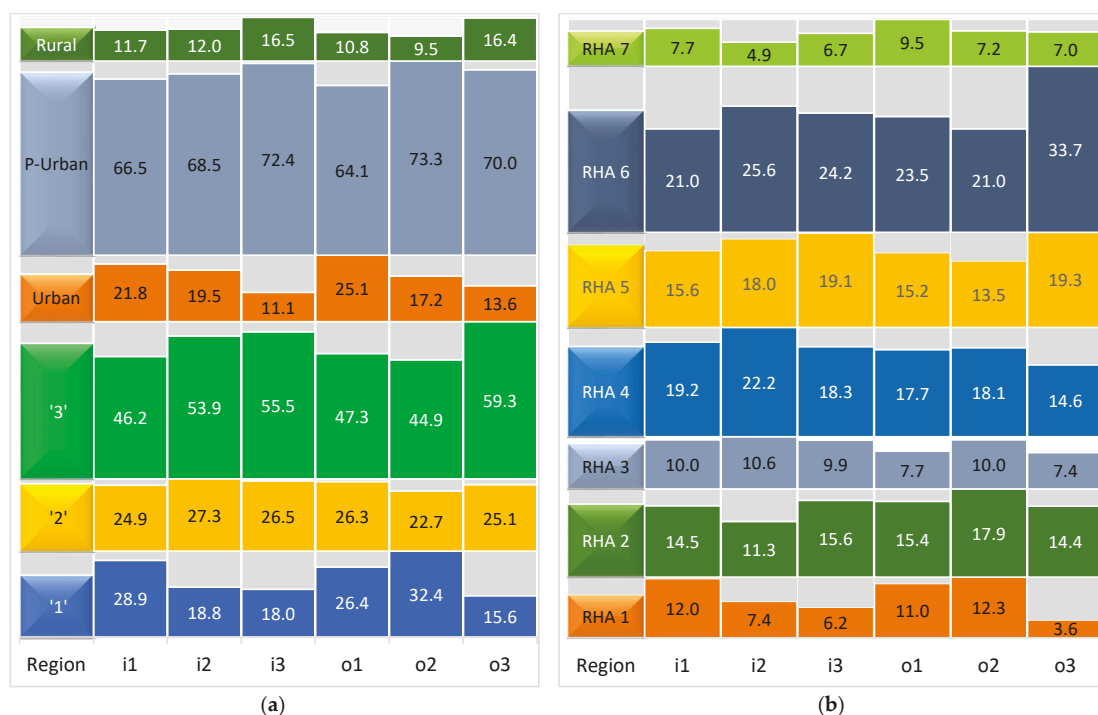


Figure 4. Percentage distribution of Health Center (HC) inputs and outputs across regions categorized by (a) Eurostat's typology ('1', '2', '3') and FAO's classification (rural, peri-urban, urban) and (b) Regional Health Authorities (RHA 1-7).

In contrast, ToMYs, which consist of 94 units, operate on a smaller scale. The average ToMY employs 2.6 medical staff, 3.1 nursing/paramedical staff, and 2.5 administrative staff. The output averages for scheduled visits (4944.7), emergency visits (1025.9), and prescription-related visits (2860.5) are significantly lower than those for HCs. The lower standard deviations and range values for ToMYs reflected more consistency and less variability among these units, suggesting that they are relatively homogeneous in terms

of staffing and patient visits. The maximum number of scheduled visits for ToMYs was 14,161, significantly lower than for HCs, implying a smaller operational scope.

Key observations include the stark difference in scale between the two types of health-care entities, with HCs serving many more patients and employing larger staff teams. HCs also show much greater variability, as indicated by the larger standard deviations and the presence of outliers, especially for scheduled patient visits. ToMYs, though smaller, still contribute substantially in terms of patient care, particularly in terms of prescription visits. The sum values reveal that across all units, HCs manage a total of about 3.7 million scheduled visits, compared to 464,801 for ToMYs, further illustrating the scale disparity. In summary, the statistical data in the table underscore the distinct operational profiles of the larger, more diverse Health Centers (HCs) compared to the smaller, more homogenous Local Health Units (ToMYs). These differences justified treating them as two separate groups in our analysis, as their underlying technologies appeared to differ significantly.

3.2. Global Returns to Scale

Regarding the type of global returns to scale, the application of Simar and Wilson's two-part test (Table 4) resulted in the rejection of both the H_0 ($ts = 1.1526$, p -value < 0.001) and H'_0 ($ts = 1.0256$, p -value $= 0.005$) null hypotheses at the 1% significance level, following 2000 bootstrap replications. Consequently, variable returns to scale (VRS) was considered the appropriate returns to scale type for the underlying technology of the Health Centers under evaluation. Nonetheless, some results under the constant, non-increasing, and non-decreasing returns to scale (CRS, NIRS, NDRS) assumptions are also provided for comparison and completeness.

Table 4. Results of the global returns-to-scale (RTS) determination test for Health Centers (HCs) using a homogenous bootstrap approach ($B = 2000$ replications).

Test	Null vs. Alternative	Statistic (ts_1 , ts_2)	Significance Level	
			$\alpha = 0.01$	$\alpha = 0.05$
test-1	H_0 : CRS H_1 : VRS	1.1526	$p < 0.001$	$p < 0.001$
test-2	H'_0 : NRS H'_1 : VRS	1.0256	$p = 0.005$	$p = 0.0025$

3.3. VRS Results

Table 5 presents DEA VRS results for HCs across various regions, highlighting their pure technical efficiency. The scores indicate how much the output of each unit could be expanded using the same level of inputs, with values closer to 1 representing higher efficiency. The table also includes mean values for uncorrected and bootstrapped (bias-corrected) efficiency scores, along with weighted means, offering insight into the efficiency across different regions and health authority areas.

The overall uncorrected mean efficiency score across all regions was 1.97, indicating that, on average, units could nearly double their outputs while maintaining the same input levels. After applying bootstrapping, the bias-corrected mean efficiency score rose to 2.31, as expected, since standard DEA scores tend to be overly optimistic. A maximum score of 8.04 revealed significant inefficiency in some units, suggesting substantial potential for output increases. The weighted mean efficiency score of 1.92 reflected slightly better performance when output adjustments were considered. In Figure 5b, the ordinary, bootstrapped, and weighted mean VRS scores are depicted across all subdivisions, alongside the CRS scores shown in Figure 5a, while the boxplots in Figure 6 provide a visual representation of the distribution of bootstrapped VRS scores, illustrating the median, quartiles, and potential outliers.

Table 5. Summary statistics of Health Centers' (HCs) VRS bootstrapped efficiency scores, conventional and bootstrapped weighted means, and number and percentage of efficient DMUs. Data are categorized by Eurostat's typology ('1', '2', '3'), FAO classification (urban, peri-urban, rural), and Regional Health Authorities (RHA 1–7).

Region	Mean	Bootstrapped Scores (B = 2000 repls.)					Efficient DMUs		Weighted Mean Eff.
		Mean	StDev	Median	Min	Max	No.	% Total	
All	1.97	2.31	1.13	2.02	1.13	8.04	38	100.00%	1.92
'1'	1.67	1.97	0.92	1.62	1.19	5.05	5	13.20%	1.69
'2'	2.02	2.37	1.21	2.01	1.13	6.19	11	28.90%	1.99
'3'	2.02	2.37	1.13	2.10	1.16	8.04	22	57.90%	2.00
Urban	1.52	1.79	0.82	1.36	1.19	4.18	6	15.80%	1.51
P-Urban	1.91	2.23	0.98	2.01	1.13	6.63	25	65.80%	1.94
Rural	2.39	2.83	1.48	2.25	1.22	8.04	7	18.40%	2.42
RHA 1	1.30	1.51	0.32	1.45	1.19	2.23	1	2.60%	1.51
RHA 2	1.98	2.32	1.24	1.78	1.20	6.63	7	18.40%	1.83
RHA 3	2.04	2.35	0.72	2.38	1.21	3.67	2	5.30%	2.12
RHA 4	2.31	2.67	1.30	2.37	1.17	6.19	2	5.30%	2.24
RHA 5	2.06	2.41	1.07	2.24	1.13	5.92	6	15.80%	2.05
RHA 6	1.88	2.24	1.15	2.01	1.16	8.04	16	42.10%	1.86
RHA 7	1.59	1.89	0.77	1.54	1.22	3.55	4	10.50%	1.64

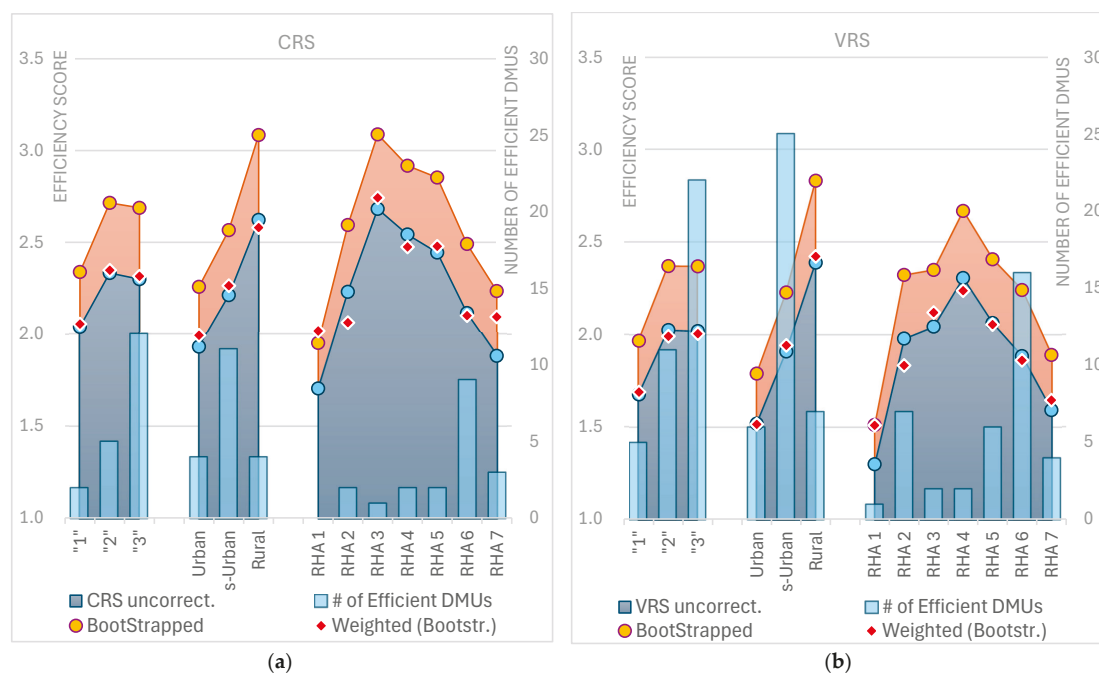


Figure 5. Comparison of the number of efficient Health Centers (HCs) and mean efficiency scores across regions. The graphs display the ordinary (uncorrected), bootstrapped (corrected), and weighted mean efficiency scores for (a) constant returns to scale (CRS) and (b) variable returns to scale (VRS). Regions are categorized according to Eurostat's typology ('1', '2', '3'), FAO's classification (urban, peri-urban, rural), and Regional Health Authorities (RHA 1–7).

Examining the regions, Region '1' had the lowest weighted mean efficiency score, with 1.69, implying that its units could enhance their outputs by 69%. The region's lower maximum value (5.05) and smaller standard deviation suggested more consistent performance. In contrast, while Region '3' had a weighted mean efficiency score of 2.00, indicating higher inefficiency, 57.9% of the efficient units were still located in this region. However, the maximum value of 8.04 for Region '3' highlighted notable inefficiencies among some units.

Regarding urbanization levels, urban areas exhibited the highest efficiency, with a weighted mean score of 1.52. The low standard deviation and maximum score of 4.18 re-

flected more consistent performance. Peri-urban areas showed higher inefficiency, with a weighted mean score of 1.94 and greater variation in performance, while rural areas exhibited the highest inefficiency, with a weighted mean score of 2.42. This indicates significant potential for output improvement across all non-urban areas.

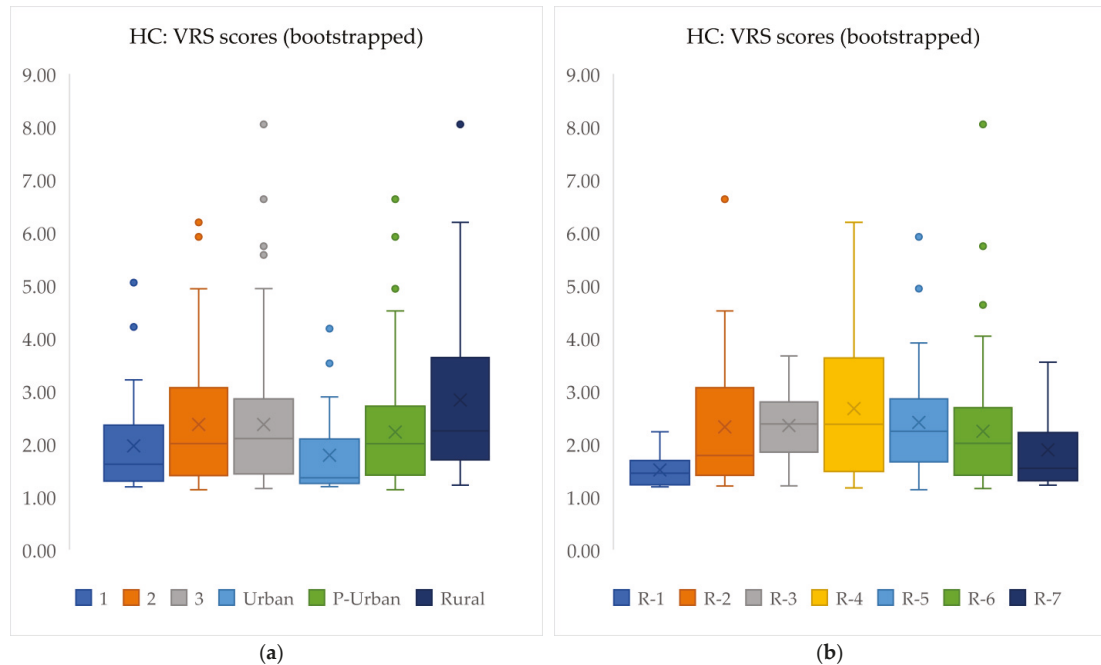


Figure 6. Boxplots of bootstrapped VRS efficiency scores for Health Centers (HCs) across regions. Panel (a) shows distributions categorized by Eurostat's typology ('1', '2', '3') and FAO's classification (urban, peri-urban, rural), while panel (b) presents distributions by Regional Health Authorities (RHA 1–7).

At the level of Regional Health Authorities, RHA 1 showed the highest efficiency with a mean score of 1.30, meaning that outputs could be increased by 30%. However, this region had only one efficient unit, indicating that few units reached top performance. In contrast, RHA 6 had a mean score of 1.88, suggesting great potential for output improvement, even though it hosted 42.1% of all efficient units. RHA 4 had the highest bootstrapped mean score (2.67), indicating greater inefficiency and variability among its units.

Similarly, Table 6 shows the corresponding figures for ToMYs across the seven Regional Health Authorities (RHAs). Overall, the mean efficiency score was 1.74, indicating that, on average, units could increase their outputs by 74%. The bootstrapped mean rose to 1.98, and the maximum score of 10.55 highlighted significant inefficiencies in certain units. The weighted mean of 1.58 reflected slightly better performance when adjusted for outputs. Since the weighted mean efficiency scores accounted for output levels, the lower score suggests that, on average, larger or higher-output units tend to be more efficient than smaller ones.

The standard deviation of 1.60 for RHA 5, one of the highest among RHAs, highlighted considerable variability in efficiency across its units. This suggested that while some units in RHA 5 performed near the average, others were significantly inefficient. Similarly, RHA 6 showed high variability, with a StDev of 1.83, further evidenced by its maximum score of 10.55, indicating significant disparities in efficiency within the region. In contrast, RHA 1 and RHA 7 exhibited more consistent performance, with lower standard deviations of 0.59 and 0.73, respectively, suggesting less variation in efficiency across their units. These findings suggest that regions with higher variability, such as RHA 5 and RHA 6, may require more targeted interventions to address inefficiencies, whereas RHA 1 and RHA 7 demonstrate more uniform, though still improvable, performance. In Figure 7, the mean values of ordinary (uncorrected) CRS/VRS scores and bias-corrected scores derived from

Simar and Wilson’s bootstrap method are presented, both unweighted and weighted, for the seven Regional Health Authorities. The number of efficient facilities per RHA is shown as bars superimposed on the graph.

Table 6. Summary statistics of ToMYs’ VRS bootstrapped efficiency scores, conventional and bootstrapped weighted means, and number and percentage of efficient DMUs. Data are categorized by Regional Health Authorities (RHA 1–7).

RHA	Mean	Bootstrapped Scores (B = 2000 repls.)					Efficient DMUs		Weighted Mean Eff.
		Mean	StDev	Median	Min	Max	No.	% Total	
All	1.74	1.98	1.33	1.48	1.11	10.55	26	100.00%	1.58
RHA 1	1.41	1.60	0.59	1.32	1.13	3.03	3	11.50%	1.46
RHA 2	1.48	1.70	0.65	1.48	1.11	3.53	6	23.10%	1.55
RHA 3	1.64	1.87		1.87	1.87	1.87	0	0.00%	1.87
RHA 4	1.65	1.88	0.95	1.52	1.13	3.94	3	11.50%	1.55
RHA 5	2.08	2.36	1.60	1.59	1.14	6.54	4	15.40%	1.69
RHA 6	1.91	2.19	1.83	1.51	1.15	10.55	7	26.90%	1.63
RHA 7	1.58	1.77	0.73	1.38	1.16	3.03	3	11.50%	1.48

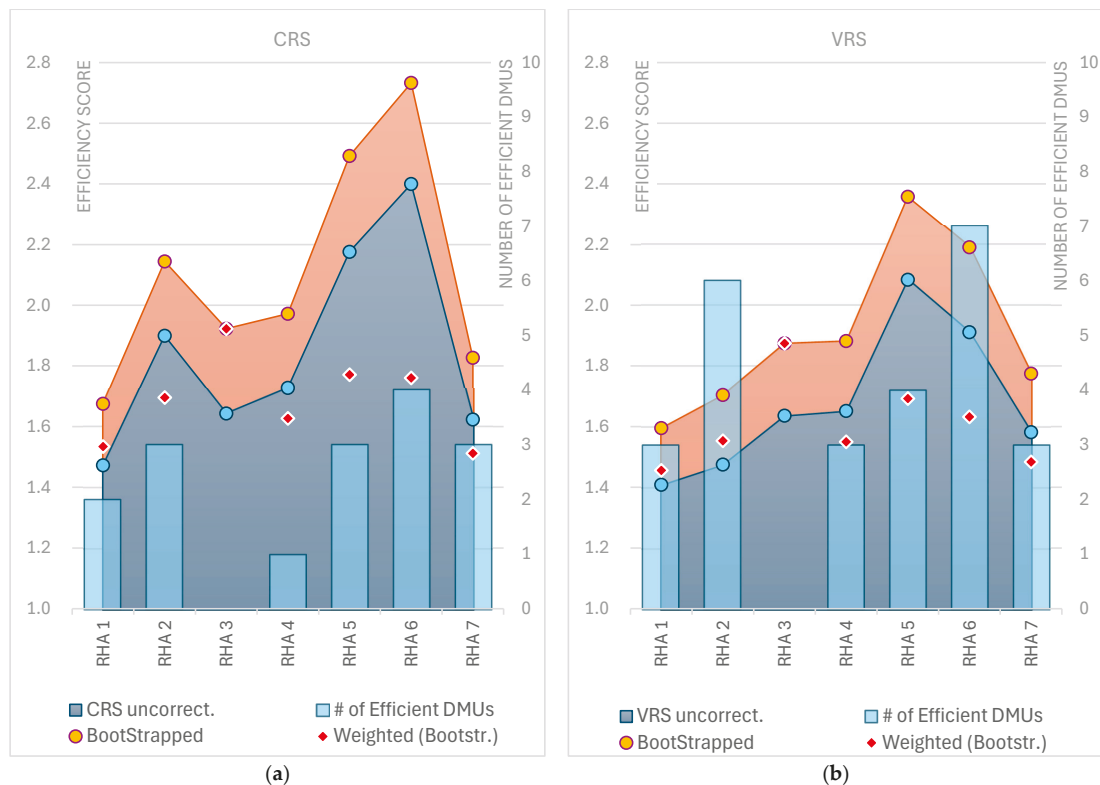


Figure 7. Comparison of the number of efficient ToMYs and mean efficiency scores across RHAs. The graphs display ordinary (uncorrected), bootstrapped (corrected), and weighted mean efficiency scores for (a) constant returns to scale (CRS) and (b) variable returns to scale (VRS) across Regional Health Authorities (RHA 1–7).

3.4. Super-Efficiency, Benchmarks, and Peer Counts

Table 7 presents the super-efficiency, output-oriented DEA scores for Health Centers, listing all of them that were super-efficient in at least one of the four models: (CRS), (VRS), (NIRS), and (NDRS). In an output-oriented framework, a super-efficiency score below 1 reflects the distance of a unit from the “reduced” efficiency frontier, which is formed by excluding that unit. In essence, this score indicates the extent of a unit’s superior

performance relative to all other units that reside on the frontier. The DMUs in the table are ranked according to their super-efficiency scores in the VRS model, with additional columns showing peer counts and relative ranks (based on super-efficiency scores) across all four models.

Table 7. Super-efficiency scores of efficient HCs, relative ranks, and peer counts as benchmarks under four different returns-to-scale (RTS) assumptions. The table is ordered in ascending order based on VRS ranks. Minimum and maximum values are denoted in bold.

DMU	Super-Eff CRS		Peer Count	Super-Eff VRS		Peer Count	Super-Eff NDRS		Peer Count	Super-Eff NIRS		Peer Count
	Score	Rank		Score	Rank		Score	Rank		Score	Rank	
D-199	0.956	19	0	-	1	34	-	1	34	0.956	26	0
D-212				-	1	11	-	1	11			
D-041				0.071	3	2	0.071	3	2			
D-184				0.211	4	2	0.211	4	2			
D-168	0.838	10	5	0.310	5	3	0.310	5	5	0.838	14	3
D-043				0.314	6	0	0.314	6	0			
D-243				0.391	7	2	0.391	7	2			
D-153				0.393	8	16	0.393	8	16			
D-173	0.476	1	108	0.412	9	61	0.412	9	103	0.476	1	66
D-048	0.745	7	33	0.428	10	14	0.428	10	35	0.745	8	12
D-159	0.598	3	67	0.550	11	62	0.598	13	61	0.550	2	68
D-172	0.611	4	94	0.555	12	66	0.555	11	94	0.611	5	66
D-037	0.614	5	66	0.590	13	69	0.614	14	61	0.590	3	74
D-252	0.596	2	70	0.594	14	70	0.594	12	67	0.596	4	73
D-178	0.798	9	9	0.623	15	3	0.623	15	8	0.798	13	4
D-256	0.695	6	97	0.682	16	70	0.695	17	94	0.682	6	73
D-211				0.693	17	0	0.693	16	0			
D-035				0.739	18	31				0.739	7	31
D-058				0.774	19	29				0.774	9	29
D-093	0.795	8	22	0.775	20	16	0.775	18	22	0.795	12	16
D-189	0.868	11	5	0.780	21	1	0.868	21	4	0.780	10	2
D-166	0.871	13	59	0.781	22	81	0.871	22	56	0.781	11	84
D-111	0.875	14	2	0.791	23	3	0.791	19	2	0.875	19	3
D-044				0.842	24	8				0.842	15	8
D-225	0.869	12	32	0.852	25	18	0.852	20	35	0.869	18	14
D-057	0.879	16	43	0.853	26	33	0.879	25	38	0.853	16	38
D-007				0.858	27	9				0.858	17	9
D-260	0.876	15	48	0.875	28	23	0.876	24	47	0.875	20	24
D-162	0.888	17	7	0.876	29	1	0.876	23	5	0.888	23	3
D-028				0.885	30	21				0.885	21	21
D-155	0.920	18	3	0.885	31	5	0.920	26	1	0.885	22	7
D-203				0.910	32	25				0.910	24	25
D-120				0.924	33	8				0.924	25	8
D-262				0.959	34	1	0.959	27	1			
D-133				0.965	35	3				0.965	27	3
D-238				0.982	36	3				0.982	28	3
D-176				0.992	37	1				0.992	29	1
D-152				0.999	38	2				0.999	30	2
# DMUs		19			38			27			30	

Note: Min and max scores are shown in bold.

First, The VRS super-efficiency scores ranged from 0.071 to 0.999, indicating a wide variability in the efficiency levels of the HCs. The highest-ranked unit in the VRS model was D-041, with a score of 0.071, indicating exceptional super-efficiency. Closely following was D-184, with a VRS score of 0.211, further demonstrating a high level of efficiency. Both units served as benchmarks for other inefficient units. However, they each acted as peers for only two other units, which may indicate that while they exhibit strong individual performance, their specific operational characteristics may not be as broadly applicable to improving the efficiency of other units.

HCs with high peer counts, such as D-173 (108 peers under CRS) and D-159 (67 peers), served as key benchmarks for other less efficient units. These HCs set the standard for performance, being frequently referenced by other units for comparison. In contrast, HC D-173, while ranking ninth in VRS with a score of 0.412, had a notable peer count of

61, indicating its significant influence as a benchmark. Similarly, D-159 (ranked 11th in VRS) and D-048 (ranked 10th) had significant peer counts, influencing 62 and 14 units, respectively, indicating their strategic importance within the system despite their mid-range VRS rankings.

Some DMUs, like D-048 and D-178, showed high super-efficiency scores despite lower peer counts, indicating that while less frequently used as benchmarks, their output performance was still exceptional. The variation in super-efficiency scores illustrates the differing capacities of DMUs to increase output, with units like D-238 (0.982) and D-176 (0.992) having limited room for further output increases compared to top-ranked units like D-173 and D-159. Overall, the analysis identified top performers and key benchmarks while highlighting the variation in super-efficiency across different models.

In the table, DMUs D-199 and D-212 have missing super-efficiency scores under the VRS model because the linear programming (LP) problem was not solvable, resulting in an infeasible solution. This issue typically arises when the DMU in question lies on the boundary of the efficiency frontier and removing it from the reference set causes the LP model to lack a feasible reference point for comparison. Essentially, this means that the DMU is located in an “area” where no other units can serve as a benchmark to evaluate its performance under the VRS assumption.

3.5. FDH Results

The Free Disposal Hull (FDH) scores presented in Table 8 provide a detailed analysis of output-oriented efficiency across different regions. Looking at all DMUs, the average FDH score was 1.34, indicating that, on average, DMUs operated 34% away from the efficient frontier, which implied a significant degree of inefficiency in terms of output generation. The bootstrapped mean score of 1.51 (with a standard deviation of 0.56) further highlighted the considerable variation in efficiency across DMUs, with some units significantly underperforming. Among the 234 DMUs analyzed, 115 were classified as efficient, yet only 35 of them served as benchmarks for the remaining 119 inefficient DMUs. The weighted mean efficiency of 1.39 reinforced the fact that although a large proportion of DMUs operated inefficiently, a few highly efficient units helped balance the overall efficiency.

Table 8. Summary statistics of Health Centers’ (HCs) FDH bootstrapped efficiency scores, conventional and bootstrapped weighted means, and number and percentage of efficient and benchmark DMUs. Data are categorized by Eurostat’s typology (‘1’, ‘2’, ‘3’), FAO classification (urban, peri-urban, rural), and Regional Health Authorities (RHA 1–7).

Region	Mean	Bootstrapped Scores (B = 2000 repls.)					Efficient DMUs		Benchmarks		Weighted Mean Eff.
		Mean	StDev	Median	Min	Max	No.	% Total	No.	Peer Count	
All	1.34	1.51	0.56	1.22	1.09	4.28	115	100.0%	35	119	1.39
‘1’	1.25	1.41	0.45	1.20	1.10	2.89	19	16.5%	3	21	1.31
‘2’	1.40	1.58	0.67	1.22	1.09	4.28	33	28.7%	6	12	1.43
‘3’	1.33	1.50	0.52	1.22	1.09	3.47	63	54.8%	26	86	1.41
Urban	1.17	1.33	0.31	1.20	1.10	2.26	15	13.0%	4	24	1.25
P-Urban	1.34	1.51	0.57	1.22	1.09	4.28	77	67.0%	24	68	1.41
Rural	1.41	1.59	0.60	1.22	1.13	3.45	23	20.0%	7	27	1.48
RHA 1	1.05	1.18	0.10	1.15	1.11	1.44	6	5.2%	0	0	1.18
RHA 2	1.30	1.47	0.55	1.21	1.10	3.44	19	16.5%	2	22	1.33
RHA 3	1.49	1.64	0.47	1.68	1.13	3.07	3	2.6%	2	2	1.54
RHA 4	1.53	1.71	0.69	1.33	1.09	3.45	19	16.5%	5	11	1.55
RHA 5	1.39	1.55	0.67	1.25	1.09	4.28	14	12.2%	2	4	1.47
RHA 6	1.24	1.42	0.43	1.22	1.09	3.31	44	38.3%	20	63	1.33
RHA 7	1.21	1.39	0.47	1.21	1.12	2.69	10	8.7%	4	17	1.29

Regionally, there were clear distinctions. Region ‘2’ demonstrated the highest mean FDH score (1.40), indicating relatively lower efficiency, with the bootstrapped mean score

of 1.58 and the highest standard deviation of 0.67 reflecting significant variation in performance across DMUs within this region. Conversely, Region '1' showed the lowest mean FDH score (1.25), making it the most efficient region on average. However, despite its higher efficiency, Region '1' did not serve as a major source of benchmarks for other regions as it had a smaller number of efficient DMUs compared to Region '2'.

When comparing the different areas according to FAO classification, urban DMUs exhibited the highest efficiency, with a mean FDH score of 1.17, suggesting that urban centers, on average, need only a 17% increase in their current output levels to reach the efficiency frontier, making them the most efficient category. The bootstrapped scores for urban DMUs also showed the lowest variability (StDev = 0.31), implying greater consistency in efficiency across urban units. Suburban and rural DMUs had similar mean FDH scores of 1.34 and 1.41, respectively, but rural DMUs showed more variability in their performance, as indicated by the wide range of bootstrapped scores (from 1.13 to 3.45).

Among the Regional Health Authorities, RHA 4 and RHA 5 stood out for their relatively low efficiency, with mean FDH scores of 1.53 and 1.39, respectively. The high standard deviations in the bootstrapped scores for these regions suggested significant variation within them. On the other hand, RHA 1 was the most efficient, with a mean FDH score of 1.05 and very little variability (StDev = 0.10). Despite its high efficiency, RHA 1 did not provide any benchmark DMUs, indicating that it may not be heavily relied upon as a reference point for other inefficient DMUs in the dataset. Figure 8a presents the visualization of ordinary (uncorrected) FDH scores averaged across areas categorized by Eurostat's typology ('1', '2', '3'), FAO's classification (urban, peri-urban, rural), and Regional Health Authorities (RHA 1–7), alongside the bootstrapped bias-corrected scores in both unweighted and weighted forms. Additionally, Figure 8b displays the total number of efficient facilities, along with the subset that served as benchmarks.

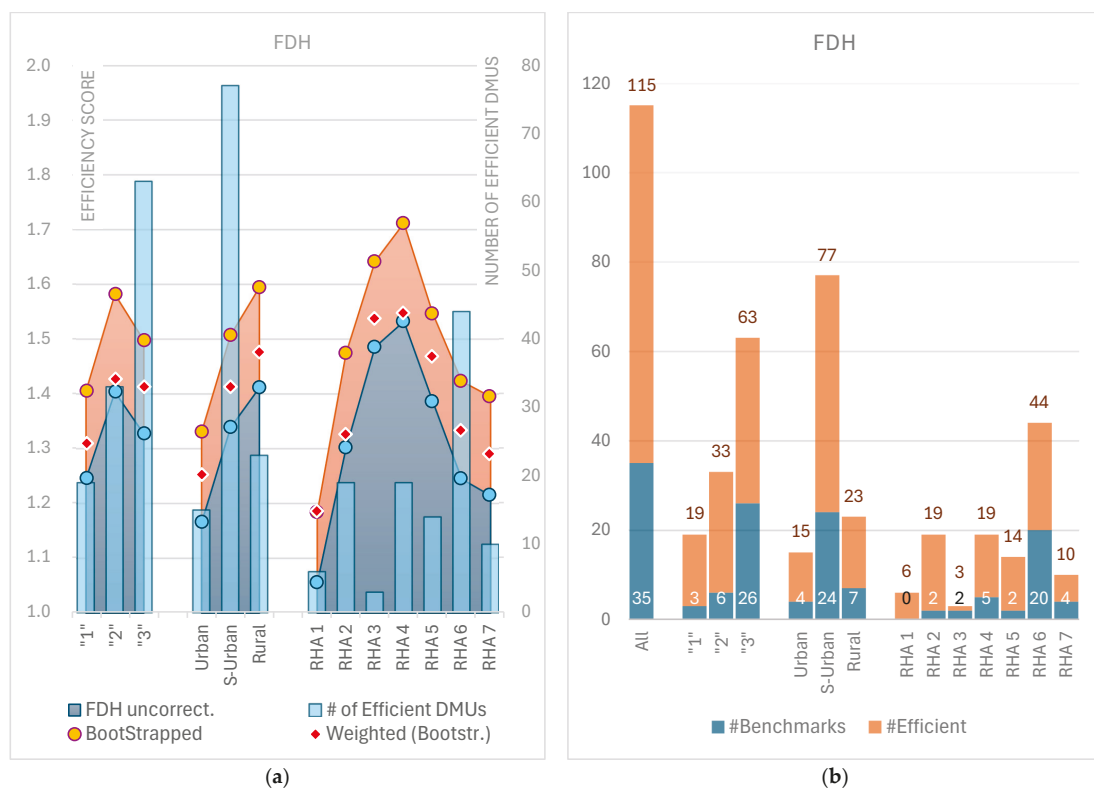


Figure 8. Distribution of Health Center (HC) FDH efficiency and benchmark units across regions, categorized by Eurostat's typology ('1', '2', '3'), FAO's classification (urban, peri-urban, rural), and Regional Health Authorities (RHA 1–7). Panel (a) shows the number of efficient facilities alongside the ordinary (uncorrected), bootstrapped (corrected), and weighted mean FDH scores. Panel (b) presents the count and percentage of efficient HCs that served as benchmarks.

On an individual basis, Table 9 provides an overview of the 35 Health Centers identified as benchmark units under FDH, alongside the frequency of their appearances as peers for inefficient units. These data points are categorized by Eurostat regions ('1', '2', '3'), FAO urbanization levels (urban, p[eri]-urban, rural), and Regional Health Authorities (RHA 1–7). The shaded cells in each row indicate the region of origin for the corresponding benchmark unit, offering a visual representation of the subcategory source and its respective RHA. The table also summarizes the total number of peer appearances for all benchmark units and the number of benchmarks within each subcategory.

Table 9. Frequency distribution of Free Disposal Hull (FDH) benchmark appearances as peers for Health Centers (HCs) across regions, categorized by Eurostat's typology ('1', '2', '3'), FAO's classification (urban, peri-urban, rural), and Regional Health Authorities (RHA 1–7).

Count	Benchmark	Number of Benchmark Appearances as Peers													
		All	'1'	'2'	'3'	Urban	P-Urban	Rural	Regional Health Authority						
									1	2	3	4	5	6	7
1	D-037	19	5	3	11	.	18	1	1	2	5	4	5	4	2
2	D-260	11		4	7		6	5		4		2		4	1
3	D-172	10		3	7		8	2		1	2	2	1	3	
4	D-203	9		3	6	1	8				1	4	1		
5	D-173	8		2	6		5	3					1	7	
6	D-166	6		3	3		6			1	1	1	2	1	
7	D-225	5		2	3	2	2	1				3	1	1	
8	D-178	4		1	3		1	3		1			1	2	
9	D-252	4	3	.	1		3	1	1			3			.
10	D-028	3		2	1		3			.			2		1
11	D-091	3			3		3			2	1	.			
12	D-092	3	1		2		3			1			1	1	
13	D-152	3		1	2	1	2				1	1	1		
14	D-104	2			2		1	1				.	1	1	
15	D-118	2		1	1	1	1				1	.		1	
16	D-208	2		2	.		1	1				1		1	
17	D-210	2			2	1	1						2	.	
18	D-222	2		1	1		2	.					1	1	
19	D-223	2			2		.	2						2	
20	D-232	2		.	2		1	1				1		.	1
21	D-236	2		1	1		.	2					1	1	
22	D-238	2	2		.	2			1			1		.	
23	D-057	1	.	1			1				.		1		
24	D-058	1	1				1		1		.				
25	D-088	1			1		.	1		1		.			
26	D-159	1		1	.	1							.	1	
27	D-162	1			1			1						1	
28	D-168	1			1			1					1	.	
29	D-176	1			1		1			1				.	
30	D-183	1			1		1				1			.	
31	D-211	1		.	1		.	1				1		.	
32	D-216	1		.	1		1						1	.	
33	D-233	1			1		.	1					1	.	
34	D-250	1			1		1	.						1	.
35	D-253	1	1	.			1	.				1			.
Total	Appearances	119	13	31	75	9	82	28	4	14	13	25	25	33	5
	Benchmarks	35	3	6	26	4	24	7	0	2	2	5	2	20	4

Note: The shaded cells in each row indicate the sub(category) of origin (i.e., column header) for the corresponding benchmark unit.

D-037 stood out as the most frequently cited benchmark unit, appearing 19 times as a peer for inefficient Health Centers. This unit primarily originated from Region '3' and peri-urban areas, with significant representation across five RHAs, particularly RHAs 3 and 5. Other notable benchmark units included D-260 and D-172, which appeared 11 and 10 times, respectively, and were also from Region '3'. The fact that Region '3' contributed the largest number of benchmarks, with 26 units, indicates that this region hosts many of the most efficient production units, making it a focal point for operational learning and

model replication. Conversely, Regions ‘1’ and ‘2’ had a smaller number of benchmark units, with only 3 and 6 benchmarks, respectively.

Peri-urban areas were the largest contributors, with 24 benchmark units, highlighting that these areas have found an optimal balance between operational complexity and resource management. This balance made peri-urban areas more likely to serve as benchmarks for less efficient units. By contrast, urban areas contributed only four benchmarks, while rural areas provided seven, suggesting that strategies implemented in peri-urban areas may be more adaptable and scalable across different settings. RHA 6 led in benchmark contributions with 20 units, signaling that its operational practices could serve as effective models for other RHAs. On the other hand, RHA 1, with no benchmarks, and RHA 7, with only four, showed room for significant improvement.

Similarly, Table 10 presents output-oriented FDH efficiency scores for ToMYs across the seven RHAs. The mean FDH score of 1.36 indicated a moderate level of inefficiency, suggesting that ToMYs have the potential to increase output by 36% with their existing resources. The bootstrapped mean score of 1.55, with a standard deviation of 0.81, highlighted significant variability in efficiency across DMUs. Bootstrapped scores ranged from 1.08 to 6.58, revealing both highly efficient and substantially inefficient units. Despite this, 52 DMUs were classified as efficient, though only 15 of these served as benchmarks for the remaining 42 units. The weighted mean efficiency score of 1.34 further supported the conclusion that while some DMUs perform well, there is considerable room for overall improvement.

Table 10. Summary statistics of ToMYs’ FDH bootstrapped efficiency scores, conventional and bootstrapped weighted means, and number and percentage of efficient and benchmark DMUs. Data are categorized by Regional Health Authorities (RHA 1–7).

Region	Mean	Bootstrapped Scores (B = 2000 repls.)					Efficient DMUs		Benchmarks		Weighted Mean Eff.
		Mean	StDev	Median	Min	Max	No.	% Total	No.	Peer Count	
All	1.36	1.55	0.81	1.21	1.08	6.58	52	100.0%	15	42	1.34
RHA 1	1.25	1.42	0.39	1.22	1.14	2.25	6	11.5%	2	6	1.34
RHA 2	1.16	1.33	0.41	1.21	1.08	2.83	9	17.3%	2	7	1.27
RHA 3	1.64	1.82		1.82	1.82	1.82	0	0.0%	0	0	1.82
RHA 4	1.30	1.47	0.66	1.20	1.09	3.47	7	13.5%	1	1	1.31
RHA 5	1.61	1.83	1.06	1.22	1.16	4.12	8	15.4%	5	20	1.43
RHA 6	1.45	1.63	1.05	1.20	1.10	6.58	18	34.6%	4	6	1.34
RHA 7	1.25	1.41	0.36	1.24	1.15	2.08	4	7.7%	1	2	1.28

RHA 2 stood out as the most efficient, with a mean FDH score of 1.16, indicating that ToMYs in this region operate near the efficiency frontier. Its bootstrapped mean of 1.33 and low standard deviation (0.41) further suggested consistent performance. In contrast, RHA 3 was the least efficient, with a mean FDH score of 1.64 and no efficient DMUs, indicating significant inefficiencies and a lack of benchmarks for other regions.

RHA 5 and RHA 6 also exhibited high inefficiency, with mean FDH scores of 1.61 and 1.45, respectively. RHA 6, in particular, showed a wide range of bootstrapped scores (from 1.10 to 6.58), highlighting significant disparities in performance among its units. Despite having the most efficient DMUs (18 units), only 4 of these served as benchmarks, suggesting that these high-performing units are underutilized for broader improvement efforts. In contrast, RHA 1 and RHA 2 demonstrated more consistent performance, with mean FDH scores of 1.25 and 1.16, respectively, and a higher proportion of efficient DMUs. Notably, in RHA 5, five benchmark units served as peers for 20 inefficient DMUs across all RHAs.

The 15 benchmark units are listed in Table 11 along with their frequency of appearance as peers for inefficient units across the seven RHAs. Again, the shaded cells indicate the region of their origin, and the total numbers of peer appearances and benchmarks per RHA are summarized at the bottom.

Table 11. Frequency distribution of Free Disposal Hull (FDH) benchmark appearances as peers for ToMYs across Regional Health Authorities (RHA 1–7).

Count	Benchmark	Number of Benchmark Appearances as Peers							
		ALL	Regional Health Authority (RHA/YPE)						
			1	2	3	4	5	6	7
1	TM-047	10		1	1	3	2	3	
2	TM-021	6	2	2			1	1	
3	TM-010	4					2		2
4	TM-051	4					2	2	
5	TM-054	4		1		1		2	
6	TM-073	3		2				1	
7	TM-006	2	1	1					
8	TM-091	2						1	1
9	TM-016	1						1	
10	TM-042	1				1			
11	TM-045	1						1	
12	TM-048	1	1						
13	TM-064	1	1						
14	TM-069	1							1
15	TM-084	1		1					
Total	Appearances	42	5	8	1	5	7	12	4
	Benchmarks	15	2	2	0	1	5	4	1

Note: The shaded cells in each row indicate the sub(category) of origin (i.e., column header) for the corresponding benchmark unit.

TM-047, originating from RHA 5, was the most frequently cited benchmark, appearing 10 times as a peer across all regions except 1 and 7. TM-021 (from RHA 2) followed with six appearances, spanning RHA 1, 2, 5 and 6. These benchmarks demonstrated high versatility and performance across regions.

RHA 5 emerged as a top performer, with five benchmark units and 20 peer appearances, indicating strong operational efficiency. RHA 6 also stood out, with four benchmark units that appeared six times as peers, though only one of these served as a peer within its own RHA, despite a total of 12 peer appearances.

3.6. Kruskal–Wallis Test

Table 12 presents the results of Kruskal–Wallis and median tests applied to all models—CRS, VRS, IRS, DRS, and FDH—both in their conventional form and bootstrapped versions. These tests assessed whether there were statistically significant differences across regions ('1', '2', '3'), urbanization levels (urban, peri-urban, rural), and Regional Health Authorities (RHA 1–7). The Kruskal–Wallis test showed significant differences in the DRS model for regions, with a p -value of 0.05, indicating regional variations in efficiency with the decreasing returns to scale model. The bootstrapped DRS version showed near significance ($p = 0.06$), suggesting potential regional differences. For urbanization levels, both VRS and DRS models revealed significant differences, with p -values < 0.001 , indicating strong efficiency variation between urban, peri-urban, and rural units, confirmed by the bootstrapped results. Similarly, the analysis of RHAs showed significant differences in the FDH ($p = 0.01$) and VRS ($p = 0.02$) models, reflecting efficiency variations across RHAs. Bootstrapped results for FDH, VRS, and DRS further reinforced these findings, with consistently significant p -values.

Table 12. Kruskal–Wallis and median test results for HCs across DEA and FDH (conventional and bootstrapped) models. Tests assessed efficiency score differences across regions, categorized by Eurostat’s typology (‘1’, ‘2’, ‘3’), FAO’s classification (urban, peri-urban, rural), and Regional Health Authorities (RHA 1–7).

(Sub)Categories Tested		CRS	VRS	IRS	DRS	FDH	Bootstrapped				
							CRS	VRS	IRS	DRS	FDH
Kruskal–Wallis test											
‘1’, ‘2’, ‘3’	χ^2 (df = 2)	1.97	3.89	0.93	5.92	1.56	2.31	4.80	1.52	5.76	4.85
	p-value	0.37	0.14	0.63	0.05	0.46	0.32	0.09	0.47	0.06	0.09
Urban, P-Urban, Rural	χ^2 (df = 2)	6.05	12.40	3.17	18.28	3.28	6.15	16.34	4.33	19.10	5.03
	p-value	0.05	0.00	0.21	0.00	0.19	0.05	0.00	0.12	0.00	0.08
RHA 1, 2, 3, 4, 5, 6, 7	χ^2 (df = 6)	10.60	15.20	12.52	14.89	16.37	9.05	14.59	9.52	14.40	16.95
	p-value	0.10	0.02	0.05	0.02	0.01	0.17	0.02	0.15	0.03	0.01
Median test											
‘1’, ‘2’, ‘3’	χ^2 (df = 2)	1.65	5.98	1.65	5.54	1.65	1.39	5.98	1.39	5.54	4.23
	p-value	0.44	0.05	0.44	0.06	0.44	0.50	0.05	0.50	0.06	0.12
Urban, P-Urban, Rural	χ^2 (df = 2)	0.71	5.76	0.35	10.47	2.00	1.28	9.32	1.28	10.47	3.63
	p-value	0.70	0.06	0.84	0.01	0.37	0.53	0.01	0.53	0.01	0.16
RHA 1, 2, 3, 4, 5, 6, 7	χ^2 (df = 6)	8.12	10.87	8.05	11.45	15.92	8.12	12.55	8.11	13.05	13.79
	p-value	0.23	0.09	0.23	0.08	0.01	0.23	0.05	0.23	0.04	0.03

In the median test, the VRS model showed significant regional differences ($p = 0.05$), while the DRS model approached significance ($p = 0.06$), indicating potential regional efficiency variation. For urbanization levels, DRS showed significant differences ($p = 0.01$), suggesting that efficiency varied notably between urban, peri-urban, and rural units, which was confirmed by the bootstrapped results. Regarding RHAs, FDH ($p = 0.01$), VRS ($p = 0.05$), and DRS ($p = 0.04$) all showed significant differences, with bootstrapped results supporting these findings.

3.7. Scale Efficiency

The summary statistics of scale efficiency scores for Health Centers (HCs) and Local Health Centers (ToMYs) in Tables 13 and 14 offered insights into how efficiently—on average—these units operated relative to their optimal size (MPSS). A score of 1 indicated full scale efficiency, while values greater than 1 suggested inefficiency, which could be caused by operating either above or below the optimal scale.

Table 13. Summary tsatistics of scale efficiency scores for Health Centers (HCs) across regions categorized by Eurostat’s typology, FAO’s classification, and Regional Health Authorities (RHA 1–7).

Statistic	All	‘1’	‘2’	‘3’	Urban	P-Urban	Rural	Regional Health Authority (RHA/YPE)						
								1	2	3	4	5	6	7
Mean	1.17	1.23	1.18	1.15	1.30	1.16	1.12	1.34	1.17	1.29	1.09	1.18	1.15	1.21
StDev	0.27	0.29	0.29	0.25	0.33	0.25	0.28	0.31	0.29	0.32	0.13	0.25	0.28	0.35
Median	1.05	1.09	1.06	1.05	1.24	1.05	1.04	1.24	1.05	1.15	1.05	1.09	1.04	1.04
Min	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.03	1.00	1.00	1.00	1.00	1.00	1.00
Max	2.71	2.12	2.44	2.71	1.98	2.44	2.71	1.80	2.44	2.12	1.76	2.12	2.71	2.12
Weighted mean	1.19	1.24	1.21	1.15	1.35	1.17	1.08	1.36	1.15	1.25	1.11	1.19	1.16	1.30

Note: Classifications ‘1’, ‘2’, and ‘3’ according to Eurostat (‘1’ = urban areas, ‘2’ = intermediate areas, ‘3’ = rural areas); classifications ‘urban’, ‘p[er]i-urban’, and ‘rural’ according to FAO.

Table 14. Summary statistics of scale efficiency scores for ToMYs across Regional Health Authorities (RHA 1–7).

Statistic	All	Regional Health Authority (RHA/YPE)						
		1	2	3	4	5	6	7
Mean	1.20	1.04	1.39	1.00	1.06	1.04	1.33	1.02
StDev	0.66	0.07	1.07		0.08	0.04	0.81	0.03
Median	1.02	1.00	1.05	1.00	1.00	1.03	1.03	1.01
Min	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Max	5.43	1.22	5.43	1.00	1.25	1.16	4.02	1.07
Weighted mean	1.06	1.04	1.10	1.00	1.05	1.03	1.08	1.01

The mean scale efficiency score across all HCs was 1.17, showing that, on average, Health Centers operate at 17% inefficiency relative to their optimal scale. This inefficiency was further highlighted by the weighted mean of 1.19, suggesting that larger or higher output centers tend to be slightly less efficient overall. The median score of 1.05 indicated that most centers were relatively close to the optimal scale, but the maximum score of 2.71 revealed the presence of highly inefficient outliers, particularly in ‘3’/Rural/RHA 6 regions. Urban Health Centers exhibited the highest mean score of 1.30, reflecting the challenges of scale in larger, more complex centers. Conversely, peri-urban (mean 1.16) and rural centers (mean 1.12) demonstrated somewhat better efficiency, though rural centers still showed some inefficiencies, likely related to resource constraints in smaller, isolated populations.

Variability in scale efficiency was also notable. The standard deviation for all HCs was 0.27, with urban centers showing the highest variability (StDev = 0.33), highlighting substantial variations in the efficiency with which these larger centers operate at scale. Among the Regional Health Authorities, RHA 7 showed the highest variability (StDev = 0.35), while RHA 4 exhibited the least (StDev = 0.13), suggesting that some regions have more consistent performance while others vary greatly in efficiency.

The findings for Local Health Centers (ToMYs) presented a similar trend. The overall mean scale efficiency score for ToMYs was 1.20, whereas the weighted mean was lower, at 1.06. This discrepancy suggested that smaller or lower-output units may have been less efficient on average, pulling up the mean score, while larger or higher-output units tended to perform closer to the optimal scale, leading to a lower weighted mean score. The weighted mean accounted for the size and output of the units, emphasizing the efficiency of more productive ToMYs, and implied that although there were significant inefficiencies in the system overall, larger or busier ToMYs were more efficient.

Furthermore, the data in the table show that there was considerable regional variation. For RHA 2, the gap between the mean (1.39) and weighted mean (1.10) was particularly pronounced, indicating that smaller or less productive ToMYs in this region were significantly less efficient, skewing the mean upward. In contrast, the larger units in this region operated closer to their optimal scale. Similar trends could be observed for RHA 6, where the mean was 1.33, but the weighted mean was lower at 1.08, further reinforcing that larger ToMYs in this region were more scale-efficient compared to smaller ones. On the other hand, RHAs 1, 4, 5, and 7 showed minimal differences between their mean and weighted mean scale efficiency scores, indicating more uniform efficiency distribution across ToMYs in these regions. Both smaller and larger units appeared to perform similarly in terms of scale efficiency. Additionally, the fact that both the mean and weighted mean scores in these RHAs were close to 1 suggested that the units in these regions operated near their optimal scale.

3.8. Outlier Influence: Bias

Table 15 compares the efficiency characteristics of two samples: the 241 HCs sample (original dataset with 241 DMUs) and the 234 HCs sample (reduced dataset after removing

seven outlier DMUs). This comparison illustrates the effects of outlier removal on efficiency scores and peer selection within a DEA VRS output-oriented model (where lower scores—being closer to 1—represent higher efficiency). The key findings are as follows.

Table 15. Comparison of efficiency metrics and peer relationships in two samples (241 HCs and 234 HCs) before and after the removal of outlier decision-making units (DMUs).

Entity	241 HCs Sample (Original)	234 HCs Sample (Outliers Removed)
Number of decision-making units (DMUs) in sample	241	234
Number of outliers	7	-
Number of efficient DMUs	31	38
Number of efficient outliers	4	-
Number of inefficient outliers	3	-
Number of efficient DMUs common to both samples	27	27
Number of DMUs with at least one efficient outlier as a peer	183	-
Percentage of inefficient DMUs using at least one efficient outlier as a peer	90.1%	-
Total occurrences of efficient outliers as peers	261	-
Total occurrences of all efficient DMUs as peers	812	-
Percentage of peer occurrences for efficient outliers (of total)	32.1%	-
Mean efficiency score of all DMUs in sample	2.33	1.97
Number of inefficient DMUs common to both samples (using at least one efficient outlier as a peer in the 241 HCs sample)	180	180
Descriptive statistics of the subset (180 common DMUs)	241 HCs Sample	234 HCs Sample
Mean efficiency score	2.65	2.14
Standard deviation	1.23	0.96
Minimum efficiency score	1.02	1.00
Maximum efficiency score	8.07	5.68

In the 241 HCs sample, the mean efficiency score of all DMUs was 2.33, while, in the 234 HCs sample, it decreased significantly to 1.97, indicating a substantial improvement in overall performance. This finding suggests that the presence of outliers in the original sample inflated the efficiency scores across DMUs. Additionally, the total number of efficient DMUs increased from 31 in the 241 HCs sample to 38 in the 234 HCs sample. This change indicates that certain DMUs achieve efficiency only after the influence of outlier peers is removed, further highlighting the effect of outliers in skewing efficiency measurements and potentially introducing errors where truly efficient units may be misclassified as inefficient.

In the 241 HCs sample, four out of the seven total outliers were identified as efficient, while the remaining three were classified as inefficient. Removing these outliers helped prevent efficiency assessments from being disproportionately influenced by extreme values, resulting in a clearer distinction between efficient and inefficient DMUs. At first glance, it may seem unusual that the data cloud method flagged three DMUs as outliers, despite their inefficiency. However, closer examination of their scores—1.02, 1.01, and 1.09 for facilities D-009, D-011, and D-069, respectively—showed that they were very close to the efficient threshold. Although these DMUs were not classified as efficient in the initial analysis, their proximity to the (extreme) efficiency boundary caused a noticeable shift in the “cloud” volume when they were removed, leading to their classification as outliers. This finding, we believe, demonstrates the robustness of the data cloud method’s underlying concept.

However, a subset of 27 DMUs remained efficient in both samples, suggesting that these units maintained their efficiency status regardless of the presence of outliers. This consistency provided robustness to the analysis, indicating a core set of efficient DMUs that acted as stable benchmarks across sample variations.

In the 241 HCs sample, 183 DMUs used at least one efficient outlier as a peer, and 90.1% of inefficient DMUs relied on efficient outliers for benchmarking. This high dependence on outliers provides strong evidence of their substantial influence on the efficiency scores of other DMUs. Efficient outliers accounted for 32.1% of all peer occurrences in the 241 HCs sample, underscoring the significant role these outliers played in shaping the efficiency

landscape. In the reduced 234 HCs sample, this reliance on outliers as peers was eliminated, potentially resulting in a more balanced and unbiased peer structure.

Finally, turning the lights on the subset of 180 DMUs common to both samples (those that used at least one efficient outlier as a peer in the 241 HCs sample), the mean efficiency score improved from 2.65 to 2.14 following outlier removal. This significant reduction indicated that outliers contributed to higher efficiency scores within this group. The standard deviation also decreased from 1.23 in the 241 HCs sample to 0.96 in the 234 HCs sample, suggesting a reduction in score variability and a more stable efficiency distribution without the influence of outliers.

Regarding extreme values, the minimum efficiency score of the 180 common DMUs subset approached 100% in the 234 HCs sample (100.0%), indicating that some DMUs achieved nearly optimal efficiency. The maximum score, however, decreased from 8.07 to 5.68, highlighting that removing outliers limited extreme values and provided a more conservative and realistic view of the efficiency range.

In Figure 9, the efficiency scores of the subset of 180 common DMUs are presented in ascending order (green line), as calculated for the 241 HCs sample. The relative size of the orange area, representing the score differences of these DMUs when calculated within the 234 HCs sample, compared to the total area under the green line visually illustrates the extent of influence exerted by the removed outliers.

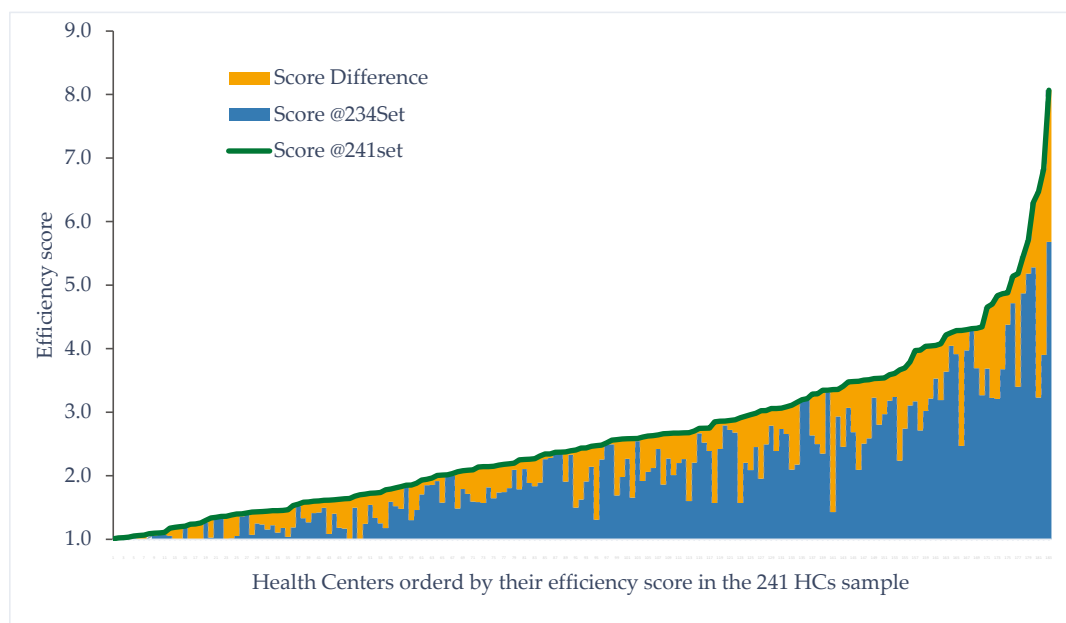


Figure 9. Efficiency scores for the subset of 180 common DMUs in ascending order, based on the 241 HCs sample (green line). The orange area represents score differences observed when calculated for the 234 HCs sample, illustrating the influence of removed outliers on efficiency score distribution.

In summary, our findings demonstrate that outliers significantly impacted efficiency scores and peer relationships in the DEA model. By removing outliers, the 234 HCs sample provided a more reliable efficiency evaluation, reducing bias from questionably extreme performers. The more consistent range and reduced variability in the subset of 180 common DMUs underscored the benefits of this adjustment, suggesting that the 234 HCs sample offered a more accurate foundation for benchmarking and policy recommendations in healthcare efficiency.

4. Discussion

Strengthening primary healthcare (PHC) services is linked to improved equity in access, better clinical outcomes and population well-being, reduced healthcare and social

costs, and increased productivity [3]. However, the growing healthcare needs of citizens—mainly due to increased life expectancy, population aging, technological innovations, and climate change—combined with limited available resources to meet these needs, make the efficient management of these resources imperative [32]. From a managerial perspective, understanding how scarce resources are utilized within the public healthcare system is essential for policymakers when making informed decisions [72].

In Greece, PHC development has been a central focus of reforms over the past decades, as it is considered essential for improving efficiency and access. To address these challenges, implementing modern methods to assess the efficiency of PHC units can provide invaluable insights to policymakers when developing health strategies. These methods facilitate the identification of inefficiencies and support corrective actions, contributing to ongoing performance monitoring and improvement. This study aimed to evaluate the efficiency of PHC units across Greece by assessing the efficiency levels of Health Centers (HCs) and Local Health Units (ToMYs) and identifying underlying factors contributing to observed inefficiencies. A variety of non-parametric methods were employed, primarily focusing on Data Envelopment Analysis (DEA), along with super-efficiency and Free Disposal Hull (FDH) techniques. Utilizing data from 2019, this study stands out as the only evaluation of Greek PHC units conducted after the financial crisis and before the COVID-19 pandemic.

The analysis of the data revealed significant inefficiency and differences in pure technical efficiency (VRS scores) between HCs and ToMYs. HCs, which operate with a much larger volume of activity, could nearly double their outputs while maintaining current input levels (mean weighted VRS bootstrapped score of 1.92), whereas ToMYs could increase their outputs by 58% (mean weighted VRS bootstrapped score of 1.58). This gap highlights the differing capacities of the two types of healthcare facilities to manage resources and serve their populations efficiently. The larger size and greater variability in outputs among HCs suggest more complex operational challenges, leading most likely to divergent operational profiles, which may be among the primary causes of their significant inefficiencies. In terms of scale efficiency, the scores showed better performance, with 1.17 for HCs and 1.20 for ToMYs, both very close to each other, indicating a slightly better proximity of HCs to their MPSS of operation.

Other findings from similar studies align with these observations. For instance, a study [34] of primary healthcare units in southern and western Greece revealed that technically efficient units were typically those covering larger populations and located near major cities. In contrast, less efficient units were in remote, sparsely populated areas that predominantly focused on acute medical services rather than preventive care. This mirrors the results of our study, where rural units generally exhibited higher inefficiencies, as these areas often face resource constraints and serve smaller populations.

In our analysis, HCs classified as '1' and urban emerged as the most efficient (weighted mean VRS bootstrapped scores of 1.69 and 1.51, respectively), followed by the intermediate ('2') and peri-urban regions. Interestingly, the upward scaling of inefficiency was aligned along the transition from urban to rural areas in both categorization typologies (1 → 2 → 3, urban → peri-urban → rural). This finding, with respect to the FAO's classification, was also found to be statistically significant according to the Kruskal–Wallis test.

The inefficiencies observed in rural and remote areas are consistent with the findings of one study [37] that reported that small, rural Health Centers, particularly those located on islands, exhibited lower efficiency, especially when lacking preventive care services. Similarly, another study [35] found that healthcare centers serving populations between 10,001 and 50,000 were the most efficient, whereas smaller centers serving fewer than 10,000 individuals demonstrated significantly lower efficiency. These findings suggest that an optimal population size, combined with proximity to urban centers, may enhance operational efficiency. Contrarily, other subsequent studies [4,36] highlighted that rural or remote and island-based health centers exhibited higher technical efficiency compared to urban and suburban centers, though the latter demonstrated superior scale efficiency. Our findings indicate that scale efficiency improves progressively from urban to rural areas.

Access to healthcare facilities is typically not a major issue for populations in large urban areas; however, residents of rural and remote regions face considerable barriers, often requiring them to travel to other areas or seek care from private practitioners. This may be attributed to the better staffing and equipment levels typically found in larger primary healthcare (PHC) units in urban areas. The challenges faced in rural settings are multifactorial, involving not only geographical and economic barriers but also differences in sociodemographic factors, perceptions, and healthcare needs, all of which influence access to and utilization of PHC services [4,6,73,74].

In our study, rural areas displayed the highest inefficiency, with a mean VRS score of 2.42, indicating the potential for a 142% increase in outputs. These findings underscore the persistent inefficiency challenges in rural settings, where geographic isolation, small population sizes, and limited resources present significant operational obstacles. This dichotomy was further emphasized in our results, where urban centers exhibited inefficiencies largely due to over-scaling, while semi-urban centers achieved a more balanced alignment between scale and resource management.

The findings across RHAs highlighted significant disparities in efficiency among them. RHA 1 emerged as the most efficient, with mean weighted VRS (pure technical) efficiency scores of 1.51 for its Health Centers (HCs) and 1.46 for its Local Health Units (ToMYs). However, the region had only a single HC classified as efficient, suggesting that top-level performance was achieved by only a small fraction of its facilities. On the other hand, RHA 3 and RHA 4 showed the highest inefficiency among HCs, with weighted mean scores of 2.12 and 2.24, respectively. RHA 6, despite contributing 42.1% of all efficient units, had a weighted mean score of 1.86, indicating significant room for output improvement. A previous study [34] reported a better efficiency level for RHA 6, suggesting that efficiency levels may have declined over time or that results may differ based on the methodologies used. Furthermore, examining the FDH results, RHA 6 accounted for 20 out of the 35 benchmark units (57%), offering strong evidence that its operational practices could serve as effective models not only for other RHAs but also for improving its own performance. On the other hand, RHA 1, with no benchmarks, and RHA 7, with only four, showed room for significant improvement. To address these disparities, it is recommended to replicate best practices from highly efficient areas in less efficient regions. Additionally, further investigation into outliers, particularly in rural areas, may reveal specific factors contributing to inefficiencies.

Regarding ToMYs, their VRS inefficiency levels across the seven RHA regions appeared to be more consistent, averaging around 1.60 and falling within a range of approximately 20 percentage points. Similarly, their FDH scores appeared to be consistent across all RHAs, remaining close to the overall weighted mean value (1.34). In terms of benchmarks, RHAs 5 and 6 accounted for the majority, hosting 5 and 4 out of the total 15, highlighting these regions as leaders in efficiency. Policymakers should focus on transferring the successful operational practices from these high-performing regions to underperforming areas. Doing so could substantially enhance the overall efficiency of the healthcare system.

In the context of super-efficiency results, several interesting points emerged from a policymaking perspective. First, the infeasibility of calculating super-efficiency VRS scores for DMUs D-199 and D-212 may suggest that these units are highly efficient and play a critical role in shaping the efficiency frontier. However, without a solvable super-efficiency score, it is difficult to directly compare their performance with other top-performing units. These units are considered hyper-efficient [75] and require a thorough examination to understand their unique operational performance. Policymakers might interpret this as an indication that D-199 and D-212 represent unique or specialized units within the dataset, potentially operating at an optimal level that cannot be surpassed by other DMUs under VRS. This finding should be considered alongside the fact that these two units had a notable presence as peers in the VRS model. As such, these units could serve as models of efficiency within the system, but their specific operational circumstances should be further analyzed to ensure sustained high performance. Second, certain DMUs such as D-041, and D-184

were ranked as super-efficient, yet they did not appear as peers for any inefficient units. This suggests that while these units operate exceptionally well, their specific input–output combinations may not be directly comparable to those of other DMUs, making them unsuitable as benchmarks. From a managerial perspective, this implies that these DMUs may be achieving efficiency through unique circumstances or specialized processes that are difficult to replicate. Although these DMUs excel in performance, their lack of peer appearances suggests limited potential for other units to model their practices, warranting further investigation into the factors driving their idiosyncratic efficiency.

The efficiency deficit identified in this study can be attributed to resource shortages, such as the understaffing of medical and nursing personnel, particularly general practitioners, due to inadequate financial incentives, educational programs, and career progression opportunities [4,9,76–78]. Additionally, there is an unequal distribution of healthcare professionals between urban and rural areas [8] and a lack of facilities and diagnostic equipment in primary healthcare (PHC) centers [5,6], which limits service delivery, particularly in rural areas [79,80].

These challenges lead to gaps in preventive and health promotion services [8], barriers to access, increased waiting times, citizen dissatisfaction [15,80], and unmet healthcare needs [74,81]. As a result, many individuals turn to private doctors [9,82,83], increasing out-of-pocket health costs, among the highest in the EU [15,84,85]. Greece's hospital-centered system further contributes to inefficiency, with PHC services often provided through hospital emergency departments without mandatory referrals from PHC structures [5,15,86]. Though the EOPYY, established in 2011, aimed to reduce hospital overload by directing PHC cases to public units, patients frequently bypass PHC facilities and opt for hospitals, viewing the referral process as bureaucratic [74]. Mandatory referrals (gatekeeping system) from general practitioners, proven to increase efficiency and lower costs in other countries [87,88], are still not implemented in Greece, where general practitioners make up only 7% of the total physicians [84]. However, the COVID-19 pandemic saw more citizens utilizing PHC units to avoid going to hospital emergency departments [89].

Despite reforms, integration remains low, particularly in prevention and public health services [8], with Greece spending just 1.4% of its health budget on these areas, compared to the EU27 average of 2.9% [84]. A study in Crete and Epirus [81] revealed gaps in health promotion activities and the limited implementation of e-health, EHR, and telemedicine services. However, later, during the COVID-19 pandemic, the push for digitalization helped PHC units meet citizen needs, particularly through remote services [89–91].

In the present analysis, there are some limitations that should be considered. First, due to data inconsistency and/or unavailability, the results are based on only a portion of the total PHC facilities (76.2% of Health Centers and 80.3% of ToMYs), leaving out a significant portion of the total volume of inputs and outputs. Although this study included the majority of PHC facilities, providing a reliable overall picture, there may still be differences at an individual level and in conclusions drawn from aggregated indicators when referring to smaller groups/subdivisions. These variations could affect the interpretation of results for specific regions or units. Second, while the quantitative variations in technical efficiency were thoroughly addressed, equally important variations related to the quality of services offered were not captured due to a lack of necessary data. Ideally, the volume of outputs should be accompanied by a measure of service quality, as high efficiency scores do not necessarily imply high-quality outcomes. However, incorporating quality measures into DEA models presents certain challenges and limitations. This remains a critical area for future research, contingent upon the availability of relevant data.

5. Conclusions

The findings of this study revealed that there is room for improving the efficiency of primary healthcare units by expanding or strengthening the services offered to better meet healthcare needs.

Primary healthcare (PHC) serves as the gateway to the healthcare system, playing a crucial role in the effective treatment of patients and the efficient management of resources. These objectives are of central importance, especially in a context where healthcare needs are continuously rising, while available resources remain limited.

By broadening the range of outputs—through the development of new services and the enhancement of existing ones, in collaboration with the other services of the National Health System—PHC could increase its efficiency and make a significant contribution to addressing healthcare needs, alleviating the burden on hospitals and reducing wasteful use of healthcare resources.

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Article

Demographic and Geographic Characteristics Associated with the Type of Prescription and Drug Expenditure: Real World Evidence for Greece During 2015–2021

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Abstract: Aim: Electronic prescribing has allowed for the collection of prescription data in real time in Greece for the first time. Hence, the aim of the current study was to present the characteristics of prescriptions for the Greek population during the period from 2015 to 2021. Methods: This retrospective study was based on data extracted from the nationwide Greek electronic prescription database between January 2015 and December 2021. Descriptive statistics methods were used for the needs of the study. As the basic figures examined depend on the size of the population, in order for the results to be comparable, we estimated the corresponding measures per inhabitant, using population data from the Greek Statistical Authority. Appropriate indicators for the comparison of consumption and expenditure over time were estimated. A study of the trend was also carried out using time series and linear regression models. In order to facilitate the design and implementation of specialized policies, it is useful to identify the drug categories with the highest consumption and expenditure, as well as the geographical areas that present similar characteristics. For the first, ABC analysis was used, which helps to identify the most popular categories of drugs, while for the second, cluster analysis was carried out. Agglomerative clustering was used to divide the regions into similar groups. This hierarchical clustering algorithm classifies the population into several clusters, with areas in the same cluster being more similar, and areas in different clusters being dissimilar. The Ward linkage method with Euclidean distance was used. Results: The analysis of prescription drug consumption and expenditure from 2015 to 2021 revealed significant fluctuations and trends across various drug categories, age groups, and geographical areas. Notably, the quantity of prescriptions increased by 20% since 2015, while expenditure surged by over 30%, with significant spikes following the end of the MoU in 2019 and the onset of the pandemic in 2020. In terms of expenditure, antineoplastic and immunomodulation agents (category L) held the largest share, driven by the introduction of new, costly drugs. The expenditure per inhabitant revealed gender and age disparities, with older populations, particularly women, incurring higher costs. Geographically, drug expenditure, and consumption varied significantly, with distinct regional clusters identified. These clusters, while showing some overlap in consumption and expenditure patterns, also highlighted unique regional characteristics. Conclusions: The insights into prescription drug consumption and expenditure trends offer a valuable basis for developing targeted interventions aimed at optimizing healthcare resource allocation. Moreover, the findings underscore the importance of addressing regional and demographic disparities in pharmaceutical use, thereby contributing to more equitable and cost-effective healthcare strategies. More specifically, the age distribution of prescriptions shows the increase in younger ages, which, as a result, anticipates the overall increase in prescriptions. The knowledge of the most convex categories of medicine, as well as the percentages of the use of generic drugs, shows where interventions should be made, with financial incentives and information through new information channels. The geographic disparities recorded should lead to policies that help the residents of hard-to-reach areas to access prescriptions. In addition, the present study provides a strategic framework for policymakers and healthcare managers to guide future studies and inform decision-making processes.

Keywords: pharmaceutical expenditure; drug consumption; cluster analysis; geographical prescription pattern; demographic differences and no demographic differences

1. Introduction

Drugs are an essential and indispensable tool for patients' prevention, diagnosis, treatment, and rehabilitation. For a rational use of drugs, patients must receive medications appropriate to their clinical needs, in doses that meet their requirements, for an adequate period, and at the lowest cost to them and the community, either through states or social insurance sickness funds [1,2]. Prescribing medications is one of general practitioners' most critical therapeutic activities, and the quality of such practices is a relevant issue [3]. Therefore, the ultimate goal of a rational medical prescription is to optimize the therapeutic results, while also keeping in mind the individual characteristics of the patients, such as sex and age differences [4,5].

Demographic and geographic characteristics significantly influence the type of prescriptions and drug expenditure [1,3,6–8]. Studies have shown that factors such as age, gender, income, and education level play crucial roles in determining the types of medications prescribed and the overall spending on drugs [3]. Geographically, there are notable variations in prescription patterns and drug costs [9]. Urban areas often have higher prescription rates for certain medications compared to rural areas, possibly due to better access to healthcare facilities and specialists. Additionally, socioeconomic status and regional healthcare policies can lead to disparities in drug utilization and spending [1,3,6,8].

During Greece's economic crisis (2010–2019), the primary goal of drug policy was to limit pharmaceutical expenditure to 1% (from 2%) of GDP (N 4336/2015—official government gazette 94/A/14.8.2015) within a total public expenditure cap of 6% [10]. Key measures included drug price reductions, the reintroduction of a positive list based initially on cash flow, mandatory discounts, and forced returns (claw backs) [11,12]. The pricing process has changed several times between 2010 and 2021 [12]. According to the latest legislative framework (N 4638/2019), the process is carried out once a year, and a revised price bulletin is issued every December with drug prices based on the average of the two lowest Eurozone prices, while the product should be priced in at least three Eurozone countries [10,13].

During the first memorandum of understanding (MoU) in 2010 to 2011 [14], Greece implemented significant structural changes in its healthcare system, including the consolidation of social health insurance funds into the EOPYY, the introduction of electronic prescription systems, and the integration of therapeutic protocols [15]. These reforms enabled the collection of prescription data and allowed the insured to choose pharmacies and opt for original drugs, instead of a generic one, by covering the cost difference. An impulse to expand the use of generic drugs aimed to reduce healthcare expenditure faced strong opposition from medical associations. Despite initial setbacks, the Ministry of Health announced that the prescriptions of active substance would be mandatory and that pharmacists must dispense the cheapest generic version. Again, this was amended due to the opposition of the doctors. Under the amendment, doctors are allowed to prescribe a specific "brand", in which case patients will have to pay the price difference (if any) between the prescribed "brand" and the price of the generic alternative. This simply caused costs to shift from the public system to patients.

The end of the economic crisis and the period of the MoU coincided with the start of the pandemic, which put even more pressure on pharmaceutical spending but also led to two prolonged periods of quarantine: the first rigorous one in May 2020 and the second at the end of 2020 and the beginning of 2021 [14,16,17]. As a consequence of this period, the average copayments increased by 10% for pharmaceutical expenditure.

It should be noted that several studies extensively investigate the health policies implemented during the economic crisis and their economic outcomes in Greece [18–22].

Although, as mentioned above, the study of prescription characteristics is an important factor for policy making. In Greece, very few studies have been published on this specific topic; there have been some on out-of-hospital prescribing [23,24] and some on in-hospital [15,25] prescribing. The reason for this is mainly due to difficulty in accessing the data.

This research focuses on the characteristics of out-of-hospital prescribing. Analytically, the prescription is analyzed by ATC-1 and -2 categories and examined by gender and age group. The main ATC-1 categories are identified in terms of quantity and cost, and the use of generic drugs is examined. Trends are analyzed according to historical data.

2. Materials and Methods

2.1. Data

In this postdoc study, we retrospectively analyzed the existing electronic health record database of the e-Government Center for Social Security Services prescription database (IDIKA), which covers almost 100% of the country's population. The e-prescription network has been available since 2011 and is the only pathway enabling the prescription of medications that can be reimbursed by the National Organization for the Provision of Health Services (EOPYY). The Minister of Digital Governance exercises the supervision and control of the IDIKA. The e-prescription includes data for the period 2015–2021, with the following distinguishing variables: therapeutic category at ATC level (level 1 to 4), year of prescription, gender and age of the patient, type of drug, geographic region, physician speciality, and the quantity variables, value, payment by the insurance agency, number of prescriptions.

The present study of the characteristics of prescription data from 2015 to 2021 is an update of a relevant Democritus University of Thrace (DUTH) research [23].

The necessary demographic data for Greece were obtained from the Hellenic Statistical Authority.

2.2. Statistical Analysis

The analysis was divided into three parts. The first one included a descriptive overview of the per capita gross pharmaceutical expenditure (expressed in EUR) and drug consumption per capita, using the Greek Statistical Authority's estimations for the population by age and year. The gross estimations were calculated as:

$$E_{pc,t} = [E_t / (P_t)]$$

$$V_{pc,t} = [V_t / (P_t)]$$

where $E_{pc,t}$ is the expenditure per capita at year t , $V_{pc,t}$ is the volume of drug consumption per capita, E_t is the expenditure at year t , V_t is the volume of drug consumption at year t , and P_t is the estimation of the population at year t .

The annual change in expenditure (ΔE_t) and volume (ΔV_t) and per capita expenditure ($\Delta E_{pc,t}$) and volume ($\Delta V_{pc,t}$) is given by the formula:

$$\Delta Q_t = \frac{(Q_{t+1} - Q_t)}{Q_t}$$

where: Q_t can be E_t , V_t , and then called annual rates, or $V_{pc,t}$, $E_{pc,t}$ and called change rates.

ABC analysis was used to determine the importance of each ATC-1 group to prescription. ABC analysis is a managerial tool that determines the value of the items based on their importance to the business. ABC ranks items on demand and cost, and groups items into classes based on those criteria. This helps leaders understand which products are most critical to the financial success of their organization. For the implementation of the ABC analysis, the total expenditure and consumption of each ATC-1 category was calculated for the period 2015–2021, and the relevant percentages were calculated.

As the volume and value of prescription drugs depend on the population of each period, we estimated an index, which compares the prescription of period t with a reference year (set in 2015). The index was calculated as a price index, as follows [26,27]:

$$I_t = \left[\left(\frac{E_t}{E_0} \right) / \left(\frac{V_t}{V_0} \right) \right] \cdot 100$$

To study the impact of age and gender on pharmaceutical expenditure, the deviation of the average expenditure and consumption of each subgroup from the average expenditure of the population was estimated using the following formula:

$$\frac{\text{Mean value}_x^G}{\text{Mean value}} \cdot 100$$

where x is the age group (0–14, 15–29, 20, 44, 45–59, 60+), and G is the gender (male, female).

The second part includes trend analysis using linear regression models to answer the question: “What is likely to happen?”.

The third part includes cluster analysis to examine similarities between regions in pharmaceutical consumption and expenditure. Cluster analysis is a method frequently used in the literature on healthcare data [28,29]. Theodorides et al. [30] present a detailed description of cluster analysis. The technique is used in case disease classification [31,32] and healthcare system classifications [33,34]. For our research purposes, an agglomerative (bottom-up) hierarchical clustering algorithm is used to divide the regions into similar groups. This is a hierarchical clustering algorithm that classifies the population into several clusters, with areas in the same cluster being more similar and areas in different clusters being dissimilar. According to the 2021 data, two data vectors for each region were created. The first includes the mean quantity per capita by anatomical therapeutic chemical (ATC)-1 group and gender, and the second is the mean value per capita by ATC-1 group and gender. The Ward linkage method with Euclidean distance was used. Cophenetic correlation coefficient (CCC) has been used to verify the cluster quality [35,36]. The analysis of the results shows the different patterns of pharmaceutical consumption and expenditure in the country, while comparing the results of the two-cluster analysis can identify possible differences in prescription policies between the regions.

IBM Statistics V.29.0.0 was used for statistical analysis and clustering analysis, and CCC calculations were performed using statistical program R v4.4.2.

3. Results

3.1. Total Consumption and Expenditure

Table 1 shows the total prescription consumption fluctuation (in quantity and expenditure). The quantity increases every year and in 2021 was 20% more than in 2015. The annual change in consumption per capita also shows a significant yearly increase, between 2.4% to 4.9%. On the expenditure side, only 2016 showed a decrease, with the following years presenting a significant increase. Compared to 2015, the 2021 expenditure showed an increase of over 30%, and there was also a significant yearly increase in expenditure per capita, especially after the end of the MoU (2019) and the pandemic (2020).

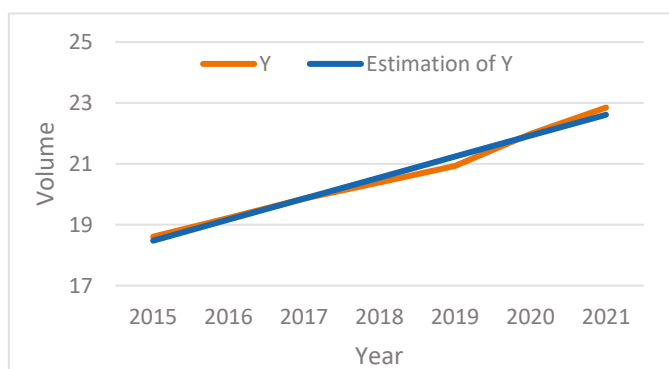
Table 2 and Figure 1 present the trend analysis of the volume and the expenditure per capita. The coefficient for the volume per capita is statistically significant (p -value < 0.001) and positive, with a value of 0.69 (95%CI: 0.60–0.79), which leads to the conclusion that the mean drug consumption will increase every year by 0.69. The coefficient for the expenditure per capita is statistically significant (p -value < 0.001) and positive, with a value of 20.29 (95%CI: 14.21–26.38), which leads to the conclusion that yearly expenditure per capita will increase by 4.5% from 2021’s mean yearly expenditure per capita (EUR 20.29).

Table 1. Quantity (volume) and expenditure by year, 2015–2021.

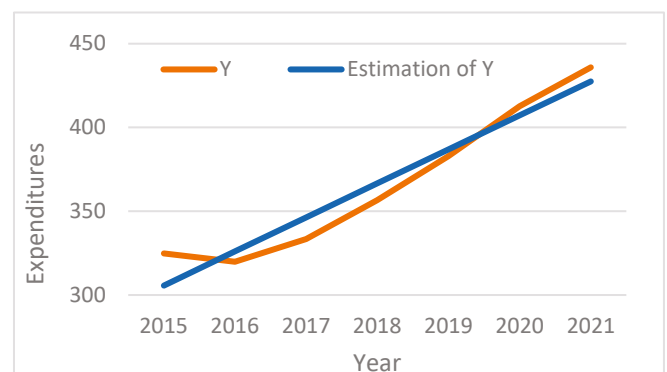
Measure	Year							Average
	2015	2016	2017	2018	2019	2020	2021	
Volume								
Total consumption (×1,000,000)	202.6	207.22	213.9	218.97	224.49	235.58	244.01	
Annual rate		2.6%	3.2%	2.4%	2.5%	4.9%	3.6%	3.1%
Consumption per capita	18.61	19.22	19.86	20.39	20.93	21.98	22.85	
Change rate		3.3%	3.4%	2.6%	2.7%	5.00%	4.00%	3.4%
Expenditure								
Total expenditure (×1,000,000 EUR)	3526.39	3449.34	3589.63	3830.06	4105.73	4421.99	4654.50	
Annual rate		−2.2%	4.1%	6.7%	7.2%	7.7%	5.3%	5.1%
Expenditure per capita (EUR)	324.77	319.86	333.36	356.58	382.83	412.55	435.87	
Change rate		−1.5%	4.2%	7.00%	7.4%	7.8%	5.7%	4.9%

Table 2. Trend analysis for volume and expenditure.

Variable	Coef.	Std. Err.	t	$p > t $	95% CI	
Volume						
Intercept	18.48	0.14	136.81	<0.001	18.13	18.83
Year	0.69	0.04	18.40	<0.001	0.60	0.79
Expenditure						
Intercept	305.67	8.53	35.82	<0.001	283.73	327.61
Year	20.29	2.37	8.57	<0.001	14.21	26.38



(a)



(b)

Figure 1. Linear trend analysis, (a) volume; (b) expenditure.

3.2. Pharmaceutical Characteristics

Figure 2 presents an ABC analysis of quantity and expenditure. As for the quantity, the drugs in category C (cardiovascular system) were double the consumption of the following categories: A—alimentary tract and metabolism, N—nervous system, B—blood and blood-forming organs. These four drug groups covered 80% of the total volume. In the annual distribution of the drug volume, group C occupied more than 30%; although, this percentage decreased from 36% in 2015 to 31.3% in 2021.

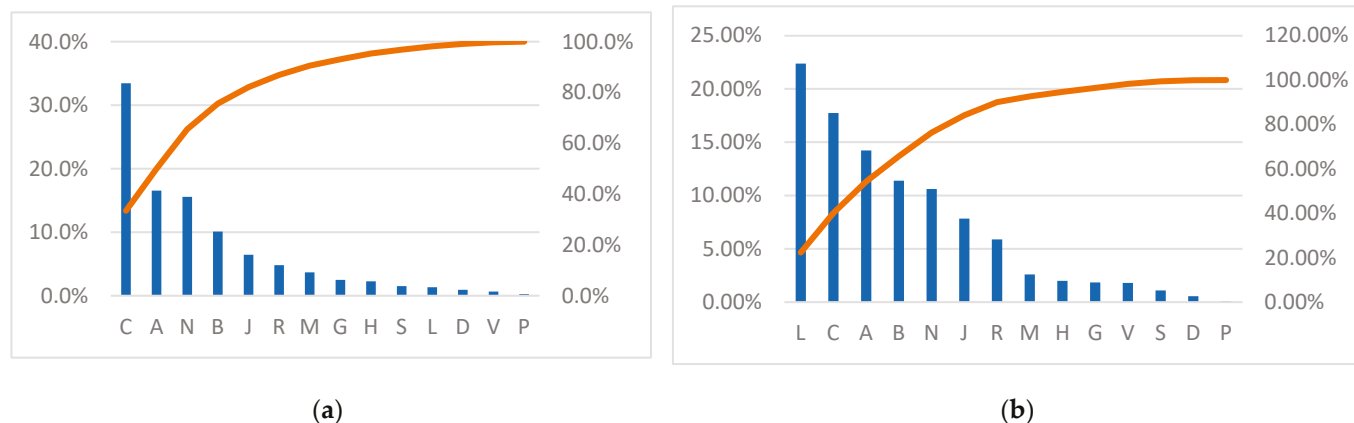


Figure 2. ABC analysis; (a) for quantity and (b) expenditure by ATC-1 categories, 2015–2021. (A: alimentary tract and metabolism; B: blood and blood-forming organs; C: cardiovascular system; D: dermatology; G: genito-urinary system and sexual hormones; H: systemic hormonal preparations; J: anti-infectives for systemic use; L: antineoplastic and immunomodulating; M: musculo-skeletal system; N: nervous system; P: antiparasitic products; R: respiratory system; S: sensory organs; V: various).

Taking into account total expenditure, category L (antineoplastic and immunomodulating agents) had the largest share of the expenditure (22.4%), followed by category C (cardiovascular system), with a percentage of 17.7%, and category A (alimentary tract and metabolism), with a percentage of 14.2%. The expenditure for these three categories exceeded 50% of the total spending (53.3%). They were followed by two other categories with a percentage of over 10%: B (blood and hematopoietic organs) with 11.4% and N (nervous system) with 10.6%.

The fluctuation of quantity and expenditure over time is significant. The expenditure/quantity ratio was calculated to compare the rate of change in quantity and expenditure of each category. Figure 3 presents, in a timeline chart, the index $I_t^K = \left[\left(\frac{E_t}{E_{2015}} \right) / \left(\frac{V_t}{V_{2015}} \right) \right] \cdot 100$, where t is the year, and K is the ATC group, with 2015 as the base where all ATC groups have index value = 100.

The following ATC-1 categories show a ratio of less than 100: G (genito-urinary system and sex hormones), H (systemic hormonal preparations, excluding sex hormones and insulins), C (cardiovascular system), N (nervous system), and S (sensory organs). Although the quantities increased, expenditure increased at a lower rate, so costs were decreasing. This may be due to the increase in generic drug consumption, the end of the protection period of original drugs, or the appearance of lower priced drugs. In contrast, for category L (antineoplastic and immunomodulating agents), the rate of change in expenditure exceeded the rate of change in quantity, possibly due to the appearance of new, more expensive drugs.

For the seven years 2015–21, the percentage of the contribution of generic drugs compared to the total expenditure on prescription drugs (Table 3) reached 16%. The five anatomical groups with the highest contribution of generic drugs are category D (dermatology), followed by the anatomical category C (cardiovascular system), showing an increase of 9%, N (nervous system) with a rise of 9%, M (musculoskeletal system) with a decrease in generic drugs of 5%. For ATC-1 category C (cardiovascular system), the generic use increased continuously, from 24.1% of total spending in this category to 33.4%, which

explains why expenditure was reduced, despite the increase in prescription volume. On the contrary, in category L, the percentage of expenditure from the prescription of generic drugs remained close to 4.5% to 5%, from the lowest percentages of generic drugs. A concluding result is a possible failure of the generic marketing to these patients.

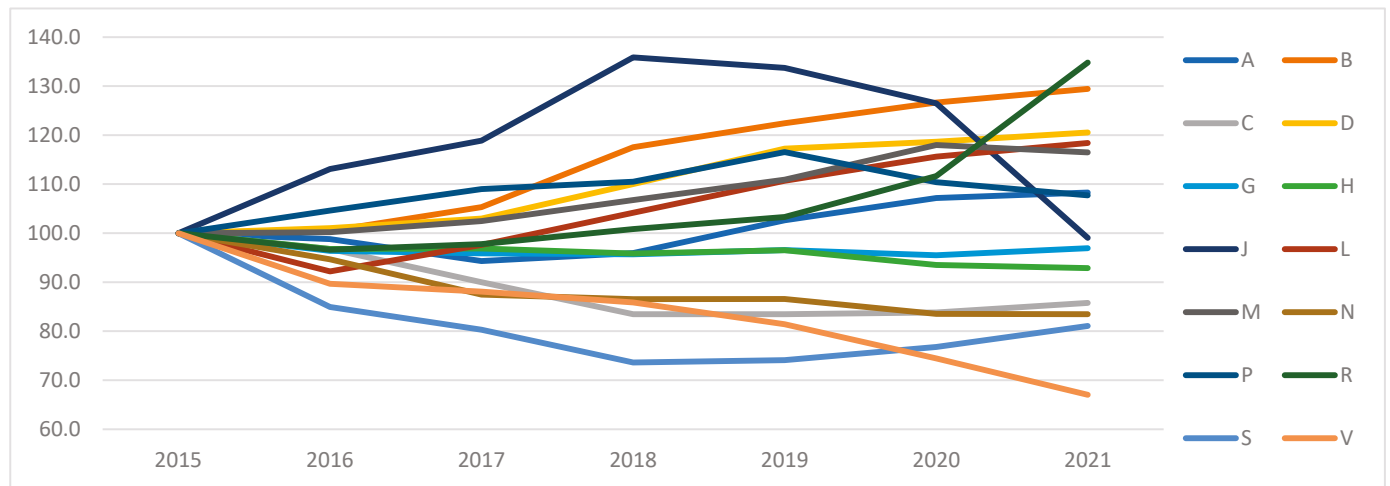


Figure 3. Ratio (expenditure/quantity) per year and ATC-1 category (A: alimentary tract and metabolism; B: blood and blood-forming organs; C: cardiovascular system; D: dermatology; G: genito-urinary system and sexual hormones; H: systemic hormonal preparations; J: anti-infectives for systemic use; L: antineoplastic and immunomodulating; M: musculo-skeletal system; N: nervous system; P: antiparasitic products; R: respiratory system; S: sensory organs; V: various).

Table 3. Percentage of expenditure for generic drugs by category ATC-1 and year, 2015–21.

ATC-1 Group ¹	2015	2016	2017	2018	2019	2020	2021	2015–2021
A	15.8%	16.7%	15.7%	17.1%	17.4%	17.5%	19.5%	17.3%
B	15.3%	15.9%	13.1%	11.7%	11.1%	10.6%	10.6%	12.2%
C	24.1%	24.8%	23.4%	24.5%	28.0%	31.6%	33.4%	27.0%
D	32.0%	38.3%	37.3%	35.6%	35.3%	35.4%	38.7%	36.2%
G	19.7%	20.2%	18.1%	17.6%	17.7%	18.1%	20.1%	18.8%
H	11.6%	14.2%	15.8%	17.1%	19.0%	20.3%	27.2%	18.5%
J	11.9%	9.6%	8.5%	9.1%	9.8%	8.4%	10.2%	9.5%
L	4.8%	5.4%	5.0%	4.6%	4.3%	3.9%	4.2%	4.5%
M	24.0%	22.5%	20.1%	18.7%	17.9%	18.0%	19.1%	20.0%
N	21.6%	23.5%	24.0%	25.6%	28.0%	28.9%	30.6%	26.1%
P	0.0%	0.0%	0.0%	2.4%	11.9%	9.7%	8.4%	5.7%
R	23.1%	21.7%	21.6%	20.5%	19.9%	18.6%	15.4%	19.9%
S	5.9%	8.9%	9.8%	11.7%	12.6%	13.8%	14.1%	10.8%
V	1.8%	4.1%	5.8%	6.6%	7.6%	9.8%	11.3%	7.0%
Total	16.1%	16.9%	15.4%	15.2%	15.7%	15.9%	16.8%	16.0%

¹ A: alimentary tract and metabolism; B: blood and blood-forming organs; C: cardiovascular system; D: dermatology; G: genito-urinary system and sexual hormones; H: systemic hormonal preparations; J: anti-infectives for systemic use; L: antineoplastic and immunomodulating; M: musculo-skeletal system; N: nervous system; P: antiparasitic products; R: respiratory system; S: sensory organs; V: various.

3.3. Demographic Characteristics

Considering gender and age group, Figure 4 shows the deviation of the pharmaceutical consumption and expenditure per capita by year, age group, and gender, as a per cent of the mean consumption and spending. For men, the consumption per capita varied from 16.7 to 20.6 with an annual increase in rates from 3.6% (2016) to 3.4% (2021). The expenditure per capita varied from EUR 307 (2015) to EUR 426 (2021), with rates increasing from 0.3% to 5.4%. For women, the consumption per capita varied from 20.4 (2015) to 25.6 (2021), with an annual increase in rates from 3.0% (2016) to 4.4% (2021). The expenditure per capita varied from EUR 342 (2015) to EUR 446 (2021), with rates increasing from −3.1% (2016) to 8.0% (2020) and 5.9% (2021). Drug consumption and expenditure for all age groups, except 0–14, were greater for women than men, but as age increased, the difference between genders reduced. For the older men (age group 60+), the deviation from the mean value decreased from 336% (2015) to 272.2% (2021) for consumption and from 304% to 243% for expenditure. Corresponding to women, the average price of the quantity changed from 236% in 2015 to 231% in 2021. The spending percentages were 263% in 2015 and 205% in 2021. The annual change rate increase in both measures was much lower than the other groups; although the absolute numbers increased, the percentages decreased.



Figure 4. Consumption and expenditure per capita by sex and age group, as a per cent of mean, 2015–2021.

As mentioned above, participation in the expenditure and consumption of medicines for the 60+ age group was much higher than the other age groups. This is why the participation rates of this age group were high in the distribution of consumption (78.1%) (Table 4a) and expenditure (75.9%) of generic drugs by age (Table 4b), even though it has been slightly reduced in the last seven years. Of course, this particular group was not the highest in the use of generic drugs, as 27.6% of the consumption and only 17.4% of the total expenditure concerned generic drugs. Of course, this percentage was the highest spending on generic drugs among the age groups.

Table 4. (a) Consumption distribution of the generic drugs prescription by category ATC-1 and age group, 2015–21. (b) Expenditure distribution of the generic drugs prescription by category ATC-1 and age group, 2015–21.

(a)					
ATC-1	Consumption				
Group ¹	0–14	15–29	30–44	45–59	60+
A	1.70%	10.40%	15.30%	16.60%	17.10%
B	2.40%	12.40%	20.90%	8.80%	9.70%
C	0.30%	1.40%	5.50%	25.30%	38.40%
D	2.00%	8.90%	2.50%	1.30%	0.50%
G	0.00%	2.50%	6.10%	2.00%	2.40%
H	3.00%	3.70%	2.80%	2.80%	2.10%
J	62.30%	27.10%	12.60%	7.60%	3.90%
L	0.70%	1.90%	2.30%	2.50%	1.10%
M	2.60%	3.00%	3.40%	4.20%	3.60%
N	2.20%	13.60%	19.40%	21.30%	14.70%
P	0.10%	0.50%	0.60%	0.50%	0.20%
R	21.60%	12.50%	6.10%	5.10%	4.10%
S	0.80%	0.80%	0.50%	0.70%	1.80%
V	0.20%	1.30%	1.80%	1.30%	0.50%
% to age	13.50%	29.10%	28.70%	28.20%	27.60%
% to pharma type	0.90%	2.20%	5.70%	13.10%	78.10%
(b)					
ATC-1	Expenditure				
Group ¹	0–14	15–29	30–44	45–59	60+
A	1.40%	7.50%	8.80%	12.50%	16.00%
B	1.40%	12.00%	13.00%	6.90%	12.60%
C	0.60%	1.00%	3.40%	12.30%	22.00%
D	0.60%	3.70%	1.10%	0.60%	0.30%
G	0.00%	0.80%	3.80%	1.30%	1.90%
H	3.60%	7.40%	1.90%	1.80%	1.70%
J	75.50%	23.60%	10.80%	7.40%	4.40%
L	4.90%	20.00%	31.50%	33.20%	19.50%
M	0.70%	1.10%	1.20%	2.00%	3.00%
N	1.20%	9.30%	13.80%	12.70%	10.20%
P	0.00%	0.10%	0.10%	0.10%	0.10%
R	9.30%	10.50%	6.20%	5.50%	5.60%
S	0.20%	0.20%	0.20%	0.40%	1.40%
V	0.50%	2.70%	4.20%	3.20%	1.20%
% to age	4.70%	11.40%	13.10%	14.10%	17.40%
% to pharma type	0.70%	2.30%	6.30%	14.80%	75.90%

¹ A: alimentary tract and metabolism; B: blood and blood-forming organs; C: cardiovascular system; D: dermatology; G: genito-urinary system and sexual hormones; H: systemic hormonal preparations; J: anti-infectives for systemic use; L: antineoplastic and immunomodulating; M: musculo-skeletal system; N: nervous system; P: antiparasitic products; R: respiratory system; S: sensory organs; V: various.

Analyzing the prescription for the age group 0–14 at the ATC-2 level, three categories (J01 (antibiotics), J07 (vaccines), and R03 (medicines for obstructive airways disease)) had the most significant volumes. On the expenditure side, therapeutic group J07 (vaccines) accounted for the most critical proportion, approaching 70% of total prescription expenditure for ages 0–14, also showing an increase in per capita expenditure of around 40%.

For the 15–29 age group, most of the volume of drugs belonged to the categories: J01 (antibiotics), B03 (drugs against anemia), J07 (vaccines), R03 (drugs for obstructive diseases of the airways), and N03 (anticonvulsants). On the expenditure side, therapeutic groups L04 (immunosuppressive agents) and J07 (vaccines) accounted for this age group's highest per capita amount. It is worth noticing that the significant expenditure of the J07 category was also due to the large volume of vaccines; on the contrary, the therapeutic category L04 did not have a large volume but a considerable treatment cost. The therapeutic group L04 also showed a significant increase from 2015 to 2021.

According to these results, for the 30–44 age group, most of the drug volume belonged to the categories: B03 (antianemia drugs), J01 (antibiotics), N05 (psychotropic drugs), A12 (mineral supplements), B01 (antithrombotics), and N06 (psychoanalgesics). The above categories covered 50% of the drug volume. On the expenditure side, the three therapeutic groups from group L (antitumor and immunomodulatory agents) were in the top six, according to per capita expenditure. Therapeutic groups L04 (immunosuppressants), L01 (antineoplastic drugs), L03 (immunostimulatory agents), B03 (antianemia drugs), J05 (antivirals), N05 (psychotropics), had the highest per capita amount for this age group. The above therapeutic groups, except L03, significantly increased from 2015 to 2021. The consumption of N05 (psychotropics) could be due to economic and pandemic crises. It should be noticed that unemployment rate increased over 20% during the previous decade and even more in these ages.

For the age group 45–59 years old, the ATC-2 categories with a higher drug consumption were C10 (hypolipidemic agents), N05 (psychotropic agents), C09 (antihypertensive agents), A10 (drugs for diabetes mellitus), N06 (psychoanalgesics), J01 (antibiotics), A02 (antacids), and B01 (antithrombotics). The above categories covered more than 50% of the total drug consumption. On the expenditure side, the therapeutic groups L04 (immunosuppressive agents) and L01 (antineoplastic drugs) were the ATC-2 categories with the highest average expenditure per capita, followed by A10 (drugs for diabetes mellitus), C10 (hypolipidemic agents), and N05 (psychotropic drugs). All the above therapeutic groups showed a significant increase from 2015 to 2021, and the average per capita expenditure difference for the same therapeutic groups between age groups is noticeable. A typical example is group L04, with an average per capita expenditure of EUR 29.1 for the 30–44 age group, compared to EUR 52.6 for the 45–59 age group.

Finally, analyzing the prescription data for the age group 60+, most of the drug volumes belonged to the following ATC-2 categories: C09 (antihypertensive agents), A10 (drugs for diabetes mellitus), B01 (antithrombotics), A02 (antacids), C07 (B-receptor blockers), N05 (psychotropics), and N06 (psychoanalgesics). The above categories covered 60% of the drug volume. These categories were similar to the categories of the 45–59 age group. On the expenditure side, therapeutic group L04 (immunosuppressants) fell to sixth place, with a higher average per capita expenditure for A10 (drugs for diabetes mellitus), L01 (antineoplastic drugs), C10 (hypolipidemic agents), C09 (antihypertensive agents), and B01 (antithrombotics).

3.4. Geographic Characteristics

Table 5a,b presents pharmaceutical consumption (Table 5a) and expenditure per capita (Table 5b) by ATC and geographical area. According to the results, the groups with the highest expenditures were L—antineoplastic and immunomodulating (22.5% of the total), C—cardiovascular system (17.5% of the total), and A—alimentary tract and metabolism (12.2% of the total). Geographically, the coefficient of variation ranged between 6% and 40%; for only three (A, V—various, and J—anti-infective for systemic use), the value was less than 10%. The regional consumption was EUR 327 per capita, ranging from EUR 278 in the South Aegean region to EUR 345 in Western Greece.

Table 5. (a) Consumption per capita by region and ATC-1, 2015–21. (b) Expenditure per capita by region and ATC-1, 2015–21.

(a)												
Consumption	ATC ¹											
	A	B	C	D	G	H	J	L	M	N	P	Total
Eastern Macedonia and Thrace	3.2	1.9	7.0	0.2	0.5	0.4	1.2	0.2	0.8	3.1	0.0	19.7
Attica	3.0	1.8	5.5	0.2	0.4	0.4	1.2	0.3	0.6	2.9	0.0	17.5
North Aegean	3.8	2.0	6.7	0.2	0.5	0.6	1.4	0.3	0.9	3.0	0.1	21.0
Western Greece	3.0	1.8	6.1	0.2	0.4	0.4	1.3	0.2	0.7	3.0	0.1	18.7
Western Macedonia	3.4	2.1	7.6	0.2	0.6	0.5	1.3	0.3	0.8	3.1	0.1	21.1
Epirus	4.7	3.0	10.1	0.3	0.7	0.6	1.9	0.3	1.1	4.2	0.1	29.0
Thessaly	2.9	1.9	6.5	0.2	0.5	0.4	1.2	0.2	0.8	2.8	0.0	18.7
Ionian Islands	3.6	2.0	7.0	0.2	0.5	0.5	1.5	0.3	0.8	3.2	0.1	21.1
Central Macedonia	2.7	1.7	5.8	0.2	0.4	0.4	1.1	0.2	0.7	2.6	0.0	16.7
Crete	3.0	1.8	5.4	0.2	0.5	0.4	1.3	0.3	0.6	2.6	0.1	17.6
South Aegean	2.0	1.2	3.9	0.1	0.3	0.3	0.8	0.2	0.4	1.5	0.0	11.4
Peloponnese	3.2	1.8	5.9	0.2	0.5	0.5	1.3	0.2	0.7	2.9	0.0	18.6
Central Greece	2.8	1.8	5.9	0.2	0.4	0.4	1.1	0.2	0.7	2.7	0.0	17.5
Total	3.0	1.8	6.0	0.2	0.4	0.4	1.2	0.2	0.7	2.8	0.0	18.0
(b)												
Expenditure (EUR)	ATC											
	A	B	C	D	G	H	J	L	M	N	P	Total
Eastern Macedonia and Thrace	51.6	39.6	63.1	1.9	6.9	4.9	23.1	57.6	8.2	31.9	0.2	314.6
Attica	46.1	35.2	53.3	1.9	5.4	6.9	29.7	85.0	8.4	36.2	0.2	337.8
North Aegean	53.2	35.8	57.1	1.6	5.7	7.0	23.1	59.2	9.4	30.1	0.2	309.5

Table 5. Cont.

(a)															
Expenditure (EUR)	ATC														
	A	B	C	D	G	H	J	L	M	N	P	R	S	V	Total
Western Greece	48.7	37.8	64.0	2.2	5.9	7.4	27.6	68.3	10.5	38.1	0.3	23.1	4.4	6.7	344.9
Western Macedonia	47.9	40.3	66.6	1.9	6.9	6.6	24.4	71.1	8.8	32.6	0.2	17.7	3.1	4.9	332.8
Epirus	45.7	37.7	70.1	1.9	5.6	5.5	24.0	62.8	9.7	36.7	0.2	21.5	3.5	4.2	329.2
Thessaly	45.1	40.7	64.7	1.9	6.6	6.6	26.0	67.6	9.2	34.8	0.2	21.4	3.9	6.6	335.2
Ionian Islands	49.1	35.2	66.4	1.7	6.0	6.4	26.8	75.5	9.2	37.2	0.2	21.1	4.3	5.5	344.5
Central Macedonia	45.8	40.9	58.3	2.1	6.4	6.6	26.7	70.8	8.3	32.7	0.2	15.8	2.8	6.0	323.5
Crete	44.6	32.1	50.4	1.8	6.4	8.1	28.2	72.5	8.1	36.8	0.5	23.6	3.9	5.0	322.2
South Aegean	44.3	27.1	47.9	1.6	4.5	5.7	25.4	69.0	6.5	23.6	0.1	14.7	3.1	4.5	278.2
Peloponnese	48.2	36.2	54.8	1.7	5.7	6.7	24.2	67.6	8.9	34.6	0.2	21.0	3.8	5.1	318.9
Central Greece	44.6	33.1	57.9	1.6	4.8	5.6	22.2	59.9	7.9	33.2	0.2	17.7	3.2	5.2	297.3
Total	46.6	36.7	57.3	1.9	5.9	6.6	27.0	73.6	8.6	34.6	0.2	19.2	3.5	5.9	327.5

¹ A: alimentary tract and metabolism; B: blood and blood-forming organs; C: cardiovascular system; D: dermatology; G: genito-urinary system and sexual hormones; H: systemic hormonal preparations; J: anti-infectives for systemic use; L: antineoplastic and immunomodulating; M: musculo-skeletal system; N: nervous system; P: antiparasitic products; R: respiratory system; S: sensory organs; V: various.

The same findings were also found for consumption: C—cardiovascular system, A—alimentary tract and metabolism, N—nervous system, and B—blood and blood-forming organs had the highest values. The accumulated consumption of these four groups exceeded 80% of the total consumption. Geographically, there was quite a high variability, with a coefficient of variation of about 20%.

3.5. Similarity Analysis by Region

Figure A1 at Appendix A presents the dendrograms of the cluster analysis. According to each cluster's results and agglomeration schedule, we defined seven clusters for quantity (CCC = 75.6%) and nine for value (CCC = 83.1%). Table 6 presents the classification of the regions.

Table 6. Cluster analysis: groups of regions.

Region	Cluster Number		Region	Cluster Number	
	Quantity	Expenditures		Quantity	Expenditures
Aetolia-Acarnania	1	1	Lefkada	4	8
Drama	1	2	Magnesia	4	3
Evros	1	6	Fokitha	4	7
Imathia	1	2	Samos	4	7
Karditsa	1	2	Viotia	4	5
Pella	1	2	Xanthi	4	7
Phiotis	1	1	Kefalonia	5	8
Pieria	1	1	Chania	5	4
Rhodope	1	6	Cyclades islands	5	4
Trikala	1	1	Dodecanese Islands	5	4
Achaia	2	3	Evia Island	5	5
Arcadia	2	3	Evrytania	5	7
Argolis	2	2	Lasithi	5	8
Attica	2	4	Rethymno	5	8
Corinthia	2	3	Thessaloniki	5	3
Heraklion	2	4	Corfu	6	2
Messenia	2	3	Florina	6	1
Zakynthos	2	4	Kastoria	6	1
Arta	3	1	Kavala	6	5
Grevena	3	1	Kozani	6	2
Kilkis	3	6	Larissa	6	1
Serres	3	9	Preveza	6	5
Elis	4	5	Thesprotia	6	5
Halkidiki	4	3	Chios	7	2
Ioannina	4	5	Lesbos	7	6
Laconia	4	5			

Looking at the results for the average amounts per inhabitant, gender, and drug category, some geographical similarities emerged in the clusters. Cluster 2 consists of

areas of the Peloponnese and Southern Greece. There are three central prefectures (Achaia, Attica, and Heraklion), and all the rest are neighboring regions. In Cluster 6, there are areas from northwestern Greece; in Cluster 5, islands and areas with difficulty in accessing medical services; and in Cluster 7, islands of the northern Aegean. The results, in terms of prescription volume, showed a similar behavior in regions where there is difficulty in accessing structures and doctors (islands and mountainous areas without a good road network). These regions were in the lowest 25% for consumption in terms of important ATC drug categories (A, C, L). One explanation may be moving to urban areas where they had easier access to medical services. Areas near Athens and other large urban centers of the country showed similar behavior.

The corresponding geographical adjacencies did not occur in the value analysis, as only the neighboring prefectures of central Greece are in Cluster 1. In Cluster 3, most areas belong to the Peloponnese and Halkidiki with Thessaloniki.

To examine the similarity of the two classifications, based on the classification of the areas by the quantity data, the authors checked the similarity of the classification of the areas based on the value analysis. According to the results, all the areas belonging to Cluster 1 in the quantity analysis joined clusters with common areas, and in the value analysis, the value cluster included 40% of the areas of quantity Cluster 1. In quantity Cluster 2, only 1 in 8 areas were classified into a value cluster that did not include other common areas. The highest common classification was 50% (4/8 in the same group). Quantity Cluster 3 had a corresponding percentage of 50% (2/4 areas). In quantity Cluster 4, 90% (9 out of 10 regions) went to value clusters, where there were common regions, with the 4 regions having the highest common classification. In quantity Cluster 5, the percentage was 67% (6 out of 9), with a maximum number of common areas of 3. Finally, in quantity Cluster 6, the percentage was at 100%, with all areas corresponding to the new classification into clusters of common areas. The maximum number was three common areas.

4. Discussion

Demographic and geographic characteristics play a significant role in shaping prescription patterns and drug expenditure. Factors such as age, gender, socioeconomic status, and regional healthcare practices influence the types of medications prescribed and their associated costs [3]. Socioeconomic factors, including income and education levels, also impact prescription behaviors, with deprived areas often experiencing higher rates of drug-related admissions and overdoses [37]. Geographic variations, such as urban versus rural settings, further contribute to disparities, with urban areas generally having better access to healthcare facilities and specialists, leading to different prescribing practices compared to rural regions [9]. Understanding these demographic and geographic influences is crucial for developing targeted strategies to ensure equitable access to medications and to optimize healthcare outcomes across diverse populations.

Although Greek healthcare policies have legislated many measures according to international practices, in the last 15 years after the signing of the MoU in 2010 and in light of fiscal consolidation, comprehensive healthcare reform has been implemented, aiming, among other things, to reduce waste, control expenditure, and increase the accountability and efficiency of the Greek pharmaceutical sector [38]. The Greek government primarily focused on applying cost-containment measures, such as flat decreases in pharmaceutical prices and the collection of rebates from pharmaceutical companies to achieve a fast reduction in pharmaceutical expenditure. The value of the medicines prescribed before the 2009 crisis was over EUR 6 billion, with over 80% covered by the EOPYY. In 2013, it was reduced to EUR 2.4 billion, a 53% decrease since 2009, and in 2022, it was estimated to be catching up to EUR 6 billion again. Almost half of this amount is covered by the Health Social Insurance Fund (EOPYY), and the other half is covered by out-of-pocket payments (OOP) and pharmaceutical companies. OOP are about EUR 1 billion, and the pharmaceutical companies cover EUR 2 billion, through clawbacks and rebate mechanisms.

European states with similar compensation systems to Greece during the same period had small annual increases. France had an increase of 0.5% for the period 2010–2016 with an increase to 2% for the period 2017–21; Germany had an increase of 3.9% for the period 2010–2021; and Spain, a country that also signed an MoU, had a decrease in the period 2010–14, then a significant increase until 2016, and then, an increase of about 2.5% [39]. Italy, the UK, and the USA, which have different health systems from Greece, but similar OOP payment rates, had bigger increases, which exceeded those of Greece [6,39,40].

To the best of our knowledge, this is the first local study that showed the need for healthcare reforms to promote generic drugs. From surveys that studied the opinions of patients [41,42], doctors, and pharmacists [43], distrust from both patients and doctors was observed toward the effectiveness of generic drugs and the appropriateness of the regulatory authorities' quality controls. Patient trust in doctors and pharmacists can dispel doubts about generic drugs. We believe that an information campaign on the efficacy and safety of generic drugs is necessary, as well as the establishment of incentives for doctors (general or internal medicine and cardiologists, who prescribe the majority of drugs) and pharmacists to promote them, alongside financial incentives given to patients [33]. At a later stage, following the practices of EU states [44] and other countries [45], it would be useful to design policies at the regional level.

Much of the expenditure is due to new high-value drugs, mainly in group L. It would be useful to consider other reimbursement models, such as risk-sharing contracts.

Moreover, our analysis showed that the 60+ age group had the highest percentage in consumption and expenditure on medicines, with the percentage remaining constant without changing from year to year of analysis. However, the younger age groups presented a significant annual increase in consumption and expenditure on medicines. This may be a consequence of the economic crisis and the pandemic and requires the state to take disease prevention measures. These findings may highlight the need for a comprehensive campaign focusing on preventive screening and lifestyle modifications. This initiative aims to enhance overall wellbeing by encouraging the early detection of health issues and fostering healthier habits.

An important finding in the research was the geographical separation of regions according to prescription and demographic data. Areas with more difficult access to health services showed different behaviour from the rest of the country, as did the residents of large urban centres. It would be useful to design policies specific to each region.

The time of the study also includes the 2020–21 period characterized by the COVID-19 pandemic. The consequences of the pandemic on prescriptions worldwide were an increase in expenditure [7,46], in particular, for specific categories of drugs such as anti-infectives for systemic use (the ATC J category) [16,47], in the period before the first vaccines were launched. In Greece, the increase in spending in 2020 was 7.7%, and in 2021, it was 5.3%. The use of anti-infectives for systemic use increased—in terms of quantity and value—significantly in 2020 but decreased in 2021. There was also a significant increase in preparations for the respiratory system (the ATC R category).

In addition, the results of the present study are the beginning of an investigation into variations in prescription characteristics. Since it is an important tool for the EOPYY (the Greek National Organization for the Provision of Health Services), policymakers and researchers must start a discussion about a real clinical and financial audit, combined with protocols for physicians and volume agreements with pharmaceutical companies that favour the healthcare system and, specifically, the patients.

Several potential limitations to this study must be considered. Firstly, we only included in our analysis drugs that are completely reimbursed by the EOPPY (another billion EUR was consumed by NHS hospitals: half of this was covered by the state and the other half by claw backs). Secondly, with the information about medications that is available in the administrative database, we were not able to identify any possible loss to follow-ups, making it impossible to assess the patients' adherence to therapy.

It would be useful for subsequent research to address these limitations. It would also be useful for a study to examine the effect of new pharmaceuticals on costs.

5. Conclusions

The study highlights significant growth in prescription drug consumption and expenditure, with notable increases driven by demographic factors, regional disparities, and the introduction of high-cost drugs. Despite the establishment of an electronic system and the rise in generic drugs, particularly in cardiovascular treatments, overall spending continues to climb, suggesting a need for targeted cost-control measures. The study findings underscore the importance of addressing regional and demographic disparities in pharmaceutical use, thereby contributing to more equitable and cost-effective healthcare strategies. Moreover, the current study can provide a strategic framework for policymakers and healthcare managers to guide future studies and inform decision-making processes. It should be repeated every year going forward in order to succeed the above and expand scientific findings.

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Data Availability Statement: The data were provided by administrative sources only for the preparation of this research, without the right to grant them.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

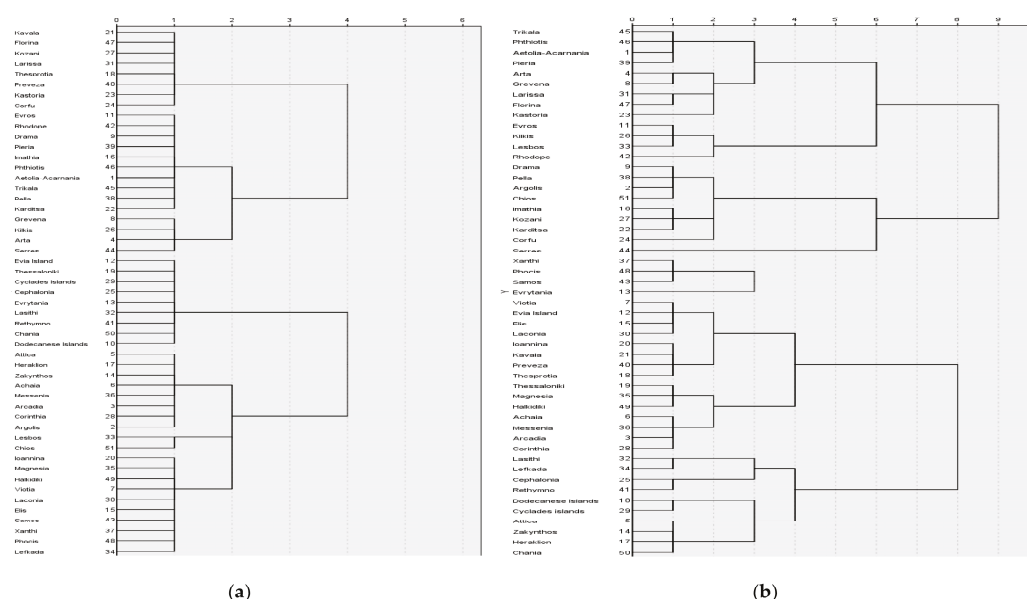


Figure A1. Cluster analysis. Dendrograms of regions by (a) quantities and (b) values.

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Article

Knowledge Management and Digital Innovation in Healthcare: A Bibliometric Analysis

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Abstract: Background/Objectives: In recent years, knowledge management and digital innovation have become pivotal in transforming healthcare systems, driving efficiency and enhancing patient outcomes. This study presents a bibliometric analysis of research trends at the intersection of knowledge management and digital innovation in healthcare, examining the scope, impact, and evolution of scholarly work in this domain. Methods: Using a comprehensive dataset from the Scopus database, we analyzed 419 publications from 1985–2023 to identify influential authors, journal collaborations, and emerging topics and methodologies in the field. Results: Our findings reveal a significant increase in research interest, highlighting themes such as data-driven healthcare, artificial intelligence in clinical decision support, and knowledge-sharing platforms' role in improving healthcare delivery. The analysis also underscores the growing importance of interdisciplinary collaboration between healthcare providers, technologists, and policy-makers. Conclusions: By mapping the intellectual structure of knowledge management and digital innovation in healthcare, this study provides valuable insights for academics, practitioners, and policy-makers seeking to harness knowledge management practices and digital technologies to foster innovation and resilience in healthcare systems.

Keywords: digital innovation; health systems; healthcare; knowledge management; bibliometric analysis

1. Introduction

The healthcare sector has witnessed a rapid transformation driven by digital innovation, encompassing technology-driven changes that enhance healthcare delivery, improve patient outcomes, and streamline operational efficiency. Digital innovation in healthcare includes advances such as artificial intelligence (AI), telemedicine, electronic health records, and wearable health devices, which have reshaped how healthcare services are provided and accessed [1–3]. This shift occurs within complex health systems—the interconnected organizations, resources, and policies designed to deliver healthcare services and improve public health outcomes [4–6]. Health systems are the backbone of healthcare delivery, ensuring accessible, equitable, and efficient healthcare for populations [7]. To improve healthcare delivery, digital innovation refers to adopting advanced technologies, including AI, telemedicine, wearable devices, and electronic health records (EHRs). Digital solutions empower providers to streamline workflows, enhance patient engagement, and guide data-driven decision-making. Key areas of digital innovation in healthcare include: (i) AI and machine learning—AI enables predictive analytics and real-time diagnostics, from early disease detection to personalized treatment recommendations. Machine learning algorithms can process vast datasets to identify patterns, flagging potential health issues

before symptoms appear; (ii) telemedicine and remote monitoring: telemedicine platforms have allowed providers to extend care to remote areas, reduce in-clinic wait times, and offer consultations across geographic barriers [8–10]. Remote monitoring, through wearables or smart devices, provides continuous patient data, allowing for timely intervention; (iii) EHRs—EHRs offer a centralized, digital repository of patient records, enhancing collaboration among providers, improving accuracy, and reducing redundant tests or procedures; (iv) blockchain technology: blockchain provides a secure, immutable record of patient information, safeguarding data privacy and enabling transparent data sharing between trusted parties.

Closely related is the concept of digital transformation, defined as: “a fundamental change process enabled by digital technologies that aim to bring radical improvement and innovation to an entity (e.g., an organization, a business network, an industry, or society) to create value for its stakeholders by strategically leveraging its essential resources and capabilities” [11]. Digital transformation extends beyond isolated innovations to encompass the strategic, organization-wide integration of digital technologies. Digital transformation involves adopting specific innovations and fundamentally reshaping processes, business models, and organizational cultures to leverage digital advancements fully. In healthcare, digital transformation includes reconfiguring care delivery models and patient engagement strategies, leading to more personalized, efficient, and accessible care. Together, these concepts, digital innovation and digital transformation, frame our study’s focus as we examine the evolving role of knowledge management in supporting digital advancements across healthcare settings.

Integrating digital solutions requires effective knowledge management, which involves systematically organizing, sharing, and analyzing medical data and expertise to enhance clinical and operational decision-making. Healthcare organizations must manage knowledge to facilitate continuity of care, uphold high standards, and ensure the latest medical advances and protocols are available to clinicians. Effective knowledge management is essential for: (i) clinical decision support—by organizing patient histories, lab results, and evidence-based guidelines, knowledge management aids clinicians in making accurate, timely diagnoses and treatment plans; (ii) continuous improvement—knowledge management allows healthcare organizations to learn from past successes and challenges, optimizing their approach to patient care and administration; (iii) interdisciplinary collaboration—knowledge management systems promote seamless information sharing between departments, enabling integrated and patient-centered care.

Integrating knowledge management and digital innovation reshapes healthcare, promising enhanced patient outcomes, operational efficiency, and accelerated decision-making [12]. This study addresses that gap by mapping the intellectual landscape of knowledge management and digital innovation in healthcare from 1985 to 2023, providing a critical resource for researchers, practitioners, and policymakers. Our analysis highlights prominent research areas, uncovers collaborative networks, and identifies future directions for research and practice. By consolidating the knowledge base, this study contributes to advancing the field and guiding future efforts in leveraging knowledge management and digital technologies to improve healthcare systems. Our analyses aim to provide a comprehensive overview of critical topics, influential researchers, and institutional collaborations in knowledge management and digital innovation in healthcare. This bibliometric mapping reveals research trends, significant publication sources, and emerging themes, ultimately guiding future research directions and supporting evidence-based innovation in healthcare management.

2. Integrating Knowledge Management and Digital Innovation in Modern Healthcare

Digital innovation and knowledge management are symbiotic in healthcare. Digital tools provide platforms for capturing, storing, and analyzing knowledge. Integrating knowledge management with digital solutions like AI or telemedicine allows healthcare providers to leverage data for immediate care and long-term learning.

2.1. Clinical Decision Support Systems (CDSS)

CDSS combines knowledge management with AI algorithms, providing healthcare professionals with real-time insights and alerts based on current patient data. For instance, a CDSS may alert a physician if a patient's symptoms match a specific condition or if their medication dosage requires adjustment, facilitating evidence-based care.

2.2. Personalized Patient Care

With wearable technology and data analytics, personalized medicine is now more accessible. Physicians can tailor treatment plans based on patient-specific factors, from genetic information to lifestyle habits. Knowledge management enables providers to retain and apply these insights across similar cases, advancing personalized care practices industry-wide.

2.3. Improved Operational Efficiency

Knowledge management and digital tools streamline hospital administration by automating scheduling, billing, and inventory management. Predictive analytics can forecast resource demand, reducing patient flow bottlenecks and ensuring efficient use of facilities and staff.

2.4. Enhanced Research and Development

Knowledge repositories and data-sharing networks facilitate research collaboration and accelerate the development of new treatments. For example, knowledge management enables research institutions to pool anonymized patient data, enhancing the understanding of disease progression and treatment outcomes and ultimately driving innovation in drug discovery.

3. Methodology

We followed a systematic approach to conduct a bibliometric analysis of healthcare knowledge management and digital innovation. Our process involved the following stages:

3.1. Data Collection

We sourced data from the Scopus database, which were collected in November 2024. Scopus is recognized for its extensive coverage of peer-reviewed literature and rigorous indexing standards [1]. We limited our search to articles published from 1985 to 2023 to capture foundational studies and recent advancements in the field. This extended time-frame allowed us to observe trends over time, offering insights into the evolution of digital innovation in healthcare.

3.2. Inclusion Criteria

We focused on articles on healthcare, knowledge management, and digital innovation and filtered results based on relevance to the study's aims. By using specific keywords ("knowledge management", "digital innovation", "healthcare systems", "digital health", etc.), we narrowed our search to articles specifically focused on healthcare settings and management applications to ensure relevance and quality of insights.

3.3. Data Extraction and Selection

After identifying relevant articles, we extracted data from titles, abstracts, and keyword sections. This targeted approach allowed us to focus on studies directly contributing to the intersections of our primary research interests.

3.4. Data Processing and Analysis

The collected data were processed using the bibliometric tool VOSviewer v.1.6.20, a software developed by Van Eck and Waltman, that enables advanced analyses of citation networks, co-authorship patterns, keyword co-occurrence, and research trends [13].

We chose this tool for its capabilities in visualizing complex networks and identifying influential research themes and collaborations.

Network analysis is an increasingly popular tool for analyzing complex relationships between sectors and industries. Measuring all aspects of networks has made network analysis a central tool in analyzing bibliometric data [14].

3.5. Citation Analysis

This approach helped us identify the most cited articles and journals, highlighting seminal works that have shaped the field [15].

3.6. Co-Authorship and Collaboration Networks

By mapping co-authorship networks, we observed influential authors and institutions and international collaboration trends in healthcare digital innovation research.

3.7. Keyword Co-Occurrence Analysis

This method enabled us to identify frequently discussed topics and emerging trends, providing insights into the most relevant themes within the field.

4. Results

Four hundred and nineteen articles were retrieved, with a growing trend in the volume of publications over the years. The most relevant keywords are listed in Table 1.

Table 1. Most Relevant Keywords.

Keywords	No of Articles	Keywords-Plus	No of Articles
Knowledge Management	99	Knowledge Management	325
Healthcare	24	Health Care	89
Big Data	18	Human	81
Digital Health	18	Humans	68
Knowledge Sharing	14	Article	56
Ontology	13	Digital storage	55
Artificial Intelligence	11	Artificial Intelligence	48
Cloud Computing	9	Medical Informatics	43
COVID-19	9	Decision Making	37
Digital Transformation	9	Health	36

The first studies date back to 1985, though no articles were published in 1986–1994, 1996, and 2001–2002. On the other hand, there has been a gradual increase in publications on managing digital health knowledge since 2004. Figure 1 presents the number of published articles per year and the number of citations per year. From 2005 onwards, we observe an increasing trend regarding the number of citations per year. However, the increase in articles per year shows fluctuations in citations, which increase exponentially per year.

Figure 2 shows the journals with the most publications.

Table 2 lists the top seven organizations publishing the most articles. The Consiglio Nazionale delle Ricerche of Italy has published seven. The University of Toronto in Canada has published six, followed by the RMIT University of Australia and the University of Washington in the USA, each of which has published four.

Figure 3 presents the number of publications by country. The United States of America is at the top, with 90 publications. The United Kingdom follows with 51 articles and Germany with 41 articles. Australia has published 36 articles, India follows with 32, Canada has published 32 articles, and Italy follows with 27.

Figure 4 shows the topic trend graph displays the frequency of utilisation for different keywords.

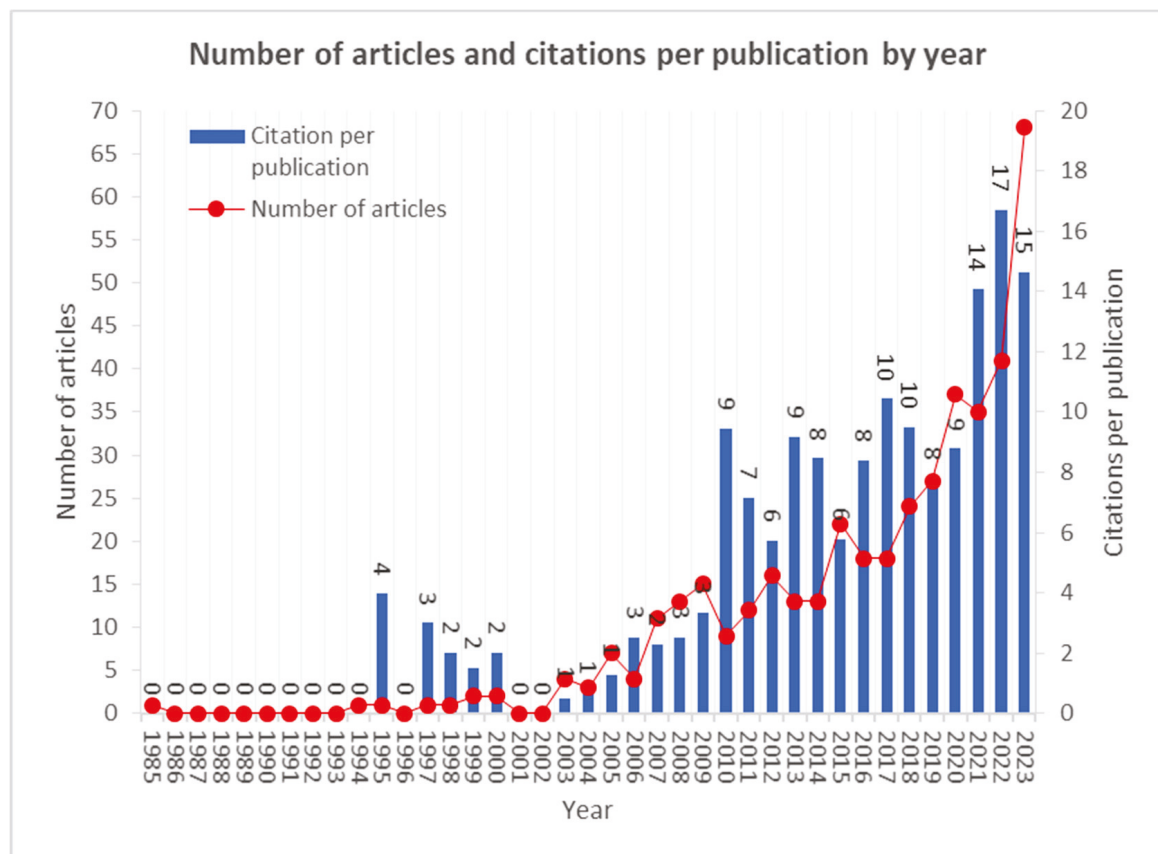


Figure 1. Number of articles and citations per publication by year.

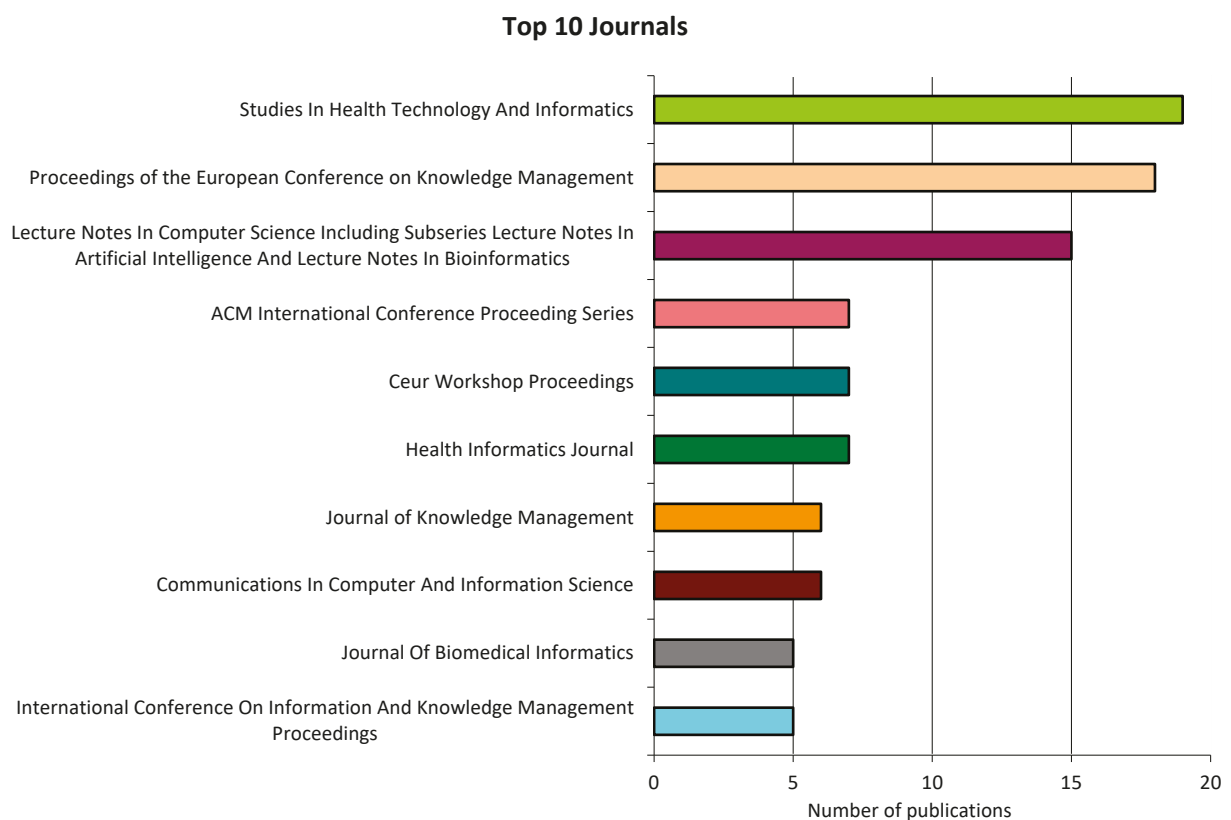
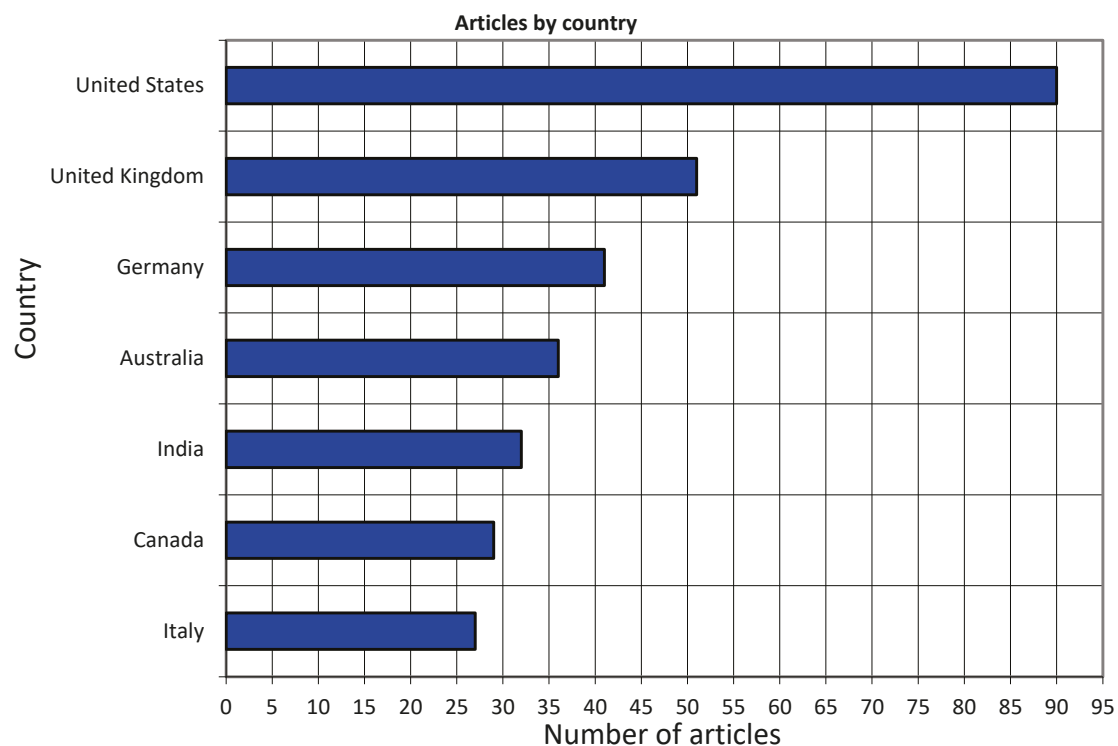


Figure 2. Top 10 journals.

Table 2. Number of Articles per Organization.

Articles per Organization		
Country	Organisation	No. of Articles
Italy	Consiglio Nazionale delle Ricerche	7
Canada	University of Toronto	6
Italy	Università degli Studi di Napoli Federico II	5
Canada	University of Alberta	5
Finland	Tampere University	4
Australia	RMIT University	4
USA	University of Washington	4

**Figure 3.** Top seven countries by number of articles.

This is an overview of the topics that are becoming important in knowledge management, innovation, and healthcare. This figure helps to show that topics are gaining significance in the field each year.

Figure 5 represents a grid focused on keyword reproduction in the literature on the general dimensions of digital knowledge management in health. It shows that knowledge management is linked to the health and digital sectors.

Figure 6 shows the density visualization map of keywords, showing that the most prevalent nodes are knowledge management, health care, health, internet, and digital storage.

Figure 7 illustrates the results of a multiple correspondence analysis (MCA) of the keywords used. The map shows six clusters, each encompassing keywords related to the knowledge management process of digital healthcare. The red cluster refers to the database systems and information retrieval during the knowledge process. The yellow cluster refers to the decision support systems procedures related to knowledge engineering and knowledge representation through artificial intelligence. The blue cluster represents digital health procedures and how these are related to human-technology interaction, such as digital storage, human-computer interaction, and medical computing. The green cluster refers to learning systems and diagnostics procedures through knowledge sharing. The blockchain is the smallest cluster (bottom right).



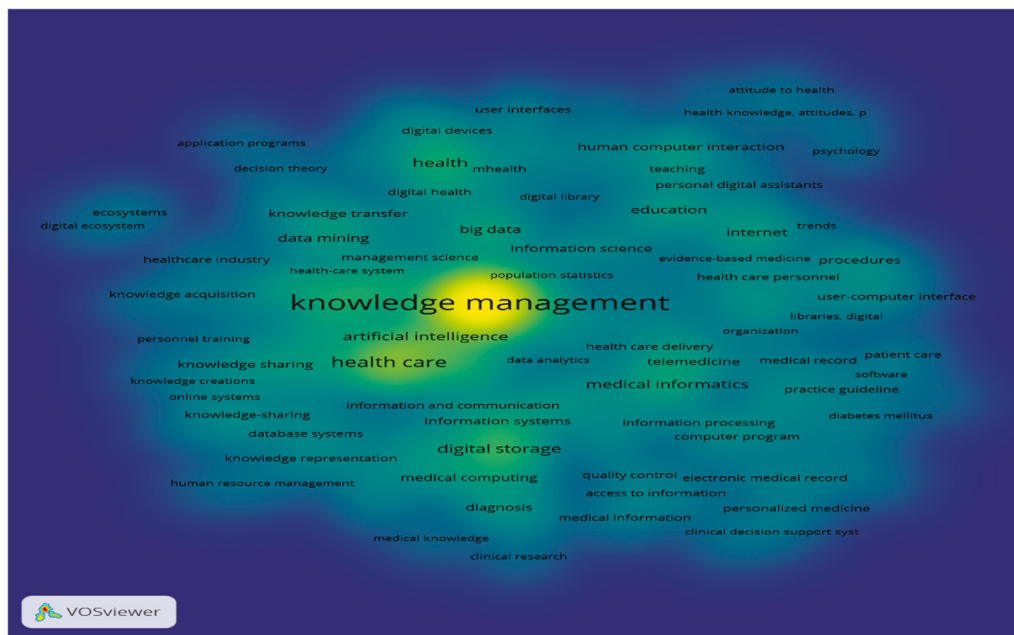


Figure 6. Density Visualization Map of Keywords.



Figure 7. Multiple Correspondence Analysis (MCA).

5. Discussion

Our results indicate that the “innovation” node is directly linked to the “knowledge management”, “health”, and “digital healthcare” nodes. In other words, a two-way relationship is crucial for the health sector. This highlights the importance of health knowledge and digitalization in health. Digital repositories of knowledge can make a decisive contribution to both the evolution of a patient’s health and to research and development. In addition, they contribute to innovative applications and solutions in the healthcare field while saving time, money, and staff. Due to their structure and nature, digital knowledge repositories can be integrated into artificial intelligence or cloud computing systems, upgrading the role and function of these systems and the patient care provided. In addition, a digital health knowledge repository is constantly being enriched by evidence yielded by

domestic and international research efforts through thematic networks of innovation and open consultation [16].

One of the things that promotes innovation is knowledge sharing. Only through knowledge exchange is innovation possible [17]. Collaboration is an efficient and beneficial way to acquire information and skills for successful innovation. Regarding creation, knowledge exchange refers to sharing skills and knowledge to produce or enhance valuable goods and services. Knowledge transfer is a critical process that enables organizations to share expertise, skills, and experience across teams, projects, and departments. Based on a meta-analysis, Mesmer-Magnus and DeChurch concluded that knowledge sharing can forecast team performance [18]. Subsequently, ignorance is the primary barrier to innovation. Darroch and McNaughton [19] asserted that a company promoting knowledge exchange is likelier to foster creative thinking and new ideas. We could extrapolate their viewpoint regarding hospitals. Furthermore, Belso and Diez found that businesses become more innovative when participating in knowledge networks [20].

Several studies have examined the connection between innovation and knowledge sharing without, however, having considered their role in the development and application of digital health. Numerous researchers have emphasized the need to investigate knowledge exchange and innovation. Tamer Cavusgil et al. [21] concluded that an organization's capacity for innovation increases with the amount of tacit knowledge transferred. The same rule could apply to hospitals. Sharing tacit information is crucial for creativity. One way of turning implicit knowledge into explicit knowledge is through knowledge sharing. Knowledge of both kinds can be used to spark innovation.

Camelo et al. [22] found that knowledge sharing positively affected innovation in a survey of Spanish organizations. This was also pointed out by Podrug et al. [23] in Croatian companies, where knowledge sharing increased the capacity for innovation. Taminiau et al. [24] found that informal knowledge sharing is the most fruitful path to innovation. Mura et al. [25] explained how knowledge sharing and innovation are linked. In their study, any health behaviors associated with knowledge sharing positively affect innovation regarding the tendency and ability to promote and implement new ideas. Wang and Hu [26] argued that knowledge sharing mediates collaborative innovation and organizational performance. It has also been shown that knowledge sharing enhances subjective well-being and individual innovation [27]. There is also evidence that knowledge sharing between employees in an industry can drive innovation [28]. On the other hand, Kamasak and Bulutlar [29] found that knowledge sharing within a group influenced exploitative innovation.

6. Conclusions

Digital health transformation is an urgent need dictated by the constant and rapid changes and innovations in the IT and healthcare sectors. By adapting to new requirements, health systems acquire new knowledge based on which new medical protocols and tools can be developed to benefit patients and healthcare staff. There is a research gap regarding digital health knowledge management. In addition, the health knowledge already acquired must be manageable. This implies adapting existing health models, theories, and practices to new conditions. New ways of collecting knowledge need to be developed in the health sector, as digital transformation allows health systems to apply new technologies for disseminating knowledge at all levels, along with automated systems often based on artificial intelligence. In addition, proper knowledge management could increase the productivity and efficiency of healthcare personnel. At the same time, patients could be served more efficiently, with greater accuracy in terms of diagnosis and best practices to their benefit.

The main conclusion of this research is the need to promote and manage health knowledge through digital systems, as the current situation cannot meet the requirements related to the daily challenges faced by patients and healthcare staff. In addition, by

adopting and using such health innovations, new knowledge can be disseminated faster, more securely, and more cost-effectively, and it can also be stored for future use.

While integrating knowledge management and digital innovation holds immense potential, several challenges persist, including: (i) Data privacy and security: protecting sensitive patient information is critical. As more data are collected and shared, ensuring confidentiality and compliance with regulations such as HIPAA (in the U.S.) or GDPR (in Europe) is paramount. Blockchain and encryption technologies offer solutions, but widespread implementation requires investment and regulatory alignment; (ii) Interoperability: different healthcare organizations often use disparate knowledge management and digital systems, hindering seamless data exchange. Building interoperable systems is necessary to maximize the potential of knowledge management and digital tools across diverse healthcare environments; (iii) Change management and training: integrating digital tools and knowledge management requires significant shifts in organizational culture and workforce skills. Training clinicians and staff on new systems is vital, as is ensuring leadership buy-in to foster an environment open to digital transformation; (iv) Cost and resource constraints: developing, implementing, and maintaining knowledge management and digital innovation systems can be costly, particularly for smaller healthcare providers. Balancing initial investments with long-term benefits is a constant challenge.

Knowledge management and digital innovation are reshaping healthcare by equipping providers with the tools to deliver more efficient, personalized, and data-driven care. As knowledge management and digital systems become increasingly sophisticated, the healthcare industry can expect even more significant improvements in patient outcomes, operational efficiency, and research capabilities. Embracing these strategies will require overcoming data privacy, interoperability, and organizational culture challenges, but the benefits outweigh the costs. By continuing to innovate and invest in knowledge management, healthcare organizations can create a resilient, patient-centered system that meets the evolving needs of modern healthcare.

7. Limitations and Further Research

While our bibliometric analysis provides a comprehensive overview of knowledge management and digital innovation in healthcare, certain limitations should be noted. First, our study relied on data from one central database, Scopus, which, although widely regarded for its extensive coverage, may exclude relevant studies indexed in other databases or non-English publications. This choice could limit the generalizability of our findings across diverse regions or languages. Future research could benefit from including additional databases, such as Web of Science (Wos), PubMed, or IEEE Xplore, to capture a broader range of studies and enhance representativeness.

Additionally, our analysis centered on citation counts, co-authorship networks, and keyword co-occurrence to identify key themes, researchers, and collaborations. These bibliometric methods provide valuable insights but may not fully capture the qualitative aspects of digital innovations or the practical impact on healthcare delivery. Future research could incorporate a qualitative review of selected articles to deepen understanding of specific innovations' impacts and applications.

Finally, our study does not address potential cultural, regulatory, or organizational factors that influence the adoption of digital innovations in healthcare across different countries. Future studies could explore these contextual factors, providing insights into how healthcare systems in various regions approach digital innovation and knowledge management differently.

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Article

Perceptions of a Hospital's Anesthesia Team Members on Precycling and Recycling of Anesthetic Gases

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Abstract: Background: Climate change poses significant challenges to global health, At the same time, the healthcare sector itself, with its high resource demands, also contributes substantially to global warming. Anesthesia, particularly through the use of volatile inhalation anesthetics, is a key contributor in this respect. The present exploratory study examines staff perceptions of precycling and recycling strategies aimed at reducing the environmental impact of anesthetic gases at the General Hospital Vienna, Austria. This large institution has recently implemented major changes, including the shutdown of the centralized nitrous oxide supply and the introduction of anesthetic gas recycling systems on anesthesia machines, alongside other precycling measures. **Methods:** We conducted a cross-sectional online survey of anesthesia team members (n = 103, 61.2% females) to assess current perceptions related to anesthetic gas usage, focusing on precycling and recycling aspects, and their willingness to engage in further sustainability efforts. **Results:** We found that participants expressed an, in general, positive attitude towards environmental protection measures and a high willingness to make additional efforts to recycle anesthetics. Thus, the anesthesia team members in our institution may be inclined to support strategies like minimizing the use of volatile anesthetics. **Conclusions:** These preliminary insights could inform actionable recommendations for advancing sustainable practices in anesthesiology at our hospital.

Keywords: green anesthesia; healthcare delivery; sustainability; sustainable development goals (SDGs); waste reduction; hospital management; charcoal adsorbers; desflurane; sevoflurane; inhaled anesthetics recapture; climate change

1. Introduction

Globally, climate change represents one of the greatest challenges for public health, with the healthcare sector itself causing significant greenhouse gas (GHG) emissions [1,2]. Anesthesia and intensive care medicine contribute significantly to this, particularly due to the use of volatile inhalation anesthetics [3]. Therefore, it is necessary to explore new ways to provide high-quality healthcare while acting sustainably. In Austria, like in all other

countries, hospitals increasingly recognize that they can contribute to this endeavor [4]. A key area where hospitals see great potential to make a significant contribution to reducing GHG emissions is in the operating rooms [3]. Technical measures aimed at reducing energy consumption and utilizing gas-capture technologies, such as activated carbon adsorber systems, can limit the release of anesthetic gases into the atmosphere [4–7]. Although further evaluation of the full life-cycle impacts of recycling these captured gases is necessary, such technologies represent a promising step toward more sustainable anesthesia practices [7,8]. Within these, the field of anesthesiology is particularly relevant due to the use of climate-damaging anesthetic gases, given the power-consuming technical equipment and the huge amount of plastic and single-use equipment [9].

The two main methods for maintaining general anesthesia are propofol-based intravenous anesthesia and inhalation anesthesia with gases. Propofol, though commonly used, is highly toxic to aquatic environments and requires separate disposal via incineration to prevent contamination [10]. The inhalation anesthetics sevoflurane, desflurane, and nitrous oxide are potent GHGs that contribute to climate change. Nitrous oxide also contributes to the depletion of the ozone layer. Since these drugs are hardly metabolized by the body during anesthesia, over 95% of the inhaled amount is exhaled and, in most hospitals, released unfiltered into the atmosphere through the exhaust system. Desflurane has a much higher GHG potential than nitrous oxide and sevoflurane, although nitrous oxide remains in the atmosphere the longest.

From food waste to broken items and excessive packaging, the global waste output, particularly plastic waste, is projected to rise dramatically [11]. While governments are drafting regulations to reduce plastic use, consumers are adopting more sustainable consumption patterns. One such approach is “precycling”—a proactive strategy where individuals prevent waste before it accumulates by purchasing unpackaged goods, reusing items, or avoiding excessive packaging, as suggested by Leila Elgaaïed-Gambier [12]. Precycling aligns with the circular economy’s goal of zero waste by promoting sustainable, responsible consumption. Initially introduced to enhance the circular economy, precycling encourages consumers to adopt mindful behaviors that prioritize waste prevention [13]. Despite its growing relevance, precycling remains under-researched, particularly in understanding consumer motivations and behaviors that drive this practice [11].

In anesthesiology, the concept of precycling is gaining attention in the context of anesthetic gas usage [14]. Just as consumers can reduce their waste through precycling in daily life, healthcare professionals can apply similar principles to minimize the environmental impact of volatile anesthetics. Precycling in this context involves rethinking anesthetic practices to prevent waste before it occurs, whether through avoiding high fresh gas flow rates for all inhaled drugs, overall reducing the use of volatile gases, reusing equipment where feasible, or avoiding unnecessary emissions and waste [10]. By adopting precycling strategies in anesthesia, hospitals can reduce their GHG footprint and contribute to broader sustainability efforts, much like individuals who reduce plastic waste through conscious consumption. This innovative approach bridges the gap between environmental responsibility and clinical practice, fostering a more sustainable healthcare system [15].

In light of the growing awareness of environmental sustainability, this exploratory study at the General Hospital Vienna seeks to address these concerns by exploring innovative strategies to mitigate the environmental impact of anesthetic gases [16]. At the General Hospital Vienna anesthetic gases were previously released unfiltered into the environment through the exhaust air. To contribute to reducing General Hospital Vienna’s CO₂ footprint, the Department of Anesthesia, General Intensive Care Medicine, and Pain Therapy decided to stop using nitrous oxide and test the anesthetic gas recycling system from the Germany-headquartered company ZeoSys Medical GmbH (Luckenwalde, Germany) [6].

This led to the following main research questions: What is the attitude of our anesthesia personnel towards measures for anesthetic gas recycling, and would our personnel be willing to accept additional effort?

2. Methods

2.1. Study Design

This cross-sectional exploratory study surveyed a non-random convenience sample of German-speaking employees at the General Hospital Vienna in Austria, who were part of the anesthesia team. For data collection, we utilized the online survey platform SoSci Survey [17]. This tool facilitated the design, distribution, and analysis of the questionnaire, allowing for secure and efficient data handling. The participants were primarily anesthesiologists and anesthesia nursing staff working at the university's main teaching hospital, the General Hospital Vienna in Austria, which was part of the publicly funded university campus of the Medical University of Vienna. Participation in the survey was voluntary. All participants were informed about the purpose of this study and gave informed consent prior to participation. Data protection policies were strictly adhered to, ensuring both the anonymity and confidentiality of participants. To recruit survey participants, the questionnaire link and reminder messages were sent to approximately 250 employees within the anesthesia team at General Hospital Vienna, who constituted the target study population at the time of this study.

This study's protocol was submitted for review to the Ethics Committee on 22 November 2023 and was approved on 19 January 2024. It was subsequently reviewed by the University's Data Protection Committee, the General Staff Council, and the Scientific Staff Council at the Medical University of Vienna. These bodies imposed specific requirements for data processing and publication. According to their guidelines, gender designations must include the legally recognized categories: male, female, non-binary, intersex, open, or no response, data must be analyzed in accordance with Good Scientific Practice Publication of results from groups with fewer than seven participants was prohibited. Data usage was restricted to the purpose stated in the application, and data analysis must ensure that individuals could not be identified, including through open-ended responses. The survey was conducted following the principles of the Helsinki Declaration and in compliance with the EU General Data Protection Regulation.

2.2. Study Questionnaire

The questionnaire collected general information, including age, gender, main residence, professional activity, and length of service. Another set of questions focused on participants' self-assessment of their interest in environmental and climate protection topics, their level of information and concern about these issues, their assignment of responsibility, and their action-oriented attitudes and personal activities related to environmental and climate protection. The central section of the questionnaire gathered information on the use of anesthetics in the hospital, personal experience with recycling volatile anesthetics, and personal attitudes toward recycling these substances. Additionally, an open-ended question, "Would you like to tell us anything else?" provided space for survey participants to offer further comments in a text field.

The questions and the overall structure of the questionnaire were tested in a qualitative-semantic pretest ($n = 23$), and the questionnaire was modified based on the test results. The pretest was conducted online using the SoSci Survey pretest function between 9 and 23 October 2023 [17]. A total of 23 participants took part in the pretest (mean 38.4 years, SD 11.5, age range from 18 to 57 years). Most participants were female ($n = 14$, 60.9%), while eight participants (34.8%) were male, and one participant (4.3%) identified as diverse. The

test subjects received the online link to the questionnaire and were asked to answer the questions to check the flow and understandability of the survey and provide feedback on the clarity of the questions, the order of the questions, and possible misunderstandings. Based on this feedback, necessary adjustments and improvements were made to the questionnaire. The pretest ensured that the survey was understandable for the actual data collection and helped identify potential errors or misunderstandings in the questions in advance, thereby improving the quality of the collected data.

2.3. Statistical Data Analysis

The statistical analysis of the survey data was conducted using SPSS Statistics for Windows (Version 29.0, IBM Corp., Armonk, NY, USA). To construct variables, mean scores were calculated from the scales measuring interest in environmental and climate protection topics. Descriptive statistics were employed to present the quantitative results, including percentages, means (M), and standard deviations (SD). For improved interpretability, items in the tables were sorted in descending order by mean score. Means were computed from the four response options ranging from “strongly disagree” to “strongly agree”, excluding neutral responses (“don’t know/no response”). However, these neutral responses were included in frequency calculations. To facilitate the interpretation of frequencies, a dichotomized variable was created for the question block on attitudes towards anesthetic gas recycling, classifying responses into “disagree” versus “agree”. For median splitting in the age variable (younger than 37 years and 37 years and older), the median was calculated. For qualitative content analysis, free-text responses were reviewed and coded to extract information from unstructured text data and derive insights [18]). To analyze subgroup differences in response patterns, a dichotomized variable was created for free-text responses (yes or no).

3. Results

3.1. General Sample Characteristics

Out of the about 250 employees in the anesthesia team of the General Hospital Vienna, a total of 192 clicks on the questionnaire were recorded, including accidental double clicks. Of these, 105 participants provided complete data, resulting in a 54.7% completion rate among those who started the survey. Data collection took place between 6 February and 26 March 2024. The average completion time was 4.5 min (SD 1.0, range between 2.4 and 7.2 min). Notably, the inclusion criteria for the survey were adults who agreed to participate in the survey (consenting to the consent form at the beginning of the survey), were employed at the General Hospital, and were able to complete an online questionnaire in German. Two data sets were subsequently excluded because the individuals indicated they did not work at the General Hospital, resulting in a total study population of $n = 103$.

The first section collected general information on age, gender, primary residence (rural or urban area), job type in the anesthesia team (anesthesiologist, resident in anesthesiology, nursing staff, operation room staff), and work experience as measured in length of service (up to 5, 5–10, more than 10 years). On average, the participants were 40.1 years old (SD 10.9 years, age range 22 to 64 years, median 37 years). Using median splitting, participants were divided into two groups with lower age ($n = 53$, 51.5%) and higher age ($n = 50$, 48.5%). The majority of participants (61.2%) were females and 81.6% lived in urban areas. Additionally, 40.8% reported being part of the operating room and nursing staff, and 51.5% had more than 10 years of work experience. The last two variables were also dichotomized, showing a balanced percentage of medical and non-medical staff as well as lower and higher service duration (Table 1). One participant selected ‘diverse/inter/open/no answer’ in the gender category. Due to the single response, gender was dichotomized into two categories (female

and male) for the gender analysis. However, the non-binary participant's data were retained in the overall data set to ensure completeness and inclusion of all responses.

Table 1. Sociodemographic characteristics of the study population (n = 103).

Item	N	%
Gender		
Female	63	61.2
Male	39	37.9
Diverse	1	1.0
Primary residence		
Rural area	19	18.4
Urban area	84	81.6
Profession		
Anesthesiologist	29	28.2
Resident in anesthesiology	24	23.3
Nursing staff	42	40.8
Operation room staff	8	7.8
Profession (dichotomous)		
Medical doctor	53	51.5
Non-doctoral staff	50	48.6
Length of service		
Up to 5 years	29	28.2
5–10 years	21	20.4
More than 10 years	53	51.5
Length of service (dichotomous)		
Lower (up to 10 years)	50	48.5
Higher (more than 10 years)	53	51.5

3.2. Interest in Environmental and Climate Protection

The third section of the online survey gathered data on topics related to environmental and climate protection. This section focused on participants' levels of interest in specific environmental and climate protection issues, as well as their personal actions and attitudes toward these topics. The response patterns indicated minimal neutrality among participants, with a neutral response rate of less than 2.0%. Table 2 shows the results of the descriptive statistics. When comparing the levels of agreement across the different areas, 'interest in environmental and climate protection actions' ranked lowest (mean = 2.8, SD = 1.0). In contrast, the highest levels of agreement were observed for 'energy saving at home' and 'protection of rare animals, plants, and habitats' (mean = 3.7 each, maximum score of 4). The remaining areas fell between these two extremes. Notably, neutral responses such as "I don't know/no answer" were excluded from the calculation of the mean scores to ensure clarity in interpreting participants' genuine interest levels.

Table 2. Interest in environmental and climate protection topics, sorted ascending by mean.

Item	Mean	SD
Saving energy in the household	3.7	0.5
Protection of rare animals, plants, and habitats	3.7	0.6
Pollutants in the environment	3.6	0.6
Sustainable, environmentally friendly products	3.5	0.6
Healthy products	3.5	0.6
Climate-friendly mobility	3.5	0.6
Climate change and climate protection	3.3	0.8
Environment and climate protection campaigns	2.8	1.0

The highest average agreement was observed on average for the statements “Our descendants will suffer from the consequences of environmental pollution” and “The economy should make a much greater contribution to environmental and climate protection” (both $M = 3.8$, $SD = 0.5$; see Table 3). In contrast, the lowest average agreement was found on average for the statements “I, as an individual, cannot make a significant contribution to environmental and climate protection” ($M = 2.5$, $SD = 1.0$) and “I don’t know what I could do for environmental and climate protection” ($M = 1.8$, $SD = 0.8$).

Table 3. Information status and current worries concerning environmental and climate protection, sorted ascending by mean.

Items	Mean	SD
Our descendants will suffer from the effects of environmental pollution.	3.8	0.5
The economy should make a much stronger contribution to environmental and climate protection.	3.8	0.5
I believe that environmental and climate protection is the responsibility of all citizens.	3.6	0.6
I personally feel responsible for preserving nature.	3.5	0.7
People have lost control over their impact on the environment.	3.4	0.7
To protect nature, many more citizens would need to commit to environmental and climate protection.	3.4	0.8
I actively contribute to environmental and climate protection.	3.2	0.7
I feel well-informed about the topic of environmental and climate protection overall.	3.1	0.7
The more information I receive about environmental pollution, the more uneasy I feel.	3.1	0.9
I am afraid for the future when I think about our environment.	3.0	0.9
The government is primarily responsible for environmental and climate protection.	2.8	0.9
As an individual, I cannot make a significant contribution to environmental and climate protection.	2.5	1.0
I do not know what I could do for environmental and climate protection.	1.8	0.8

3.3. Attitudes Toward Recycling Anesthetics

The survey explored current practices and perceptions regarding sustainable anesthesia in the hospital setting. At the time of data collection, the adsorber system, i.e., the charcoal-based system for capturing anesthetic gases from Zeosys, was only used in 3 out of 60 operating rooms as part of a test phase, and the nursing staff was rarely assigned to surgeries outside their specialty unlike the medical staff [6]. The rollout to additional operating rooms is already planned. Table 4 shows the frequencies of the response options regarding the practices of anesthetic use at the General Hospital Vienna, as well as their average values, the latter excluding the neutral response option.

The practice of low-flow anesthesia was highly reported, with a mean score of 3.6 ($SD = 0.6$), indicating frequent use by most respondents; 68% indicated that low-flow anesthesia was regularly or always applied to reduce volatile anesthetic consumption. Automated regulation of fresh gas flow and volatile anesthetic dosing showed a lower mean score of 1.9 ($SD = 1.1$), with only 21% of respondents reporting regular or frequent use.

As for the use of the Zeosys adsorber system to capture and recycle anesthetic gases, respondents reported a moderate average score of 2.7 ($SD = 1.0$). Around 40% of respondents reported some level of use, though 34% indicated infrequent or no implementation. In terms of specific anesthetic agents, the avoidance of desflurane—recognized for its environmental impact—was reported with a mean of 2.9 ($SD = 1.1$). Approximately 45% of respondents reported often or always avoiding desflurane, while the remaining responses indicated inconsistent avoidance. Lastly, the presence of a “green team” to support sustainability efforts was prominent, with a mean score of 3.7 ($SD = 0.7$). More than 80% of respondents acknowledged regular or consistent efforts by such teams, suggesting that institutional support for environmentally friendly practices was generally strong.

Table 4. Information on anesthetic use practices at the General Hospital Vienna.

Items	Strongly Disagree		Disagree		Somewhat Agree		Agree		Neutral		Mean	SD
In My Hospital...	n	%	n	%	n	%	n	%	n	%		
...the use of low-flow anesthesia to reduce the consumption of volatile anesthetics is practiced.	0	0	6	5.8	27	26.2	56	54.4	14	13.6	3.6	0.6
...an automatic regulation of the fresh gas flow and the dosing of the volatile anesthetics is used.	39	37.9	23	22.3	10	9.7	12	11.7	19	18.4	1.9	1.1
...special adsorber systems are used to capture and recycle anesthetic gases.	13	12.6	22	21.4	26	25.2	23	22.3	19	18.4	2.7	1.0
...desflurane is avoided as an inhalation anesthetic.	12	11.7	20	19.4	24	23.3	31	30.1	16	15.5	2.9	1.1
...there is a 'green team' to promote sustainability in healthcare facilities.	3	2.9	4	3.9	12	11.7	63	61.2	21	20.4	3.7	0.7

The analysis of personal attitudes towards the recycling of volatile anesthetics showed a significant number of neutral responses, particularly for the statement regarding cost savings in healthcare through recycling. More than a quarter of respondents selected “don’t know” or gave no answer for this item, while around 10% chose the same response for other items in the question block. To simplify interpretation, the data were dichotomized (disagree vs. agree, along with the neutral response), which provided clearer insights into overall attitudes (Table 5).

Table 5. Personal attitude towards recycling volatile anesthetics (frequency). To better interpret the results, the dichotomized variables (disagree vs. agree, along with the neutral response) were created.

Items	Neutral		Disagree		Agree	
	n	%	n	%	n	%
I already have experience and knowledge about the recycling of volatile anesthetics.	11	10.7	31	30.1	61	59.2
Recycling anesthetics is beneficial for environmental and climate protection.	12	11.7	0	0.0	91	88.3
Recycling anesthetics saves costs in the healthcare sector.	29	28.2	4	3.9	70	68.0
From a health perspective, recycled anesthetics are safe.	12	11.7	0	0.0	91	88.3
I accept the additional effort required to recycle anesthetics.	8	7.8	1	1.0	94	91.3
I believe that recycling of volatile anesthetics will soon be the standard in my hospital.	10	9.7	36	35.0	67	65.0

The majority of participants expressed support for recycling anesthetics, with 91% willing to accept the additional effort involved. A large proportion, 88%, agreed that recycling is beneficial for environmental and climate protection and considered recycled anesthetics safe from a health perspective. Additionally, about two-thirds of respondents believed that recycling would save costs in healthcare and expected that it would soon become standard practice at their hospital. Lastly, nearly 60% of participants indicated that they were knowledgeable about the recycling of volatile anesthetics, reflecting a general awareness of the issue among the respondents.

3.4. Free-Text Analysis

Qualitative feedback was gathered through an open-ended question, with only 15 participants (14.6%) voluntarily providing responses, constituting a small fraction of the total sample. These comments were analyzed using qualitative content analysis, employing an inductive, data-driven approach to identify three main themes: sustainable practices, waste management, and general comments. Table 6 presents the free-text responses with subgroup comparisons based on demographic and professional factors. A slightly higher number of younger participants (n = 8) compared to older participants (n = 7) contributed

comments. The responses were predominantly from women (n = 11) and medical doctors (n = 10), with fewer men (n = 4) and non-doctoral staff (n = 5) contributing.

Table 6. Free-text responses (n = 15), stratified by the dichotomous variables age category, gender, and profession.

Number	Free Text	Age Group	Gender	Profession
I.	Sustainable practices			
1	Anesthesia/intensive care is a very energy-intensive field (especially compared to others like psychiatry, etc.). Hospitals should establish innovations for sustainable energy generation (e.g., solar panels on parking lot roofs, wind turbines at the hospital, greening of facades, ...).	Younger	Male	Medical doctor
2	I would like my employer to promote “green mobility”, such as offering annual public transportation passes for those who do not use a garage space, or providing secure bike parking.	Younger	Female	Medical doctor
3	Volatile anesthetics can largely be replaced without negative effects!	Older	Male	Medical doctor
4	It would be desirable if surgery (nurses and doctors) would get involved in the sustainability issue.	Older	Female	Non-doctoral staff
5	I believe that the people from my department who are participating in this survey are those who already find sustainability important. Thus, I believe the survey is subject to strong selection bias. Nevertheless, I think it is great that you are addressing this issue, and I am already trying to make my work and life as environmentally friendly as possible.	Younger	Female	Medical doctor
II.	Waste management			Medical doctor
6	Waste reduction and control. Infusions are left behind after surgery. New arterial sets are opened in the ICU, and ventilation tubes and accessories are not used according to manufacturer recommendations. A breathing tube with a filter can be used for up to a week. A monitor can be used for over 48 h, and there are many more examples.	Older	Female	Medical doctor
7	Waste separation in the OR still does not work; no one follows the guidelines. Waste separation training for all staff is needed.	Younger	Female	Non-doctoral staff
III.	General comments			
8	Nuclear power, no thanks.	Younger	Female	Non-doctoral staff
9	Thank you for your initiative.	Older	Female	Non-doctoral staff
10	Thank you for your efforts!	Older	Female	Medical doctor
11	I think these actions are good and important. However, we are dealing with about 0.1% impact. I know everyone should start with themselves first, but we shouldn't lose sight of the “big picture”!	Older	Male	Medical doctor
12	I mostly perform TIVAs (Total Intravenous Anesthesia).	Younger	Female	Medical doctor
13	I wish there were more information and engagement from all employees in this direction! Thank you!	Older	Female	Non-doctoral staff
14	Great initiatives!	Younger	Male	Medical doctor
15	Thank you for your continuous work and dedication.	Younger	Female	Medical doctor

4. Discussion

The growing concern over the environmental impact of processes has led to an increasing body of literature addressing the necessity for sustainable practices in healthcare, particularly in anesthesia [3,9,10,19]. In addition to precycling strategies, such as minimizing fresh gas flow rates, anesthetic gas recycling technologies are already available to reduce greenhouse gas (GHG) emissions without compromising patient safety or care quality [7,14]. We surveyed the anesthesia team at the General Hospital Vienna to explore

their attitudes toward environmental measures, focusing on their support for anesthetic gas precycling and recycling, including the feasibility of adopting ZeoSys Medical GmbH's novel recycling system [6].

Our findings revealed strong support for sustainability initiatives, with over 80% of respondents willing to adopt anesthetic gas recycling. However, nearly 60% indicated limited knowledge about recycling volatile anesthetics, underscoring the need for targeted education and training to improve awareness and facilitate implementation [19]. Additionally, we explored interest in environmental and climate protection topics. The results suggest that respondents are primarily motivated by personal, actionable steps, but show less enthusiasm for broader systemic or collective climate protection efforts [20]. Respondents reported a high engagement with household energy conservation and protecting rare species and habitats—actions that are usually immediate and accessible in daily life [21]. In addition, we found notable concerns about environmental pollutants and a preference for sustainable products, reflecting mindfulness of how consumption affects health and the environment. In contrast, engagement was lower when it comes to climate change and climate protection, which may seem broader, more abstract, and harder to influence individually [22].

The qualitative content analysis of open-ended responses utilized a data-driven, inductive approach to categorize and interpret themes relevant to the research questions [18]. Despite a limited number of comments from a small subset of the most motivated respondents ($n = 15$), which may not be representative of the target population or the broader respondent pool, the feedback indicated support for sustainability initiatives at the General Hospital Vienna, and these preliminary insights may not be generalizable to other institutions. However, concerns were raised regarding waste segregation in operating rooms and the need for additional staff training. Several key points emerge from the comments: the energy-intensive nature of these medical fields, the necessity for hospitals to embrace sustainable innovations, and the perception that volatile anesthetics can be replaced with minimal clinical consequences. These findings point to the necessity of further efforts to effectively implement and integrate eco-friendly practices throughout the hospital [23].

Under the theme of sustainable practices, comments reflect an awareness of the energy-intensive nature of anesthesia and interest in innovations like renewable energy solutions and green mobility. One respondent highlighted, “Volatile anesthetics can largely be replaced without negative effects!” (male, medical doctor), which aligns with existing literature on reducing the environmental impact of anesthetics [1,2,4,20,23,24]. These perspectives suggest that the respondents were open to adopting more sustainable practices, although the broader hospital population may not share this enthusiasm due to the limited exposure to these options. In the waste management category, respondents pointed out inefficiencies in current practices, such as unused equipment and improper waste separation. As one comment noted, “Waste separation in the OR still doesn't work; no one follows the guidelines. Waste separation training for all staff is needed”. (female, non-doctoral staff, with OR meaning operation room). This highlights the gap in training and compliance, which is consistent with research emphasizing the need for improved waste management protocols [15].

The general comments category contained responses that appreciated the sustainability initiatives but also acknowledged their limited impact in the broader context. As one respondent stated, “I wish there were more information and engagement from all employees in this direction! Thank you!” (female, non-doctoral staff). This suggests that while there is support for sustainability efforts, greater engagement and education across departments are necessary to create a culture of sustainability [19,25]. Overall, while these insights are valuable, they represent the opinions of a small portion of respondents, and

further research is needed to assess the broader applicability of these attitudes and identify strategies to overcome barriers to sustainable practice adoption in our institution [4]. To effectively integrate sustainability into healthcare practices, it is crucial to develop and establish sustainable management methods that enhance motivation for environmental protection among employees. Evidence suggests that employee engagement is a key driver of successful sustainability initiatives in healthcare settings [26]. Training and awareness-raising initiatives can educate staff on the importance of environmental protection, helping them understand the direct impact of their actions on the environment and the positive outcomes their efforts can achieve [1].

While this exploratory study revealed high interest from anesthesia personnel, reflected in a response rate of over 50%, it is important to note that few respondents reported using technology to support environmentally efficient anesthetic agent delivery. This was primarily due to the limited availability of such technologies in our hospital, rather than a lack of practitioner involvement. As this area is still in its early stages at our institution, further research is needed to explore the barriers to technology adoption and how increased access to these tools could promote more sustainable practices [25,26]. Understanding the full impact of precycling and recycling on anesthetic gas emissions will require additional studies to provide deeper insights into the challenges and opportunities for practice improvement in our hospital. Notably, proactive support from hospital management is critical in promoting sustainable practices [27]. Healthcare organizations should motivate staff to adopt environmentally friendly practices, contributing to environmental protection [28]. Given the usefulness of precycling and recycling attempts, understanding anesthesia team members' attitudes and practices is crucial for developing effective GHG reduction strategies [13,27]. Moreover, this research fills a significant gap in the literature by collecting the perspectives of those directly involved in anesthetic practices [14]. However, further research is needed to evaluate the long-term effectiveness and feasibility of these approaches in clinical settings [7,10,15].

The aim of our exploratory study was to provide an exploration of attitudes toward anesthetic gas usage within the unique setting of the General Hospital Vienna. Given the size of our hospital, understanding the perceptions of its staff, in general, and anesthesia team members specifically provided preliminary insights that may guide similar initiatives in other large hospitals. As healthcare systems globally strive for greater sustainability, this research provides a timely and necessary contribution to the dialog surrounding waste management in anesthesia [24].

As for the practical implications of this study's findings, staff enthusiasm for sustainable strategies highlights opportunities to reduce the environmental impact of anesthetic practices, but implementation is hindered by practical barriers. Limited access to low-flow anesthesia technology and minimal experience with anesthetic gas recycling systems constrain adoption. While recycling holds promise, its current impact is negligible due to technological and infrastructural challenges. Precycling, on the other hand, appears more feasible in our setting. Advancing these practices requires increasing access to low-flow equipment, enhancing staff training, and addressing institutional barriers. These insights can guide hospitals toward more sustainable anesthetic practices while underscoring the importance of employing multivariate methods and using larger, more diverse samples to enhance the generalizability of findings [1,23,24,29].

Limitations

This exploratory study used an online survey to gather perceptions from anesthesia team members at the General Hospital Vienna, with some limitations. Primarily, online surveys are prone to selection bias, attracting more motivated, environmentally conscious

respondents, and limiting generalizability to the entire workforce. While recycling technologies were explored, they were not widely implemented at our hospital, with precycling efforts being more feasible. Future research should include a more representative sample to better assess sustainable practices across healthcare disciplines. Secondly, the self-reported nature of the data introduces social desirability bias, where respondents may over-report behaviors perceived as desirable [30]. This bias may lead to an overestimation of environmental awareness and sustainable practices among participants. Additionally, the cross-sectional design captures only a single point in time, which limits the ability to track changes in environmental attitudes or practices over time [2]. Longitudinal studies would be beneficial to assess how these attitudes evolve in response to interventions or over time.

While free-text responses can provide rich, qualitative insights, they are also subject to interpretative bias during coding and analysis [18]. Variability in how different researchers interpret and categorize responses can affect the consistency and reliability of the findings [31]. Finally, this exploratory study's focus on a single institution may restrict the applicability of findings to other healthcare settings with different organizational cultures or resources. Forthcoming research should aim to include multiple institutions to enhance the generalizability of the results and to explore how different contexts influence sustainable practices in anesthesiology [32]. By acknowledging these limitations, these findings provide a foundation for more comprehensive research that can better inform strategies for enhancing sustainability in anesthesiology and contribute to climate-neutral hospital operations—achieving net-zero GHG emissions through a combination of emissions reduction and offsetting measures.

5. Conclusions

This exploratory study of our hospital's anesthesia personnel bridges theory and practice by highlighting the critical role of staff involvement in developing effective strategies for recycling and precycling anesthetic gases. As the medical community becomes more aware of sustainability challenges, exploring innovative solutions to mitigate waste and enhance anesthetic practices is crucial. Recycling and precycling play key roles in this effort. Recycling recovers and reuses anesthetic gases while precycling focuses on preventing waste at the source by optimizing usage and reducing gas flow. While precycling is crucial for waste prevention, this survey offers preliminary insights into recycling adoption, influenced by limited access to recycling technology and respondents' general environmental predisposition, rather than direct experience with the practice. Future research should further explore the barriers to precycling and recycling adoption, focusing on the role of technology, training, and institutional support in overcoming these challenges. Such research will be crucial for understanding how to translate positive attitudes into practical, sustainable changes that reduce anesthetic gas emissions in real-world clinical settings.

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Article

Assessing the Relationships of Expenditure and Health Outcomes in Healthcare Systems: A System Design Approach

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Abstract: Background/Objectives: The COVID-19 pandemic has significantly altered healthcare systems worldwide, highlighting healthcare expenditure's critical role in fostering population resilience and wellness. This extraordinary situation has brought to light the delicate balance that governments must maintain between the need to protect public health and budgetary restraints. The relationship between healthcare expenditure and outcomes, such as healthy life years, health expectancy, and standardized death rate, has become a central point in understanding the dynamics of healthcare systems and their capacity to adapt to emerging challenges. **Methods:** Using extensive datasets and predictive approaches such as artificial neural networks, exponential smoothing models, and ARIMA techniques, this study explores these connections in the context of the European Union. **Results:** The study better explains how healthcare financing schemes influence important health outcomes by examining past trends and forecasting future developments. The results show that household healthcare expenditures correlate negatively with standardized death rates and substantially benefit healthy life years and health expectancy. These findings underline the significance of household contributions in influencing health outcomes across various healthcare systems. Long-term and strategic investments in health services are essential, as the pandemic has demonstrated the proactive capacity of well-designed healthcare systems to reduce risks and enhance overall resilience. The results suggest that focused investments can raise life expectancy and lower death rates, supporting the development of robust, adaptable healthcare systems in the post-pandemic era. **Conclusions:** The main contribution of this research is demonstrating the significant role of healthcare expenditure, particularly household contributions, in improving key health outcomes and fostering healthcare system resilience in the EU context.

Keywords: healthcare systems; healthcare expenditure; healthcare outcomes; system design; healthy life years; health expectancy; standardized death rate; artificial neural networks; predictive models

1. Introduction

Over the past few decades, healthcare expenditures have become a key indicator of governments' commitment to the well-being of their populations. Research indicates that a 1% increase in healthcare expenditure as a percentage of GDP leads to an increase in life expectancy at birth by approximately 0.376 years [1]. This relationship underscores the significant returns on investment in public health, emphasizing the role of adequate funding in improving population health [2].

The COVID-19 pandemic highlighted the critical role of sustainable and efficient healthcare funding. Beyond the absolute amounts spent, the structure and predictability of healthcare financing proved essential in mitigating inequalities in access to care. Nations with robust funding mechanisms faced fewer disparities in healthcare access for vulnerable groups even amidst unprecedented challenges [3].

Efficient healthcare expenditure improves societal well-being and yields long-term economic benefits. Healthy populations are more productive, and the costs associated with managing chronic diseases decrease substantially [4]. For instance, preventive healthcare programs in Nordic countries have significantly reduced the incidence of lifestyle-related diseases, saving billions annually in treatment costs [5]. Therefore, integrating prevention, health education, and infrastructure development into healthcare strategies is crucial for addressing immediate needs and enhancing systemic resilience.

The financial pressures exacerbated by the pandemic have further exposed pre-existing gaps in healthcare systems. Acute shortages of medical personnel, inadequate infrastructure, and inefficient resource allocation have highlighted structural vulnerabilities and amplified healthcare access inequalities [6,7]. However, these issues are not new. Noura [8] emphasized that the deficiencies highlighted by the pandemic had existed long before with the crisis intensifying their impact. Addressing these challenges requires coherent strategies and evidence-based policies to ensure adequate resource utilization and equitable healthcare access [2,7,8].

This study investigates the impact of healthcare expenditure on key indicators such as healthy life years, health expectancy, and standardized death rates both before and after the COVID-19 pandemic. The research provides a differentiated analysis of financing schemes by leveraging artificial neural network analysis and predictive modeling techniques such as ARIMA and exponential smoothing.

The originality of this study lies in its integration of predictive analysis for health outcomes based on historical Eurostat data, emphasizing differences in the effectiveness of various healthcare financing schemes. By exploring the interplay between financial structures and health outcomes in the context of profound economic and social transformations, this research contributes to a deeper understanding of sustainable healthcare funding strategies.

The paper is organized as follows: the first section provides an introduction to the study; the second section details the materials and methods employed; this is followed by the presentation of results, analysis, and discussion; and finally, conclusions and recommendations for future public policy are presented.

2. Materials and Methods

2.1. Theoretical Background and Hypotheses

2.1.1. Influence of Healthcare Expenditure on Healthcare Outcomes

The relationship between health expenditures and health outcomes, such as death rate and life expectancy, is complex and needs to be better understood [7,8]. While there is a consensus that increased investments in health correlate with higher healthy life expectancy and lower death rates, the mechanisms through which these expenditures directly influence outcomes still need to be explored.

Global studies suggest that countries with higher health expenditures tend to have healthier populations, reporting reductions in preventable disease mortality and improvements in quality of life [8–11]. However, the relationship between expenditure levels and outcomes is not linear. A larger health budget does not automatically translate into significant improvements, mainly if funds are not used efficiently or distributed equitably. Health

expenditures alone are necessary but insufficient to improve health outcomes. Strategic allocation, custom-made to each population's specific needs, is essential to transform investments into tangible and sustainable benefits for public health [12–18].

Increasing government expenditure on health in developing countries, particularly those with low and middle incomes, and introducing state regulation in the healthcare sector have been widely advocated [19]. The central argument emphasizes that allocating more public resources to health is vital for improving health conditions and the overall well-being of populations. Higher public health spending reduces disparities in access to medical services, enhances healthcare infrastructure, and supports prevention and education initiatives. Moreover, effective regulation of the healthcare sector plays a crucial role in optimizing resource use and ensuring equitable access to essential services [2,8,10]. Some authors argue that monopolization in purchasing healthcare services can help control costs through economies of scale, reducing inefficiencies and enabling bulk negotiations for better pricing [15,16]. However, others suggest fostering competition among service providers may enhance patient satisfaction, stimulate innovation, and improve service quality [17,18]. Both perspectives highlight the complexity of designing regulatory frameworks that balance cost containment with service quality and accessibility.

Health expenditures remain a determining factor in improving the nation's overall health [8,19,20]. Governments contribute to enhancing public health through interventions and resource allocations and indirectly through policies that influence the access to and quality of healthcare services. Berger and Messer [21] highlight how changes in public health expenditure can significantly reshape service delivery systems and usage patterns. When governments allocate resources to strengthen healthcare infrastructure, develop preventive programs, and ensure equitable access to quality medical services, the impact becomes evident individually and at the community level.

Moreover, well-directed health expenditures equip countries to respond more effectively to large-scale health crises, such as the COVID-19 pandemic. Robust health systems supported by adequate financial allocations can react swiftly to such events, minimizing their impact on lives and economies [20]. The pandemic demonstrated that countries with well-funded healthcare systems, skilled personnel, infrastructure, and necessary resources managed the crisis more efficiently, reducing mortality rates and adverse economic effects [3,6].

In this context, allocating public resources to healthcare is a moral obligation and an intelligent strategy for ensuring long-term social and economic resilience. Investments in healthcare save lives and lay the foundation for sustainable development by shielding societies from future shocks and reinforcing public trust in the state's ability to safeguard their well-being [8].

Public funding contributes to providing and optimizing healthcare service consumption. It helps reduce catastrophic health expenditures that could push households into poverty while improving the accessibility and availability of essential services for all citizens regardless of socioeconomic status [22]. Governments must also carefully manage limited budgets to enhance equitable access to healthcare and improve population health [23]. Austerity policies and strict cost-control measures implemented by governments can significantly affect the healthcare sector, influencing financial resources and creating opportunities and challenges for the system [2].

Reducing public expenditures can lead to underfunding essential services, affecting their quality and accessibility. Such policies often exacerbate existing inequalities in access to care, particularly for vulnerable groups. In response to fiscal constraints, governments may turn to alternatives like public–private partnerships or increased user contributions.

While these measures can improve efficiency and service variety, they may also deepen reliance on the private sector, raising costs for citizens [24].

Makin and Layton [25] highlight how governments responded to the challenges of the COVID-19 pandemic by adopting highly expansive fiscal policies to increase healthcare expenditure. While these measures were critical in addressing immediate needs, they significantly raised public debt levels, intensifying pressure on fiscal sustainability [2]. Concrete, essential, well-planned measures include optimizing public spending, diversifying tax revenues, and prioritizing strategic health investments. Makina and Layton [25] argue that the effectiveness of these policies hinges on governments' ability to balance short-term needs with long-term sustainability goals. Fiscal reforms must address current financial pressures and establish a solid framework for resilience against future economic or public health shocks.

Asiskovitch [26] demonstrated that during the COVID-19 pandemic, life expectancy at age 65 was closely linked to public healthcare financing systems. This finding underscores the importance of well-funded and equitable health systems in ensuring longer lives and better quality of life for older populations. Publicly funded healthcare systems provide more consistent support and broader access to medical care for vulnerable groups, which is a key factor during global health crises [27–30]. A balance between fiscal discipline and sufficient healthcare funding can optimize health outcomes, improve healthy life years, increase health expectancy, and safeguard standardized death rates.

This paper examines the hypothesis that healthcare expenditure schemes significantly influence healthy life years, healthy expectancy and standardized death rates, emphasizing the importance of efficient ways of structuring the healthcare system.

Hypothesis 1. *Increased healthcare expenditure significantly influences healthy life years, health expectancy, and standardized death rates.*

Figure 1 graphically illustrates Hypothesis 1, visually representing the proposed relationship between the variables. This figure highlights the underlying connections and pathways that support the hypothesis.

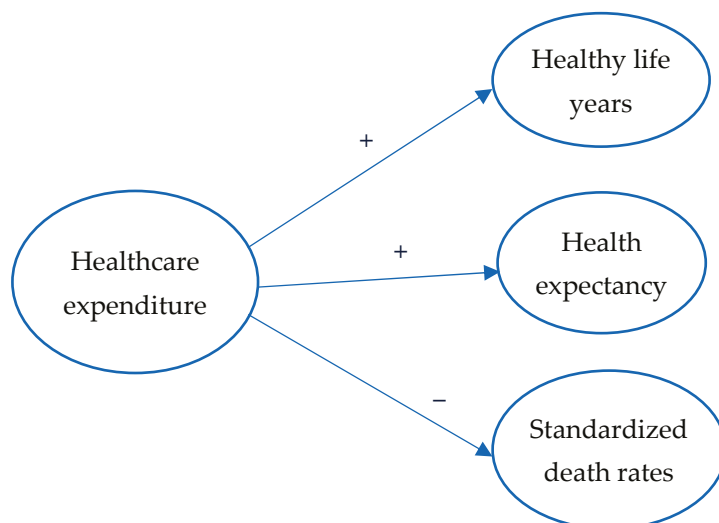


Figure 1. Theoretical model. Source: developed by the author. Note: + positive influences; – negative influences.

According to this framework, healthcare expenditure is a decisive input that improves health outcomes by enhancing the quality, accessibility, and efficiency of healthcare ser-

vices. Healthy life years and health expectancy were chosen because they extend beyond traditional mortality metrics to incorporate the quality of life and the duration of time individuals can expect to live in good health. These indicators comprehensively assess healthcare systems' effectiveness, reflecting preventative and curative care impacts. Furthermore, standardized death rates were included as they capture the broader influence of healthcare interventions on population-wide mortality trends, offering a direct measure of healthcare system performance.

2.1.2. Forecasting Healthy Life Expectancy Based on Healthcare Expenditure Levels

While not all budget allocations immediately or directly enhance population health, well-managed strategic investments in the healthcare sector can yield significant long-term benefits. These investments reduce health risks and build the foundation for healthier societies, fostering broader economic and social well-being [31–33].

Two primary approaches dominate the analysis of how government expenditures influence health outcomes. The first draws on Grossman's model [34,35], which views health as a form of capital that can accumulate or deteriorate over time. The second, proposed by Zweifel and Breyer [36], considers health as an outcome of the healthcare system as a whole. This approach frames health as the product of various inputs, such as public spending, administrative efficiency, and service quality. It highlights the importance of balancing financial investment with the effective allocation of resources to achieve public health goals. Within these frameworks, the efficiency of public health expenditures holds as much significance as the magnitude of expenditure itself [2]. Policymakers face the challenge of increasing health budgets while ensuring these funds are responsibly managed to maximize their impact on public health.

Higher total healthcare expenditure have been strongly linked to a reduction in overall death rates and years of life lost. This fact suggests that increased funding for health systems prevents premature deaths and contributes positively to indicators such as life expectancy and the prevalence of chronic diseases [37]. Moreover, increased health expenditure correlates with lower infant mortality rates, further supporting the argument that investing in healthcare is critical to improving overall health outcomes. This positive effect can be attributed to enhanced access to essential services such as vaccinations, prenatal and postnatal care, and health education programs, particularly in vulnerable communities where economic or geographic barriers often limit access.

The relationship between healthcare expenditure and improved outcomes also underscores the value of effective public policies. The strategic allocation of resources to prevention, healthcare infrastructure, and skilled personnel can amplify the benefits, reducing health inequalities and improving overall societal well-being. Research indicates that countries prioritizing public health expenditure and related social programs often experience substantial improvements in population health, narrowing socioeconomic gaps and fostering social cohesion [38,39].

Every nation must allocate sufficient resources to the health sector to strengthen the link between longevity and economic benefits. Effective healthcare investments have multiplier effects, such as reducing disease burdens, creating healthier and more productive workforces, and lowering future costs associated with chronic illnesses [40,41]. Public funds must be efficiently managed through robust governance and carefully designed policies to optimize resource use and minimize waste.

In addition to strategic spending, countries must establish monitoring and evaluation mechanisms to measure the impact of healthcare investments on development indicators, including reductions in infant mortality, longer life expectancy, and improved quality of life.

Success stories in economic literature demonstrate that solid governance and innovative public policies can transform healthcare investments into economic and social progress engines, enhancing financial stability and social cohesion [2].

Health expectancy is a critical global metric for assessing population health. It reflects the average number of healthy years a person can expect, offering insights into the interplay between environmental factors, access to healthcare services, social structures, cultural influences, economic conditions, and genetic predispositions [42,43].

The upward trend in health expectancy observed in recent decades can largely be attributed to improved living standards, diverse lifestyle choices, and expanded educational opportunities [44]. This progress highlights the urgency of addressing current challenges, such as socioeconomic inequalities, pollution, and climate change, which negatively affect health outcomes in many parts of the world.

This study proposes a second hypothesis for forecasting future trends in healthy life years and health expectancy:

Hypothesis 2. *Levels of healthy life years and health expectancy projected based on increased healthcare expenditure growth will be higher than those estimated by continuing historical trends.*

2.2. Research Design

This study employs a longitudinal research design to analyze the impact of healthcare expenditure on public health outcomes during the pre- and post-pandemic periods, spanning 2004–2022. The research adopts a quantitative approach to analyze secondary data from Eurostat, covering all 27 European Union member states. The analysis relies explicitly on datasets from the “Health care” and “Health status” sections of Eurostat, ensuring comprehensive and authoritative data for the study. The relationships between healthcare expenditure and public health outcomes were further explored using artificial neural network (ANN) analysis, which provided insights into these connections’ dynamics and assessed their impact.

Predictive modeling techniques were employed, including the ARIMA and Holt and Brown models based on exponential smoothing. These methods facilitated the generation of detailed forecasts regarding the evolution of health outcomes, offering a data-driven perspective on future trends. The results were then interpreted within the socioeconomic context of the European Union with particular attention to contrasts between the pre- and post-pandemic periods. An SEM model was used to assess the extent to which multicollinearity could impact the robustness of the results in the context of these methods. In the case of using artificial neural networks (ANNs), these models have the advantage of being less affected by multicollinearity due to their nonlinear and adaptive nature.

The combination of these methods provides a comprehensive analytical framework. The predictive capabilities of ARIMA, Holt and Brown models complement the nonlinear modeling strengths of ANNs, offering an integrative view of historical trends and future possibilities. SEM further strengthens the analysis by elucidating the structural relationships between variables, ensuring robust results, and testing multicollinearity for ARIMA, Holt, and Brown variables. The study captures the intricate dynamics between healthcare expenditure and outcomes by employing these methods, offering theoretically informed and practically relevant insights. Using multiple methodologies ensures that the research findings are statistically robust and applicable across diverse socioeconomic contexts within the European Union.

The data analysis in this study was conducted using statistical software to ensure robust and reliable results. For artificial neural network (ANN) models and forecasting

analyses, SPSS v27.0 was employed. The structural equation modeling (SEM) was performed using SmartPLS v3.0, enabling the examination of complex relationships between variables with high precision and efficiency.

2.3. Selected Variables

This research carefully selected variables to comprehensively capture the relationship between healthcare expenditure and public health outcomes, considering various dimensions of investments and their impact on population health. The variables include measures of overall healthcare expenditure and their specific components, alongside essential population health outcomes that reflect health across different life stages. Table 1 shows the research variables.

Table 1. Research variables.

Variable	Dataset	Measures	References
HCE_AS	Healthcare expenditure—all financing schemes	Euro per inhabitant	[45]
HCE_GCS	Healthcare expenditure—government schemes and compulsory contributory healthcare financing schemes	Euro per inhabitant	[45]
HCE_VS	Healthcare expenditure—voluntary healthcare payment schemes	Euro per inhabitant	[45]
HCE_OPP	Healthcare expenditure—household out-of-pocket payment	Euro per inhabitant	[45]
HLYB	Healthy life years in absolute value at birth	Year	[46]
HLY65	Healthy life years in absolute value at 65	Year	[46]
HLEB	Health expectancy in absolute values at birth	Year	[47]
HLE65	Health expectancy in absolute values at 65	Year	[47]
SDR	Standardized death rate	Rate	[48]

Source: developed by the author based on Eurostat data [45–48].

Total healthcare expenditure (HCE_AS) represents the aggregated investments in healthcare within a country, regardless of funding source. This variable offers a broad overview of financial efforts to sustain healthcare systems. Public contributions, captured through HCE_GCS, highlight the role of government schemes and mandatory contributions in ensuring access to healthcare services. Meanwhile, HCE_VS reflects private sector and voluntary insurance contributions, illustrating how individuals rely on alternative mechanisms to cover healthcare needs. Out-of-pocket payments (HCE_OPP) measure direct household expenditures, highlighting the population's financial burden and the healthcare system's equity.

Health outcomes focus on key dimensions of quality of life and mortality. Healthy life years at birth (HLYB) and at age 65 (HLY65) reflect the duration of life free from severe health problems or disabilities, providing insights into both the active years of life and quality of life in old age. Healthy life expectancy at birth (HLEB) and at age 65 (HLE65) combines life expectancy with health status to offer a nuanced perspective on the years lived in optimal health conditions. These indicators are critical for evaluating the impact of healthcare investments on overall well-being.

The standardized death rate (SDR) measures mortality adjusted for the population's demographic structure [48]. Its formula is expressed as follows (1):

$$SDR = \frac{\sum_{i=1}^n (d_i + w_i)}{\sum_{i=1}^n w_i} \quad (1)$$

d_i —the age-specific death rate for age group i ;
 w_i —standard population weight for age group i (e.g., the population size in that age group in a standard population);
 n —total number of age groups.

Table 2 shows the descriptive statistics of selected data.

The skewness values for most variables suggest a mild rightward skew, particularly for HCE_VS (1.724), indicating the presence of outliers or countries with exceptionally high healthcare expenditures (voluntary healthcare payment schemes). The kurtosis values for most variables show relatively platykurtic distributions, except for SDR, which exhibits a leptokurtic distribution (8.601), reflecting a higher concentration of values around the mean. The health outcomes, such as HLYB and HLEB, show a more balanced distribution, with mean values around 61–73 years and moderate deviations. The data indicate a mix of normal and non-normal distributions, with some variables exhibiting more extreme values, particularly in healthcare expenditure (voluntary healthcare payment schemes) and mortality-related outcomes.

Table 2. Descriptive statistics.

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
HCE_AS	243	380.1	6590.2	2678.275	1732.6539	0.462	−1.225
HCE_GCS	243	264.8	5674.7	2071.226	1486.9339	0.597	−1.054
HCE_VS	243	2.6	718.0	139.458	143.7818	1.724	3.461
HCE_OPP	243	77.2	1023.3	464.668	226.6792	0.092	−1.038
HLYB	243	51.4	73.6	61.965	4.8000	0.384	−0.281
HLY65	243	3.9	16.2	8.876	2.7729	0.310	−0.211
HLEB	243	64.8	80.3	73.565	4.1875	−0.349	−1.203
HLE65	243	8.5	19.5	14.741	2.9840	−0.320	−1.299
SDR	243	790.7	9160.8	1590.514	1436.6893	2.967	8.601

Source: developed by the authors using SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

2.4. Research Methods

The study employed various statistical and modeling methods to analyze the data and generate forecasts, capturing the complex relationships between healthcare expenditure and public health outcomes. Artificial neural networks, an advanced machine learning technique capable of modeling often nonlinear relationships between variables, were central to the analysis [49]. By learning and adapting based on patterns in historical data, these networks proved essential in identifying determinants of variations in population health. The multilayer perceptron (MLP) model, based on back-propagation, was chosen to determine these influences, as shown in the following Equation (2):

$$y = \left(\sum_{i=1}^n w_i x_i + b \right) = \varphi(W^T X + b) \quad (2)$$

w, x —vectors of weights and inputs;

b —bias;

i —cases;

φ —activation functions.

As activation functions, we used a hyperbolic tangent function (3):

$$f(n) = \frac{1}{1 + e^{-n}} \quad (3)$$

n —input variables;

$f(n)$ —output variables.

Complementing this method, Holt's exponential smoothing method was applied to analyze and forecast trends. This approach efficiently evaluated current indicator levels

and medium-term rates of change. Its forecasting Equation (4), along with smoothing equations for level (5) and trend (6), is as follows [50]:

$$\hat{y}_{t+h|t} = l_t + hb_t \quad (4)$$

$$l_t = \alpha y_t + (1 - \alpha)(l_{t-1} + b_{t-1}) \quad (5)$$

$$b_t = \beta(l_t - l_{t-1}) + (1 - \beta)b_{t-1} \quad (6)$$

l_t —an estimate of the level of the series at time t ;

b_t —an estimate of the trend (slope) of the series at time t ;

α —the smoothing parameter for the level;

β —the smoothing parameter for the trend;

Brown's exponential smoothing method further enhanced forecast precision by minimizing seasonal fluctuations in the data. This technique captured subtle dynamics within time series, yielding more accurate and context-specific predictions [51]. This method includes the level (7), the trend (8), and the forecast for the next step (9).

$$S_t = \alpha y_t + (1 - \alpha)(S_{t-1} + b_{t-1}) \quad (7)$$

$$b_t = \beta(S_t - S_{t-1}) + (1 - \beta)b_{t-1} \quad (8)$$

$$F_{t+m} = S_t + mb_t \quad (9)$$

y_t —the observed value at time t ;

S_t —the smoothed value for the level at time t ;

b_t —the estimated trend at time t ;

α —the smoothing parameter for the level;

β —the smoothing parameter for the trend;

F_{t+m} —the forecasted value for m steps ahead of time t .

The ARIMA (autoregressive integrated moving average) model provides a rigorous time series analysis, delivering robust and statistically grounded forecasts [52]. This model was chosen for its ability to combine autoregressive and moving average components, effectively capturing the dynamic relationships among the variables. The ARIMA formula is as follows (10):

$$\left(1 - \sum_{i=1}^p \varphi_i L^i\right)(1 - L)^d X_t = \left(1 + \sum_{i=1}^q \theta_i L^i\right) \varepsilon_t \quad (10)$$

X_t —data series;

L —lag operator;

φ_i —parameters of the autoregressive part of the model;

θ_i —parameters of the moving average part;

ε_t —error.

An SEM model was employed to evaluate the potential impact of multicollinearity on the robustness of the results within the context of these methods. Structural equation modeling (SEM) is the appropriate method because it examines the complex relationships among multiple variables and evaluates the factors' direct and indirect impacts on the final variables [53]. In the context of testing multicollinearity among the three variables—HLYB (healthy life years at birth), HLEB (health expectancy at birth), and HCE_AS (healthcare expenditure—all financing Schemes), SEM provides a robust framework for understanding the interactions and dependencies between them.

Each method was applied integrated, leveraging each technique's strengths to address the research's objectives. This combined approach enabled the analysis of current relationships between variables and allowed for the projection of future trends in health outcomes.

3. Results

We tested Hypothesis H1 using artificial neural network analysis with a multilayer perceptron (MLP) model, which provided insights into the intricate relationships between healthcare expenditure and public health outcomes. The MLP model facilitated an in-depth exploration of how different types of health-related expenditure contribute to outcomes such as healthy life years, health expectancy, and the standardized death rate. The independent variables included total healthcare expenditure (HCE_AS), expenditures funded through government schemes (HCE_GCS), voluntary schemes (HCE_VS), and out-of-pocket payments by households (HCE_OPP). These variables were analyzed concerning public health outcomes such as healthy life years at birth and age 65, health expectancy at birth and age 65, and standardized death rate. Between the input layer, containing the independent variables, and the output layer, containing the dependent variables, the model incorporated a hidden layer representing the efficiency of healthcare expenditure. The hidden and output layers employed sigmoid activation functions.

Figure 2 illustrates the relationships between healthcare expenditure, healthy life years, health expectancy, and standardized death rate.

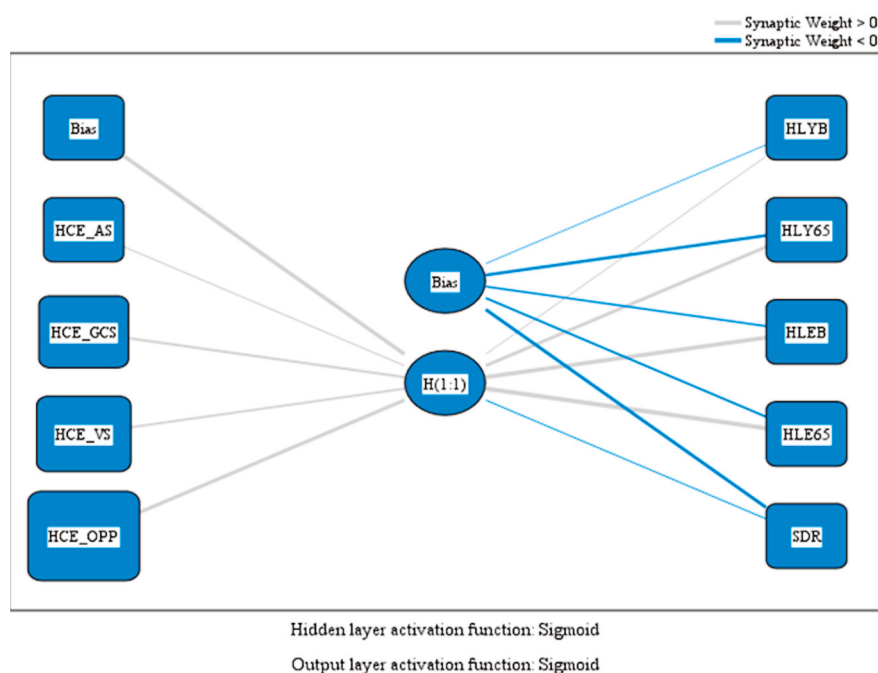


Figure 2. MLP model. Source: authors' design using SPSS v27.0 (IBM Corporation, Armonk, NY, USA).

Table 3 shows the predicted values of the model variables within the perceptron.

Table 3. MLP parameters.

		Hidden Layer 1 H(1:1)	HLYB	HLY65	Output Layer		SDR
Input Layer	(Bias)	1.825					
	HCE_AS	1.096					
	HCE_GCS	1.396					
	HCE_VS	1.324					
	HCE_OPP	1.816					
Hidden Layer 1	(Bias)		−0.683	−1.519	−1.099	−1.124	−1.757
	H(1:1)		0.979	1.799	2.417	2.445	−0.715

Source: developed by the authors using SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

The results reveal both direct and indirect effects of healthcare expenditure on health outcomes via the hidden layer. Each input variable was weighted according to its relevance to the model, as reflected in the values assigned to various neural connections. Out-of-pocket payments (HCE_OPP) demonstrated the highest weight at the input layer, with a coefficient of 1.816, underscoring their significant contribution to the predictive process. Similarly, expenditures through government schemes (HCE_GCS) and voluntary schemes (HCE_VS) also played important roles, albeit less prominently than household payments.

Investments in healthcare, mainly through out-of-pocket payments (HCE_OPP) and government schemes (HCE_GCS), have demonstrated a consistently positive impact on healthy life years at birth (HLYB), supported by a significant baseline bias (1.825). The data further reinforce this trend for individuals aged 65 (HLY65), with substantial contributions from the hidden layer (1.799), highlighting that health investments provide enduring benefits, especially for older populations.

Health expectancy at birth and age 65 also displayed strong positive coefficients with values of 2.417 for HLEB and 2.445 for HLE65. These findings suggest that increased healthcare resources not only extend life expectancy but also enhance its quality. In contrast, the standardized death rate revealed a negative correlation with the hidden layer (−0.715), indicating that higher healthcare expenditure contributes to reduced mortality, underscoring their critical role in mitigating disease burdens.

Figure 3 visually represents the absolute and normalized importance of the model variables.

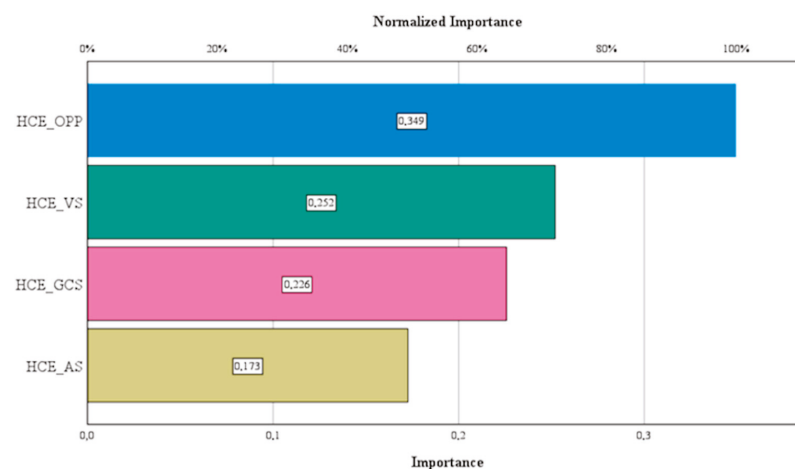


Figure 3. Absolute and normalized importance within the model. Source: authors' design using SPSS v27.0 (IBM Corporation, Armonk, NY, USA).

Based on normalized values, the analysis identifies household out-of-pocket payments (HCE_OPP) as the most influential factor with a normalized importance of 100%. This influence is followed by voluntary payment schemes (HCE_VS) at 72.1% and government schemes (HCE_GCS) at 64.6%. These findings emphasize the pivotal role of diverse healthcare financing mechanisms in improving health outcomes.

Overall, the findings strongly support Hypothesis H1. Healthcare expenditure significantly impacted healthy life years and health expectancy, reflecting better quality of life and improved public health outcomes. The results highlighted a positive but nuanced influence on the health system's ability to reduce mortality. This analysis provides empirical evidence reinforcing the role of healthcare investments as a key driver for improving population health outcomes. These conclusions are valuable for formulating evidence-based public policies prioritizing sustainable and equitable healthcare funding.

Hypothesis H2 explores the long-term impact of healthcare expenditure on health outcomes using Holt, Brown, and ARIMA models [50–52].

To test the multicollinearity of variables included in the context of Holt, Brown, and ARIMA models, structural equation modeling (SEM) was employed. The SEM model incorporates three key variables: HLYB (healthy life years at birth), HLEB (health expectancy at birth), and HCE_AS (healthcare expenditure—all financing schemes), which are also included in the forecasting models. Figure 4 illustrates the SEM model, visually representing the relationships among these variables.

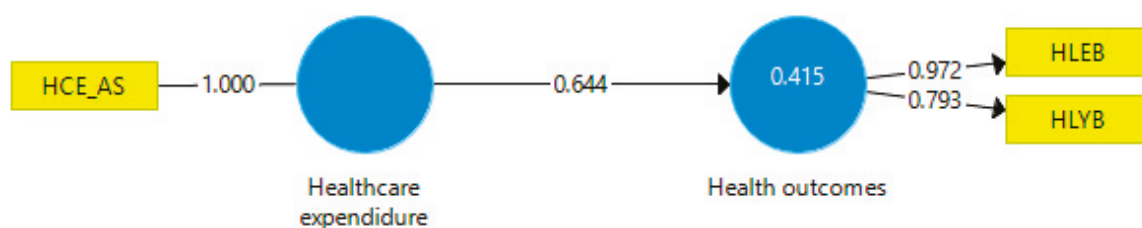


Figure 4. SEM model. Source: authors' design using SmartPLS v3.0 (SmartPLS GmbH, Bönningstedt, Germany).

The model's reliability and validity exposed the indicators presented in Table 4.

Table 4. Reliability, validity and path coefficients.

	Original Sample	Sample Mean	Standard Deviation	T Statistics	<i>p</i> Values
Average Variance Extracted	0.787	0.783	0.030	26.482	0.000
Composite Reliability	0.880	0.877	0.020	44.062	0.000
Cronbach's alpha	0.772	0.769	0.031	24.937	0.000
Path coefficient (Healthcare expenditure → Health outcomes)	0.644	0.645	0.025	25.599	0.000

Source: author's design using SmartPLS v3.0 (SmartPLS GmbH, Bönningstedt, Germany).

The average variance extracted (AVE) of 0.787 confirms convergent validity, as it exceeds the recommended threshold of 0.5. A composite reliability (CR) of 0.880 indicates a high level of internal consistency among the latent constructs. Cronbach's alpha of 0.772 further demonstrates the reliability of the model's measurement instruments. Moreover, the path coefficient for the relationship between healthcare expenditure and health outcomes is 0.644, with a T-statistic of 25.599 and a *p*-value of 0.000, indicating a strong and statistically significant positive association.

The SRMR (standardized root mean square residual) in the SEM model is 0.079. This value indicates a good fit for the model, as SRMR values below 0.08 are generally considered acceptable. A lower SRMR value suggests that the differences between the

observed and predicted covariance matrices are slight, which means the model represents the data well [53].

Multicollinearity analysis, detailed in Table 5, shows variance inflation factor (VIF) values.

Table 5. Variance inflation factor.

	VIF
HCE_AS	1.000
HLEB	1.654
HLYB	1.654

Source: author's design using SmartPLS v3.0 (SmartPLS GmbH, Bönningstedt, Germany).

These values are below the commonly accepted threshold of 5, suggesting that multicollinearity is not a concern in this model [53].

The results of the SEM analysis confirm the robustness of the model with high reliability and validity indicators. The low VIF values in Table 4 further support the model's stability, ensuring that the relationships observed are not biased by multicollinearity among the variables. This comprehensive approach strengthens the predictive power and interpretability of the SEM model in the context of forecasting and causal analysis.

The forecasting model based on Holt's exponential smoothing method was applied to estimate the evolution of healthy life years at birth (HLYB) using historical data from 2004 to 2022. Several models were tested, and the Holt model demonstrated excellent significance ($p < 0.001$). This method captures long-term trends and recent variations, offering a detailed view of this demographic indicator progression (Table 6).

Table 6. Exponential smoothing model parameters for HLYB forecasting.

	Model		Estimate	SE	t	Sig.
HLYB-Model_1	No Transformation	Alpha (Level)	1.000	0.217	4.602	0.000

Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

The model parameters indicate an alpha (level) value of 1.000, reflecting the model's emphasis on recent observations when estimating future trends. This result suggests that recent dynamics of the HLYB indicator, shaped significantly by the COVID-19 pandemic, play a critical role in the projections. The high statistical significance ($p = 0.000$) confirms the parameter's reliability and the robustness of the model. Figure 5 and Table A1 (in the Appendix A) provide a comprehensive forecast breakdown for HLYB's trajectory.

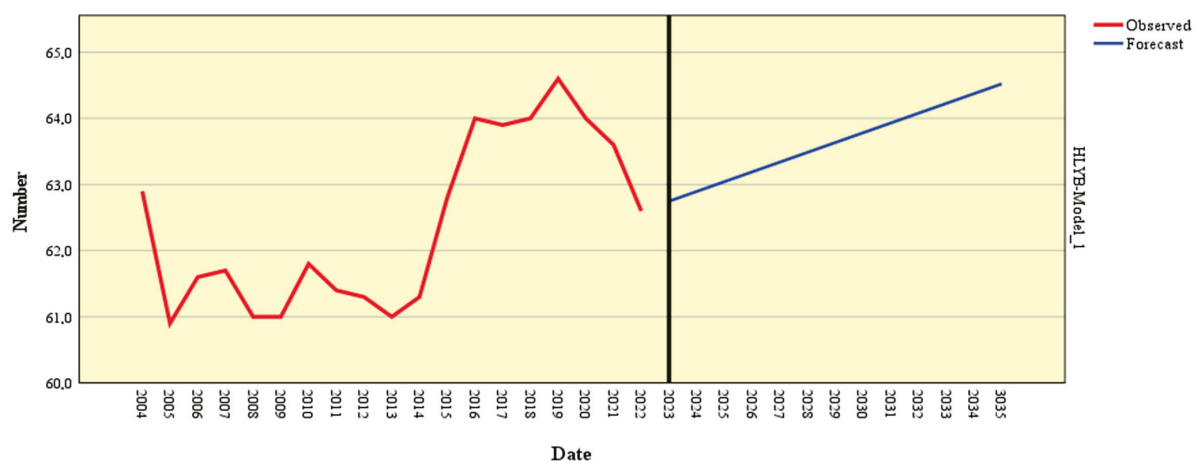


Figure 5. Forecast of HLYB using the Holt model. Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

Historical data reveal a fluctuating pattern in the HLYB indicator between 2004 and 2022 with a notable decline during the pandemic (2020–2022). For instance, after peaking at 64.6 years in 2019, the indicator fell to 62.6 years in 2022, likely reflecting the adverse effects of the COVID-19 crisis on quality of life.

Projections for 2023–2035 indicate a gradual recovery in the HLYB indicator. The trend suggests an increase from 62.7 years in 2023 to 64.5 years in 2035. This result reflects a slow return to pre-pandemic levels, emphasizing that public health measures and healthcare investments will improve quality of life in the coming years. By 2030, HLYB is projected to reach 63.8 years, and by 2035, it is expected to climb to 64.5 years, signifying a steady but modest growth.

The Brown forecasting model, applied to predict the evolution of health expectancy at birth (HLEB), offered a comprehensive analysis of historical trends and future projections. Several models were tested, and the Brown model demonstrated excellent significance ($p < 0.001$). Historical data (2004–2022) point to a gradual increase in HLEB, reflecting consistent improvements in population health (Table 7).

Table 7. Exponential smoothing model parameters for HLEB forecasting.

	Model		Estimate	SE	t	Sig.
HLEB-Model_1	No Transformation	Alpha (Level and Trend)	0.593	0.101	5.864	0.000

Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

The model's alpha parameter, estimated at 0.593, reflects a balance between sensitivity to recent fluctuations and the ability to capture long-term trends. Its high statistical significance ($t = 5.864$, $p < 0.001$) confirms the model's reliability and the robustness of its projections. This parameter indicates that the model moderately weighs recent data while emphasizing underlying trends.

Figure 6 and Table A1 in the Appendix A offer a comprehensive overview of the projected expansion of HLEB.

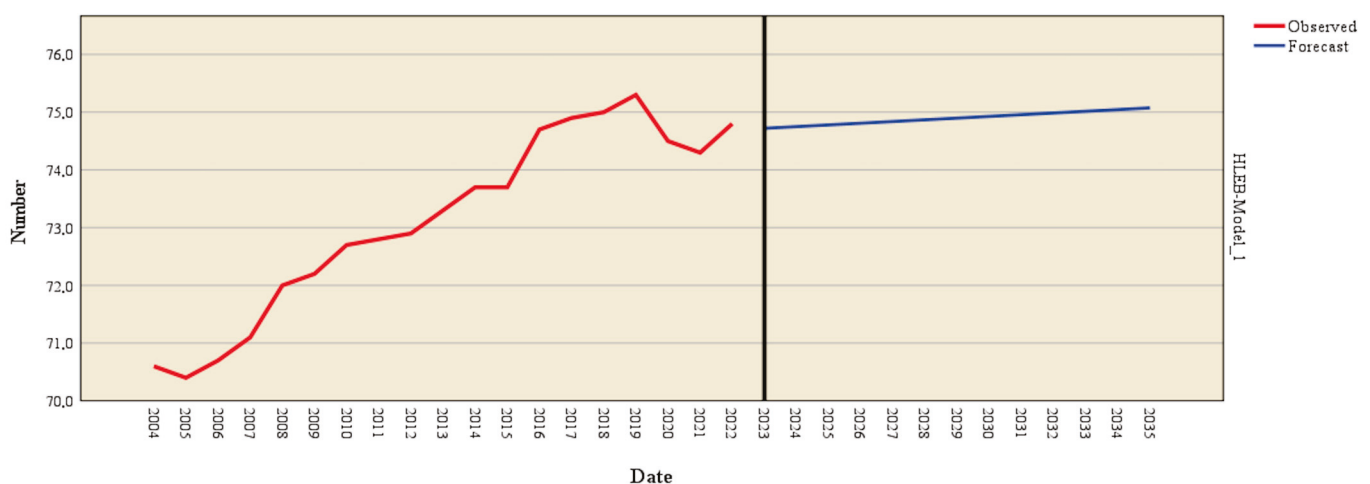


Figure 6. Forecast of HLYB using the Brown model. Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

An analysis of historical data shows a steady increase in HLYB from 2004, when it was 70.6 years, to 2019, when it peaked at 75.3 years. However, the negative impact of the COVID-19 pandemic is evident in 2020 and 2021, with HLYB declining to 74.5 and 74.3 years, respectively. By 2022, HLYB rebounded slightly to 74.8 years, signaling potential recovery.

Model forecasts for 2023–2035 suggest a stabilization and gradual rise in HLYB. For instance, the model estimates HLYB at 74.7 years in 2023, climbing incrementally to 75.1 years by 2035. This trend suggests that despite disruptions caused by extraordinary events, structural improvements in public health and quality of life will likely continue to yield positive outcomes.

The ARIMA forecasting model was employed to determine future trends in healthcare expenditure (HCE_AS), leveraging a robust time-series analysis ($p = 0.002$) based on historical data from 2014 to 2022 (Table 8).

Table 8. ARIMA model parameters for HCE_AS.

	Model		Estimate	SE	t	Sig.
HCE_AS-Model_1	HCE_AS	No Transformation	128.302	25.498	5.032	0.002

Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

According to Table 8, the estimated coefficient for HCE_AS is 128.302, with a standard error of 25.498, indicating precise and stable estimates. The t-value of 5.032 and statistical significance (Sig. = 0.002) confirm the validity of this coefficient with a high degree of confidence, underlining the model's capacity to deliver accurate forecasts.

Figure 7 and Table A1 in the Appendix A present detailed projections for expanding HCE_AC using ARIMA.

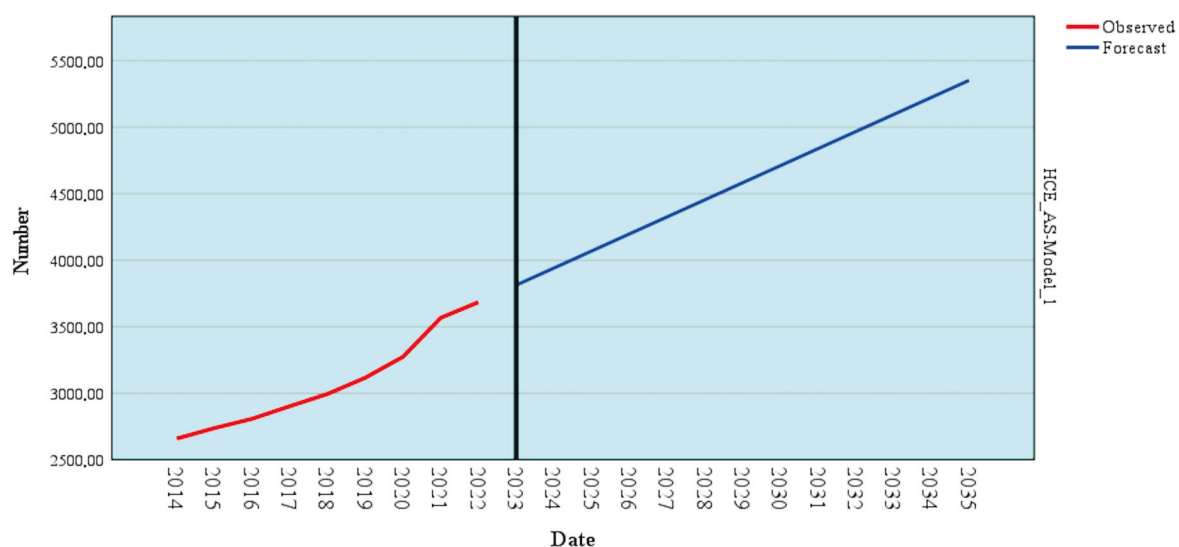


Figure 7. The forecast of HCE_AS depends on the previous annual evolution using the ARIMA model. Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

The forecast reveals an upward trajectory in healthcare expenditure over the medium and long term. Projected expenditures rise steadily, reaching 3812.85 in 2023 and climbing to 5352.48 by 2035. This result sustained an upward trend that reflects increasing budgetary allocations to the healthcare sector.

The model also highlights a relatively consistent growth rate over the forecasted period, indicating stability in economic and funding trends for healthcare. The results underscore the need for strategic planning to use allocated funds efficiently.

Two additional ARIMA models were developed to forecast future trends in HLYB and HLEB based on HCE_AS. Several models were tested, and the ARIMA models demonstrated excellent significance ($p < 0.001$). These models, calibrated with data from 2004 to 2022, offer an in-depth perspective on the relationship between healthcare expenditure and health outcomes (Table 9).

Table 9. ARIMA model parameters for HLYB and HLEB.

	Model		Estimate	SE	t	Sig.
HLYB-Model_1	HLYB	No Transformation	61.777	3.218	19.196	0.000
HLEB-Model_2	HLEB	No Transformation	72.915	1.692	43.090	0.000

Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

The parameters derived from these ARIMA models indicate a strong correlation between financial allocations and health outcomes. For HLYB, the estimated coefficient is 61.777, with a standard error of 3.218 and a t-value of 19.196, showing high statistical significance ($p = 0.000$). This result implies that increased healthcare expenditure substantially impacts healthy life years at birth. Similarly, for HLEB, the estimated coefficient is 72.915, with a standard error of 1.692 and a t-value of 43.090 ($p = 0.000$), further emphasizing the critical role of financial resources in improving health expectancy.

Figure 8 and Table A1 in the Appendix A provide detailed forecasts for HLYB and HLEB using ARIMA.

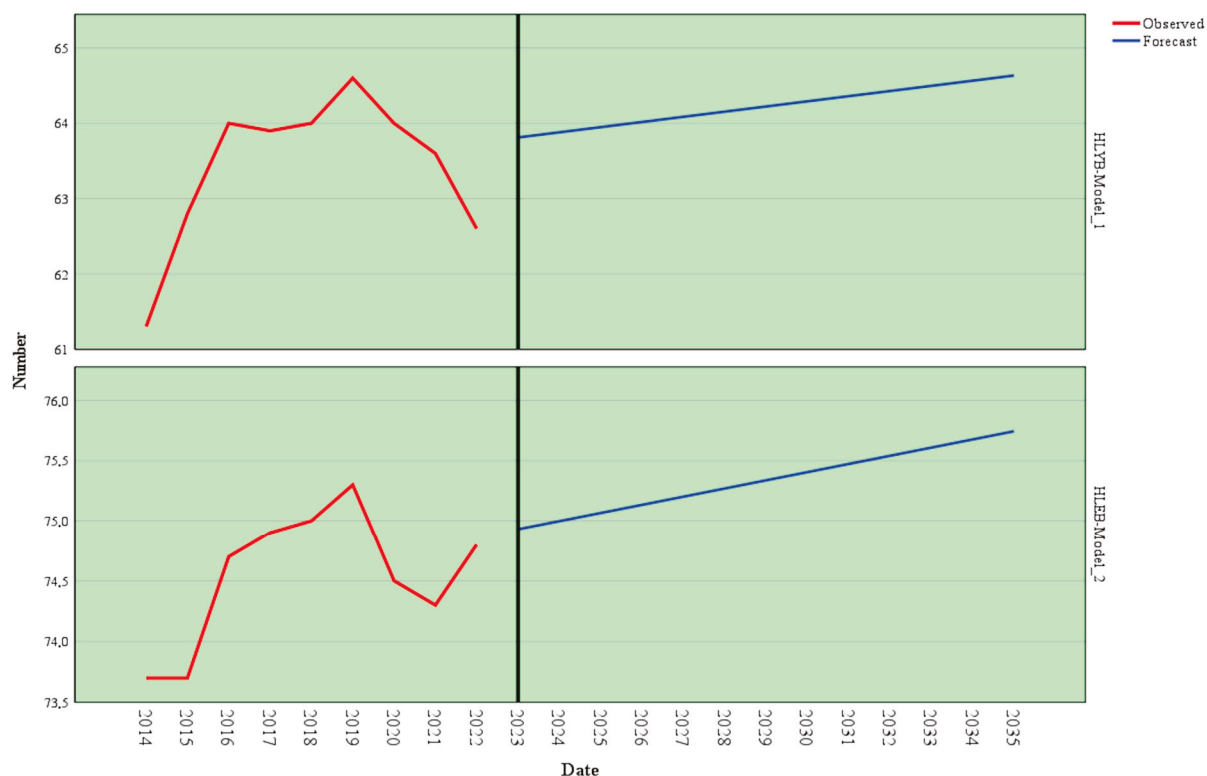


Figure 8. Forecast of HLYB and HLEB depending on the HCE_AS using the ARIMA model. Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

Long-term forecasts for these indicators show a positive yet moderate trend. HLYB is projected to start at 63.8 in 2023, gradually increasing to 64.6 by 2035, while HLEB is expected to rise from 74.9 in 2023 to 75.7 by 2035. While this growth is steady, it remains relatively moderate, indicating that while financial allocation is central, its effects are gradual and influenced by factors such as the efficiency of fund utilization, healthcare accessibility, and public policy measures.

These findings underscore the significant potential of healthcare expenditure to enhance population health over the long term. However, they also highlight the decisive role of efficient resource use. The forecasted results suggest that well-designed and effectively implemented healthcare policies can lead to sustained improvements in health outcomes supported by adequate funding and accessible prevention and treatment measures.

Comparisons between Holt and Brown models (used to forecast HLYB and HLEB based on historical trends) and ARIMA models (forecasting the same indicators using HCE_AS data) reveal notable differences in their growth rates over the long term. HLYB and HLEB show moderate growth trends in the Holt and Brown models. However, ARIMA models, incorporating healthcare expenditure as an independent factor, predict significantly faster and more consistent growth (Figure 9).

For HLYB, the Holt models suggest a steady annual increase of about 0.16% in 2023, gradually accelerating to 3.04% by 2035. In contrast, the ARIMA model, which factors in healthcare expenditure, forecasts a significantly faster growth, starting at 1.92% in 2023 and steadily climbing to 3.19% by 2035. This substantial difference strongly supports hypothesis H2, which suggests that healthy life years and health expectancy levels, projected based on increased healthcare expenditure, are higher than those derived solely from historical trends.

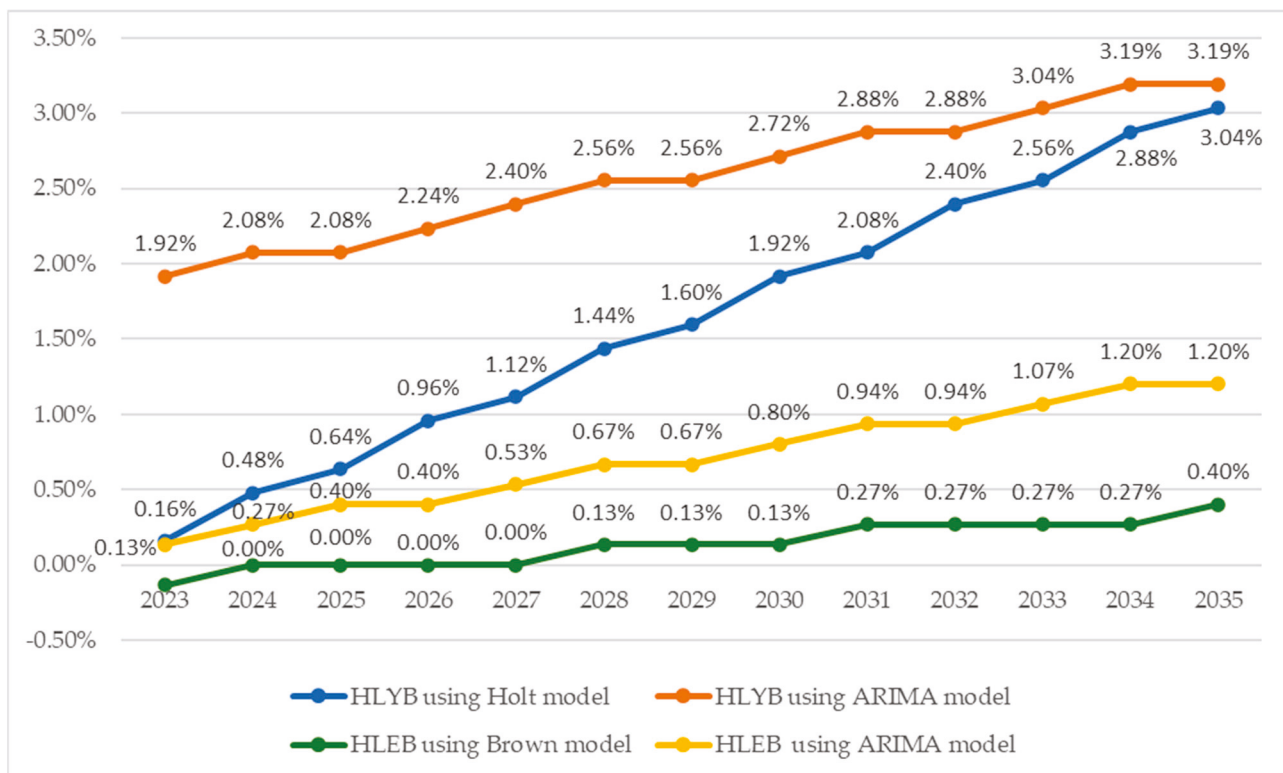


Figure 9. Comparison of the forecasting models. Source: author's design based on data computed using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

The Brown model offers a cautious perspective on healthy life expectancy at birth (HLEB), forecasting slow and gradual growth. It predicts a slight decline of -0.13% in 2023, with a modest improvement to 0.40% by 2035, suggesting limited progress without significant changes in health policies. In contrast, the ARIMA model is more optimistic, projecting a 0.13% increase in 2023 and a robust annual growth rate of 1.20% by 2035. These projections reinforce Hypothesis H2, emphasizing the transformative potential of additional healthcare investments to improve health expectancy, surpassing historical trends substantially.

4. Discussion

Global research highlights that government health expenditures significantly improve public health outcomes, especially in developing nations, by reducing inequalities, enhancing healthcare access, and addressing systemic vulnerabilities through preventive measures and infrastructure development [54–60].

During pandemic situations, such as the COVID-19 crisis, severe shortages of essential medical equipment, including personal protective equipment, ventilators, and high-flow oxygen systems, exposed significant vulnerabilities [8]. These deficiencies undermined healthcare systems' capacity to effectively address patient needs, resulting in higher mortality rates and immense stress on healthcare workers. Hospitals often face limited isolation facilities, increasing the risk of virus transmission among medical staff and patients.

Furthermore, the lack of preparedness among healthcare professionals to handle pandemics and insufficient protective equipment and transportation systems further aggravated the crisis. The continuous training of medical staff and establishing efficient patient and personnel transport systems are essential to prevent contamination and ensure a coordinated response in extreme situations. Investments in staff preparedness and resource allocation for patient care and protecting healthcare workers are critical during global health emergencies [61]. Deficiencies in these areas significantly amplified the adverse effects of the pandemic.

Enhanced investments in public health can address these vulnerabilities, enabling more effective crisis responses while improving long-term health outcomes. Thoughtfully planned expenditures can support workforce training, expand infrastructure, and implement policies ensuring equitable access to healthcare services, reducing inequalities in many developing countries [8].

The study proposed two hypotheses to investigate the relationship between healthcare expenditure schemes and three key public health outcomes: healthy life years, health expectancy, and standardized death rates.

The findings from the analysis of Hypothesis H1 confirm a positive and significant influence of health expenditure on indicators such as healthy life years, health expectancy, and standardized mortality rates. These results underscore the importance of consistent investment in the health sector, aligning with trends identified in the literature. Recent studies, such as those by Sultana et al. [8], show that per capita health expenditures positively impact mortality reduction and life expectancy improvement. Better resource allocation toward prevention, primary care, and treatment accessibility for the entire population is decisive for enhancing overall health outcomes. Similarly, this study demonstrates that increasing health budgets has tangible effects on improving public health outcomes.

Moreover, research by Morina et al. [14] reinforces this relationship, showing that a 10% increase in health expenditure per capita correlates with a 3.5-month rise in life expectancy. This finding highlights the substantial influence of health expenditures on population health alongside other factors such as economic development and infrastructure improvements. Evidence from other studies emphasizes that well-targeted public interventions are central to ensuring access to quality healthcare services, especially in rural or disadvantaged areas [62,63]. These findings align with the current study's conclusions, highlighting the long-term benefits of efficiently directed government expenditure.

However, some voices in the literature question the efficiency of public health expenditures. For instance, studies by Berger and Messer [21] and Sede and Ohemeng [64] suggest that public expenditure only sometimes leads to notable health improvements. From this perspective, individual access to financial resources and quality healthcare services might directly impact health outcomes [65,66]. Nonetheless, these observations do not negate the importance of government intervention but rather point to the need for optimizing resource allocation. This study also highlighted the contributions of household health expenditures, concluding that all funding schemes positively and significantly influence health outcomes.

Research supporting government interventions, such as those by Akinkugbe and Mohanoe [67] or Heijink et al. [68], provides a more comprehensive perspective. These studies demonstrate that adequate public funding reduces avoidable mortality and inequalities in healthcare access, particularly in low- and middle-income countries. Similarly, Novignon et al. [69] found that while private expenditure has a positive impact, public expenditures are essential for ensuring equity in healthcare.

In conclusion, this study's findings align with the broader body of literature, confirming Hypothesis H1. Increased health expenditure can significantly improve population health by reducing mortality rates, extending life expectancy, and increasing years of good health. These investments become a foundation for enhancing public health and reducing social inequalities within the framework of effective public interventions.

The analysis of Hypothesis H2, which suggests that projected increases in healthcare expenditure lead to higher levels of healthy life years and health expectancy compared to historical trends, yielded results that underscore a significant reality. Findings indicate that sustained increases in health expenditure bolster key public health outcomes and enhance society's capacity to maintain high levels of well-being over the long term.

These conclusions align with studies by Morina et al. [14], highlighting a direct and positive relationship between healthcare expenditure and health expectancy growth. These findings underscore that well-targeted resources in the healthcare sector contribute to reduced death rates and an extended lifespan in optimal health conditions [70,71]. Similarly, Mohapatra [66] demonstrates that investments in essential services, such as immunization programs and treatments for chronic illnesses, significantly improve population health outcomes. These findings strongly support our hypothesis by emphasizing the role of well-directed public interventions in generating broad benefits for public health.

However, it is essential to consider the broader socioeconomic context. Van den Heuvel and Olariou [7] highlight that despite public investments, unequal access to healthcare and socioeconomic disparities can limit the positive effects of health expenditure. Populations with lower incomes or reduced access to medical services remain vulnerable, suggesting that the impact of healthcare expenditure must be understood within an integrated framework of social and economic policies. Similarly, Mosadeghrad [61] stresses the need to incorporate social and economic dimensions into the analysis, pointing out that factors such

as education, living conditions, and access to essential resources can amplify or diminish healthcare investments' effects.

In contrast, our findings partially challenge some more pessimistic perspectives in the literature, arguing that public health expenditures do not always directly impact population health. Studies by Kousar et al. [72] suggest that human capital and population health influence may depend on how efficiently resources are allocated and managed. In this context, health expenditure becomes more effective when complemented by measures to reduce social and economic inequalities and improve healthcare infrastructure [32].

Our results thus support the notion that projected increases in healthcare expenditure have a more substantial impact on health outcomes than mere extrapolations of historical trends. These findings, consistent with the broader literature, underscore the need for an integrated approach that combines increased public funding with complementary measures to address medical but also social, economic, and educational factors [73]. Consequently, Hypothesis H2 is validated, highlighting the importance of coherent and well-coordinated health policies for improving quality of life and ensuring sustainable economic growth.

Healthcare expenditure is a critical indicator of a state's commitment to the well-being of its citizens. Investments in healthcare infrastructure, advanced medical technologies, and professional training for healthcare workers directly enhance the quality and accessibility of health services [43]. However, the impact is not solely determined by the amount invested but also by how resources are distributed and utilized to meet the actual needs of the population.

Economic growth enables governments to allocate more resources toward building and modernizing healthcare facilities, acquiring state-of-the-art medical equipment, and improving the training of healthcare professionals [74,75]. These investments translate into healthcare services that are not only more accessible but also more efficient in addressing the diverse needs of the population. The development of modern healthcare infrastructure not only improves the immediate health of the population but also stimulates long-term economic growth by reducing healthcare-related costs and creating employment opportunities in the medical sector. An efficient healthcare system directly impacts economic productivity, as a healthy population is better equipped to engage actively in professional and social life. Therefore, prioritizing investments in healthcare infrastructure becomes a strategic imperative for any developing economy aiming to support sustainable health and longevity gains [76–78].

4.1. Theoretical Implications

The findings of this study offer valuable insights into the interaction between public health expenditure and the performance of healthcare systems, highlighting how public resources can generate positive outcomes in health economic and social terms. Fundamentally, the research emphasizes that the efficiency of allocating these funds is as critical as their absolute level. Targeted investments in healthcare infrastructure, preventive measures, and reducing access inequities can significantly amplify public expenditure's impact on the quality of life.

In addition to public funding, the study examines the role of out-of-pocket expenditures and compulsory/voluntary healthcare payment schemes. While out-of-pocket payments can increase access in underfunded systems, they often exacerbate inequalities and lead to financial barriers for vulnerable populations. Conversely, depending on their design and implementation, compulsory and voluntary healthcare payment schemes can contribute to more equitable and predictable financing. Integrating these mechanisms

into broader health financing strategies is critical to achieving sustainable and inclusive health outcomes.

The COVID-19 pandemic exposed the vulnerabilities of healthcare systems, presenting a timely opportunity to reassess how resources are managed in this sector. The lessons from this challenging period reinforce the urgency of investing in prevention and strengthening healthcare systems' resilience. When applied to health, resilience theory focuses on a system's capacity to withstand shocks and adapt swiftly to meet population needs during crises.

This study emphasizes the need for health policies that integrate social and economic dimensions, addressing inequities through custom-made strategies while framing healthcare funding as a strategic investment in equity, resilience, and long-term societal and economic sustainability.

4.2. Practical Implications

The research highlights the strategic importance of investing in healthcare infrastructure to improve access, enhance crisis response, and reduce disparities through equitable and well-monitored resource allocation.

Furthermore, the study underscores the impact of financing schemes on healthcare outcomes. Out-of-pocket payments, while providing immediate resources, can result in significant inequities and financial distress for low-income populations. Compulsory health insurance schemes ensure a more stable flow of funds but require careful design to avoid excessive burdens on contributors and to guarantee inclusivity. Voluntary schemes, though flexible, often result in limited coverage and may fail to address systemic inequities unless complemented by strong regulatory frameworks.

Another practical issue arises from the need for a collaborative model between the public and private sectors. The study highlights that healthcare systems relying exclusively on public funding often struggle to address economic and infrastructural challenges. Appropriately regulated private investments can accelerate the adoption of innovative technologies and improve resource efficiency. However, for such collaboration to be effective, authorities must ensure a transparent legislative framework that prevents disparities in access and guarantees equitable treatment for all.

The study highlights the critical need for investing in healthcare infrastructure, focusing on building resilient health systems that can effectively respond to emergencies. This need includes developing a framework for resource allocation, modernizing hospitals, improving emergency care facilities, and expanding digital health systems. A robust system for monitoring and evaluating public fund usage should be implemented, ensuring accountability and transparency through regular audits and performance reviews.

Furthermore, policies for transparent healthcare budgeting should be established to maximize the impact of public funds. Investment in preventive healthcare programs (such as vaccination and screening) is essential to reduce long-term costs and improve population health. Integrating prevention into health planning can lower healthcare costs and improve productivity.

Finally, a collaborative, multi-sectoral approach to policy is necessary with partnerships between the healthcare sector, private industry, academia, and civil society. This approach will help create adaptive and sustainable policies, improving healthcare systems' resilience and ensuring equitable access to medical care for all populations.

4.3. Limitations and Further Research

While offering valuable contributions to understanding the relationship between public health expenditures and healthcare system performance, this research has limitations. First, it excludes GDP and GDP per capita, despite their relevance to healthcare funding, to focus on the direct impact of resource allocation; future research should consider these economic factors for a deeper analysis. Second, demographic variables like the mean age of the population, which significantly affect health indicators such as life expectancy and mortality, were omitted and should be integrated into subsequent studies. Third, lifestyle factors such as smoking, alcohol consumption, and diet, which are key determinants of health outcomes, were not analyzed. Their inclusion in future research could enhance the study's validity and provide a more comprehensive understanding. While significant correlations between expenditures and health outcomes have been highlighted, the underlying causal mechanisms have yet to be explored in depth. Addressing these mechanisms would require more detailed and interdisciplinary investigations.

Another limitation of this study is the lack of detailed analysis of the structure of healthcare expenditures, such as allocations for medicines, prevention, or infrastructure. While the study focuses on the overall impact of healthcare spending, the specific distribution of these resources likely influences health outcomes significantly. Future research should incorporate data from sources like Eurostat on healthcare spending by category to provide a more granular understanding of how resource allocation impacts public health.

Another key limitation is the exclusion of potential confounding factors such as the mean age of the population, preexisting comorbidities, and the estimated pre-existing quality of life. These variables are often associated with health outcomes and may have moderated or mediated the observed effects. Furthermore, the study does not account for the heterogeneity of healthcare systems across countries, including variations in policy implementation, healthcare access, and cultural factors influencing health-seeking behavior. These aspects could introduce variability in outcomes not addressed in the current analysis.

However, these limitations pave the way for future research directions. Future research should consider incorporating these confounding factors into the analysis, employing more comprehensive datasets that include demographic, epidemiological, and qualitative variables. Such an approach could offer a more nuanced understanding of the mechanisms linking healthcare expenditure with health outcomes and enhance the generalizability of findings across different contexts.

Another area for improvement lies in measuring the efficiency of public health funding. Traditional indicators such as health expectancy or death rate provide an overarching view but often fail to capture nuances related to quality of life or inequalities in access to healthcare services. External factors, such as pandemics or economic crises, further complicate predictive analysis and may distort conclusions, underscoring the need for sensitive approaches.

Subsequent studies could also investigate more profound expenditure efficiency, examining not only their volume but also their allocation across various areas of public health. Investigating regional disparities and the impact of factors such as income levels or education on expenditure efficiency could yield valuable insights for policies more tailored to local needs.

Another promising research direction involves analyzing the integration of private funding into public healthcare systems. Answering this question would require study models incorporating economic data and social perspectives. Considering the lessons learned from the COVID-19 pandemic, future research could explore how healthcare expenditure can enhance system resilience to global crises, accounting for medical dimensions and social and economic stability.

5. Conclusions

Under increasingly complex global challenges, from health crises to economic and social pressures, a well-funded and efficiently managed healthcare system is central to ensuring population well-being and long-term stability. This study underscores the fundamental importance of adequate and efficient healthcare expenditure in securing public welfare and economic stability over the long term. The findings demonstrate a clear relationship between public health expenditures and the performance of healthcare systems, which are measured through indicators such as health expectancy and mortality rates. Furthermore, they show that increased financial allocations, coupled with well-targeted policies, can significantly improve quality of life while simultaneously alleviating pressures on economic and social systems.

The COVID-19 pandemic has highlighted the vulnerabilities of many healthcare systems and the urgent need for reforms prioritizing prevention and strengthening health infrastructure. In this context, well-planned public investments in healthcare emerge as a necessity and a critical strategy to prepare medical systems for future crises and support sustainable economic development. Resilience in healthcare systems forms a central part of this equation with the study's conclusions pointing to the need for responsible and transparent resource management to achieve it.

At the same time, the research shows that more than simply increasing expenditures is needed. Efficiency in using funds, directing them toward strategic priorities, and reducing inequalities in access to healthcare are all aspects that must be integrated into public policies. Particularly in countries with limited resources, balancing public funding with private sector involvement, supported by a well-structured legislative framework, becomes decisive for modernizing and ensuring the sustainability of healthcare systems.

This study contributes to understanding the complex relationship between public health expenditures and outcomes, providing a solid foundation for shaping better-adapted public policies. Its conclusions also highlight the need for continued research in this area to better address the needs of an ever-changing world. Therefore, a well-funded and efficiently managed healthcare system is a priority for the present and a strategic investment in a more equitable, healthy, and prosperous future.

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Appendix A

Table A1. Historical and future trends.

Historical Trend				Forecast of HLYB Using Holt Model	Forecast of HLYB Using Brown Model	Forecast of HCE_AS Using ARIMA Model	Forecast of HLYB Using ARIMA Model	Forecast of HLEB Using ARIMA Model
Year	HLYB	HCE_AS	HLEB	Predicted HLYB	Predicted HLEB	Predicted HCE_AS	Predicted HLYB	Predicted HLEB
2004	62.9	-	70.6	-	-	-	-	-
2005	60.9	-	70.4	-	-	-	-	-
2006	61.6	-	70.7	-	-	-	-	-
2007	61.7	-	71.1	-	-	-	-	-
2008	61.0	-	72.0	-	-	-	-	-
2009	61.0	-	72.2	-	-	-	-	-
2010	61.8	-	72.7	-	-	-	-	-
2011	61.4	-	72.8	-	-	-	-	-
2012	61.3	-	72.9	-	-	-	-	-
2013	61.0	-	73.3	-	-	-	-	-
2014	61.3	2658.13	73.7	-	-	-	-	-
2015	62.8	2737.20	73.7	-	-	-	-	-
2016	64.0	2807.27	74.7	-	-	-	-	-
2017	63.9	2902.08	74.9	-	-	-	-	-
2018	64.0	2994.18	75.0	-	-	-	-	-
2019	64.6	3116.25	75.3	-	-	-	-	-
2020	64.0	3273.66	74.5	-	-	-	-	-
2021	63.6	3566.78	74.3	-	-	-	-	-
2022	62.6	3684.55	74.8	-	-	-	-	-
2023	-	-	-	62.7	74.7	3812.85	63.8	74.9
2024	-	-	-	62.9	74.8	3941.15	63.9	75.0
2025	-	-	-	63.0	74.8	4069.46	63.9	75.1
2026	-	-	-	63.2	74.8	4197.76	64.0	75.1
2027	-	-	-	63.3	74.8	4326.06	64.1	75.2
2028	-	-	-	63.5	74.9	4454.36	64.2	75.3
2029	-	-	-	63.6	74.9	4582.67	64.2	75.3
2030	-	-	-	63.8	74.9	4710.97	64.3	75.4
2031	-	-	-	63.9	75.0	4839.27	64.4	75.5
2032	-	-	-	64.1	75.0	4967.57	64.4	75.5
2033	-	-	-	64.2	75.0	5095.88	64.5	75.6
2034	-	-	-	64.4	75.0	5224.18	64.6	75.7
2035	-	-	-	64.5	75.1	5352.48	64.6	75.7

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Article

Facility Management Costs for Hospital Infrastructures: Insights from the Italian Healthcare System

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Abstract: Background: Hospital infrastructures account for a significant portion of healthcare expenditures, yet the factors driving facility management costs (FMCs) remain under-explored, particularly in the Italian context. This study aims to analyze FMCs in hospitals, focusing on utility and maintenance expenses, while providing benchmarking values to support decision making. **Methods:** This study employed a mixed-methods approach, integrating a literature review, financial data analysis, and a case study of 27 hospital facilities in Lombardy. Data on utility and maintenance costs were collected from financial statements and supplemented with targeted questionnaires to enhance precision. Descriptive statistics and parametric cost indicators (e.g., EUR/sqm, EUR/bed) were analyzed to identify trends and disparities. **Results:** FMC increased by an average of 32.90% between 2019 and 2022, with utility expenses constituting 77.45% of total costs and maintenance accounting for 22.45%. Utility costs rose significantly (37.34%), driven by energy and cleaning services, while maintenance costs grew more moderately (18.66%). Cost variability was evident across hospital typologies, with Basic Healthcare Centers averaging 122.86 EUR/sqm compared to 232.66 EUR/sqm for Level II Emergency Hospitals. **Conclusions:** This study highlights significant variability in FMCs across Italian hospitals and underscores the need for benchmarking to optimize resource allocation. Future research should expand the dataset, incorporating extraordinary maintenance costs, and examine management models to enhance cost efficiency. These findings provide actionable insights for policymakers and healthcare administrators to improve hospital infrastructure sustainability and efficiency.

Keywords: healthcare infrastructures; hospital facilities; hospital administration; hospital costs

1. Introduction

1.1. Hospital Facilities Within Healthcare Systems

Hospital facilities represent the core of healthcare organizations, embedding the highest requirements in terms of organizational processes and building factors [1]. As one of the most complex and resource-intensive civil infrastructures, hospitals account for a significant proportion of total healthcare costs at the national level [2]. In the European context, hospital-related expenses constitute the highest share of healthcare expenditures, ranging from 28% in Germany to 48% in Romania, with an average share of 35% [3]. This study focuses on the Italian context, positioned in the highest section with 43.5%. As

a pivotal element in the healthcare service, optimizing costs in the sector can positively influence other interconnected components of the system [4].

1.2. The Italian Hospital Building Stock

The hospital building stock plays a critical role in cost containment strategies within the healthcare delivery sector, as well as in mitigating the environmental and economic impacts of healthcare activities [5]. Maintaining high standards in hospital infrastructure requires the modernization of the existing building stock, facilitating the adoption of more innovative models better suited to contemporary contexts [6]. This process is essential for optimizing operational costs and improving the overall efficiency and sustainability of healthcare facilities [7].

Due to national reforms and optimization targets, Italian hospital facilities experienced a significant decrease in terms of numbers over the last few decades. From 1954 to 2021, the total number of hospitals decreased by 53.7%, with public hospitals experiencing a more dramatic reduction of 64%. Similarly, in the past fifty years, from 1971 to 2021, the number of healthcare institutions dropped from 2253 to only 1060. As of the most recent census in 2021, the number of hospitals represented 74.4% of the total compared to twenty years earlier (Annuario Statistico del SSN, 1955–2021) (Figure 1). Despite a growing population, the number of hospital facilities has declined, leading to a reduced ratio of hospitals available to meet the needs of the population (Figure 2). Specifically, the total number of available beds, including both public and accredited hospitals, decreased significantly from 295,809 in 2001 to 236,481 in 2021 [8].

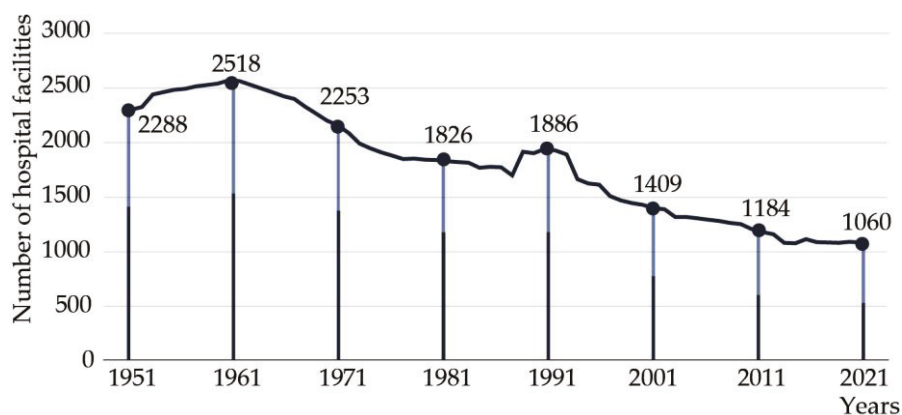


Figure 1. Decline in the number of public and private hospitals (Annuario Statistico del SSN).

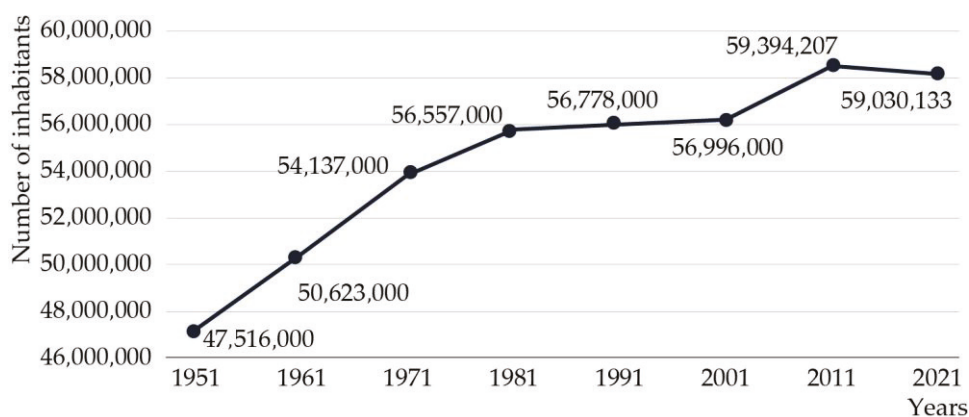


Figure 2. Italian population growth (ISTAT, 1951–2021).

A report by the Observatory on Italian Healthcare Companies and Systems, based on 2020 data from the Ministry of Economy and Finance (MEF), provided a comprehensive

overview of the aging real estate assets within the National Health Service (SSN), encompassing both hospital and non-hospital infrastructures. As highlighted in the report, most of the building stock owned by Italian healthcare organizations has exceeded its optimal lifespan of 50 years. Over 60% of the building stock in the Italian regions of Piedmont, Lombardy, Liguria, Tuscany, Marche, Lazio, and Sicily, which together account for 52.39% of the population [9], was built before 1969.

1.3. Facility Management in Healthcare Infrastructures

Facility management in hospitals plays a fundamental role in ensuring the efficiency, safety, and sustainability of healthcare infrastructures. Facility management has been defined as “an integrated approach to maintaining, improving and adapting the buildings of an organisation in order to create an environment that strongly supports the primary objectives of that organisation” [10]. It presents unique challenges compared to other real estate sectors, such as education, public sector buildings, and office facilities. First, the management of healthcare facilities, given their nature of complex and dynamic environments, requires a robust specialized knowledge base for making informed decisions. Furthermore, facility management for complex assets like hospitals involves several activities, ranging from managing day-to-day operations, preventive, routine, and corrective maintenance, ensuring certification and compliance with international standards, monitoring energy management, space planning, and facility utilization analysis [11]. The complexity stemming from dealing with multiple activities often clashes with the resource constraints, affecting many hospital realities, especially the public ones [12]. These constraints negatively impact the quality and availability of services, as well as the capacity to meet the demands for timely structural and functional upgrades in healthcare facilities, which require significant investments [13].

In this context, the consequent demand for management efficiency and cost containment in healthcare has led hospital administrators to focus on optimizing FM costs through preventive strategies, energy-efficient solutions, and data-driven asset management through the integration of advanced technologies such as Building Information Modeling (BIM), artificial intelligence (AI), and the Internet of Things (IoT) [14,15]. Such a focus calls for devoting particular attention to facility management concerning maintenance, one of the most challenging and costly activities within hospitals [16]. Facility management, indeed, ensures the operational continuity of hospital structures by minimizing disruptions, preserving the quality of patient care, and mitigating the effects of infrastructure obsolescence [17]. Infrastructure obsolescence, a key factor influencing hospital operational efficiency, can be categorized into functional and technological obsolescence [18]. Functional obsolescence occurs when changes in healthcare demands, operational workflows, and regulatory requirements outpace the capabilities of the existing infrastructure, making it inadequate for current needs. Furthermore, technological obsolescence pertains to the outdated nature of building systems and technical components. Hospitals that are not designed to accommodate modern medical technologies or advanced infrastructure solutions may struggle to integrate innovations, ultimately reducing their adaptability and effectiveness [19,20]. Addressing these challenges requires a forward-looking approach to facility management, incorporating strategic planning, lifecycle cost analysis, and proactive maintenance frameworks.

1.4. Study Objective

The objective of this research is to investigate the facility management costs (FMCs) associated with hospital infrastructures within the Italian healthcare system, with a specific focus on Lombardy, Italy’s most populous region [21]. In particular, this study aims at ob-

serving the variation over time to understand the evolution of expenditures and identifying the key factors that contribute to the differences in costs across various hospital facilities, such as their typology, complexity, age, and maintenance. Furthermore, the contribution aims to provide benchmarking values for parametric cost indicators to compare hospital facilities' expenditures and offer comparative insights for different hospital typologies. Benchmarking is widely utilized by organizations to drive continuous improvements in the management of building assets. Although benchmarking is recognized as a valuable tool for optimizing operational processes in healthcare facilities, its application in the healthcare infrastructure domain remains very narrow, with limited scientific research available. In Italy, benchmarking tools are widely underutilized, since there is a notable lack of comprehensive data on the operational and maintenance costs of healthcare facilities [22]. The results obtained in the contribution aim to provide information for hospital facility managers and healthcare decision makers to optimize resource allocation and improve cost efficiency and strategic planning.

1.5. Research Questions

To explore the facility management costs of hospital facilities, this research addresses the following research questions:

1. What are the facility management cost patterns across hospitals with varying levels of infrastructure and organizational complexity?
2. How do facility management costs evolve over time, and what are the main drivers of variability in operational and management costs across different types of hospital facilities?

1.6. Research Context

This research focused on the Italian hospital system, with a particular emphasis on the Lombardy region. Lombardy was chosen as the primary case study as a representative example in the Italian healthcare delivery scenario [23]. This region was deemed appropriate for in-depth analysis due to the following: (i) the significance in the number of hospitals built during different periods; (ii) the variety of hospital types, including new constructions and older facilities, which allows for comparative analysis; (iii) it is the Italian region with the highest population and the most significant contribution of private accredited providers in the healthcare system. Furthermore, the region has a diversified mix of urban and rural healthcare infrastructures, as well as a significant presence of public and accredited private providers, making it a robust case for analysis. While the healthcare systems vary across regions, the diversity and scale of the Lombardy system allow for meaningful insights and serve as a proxy for national-level trends [24].

2. Materials and Methods

This paper explores various approaches to address the complexity of managing hospital facility costs. The adopted methodology can be categorized into three distinct phases: (i) theoretical, (ii) practical, and (iii) interactive (Table 1). Each phase is unified by the objective of collecting data and generating insights into the facility management costs of hospital infrastructures. In the theoretical phase, the authors conducted a comprehensive review of both the scientific and gray literature to assess the existing knowledge regarding the costs associated with managing healthcare facilities and to determine the Italian building stock. The practical phase involved analyzing case studies from the Lombardy region to establish parametric cost values. Finally, in the interactive phase, data were gathered through direct engagement with hospital officials. This allowed for a more detailed and coherent analysis

of parametric values, particularly for those not readily available from publicly accessible financial documents.

Table 1. Research methodological approach in three phases.

Approach	Methods	Source	Data Source
1. Theoretical	Literature Review	Scopus, WoS, PubMed, and Gray Literature	Secondary
2. Practical	Healthcare Organization	Balance Sheet	Secondary
3. Interactive	Case Studies	Questionnaire	Primary

2.1. Literature Review: Theoretical Phase

The first phase focused on reviewing the scientific literature on facility management within healthcare facilities to explore existing contributions on the topic of hospital management costs in healthcare environments. The analysis was conducted according to the PRISMA protocol for a systematic literature review in June–July 2024 using the scientific databases Scopus, Web of Science, and PubMed (Figure 3). The following keywords were employed: “maintenance cost”, “utilities cost”, “operating cost”, “management cost”, and “facility management cost”, combined with terms defining the healthcare setting, such as “hospital”, “hospital building”, “hospital center”, “healthcare facilities”, and “healthcare infrastructure”. To ensure the relevance of the researched contributions and of the data retrieved, the following exclusion criteria were applied during the literature review: studies prior to the year 2002, with the adoption of the EU common currency. Papers in the field of medicine, clinical practice, and nursing were excluded since these disciplines do not address the research focus on facility management and operational costs. Non-peer-reviewed documents, such as opinion pieces, letters, or editorials, were excluded from the search on scientific databases. The literature review returned a result of ($n = 87$) papers by reading the title, then 53 were excluded by reading the abstract and keywords, and a final result of ($n = 34$) papers was included in the final full text, in addition to ($n = 3$) contributions from the gray literature. After full-text screening, only the results of ($n = 7$) papers were considered. The second step involved the analysis of the available gray literature by searching online for the keywords “facility management cost”, “operational costs”, “O&M costs”, and “Italy”.

2.2. Data Collection: Practical and Interactive Phase

This phase focused on gathering hospital operational cost data from balance sheets from a selection of healthcare organizations within the Lombardy region. A total of 27 hospital organizations (“Aziende Socio Sanitarie Territoriali” ASST) were analyzed. Data on hospital infrastructure management costs were gathered by collecting costs and operational data from hospital balance sheets and financial statements, available on the official websites, covering the years 2018 to 2022. The timeframe was chosen to analyze the most recent data available and to mitigate fluctuations in expenses caused by the extraordinary circumstances that affected Italy during these years. The following balance sheet items were included in the analysis: 1. Utilities: non-healthcare service purchases; cleaning; heating; waste disposal; electricity; water, gas, and fuel; other utilities. 2. Outsourced ordinary maintenance and repair: routine maintenance and repair of buildings and their related assets; routine maintenance and repair of equipment and machinery; routine maintenance and repair of furniture and vehicles; other maintenance and repair activities (Table 2).

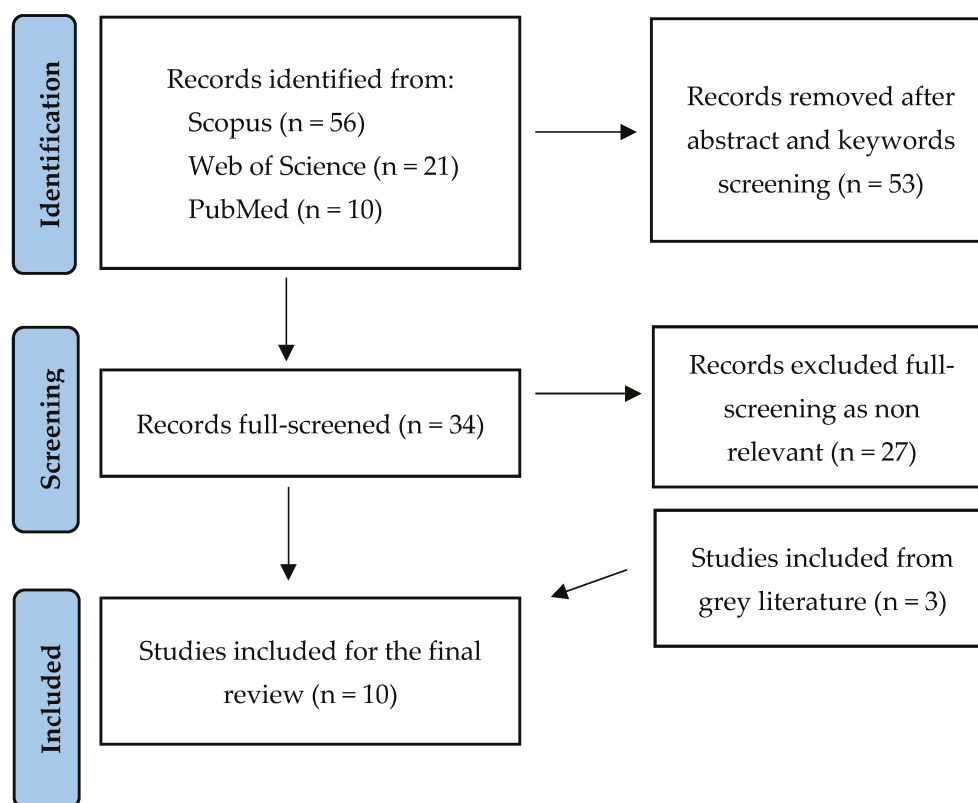


Figure 3. PRISMA chart for literature review.

Table 2. Key inputs collected for operational and maintenance cost assessment.

Input	Definition
Total utilities cost	The total annual cost of energy consumed by the hospital site, inclusive of the cost items: heating, waste disposal, cleaning, electricity utilities, water, gas, fuel, and other utilities.
Total maintenance cost	Total costs for external services for the provision of maintenance services, including cost of routine maintenance and repair of the building, cost of routine maintenance and repair of systems and machinery, cost of routine maintenance for furniture and equipment, and other maintenance and repair costs.
Total operational and maintenance costs	Total utilities costs + total maintenance costs

2.3. Interactive Phase: Case Studies Analysis

The interactive phase of the analysis, through its focus on specific case studies, aimed to collect detailed data directly from hospital facilities rather than relying solely on aggregated values obtained from the financial statements of healthcare organizations. In balance sheets and financial statements, available online for all healthcare public companies, facility management costs (FMCs) were not exclusively related to hospital facilities, but they also included buildings used for other purposes. To isolate the specific costs related to hospital facilities, a customized survey-based data collection form (Google Forms) was developed. A customized data collection form was designed and distributed to all technical departments in selected public hospitals across Lombardy (n = 132). For the description analysis, key indicators such as mean, median, standard deviation, and minimum and maximum values were calculated to summarize the distribution of facility management

costs, both in terms of EUR/m² and EUR/bed, across hospital types and years. For group comparison analysis, to compare cost values across hospital typologies (Basic, DEA I, and DEA II), the authors used ANOVA for normally distributed data and the Kruskal–Wallis test for non-normally distributed variables. Finally, to determine the relationship between facility characteristics (e.g., age, surface area, and number of beds) and cost, variables were examined using Pearson or Spearman correlation coefficients, depending on the distributional characteristics of the data.

2.3.1. Sample Description

A customized data collection form was designed and distributed to all technical departments in the selected public hospitals across Lombardy (n = 132). Data were collected from (n = 27) hospitals, corresponding to a response rate of 20.4%. The facilities vary in complexity and typology, including Basic Healthcare Centers, Level I Emergency Hospitals (DEA I), and Level II Emergency Hospitals (DEA II). These hospitals also differ in size (ranging from 65 to 1200 beds), gross floor area (from 6013 m² to nearly 200,000 m²), and building age (constructed between 1907 and 2012). All the facilities are publicly owned and operated by the ASST (Appendix A). This diversity enabled a meaningful comparative analysis across various levels of infrastructural and organizational complexity. The localization of the 27 hospitals included in the case studies' analysis can be observed in Figure 4.

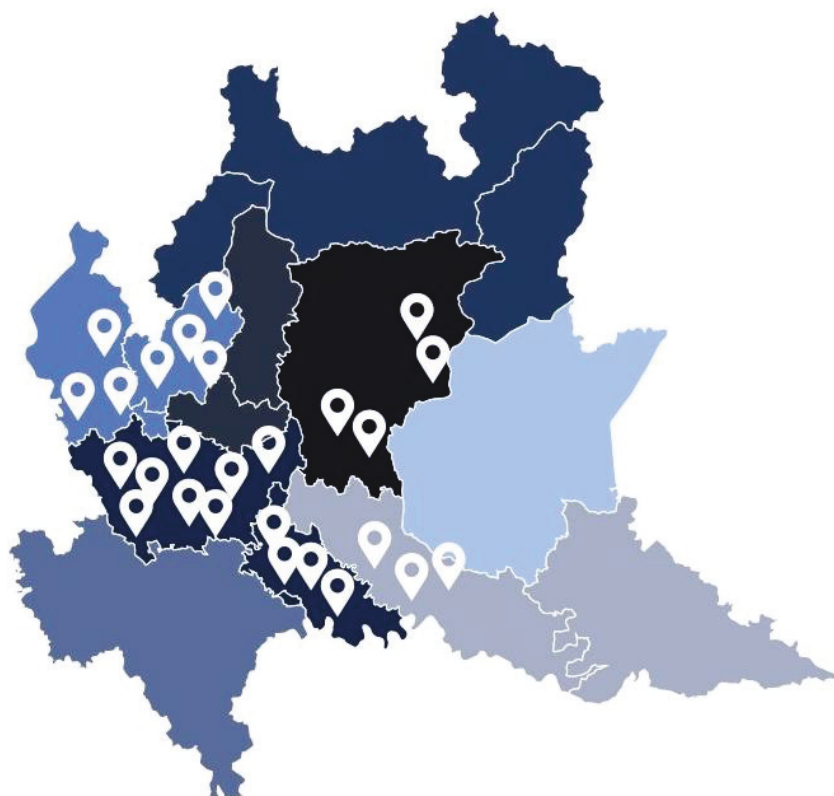


Figure 4. Geographic distribution of sampled hospitals across Lombardy's health districts.

2.3.2. Sampling Method

The sampling method adopted in this study was a comprehensive outreach to all publicly owned hospital facilities in the Lombardy region. A standardized data collection form was distributed via email and telephone contact to the entire population of 132 public hospitals, with the aim of maximizing participation and ensuring broad representativeness across different facility typologies.

2.3.3. Questionnaire Design

To ensure the reliability and clarity of the data collection instrument, the questionnaire underwent a two-step validation process. First, the content was developed based on the established classifications used in Italian public healthcare financial reporting, specifically aligning with cost categories outlined in regional and national health accounting frameworks. This provided a consistent basis for capturing facility-related operational costs (e.g., utilities, cleaning, and maintenance) across multiple institutions. Second, the questionnaire was pre-tested with a technical officer from a hospital not included in the final sample. The pilot test was used to assess the clarity of the questions, the appropriateness of the terminology, and the feasibility of retrieving the requested data from internal systems. Finally, the questionnaire was structured into the following three sections: 1. Research objectives and context. 2. Facility identification and structural characteristics (e.g., year of construction, gross floor area, and number of beds). 3. Operational cost data from 2018 to 2022. The survey items were derived from national health budget classification systems and adapted to isolate hospital-specific costs. The form was developed in consultation with technical departments and pre-tested with three pilot facilities to ensure clarity, data consistency, and content validity (Table 3).

Table 3. Variables collected through the survey.

Variable	Definition
Year of Construction	The year in which the hospital was built or significantly renovated. For hospitals with multiple buildings, the average year of construction, weighted by the gross floor area, was considered.
Gross Floor Area	The area within the perimeter of the outside walls of a building as measured from the inside surface of the exterior walls, with no deduction for hallways, stairs, closets, thickness of walls, columns, or other interior features; this is used in determining the required number of exits or in determining occupancy classification.
Number of Beds	The total number of available hospital beds, which is used to calculate the operational costs per bed.
Number of Floors	The total number of levels in the hospital building was considered.
Building Typology	Building classification based on their architectural design, layout, and functional characteristics.

3. Results

3.1. Literature Review

As mentioned in the Methodology Section, the search conducted in the scientific databases yielded only limited significant results. The reviewed studies provided partial insights into the research questions. Among the most significant contributions in this area is the work by Sliteen et al., who analyzed the operational costs of 19 French hospitals [22]. Their findings revealed that, on average, 38% of the total operational and maintenance costs in hospitals are attributed to utilities, 29% to maintenance expenses, and the remaining 33% to staffing costs for real estate functions. This analysis underscores the fragmented nature of existing research on hospital operational costs and highlights the importance of conducting further empirical studies to develop comprehensive benchmarks and better understand cost drivers in hospital facility management. The literature review revealed a significant gap in studies focusing on the identification of benchmark values for hospital

management costs and the key factors contributing to increases in operational expenses. This lack of research has hindered the development of standardized benchmarks for hospital management costs. Consequently, an inductive approach, involving the empirical observation of hospital facilities, was necessary to address these gaps. Several studies have confirmed the use of gross floor area (GFA) as the primary functional unit for determining management and maintenance costs [25]. Gómez-Chaparro and colleagues established a relationship between maintenance and hospital characteristics, which is that hospitals with more than 25,000 annual stays exhibit lower maintenance costs per area, fewer maintenance reports per bed, and fewer reports per unit area compared to hospitals with fewer stays, while large hospitals show later maintenance costs per unit area and fewer maintenance costs per bed than smaller hospitals, confirming an expected economy of scale principle. Their analysis also addressed the most critical maintenance variables identified: heating, ventilation, and air conditioning (HVAC) systems, refurbishment works, and plumbing installations. Finally, Hassanain and colleagues identified, through a questionnaire with 40 hospitals, the key factors affecting rising maintenance costs, and the most critical factor affecting costs was linked to some problems in the design and construction phase, followed by the absence of quality control during system installations [26].

In the Italian context, there is a noticeable absence of scientific contributions specifically addressing management and maintenance costs. However, the review of the gray literature described in the Methodology Section provided some results, and three technical reports were analyzed: the first published by the AGENAS (National Agency for Regional Healthcare Services), the IRES (Institute for Economic and Social Research of the Piedmont Region), and the OASI 2021 Report. The OASI Report highlights a linear relationship between the costs incurred for the routine maintenance of buildings, systems, and machinery, and the aging of the building stock [27]. As mentioned earlier in this section, greater wear and tear on an asset's conventional useful life should correspond to a higher intensity of maintenance requirements. This underscores the importance of integrating lifecycle considerations into facility management strategies to address the aging infrastructure and optimize resource allocation. The IRES contribution from a sample of Italian hospitals provided a value for maintenance cost per square meter parametric value based on 2016 data. The study estimates an average maintenance cost of EUR 58.3 per square meter per year. These costs are influenced by the obsolescence level of hospital facilities. The study provides differentiated ranges of annual costs based on obsolescence: between 30 EUR/sqm per year for new infrastructures and up to 100 EUR/sqm for the hospitals with the highest level of obsolescence [18].

An AGENAS analysis similarly analyzed a sample of 29 hospital facilities across five Italian regions and provided an average operating cost of 45.05 EUR/sqm. Maintenance accounted for the largest share of operational costs at 47%, followed by electricity (30%), heating (19%), and water (4%). The study also highlighted regional differences between urban areas and suburban or rural areas (27.4%). Building typologies and characteristics also influence operational expenses, with hospitals with pavilion-style layouts reporting higher operational costs (48.85 EUR/sqm) compared to monoblock structures (40.63 EUR/sqm). Additionally, older buildings showed higher operational costs (52.79 EUR/sqm) than newer facilities (37.29 EUR/sqm) with the analyzed sample. These findings emphasize the impact of design factors on hospital operating costs [28].

3.2. *An Aging Italian Hospital Building Stock*

The state-of-the-art assessment of a sample of 500 facilities in Italian healthcare, conducted through the information available online, revealed a significant proportion of healthcare institutions exceeding 50 years of age, the typical useful life limit [29]. Notably,

29% of these structures were built between 1941 and 1970, making this period the most significant in terms of hospital development. Buildings constructed between 1901–1940 and 1971–2000 each account for 22%, while only 19% of hospitals were built after 2001, reflecting a decline in recent construction efforts. Meanwhile, 8% of hospitals date back to before 1900, showcasing a portion of the building stock that is over a century old. This distribution highlights potential challenges related to aging infrastructure, as nearly 60% of these facilities were built before modern construction standards, possibly requiring significant upgrades to meet current safety, functionality, and sustainability requirements.

The findings highlight a significant issue: many hospitals across Italy are housed in outdated and aging structures, making it increasingly challenging for them to adapt to the rapid advancements in modern medicine. These facilities, often inherited from decades of healthcare history, face significant maintenance and operational challenges that lead to substantial and frequently unsustainable costs. The situation not only affects the quality of care provided but also places a considerable strain on the financial resources of healthcare facilities, as significant funds must be allocated to maintain buildings that are often inadequate for current needs. Consequently, there is an urgent need to renew and modernize the national hospital infrastructure.

The data presented in Figure 5, concerning the construction year of Italian hospital buildings, refer to a broader sample of 500 facilities for which publicly available information was collected. This investigation was exclusively aimed at identifying the year or period of construction, without considering building typology or specific hospital characteristics, and relied solely on data accessible through institutional websites. These data are entirely distinct from the primary cost analysis sample, which includes 27 hospitals selected through a targeted, questionnaire-based investigation.

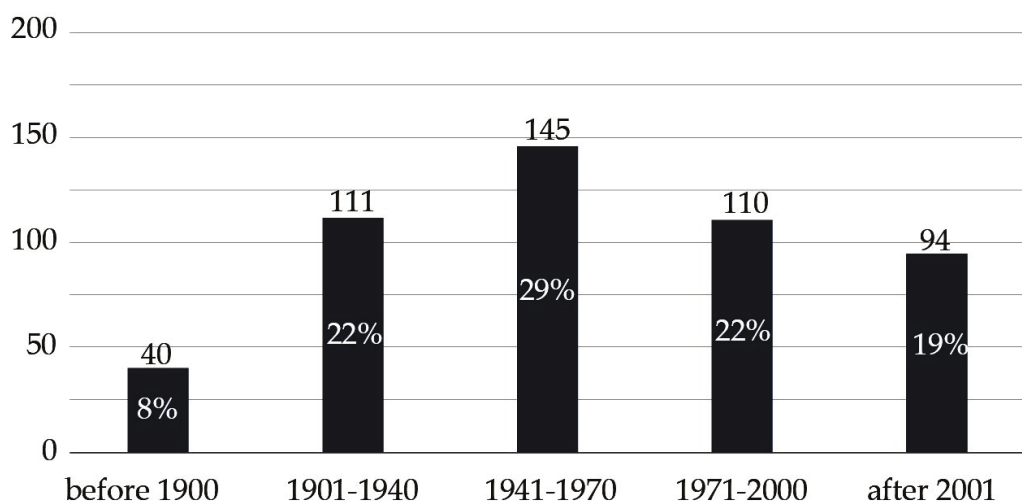


Figure 5. Year of construction of Italian hospitals, based on a sample of 500 hospitals collected from healthcare companies' websites.

3.3. Hospital Organizations' Facility Management Costs

An analysis of the Lombardy hospital facilities examined reveals that 70% have exceeded the useful life of 50 years, with construction dates ranging from 1907 to 2012. The hospitals studied have an average gross floor area of 56,193 sqm and a capacity ranging from 65 to 1200 beds. Despite the considerable diversity of the sample, it was still possible to identify the average utility and routine maintenance costs (Figure 6).

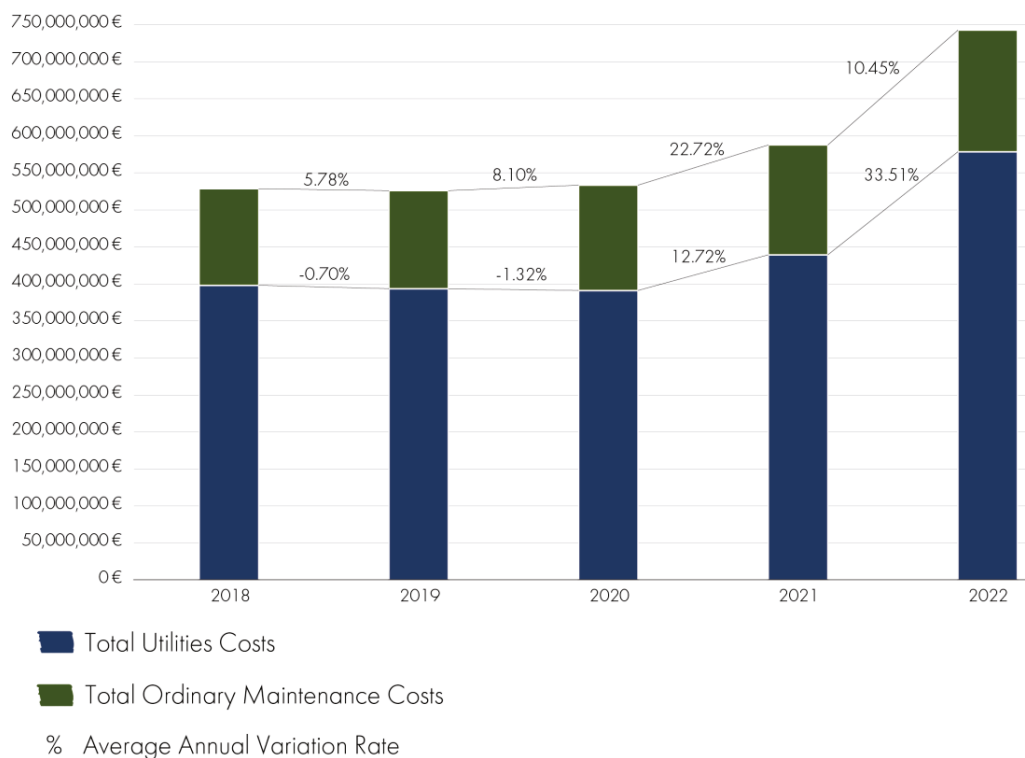


Figure 6. Trend of FM costs across the analyzed hospital sample (2018–2022, EUR).

The analysis illustrates the aggregated trend in facility management costs across the 27 hospital facilities included in the analysis. The *y*-axis represents the total annual costs expressed in millions of euros (€M). This aggregation provides a macro-level perspective on how overall facility management expenditures have evolved from 2019 to 2022 across the entire sample. The graph clearly demonstrates a consistent increase in costs over the observed period, with a notable surge between 2021 and 2022. This trend is largely attributed to rising energy prices and pandemic-related impacts on operational services. By presenting total costs rather than average or per-unit values, this figure supports a broader understanding of the cumulative financial burden borne by hospital infrastructures in the region.

3.4. Interactive Phase: A Questionnaire on Operational Costs of Healthcare Infrastructures

Following the analysis of the financial statements of hospital organizations, a targeted questionnaire was implemented to enhance the precision of the analysis by selecting a specific sample of hospital facilities. The objective was to gather more detailed and granular information compared to what was available from the financial statements. While financial statements provide an aggregated and retrospective view of data, enabling large-scale application at the national level, they are inadequate for in-depth scientific investigations into facility management (FM) parameters at the level of individual hospital facilities. Through the questionnaire and the data collected, a range of parameters was derived for analysis. These included costs per square meter for aggregated items (e.g., total utility expenses), total routine maintenance costs, and the overall running costs for infrastructure management. Firstly, the data collected reveal that utility expenses constitute the primary cost component, accounting for 77.45% of the total management costs. In contrast, routine maintenance expenses represent a smaller proportion, amounting to 22.45% of the total. These findings underscore the significance of utilities in hospital infrastructure management and provide valuable insights for optimizing cost efficiency across facilities.

An analysis of cost data for hospital facilities over five years (2018–2022) reveals a consistent upward trend in expenditures. During this timeframe, utility costs increased by 10.64%, with a notable decline in 2019 attributed to a 46.92% reduction in heating expenses. Conversely, a substantial 34.19% rise in heating-related costs drove the overall increase in 2022. Other utility expenses displayed steady growth, albeit at varying rates. Ordinary maintenance costs exhibited consistent growth until 2021, followed by a slight decrease between 2021 and 2022. A significant surge in maintenance expenses occurred between 2020 and 2021, primarily due to the adaptation of buildings and systems to address the challenges posed by the COVID-19 pandemic. This analysis underscores that utility costs are the most significant and impactful component of hospital infrastructure management services, while ordinary maintenance costs showed less dramatic fluctuations within the broader trend. From 2018 to 2022, the total management services costs rose by 16.48%, with a cumulative increase of 32.90% observed since 2019. Notably, this period includes the economic effects of the COVID-19 pandemic, which disrupted supply chains, increased demand for cleaning and sanitization, and led to inflationary pressures in the energy and service sectors. Additionally, policy-driven adjustments, including stricter hygiene regulations and energy consumption standards, may have further elevated costs, especially in hospital facilities operating with outdated systems. As such, part of the cost variability observed in this study can be reasonably attributed to time-bound conditions (Figure 7).

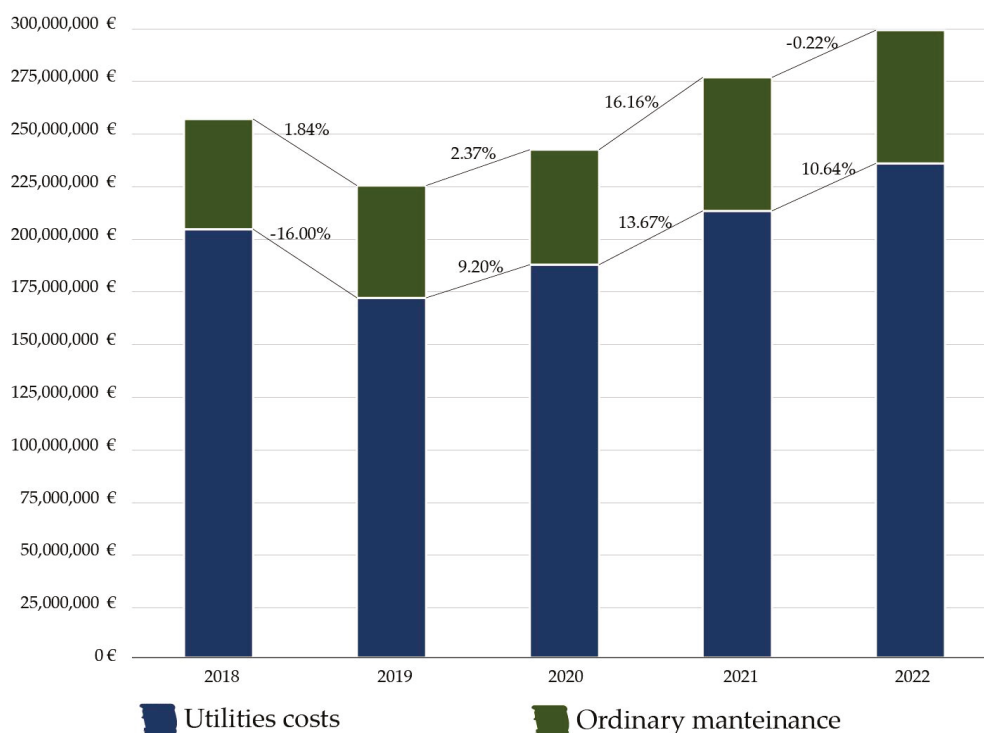


Figure 7. Annual trend of utilities and ordinary maintenance costs (2018–2022, EUR).

Figure 8 presents the average parametric costs for hospital facility management, disaggregated into three main components: utilities costs, ordinary maintenance, and overall management services. The left panel displays the cost distribution expressed in euros per square meter (EUR/m²), while the right panel shows the same categories expressed in euros per hospital bed (EUR/PL). The average total costs of utilities and maintenance amount to EUR 161.58 per sqm, ranging from EUR 66.67 to 341.44 per sqm. These expenses consist of utility services, with an average value of 128.78 EUR/sqm, and maintenance costs, averaging 32.8 EUR/sqm on an annual basis.

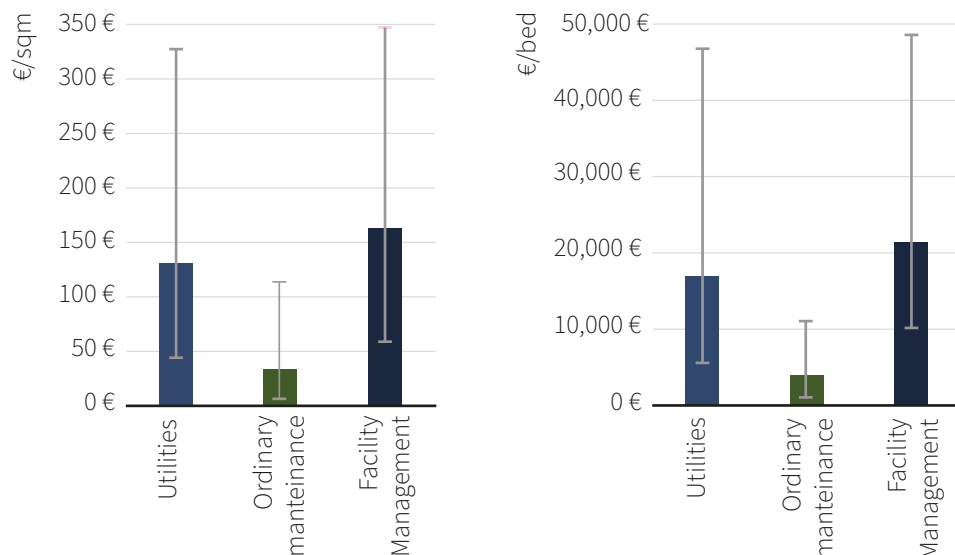


Figure 8. Average facility management costs by type and complexity of hospital (EUR/m²) and EUR/bed.

3.5. Variability and Trends in Hospital Facility Management Parametric Costs

The descriptive analysis revealed significant variability in parametric management costs across the analyzed hospital facilities, influenced by the type and complexity level of the structures. The classification of different hospital typologies are defined as Basic Healthcare Centers, Level I Emergency Departments (DEA I), and Level II Emergency Departments (DEA II) and are regulated by Ministerial Decree 70/2015. Basic Healthcare Centers (“Presidi di base”) reported an average parametric cost of 122.86 EUR/sqm. These facilities generally have simpler layouts, lower patient throughput, and reduced technical infrastructure, which translate into lower energy consumption, minimal specialized cleaning requirements, and simplified maintenance routines. In contrast, hospitals classified as Level I Emergency Departments (DEA I) and Level II Emergency Departments (DEA II) demonstrate higher average values, amounting to 159.10 EUR/sqm and 233.70 EUR/sqm, respectively. These differences reflect the greater infrastructural and operational complexity required by higher-level facilities (Table 4).

Table 4. Facility management costs (€/sqm) by hospital typology.

Hospital Typology and Complexity	EUR/sqm
Basic Healthcare Centers	EUR 122.86
Level I Emergency Hospital (“DEA di I Livello”)	EUR 159.10
Level II Emergency Hospital (“DEA di II Livello”)	EUR 233.70

When considering parametric cost per bed, the data highlights significant differences in facility management costs across healthcare facilities of varying complexity. The average costs for Basic Healthcare Centers are the lowest, with a parametric cost of EUR 122.86 per square meter and an average cost per bed of EUR 18,509.24. These values reflect the relatively simple infrastructure and operational requirements of these facilities (Table 5).

Table 5. Facility management costs (€/bed) by hospital typology.

Hospital Typology and Complexity	EUR/Bed
Basic Healthcare Centers	EUR 18,509.24
Level I Emergency Hospital (“DEA di I Livello”)	EUR 24,272.40
Level II Emergency Hospital (“DEA di II Livello”)	EUR 35,458.13

Further statistical analysis provided a more detailed overview of the data distribution. The overall mean parametric cost was 151.47 EUR/sqm, with a median value of 137.31 EUR/sqm, suggesting a moderately right-skewed distribution. The minimum observed value was 66.67 EUR/sqm, while the maximum reached 340.92 EUR/sqm, resulting in a total range of 274.25 EUR/sqm. The standard deviation, calculated as 79.45 EUR/sqm, highlights significant variability in costs, indicative of structural and operational differences among the analyzed facilities (Table 6).

Table 6. Descriptive statistics of hospital total utilities and maintenance costs.

Mean	EUR 151.47
Median	EUR 137.31
Standard Deviation	EUR 79.45
Minimum Value	EUR 66.67
Maximum Value	EUR 340.92

Considering the total expenses incurred for facility management, an increase of 32.90% was observed over the period of 2019–2022. In this range, all 27 hospital facilities involved in the analysis provided data. Among the facilities analyzed, only one recorded stable or negative costs (−1.9%), while the highest increase reached 119%. The analysis particularly highlighted a more significant rise in utility-related expenses, with a total increase of 37.34%, primarily driven by energy costs and cleaning services. This trend reflects the impact of years marked by the COVID-19 pandemic. In contrast, maintenance expenses exhibited a more moderate yet still notable increase of 18.66% over the same period. These findings underscore the varying drivers of cost growth in hospital facility management and provide valuable insights for targeting resource optimization. This trend reflects system-wide dynamics in the healthcare sector, influenced by factors such as rising energy costs, the need for extraordinary maintenance, and the adaptation of facilities to new operational requirements, including those arising from the COVID-19 pandemic. Larger and more complex hospital facilities experienced significant absolute cost increases. However, smaller facilities also showed substantial percentage increases, indicating that operational management costs are systematically growing across all facilities in the sample.

Another key variable analyzed is the conventional age of hospitals. While a general inverse relationship is observable—whereby newer facilities tend to report lower operational costs—this trend shows considerable variability. Such dispersion suggests that building age alone does not fully explain cost differences and that other structural and managerial factors may play a critical role. For instance, hospitals with similar years of construction display substantial cost differences, which may be influenced by divergent building typologies (e.g., monoblock vs. pavilion layout), variations in surface area per bed, energy efficiency measures, and the degree of outsourcing of facility services. Additionally, some older hospitals may have undergone recent minor retrofits or infrastructure upgrades, which mitigate their operational inefficiencies, while others continue to function with legacy systems that drive up maintenance and energy expenses. These findings reinforce the need to adopt a multivariate analytical approach in future studies when assessing cost determinants (Figure 9).

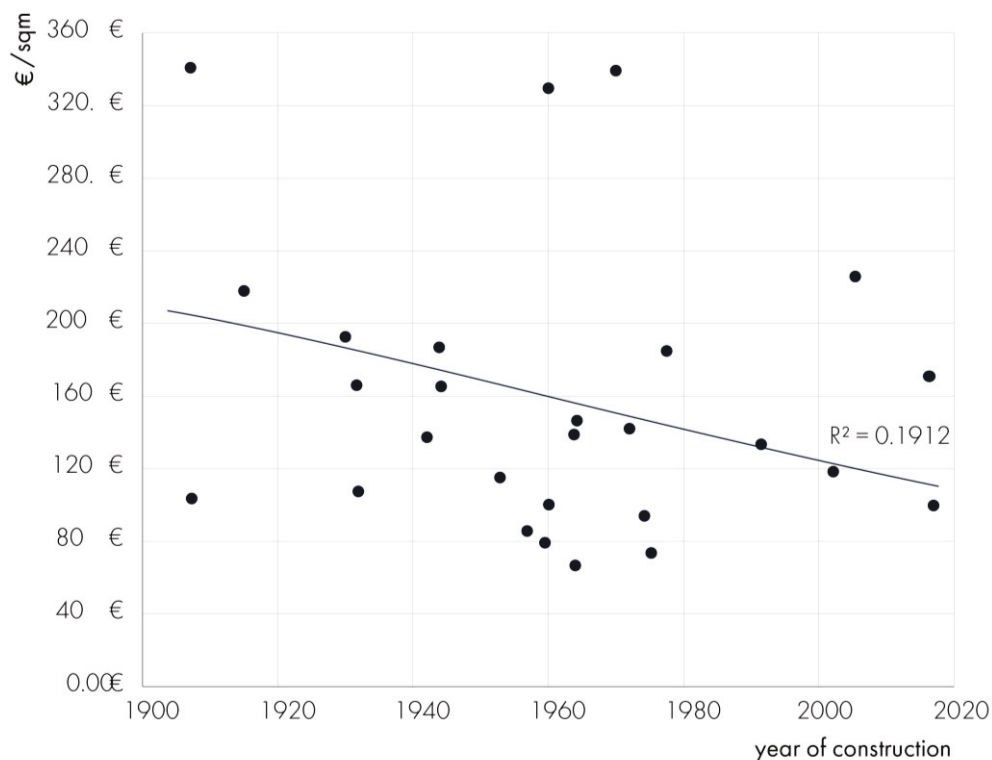


Figure 9. The relationship between operational costs per sqm and the year of construction of healthcare infrastructures.

4. Discussion

This contribution addressed the management costs of Italian healthcare facilities with different approaches. The findings from this research provide critical insights into the operational costs associated with hospital infrastructure management in the selected sample of 27 hospitals over the period of 2018–2022. The analysis highlights significant variability in costs across facilities and over time, reflecting the diversity of the Italian healthcare building stocks in terms of operational needs, infrastructure age, technology equipment, and the level of complexity. The emerging disparities in cost efficiency among hospitals also suggest opportunities for benchmarking and the adoption of best practices.

The comparison between the data collected from the empirical survey and the findings from the literature review suggests that hospital management costs in Italian facilities tend to be higher. Specifically, the average operational costs observed in the Italian sample exceed those reported in the international studies analyzed in the literature. However, this disparity requires further investigation, considering the need for comparable data in terms of the time of data collection and the complexity of hospital typologies. A more refined analysis accounting for these variables would provide a clearer understanding of the factors influencing cost differentials and provide a robust benchmarking framework.

The findings shed light on cost variability across hospital typologies, operational dynamics, and structural factors, answering the following two primary research questions: (i) What are the costs associated with the facility management of hospitals of different complexities? (ii) How do facility management costs evolve over time, and what are the main drivers of cost variability across different types of hospital facilities? As presented in the Results Section, facilities classified as Basic Healthcare Centers report the lowest average costs compared to Level I and Level II hospitals, showing progressively higher costs associated with their activities and greater operational demands. These results align with previous findings [22,26], which emphasized the correlation between hospital complexity and FMC due to advanced infrastructure and service demands. The data collected in

this study differ from the literature regarding the proportion of maintenance costs, as the studies reviewed include extraordinary maintenance costs within their calculations.

While the results provide valuable parametric benchmarks for FM costs in hospital infrastructure, it is crucial to acknowledge that the findings are based on a limited sample of 27 hospitals in the Lombardy region, corresponding to a 20.4% response rate. Although this sample includes a heterogeneous mix of hospital typologies and sizes, the relatively low participation constrains the generalizability of the parametric values (EUR/m² and EUR/bed) both within the region and nationally. Therefore, the results and the values presented should be interpreted as exploratory and indicative rather than statistically representative of the broader healthcare system.

5. Conclusions

In this study, through an empirical analysis of a sample of Italian hospitals, the authors explored the feasibility of developing benchmarking metrics to evaluate the facility management costs of hospital assets. The investigation conducted for this contribution on hospital facility management costs has confirmed the fragmented and uneven nature of the Italian hospital building stock, highlighting the significant infrastructural and managerial differences across these facilities.

This study acknowledges some limitations. One of the primary limitations lies in the use of data extracted from hospital financial statements. As discussed in the text, this level of analysis enables a broader national sampling due to the public availability of such data and facilitates the identification of trends. However, it presents constraints since the financial statements of hospital organizations aggregate facility management costs for both hospital and non-hospital healthcare facilities. A significant limitation of this study is thus the limited number of case studies analyzed. Additionally, the scope of the research was geographically limited to the Lombardy region, which, despite being the most populous Italian region and possessing the most extensive hospital numbers, limits the generalizability of the findings to a national context.

Moreover, this study did not delve deeply into hospital management models or the relationship between in-house management and the outsourcing of certain activities. In light of these considerations, future research can be developed along the following three directions: (i) Introducing longitudinal studies that extend beyond the Lombardy region and incorporate cross-country comparisons to enhance the generalizability and contextual relevance of the findings. (ii) Including costs related to extraordinary maintenance to provide a more comprehensive overview. (iii) Investigating hospital management models, particularly examining the differences between internal management and outsourcing for activities such as maintenance, cleaning, energy production, and the management of climate control and lighting systems. This would help assess potential discrepancies in cost and performance between internally managed operations and those entrusted to external facility managers.

This work represents an initial and innovative attempt to map parametric cost indicators based on real operational data, collected directly from healthcare organizations. Given the scarcity of prior benchmarks in this domain, the research prioritizes the establishment of empirical reference values and trends that may serve as a foundation for further investigations. Therefore, the focus has been placed on descriptive and exploratory analysis, which allows for the identification of cost patterns and key areas of variability across hospital facilities of different types and complexity levels. By providing valuable benchmarks and actionable insights for hospital facility managers, our contribution offers preliminary guidance on the optimization of facility management, the allocation of public resources, and the enhancement of the efficiency of hospital organizations. Future research

may build upon this work by expanding the sample, applying inferential methods, and integrating multivariate models to explore causal relationships.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

	Hospital	City
1	Ospedale Delmati	Sant’Angelo Lodigiano
2	Ospedale Enzo e Rosy Rossi	Casalpusterlengo
3	Ospedale Cesare Cantù	Abbiategrosso
4	Ospedale Carlo Ondoli	Angera
5	Ospedale Causa Pia Luvini	Cittiglio
6	Ospedale del Ponte	Varese
7	Ospedale Luigi Galmarini	Tradate
8	Ospedale Luigi Confalonieri	Luino
9	Ospedale SS Trinità	Romano di Lombardia
10	Ospedale Civico	Codogno
11	Presidio R.M.D.P Mazzolari	Bozzolo
12	Osp. S. Benedetto e Geltrude	Cuggiono
13	Ospedale Civile	San Giovanni Bianco
14	Ospedale G.Casati	Rho
15	Ospedale Luigi Sacco	Milano
16	Ospedale di Circolo	Rho
17	Ospedale G. Salvini	Garbagnate Milanese
18	Osp. Treviglio Caravaggio	Treviglio
19	Ospedale Maggiore	Lodi
20	Ospedale Carlo Poma	Mantova
21	Ospedale Civ. Destra Secchia	Borgo Mantovano
22	Ospedale G. Fornaroli	Magenta
23	Ospedale di Circolo	Varese
24	Ospedale Ca’Granda	Milano
25	Ospedale S. Anna	Como
26	Ospedale Civile	Legnano
27	Ospedale P. Giovanni XXIII	Bergamo

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Article

Evaluating the Efficiency and Productivity of Opioid Substitution Treatment Units in Greece: A DEA-Malmquist Analysis

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Abstract: Background: This study examined shifts in the productivity and efficiency of Opioid Substitution Treatment (OST) units in Greece from 2019 to 2022. OST units address withdrawal symptoms in individuals discontinuing psychoactive substances. They also offer mental health care, primary healthcare, psychosocial support, and other integrated services, aiming to provide holistic addiction treatment and promote social reintegration. Methods: We assessed the contributions of 54 OST units addressing opioid addiction using non-parametric Malmquist Data Envelopment Analysis (DEA). Data were collected from all OST units operating in Greece during this period, with a focus on key external factors such as the COVID-19 pandemic and rising global trends in stimulant and synthetic opioid use. Results: The analysis revealed a productivity decline in 2020, followed by improvements in the next two years. However, technical efficiency declined, suggesting a decrease in resource utilization. Conclusions: This dip in efficiency likely reflects the impact of emerging drug trends, particularly stimulants and synthetic opioids, which lack standardized treatment protocols. These findings highlight the urgent need for new treatment options to address evolving addiction trends. The study also underscored the need for improved data collection and monitoring to optimize resource allocation and enhance operational efficiency in OST units. Strengthening evidence-based policies and expanding access with low-threshold treatment services could improve patient outcomes and the overall effectiveness of OST programs.

Keywords: efficiency; productivity; data envelopment analysis; Malmquist productivity index; addiction treatment

1. Introduction

This study evaluated the efficiency and productivity of Opioid Substitution Treatment (OST) units operated by the Organization Against Drugs (OKANA) in Greece from 2019 to 2022. These units provide substitution therapy with buprenorphine or methadone, along with mental health support, primary healthcare, and psychosocial services to facilitate addiction treatment and social reintegration [1]. By analyzing changes in technical efficiency and productivity over this period, the study aimed to identify key strengths and areas for improvement, optimize resource allocation, and enhance the effectiveness in operations of OST units within the public health framework. Additionally, this paper seeks to provide insights into the strengths and weaknesses of OST units, potentially laying the groundwork for further research in the field of addiction treatment and policy development.

OKANA is the largest government agency in Greece with the aim of preventing and addressing addiction, addictive behaviors, and addiction-related issues in the country. Within its scope of responsibilities, OKANA covers areas such as prevention, harm reduction, treatment, and the social reintegration of individuals facing addiction issues, whether related to legal or illegal substances [1].

In Greece, the total number of individuals using opioid drugs ranges from 1.5 to 2.3 per 1000 persons. This provides us with an estimate of 12,351 active opioid drug users in the country (95% confidence interval: 9920–15,746), as reported in the European Monitor Center for Drugs and Drug Addictions (EMCDDA) Drug Report, 2022 [2].

Cocaine and other stimulants, such as crystal methamphetamine, are gaining popularity in Greece, following the trend seen in other European Union countries. However, heroin remains the primary substance of choice among individuals using drugs, accounting for 53% of the population [2]. Additionally, the EMCDDA's European Syringe Collection and Analysis Project Enterprise, widely known as the ESCAPE project, which focuses on the collection and analysis of syringes containing blood residuals found in the streets, revealed that the majority of these syringes in Greece contained a combination of substances. For instance, in Thessaloniki, 50% of the syringes contained both heroin and cocaine, commonly referred to as a "speedball" in street language [3].

In 2017, a total of 2593 individuals sought and eventually entered treatment for their addiction. The annual numbers remained relatively stable in the next years, except during the COVID-19 pandemic in 2020, when there was a 17% reduction in the number of people seeking treatment [2,4].

In 2017, approximately 9388 people were receiving Opioid Substitution Treatment (OST). Today, however, the number has decreased to 7340 individuals. This decline reflects a diminishing trend in heroin use within the country. Treatment for individuals with opioid addiction in Greece includes programs that provide substitution therapy alongside mental, psychological, and social support, as well as "drug-free" programs where individuals receive intensive mental, psychological, and social support without the use of substitution therapy [1].

Currently, there are 58 OST units of OKANA, covering the entire spectrum of needs for individuals looking to overcome their addiction. Treatment includes the administration of buprenorphine or methadone to address withdrawal symptoms that individuals often experience when discontinuing the use of psychoactive substances [5]. Specifically, OST units administer Prenorvine tablets and liquid methadone (10 mg/mL), manufactured by the Institute of Pharmaceutical Research & Technology (IFET) in Greece. Moreover, during COVID-19, take-home therapy was provided, including Libroxar, which contains Buprenorphine and Naloxone [1]. Additionally, mental health services, primary healthcare services, psychosocial support, and other accompanying services are provided to achieve holistic addiction treatment and social reintegration [1].

OKANA's OST units are located within the country's hospitals and cover most of the territory. Among the 58 OST units, 24 are located in Attica, 11 in Thessaloniki, and 23 in various regions of Greece. Two OST units also operate within the prisons of Korydallos in Athens and Agios Stefanos in Patra [1]. These units were excluded from the study as they operate in a different context, targeting a specific category of individuals, and their operational methods cannot be easily compared to the other units operating within hospitals. Moreover, four out of fifty-eight OST units were excluded from the analysis due to a lack of data to avoid bias.

The contribution of OST units to address addiction has been emphasized internationally [6,7], with significant focus at both the European and global levels on evaluating their effectiveness concerning resource allocation [2,8,9]. However, in both Greece and abroad,

the efficiency and productivity of OST units have not received comparable attention, creating a significant research gap. While previous studies have examined treatment approaches and economic aspects [10–12], they have often overlooked other critical factors such as mental health consultations, primary care services, and operational elements like staffing levels and associated costs. This study conducted an operational evaluation, considering the impact of the pandemic alongside other external and internal factors, to inform policymaking and enhance decision-making beyond treatment efficacy.

2. Materials and Methods

2.1. Data Envelopment Analysis and Malmquist Index

Efficiency measurement in research often relies on econometric models, hinging on certain assumptions, mathematical functions, and techniques. These models typically fall into the category of parametric methods for estimating efficiency. However, the healthcare sector presents unique challenges for parametric methods due to the intricate and less definable nature of healthcare processes [13,14]. Notably, parametric methods tend to perform better when dealing with either single inputs or single outputs and necessitate assumptions regarding the model type. In this paper, our analysis encompasses multiple inputs and outputs, a scenario that poses challenges for parametric methods, particularly in model specification. To overcome these challenges, the non-parametric method of Data Envelopment Analysis (DEA) is used, which is also commonly favored in healthcare research for its versatility and adaptability [15].

DEA, developed by Charnes, Cooper, and Rhodes in 1978 [16], represents a significant advancement in efficiency analysis, building upon earlier work by Farrell in 1957 [17], which was rooted in the concepts of Debreu (1951) and Koopmans (1951) [18–20]. DEA is essentially a linear programming approach aimed at estimating relative efficiency among production units, often referred to as Decision-Making Units (DMUs), that employ multiple inputs and outputs [15]. Each production unit's efficiency is assessed individually, making them directly comparable, as they share identical functions, resource consumption (inputs), and product or service generation (outputs), differing solely in price levels. In this context, inputs denote the resources utilized in output production while outputs signify the products or services generated by DMUs [15].

The advantages of DEA are multifaceted. Firstly, it is firmly rooted in robust economic theories and methods. Secondly, DEA centers its analysis on relative efficiency rather than absolute efficiency, providing valuable insights into unit performance comparisons. Furthermore, DEA's capability to simultaneously incorporate numerous inputs and outputs into the model in question, regardless of differing units of measurement, is a notable asset. Additionally, it operates without the need for prior knowledge of specific input–output functions, a particularly advantageous feature in the complex healthcare domain. Nonetheless, it is essential to acknowledge DEA's limitations. Challenges arise in the selection of appropriate inputs and outputs and in defining the model with reliable data. The method can also be sensitive to outliers, potentially affecting results [21]. DEA was chosen over Stochastic Frontier Analysis (SFA) because it is a non-parametric approach that does not require a predefined functional form, making it more flexible in evaluating OST unit efficiency. Moreover, “DEA is particularly suitable for healthcare settings where inputs and outputs are diverse and difficult to model with a specific functional relationship, unlike SFA, which assumes a predefined production function and separates inefficiency from random noise” [22].

To address these limitations, this study employed “clean data”, ensuring that the dataset was free from inconsistencies, errors, or missing values in input and output variables, thereby enhancing its reliability for analysis. Moreover, this study adhered to a

practical rule, ensuring a satisfactory level of DEA's discriminatory power. The practical rule stipulates "that the number of DMUs should be greater than or equal to three times the sum of inputs and outputs ($n \geq 3 \times (m + s)$) to ensure reliable results" [23].

Efficiency estimation within DEA consists of two stages: first, the calculation of the frontier of best performance, comprising efficient DMUs (100% technical efficiency); and second, the computation of radial distances from the remaining, less efficient DMUs to this frontier [13,24].

DEA measures technical efficiency with two orientations: "The input orientation binds outputs to a linear programming equation that minimizes inputs, while the output orientation binds inputs to maximize outputs" [16,21]. Also, DEA can be employed with two methods: constant returns to scale (CRS) or variable returns to scale (VRS). CRS assumes all DMUs are operating optimally while VRS considers variations in efficiency levels [16,21].

A disadvantage of DEA is that it cannot analyze the impact of time on efficiencies. To address this, the Malmquist productivity index (MPI) is utilized alongside DEA, allowing for the assessment of productivity and efficiency changes over time [25], which was the purpose of this study.

MPI DEA is a non-parametric mathematical programming approach "commonly used to incorporate panel data into analyses and calculate indices for total factor productivity, technical efficiency, pure technical efficiency, scale efficiency, and technological change over time" [26].

In this paper, the input-oriented MPI DEA is employed due to its suitability for the healthcare sector, where controlling inputs is often more feasible than directly influencing outputs, and the availability of panel data. Input-oriented MPI DEA is widely applied in healthcare settings, where resource regulation plays a crucial role in optimizing performance. This approach was also particularly relevant to our study since it provides results that can guide management decisions on resource allocation and utilization. By leveraging these insights, OST units can take targeted actions to enhance efficiency and productivity, ensuring optimal resource use in the future [27–29].

While parametric and non-parametric methods have been applied extensively in assessing hospital and healthcare service efficiency [30,31], this study focused specifically on addiction treatment within the domain of public health. While research on the efficiency of OST units in Greece is limited, this study represented one of the first to apply MPI DEA to assess their productivity and efficiency over time.

2.2. The Model: Input-Oriented MPI DEA

The primary objective of this research was to assess the technical efficiency and productivity of the 54 OST units operated by OKANA in Greece during the period from 2019 to 2022. While this paper provides an overview of DEA and MPI, it is essential to acknowledge that a comprehensive mathematical analysis of these methodologies exists within the available literature.

Before delving into the MPI, we will first analyze DEA. The mathematical analysis pertains to an input-oriented DEA model under the assumptions of CRS and VRS as both assumptions are crucial for estimating MPI [26].

The analysis operates under the assumption that there are N Decision-Making Units under examination, each employing K inputs to generate M outputs. This leads to the construction of two matrices: a KN matrix representing the utilized inputs (referred to as X) and an MN matrix representing the generated outputs (referred to as Y) [24]. To assess

the efficiency of each DMU, T.J. Coelli introduced a mathematical linear programming equation in 1996, which calculates “the ratio of all outputs over all inputs:

$$\begin{aligned} &\text{minimize } \theta, \lambda \\ &\text{subject to:} \\ &-y_i + Y\lambda \geq 0; \theta x_i - X\lambda \geq 0; \lambda \geq 0. \end{aligned}$$

Within this equation, θ serves as a scalar taking values within the closed interval $[0, 1]$ and serving as an indicator of the efficiency level of the DMUs, and λ represents an $N \times 1$ vector of constants. DMUs achieving a θ value of 1 operate at optimal efficiency, whereas values less than 1 signify inefficiency” [24]. It is worth noting that this mathematical problem necessitates solving the equation N times for each DMU [24].

The linear programming problem described above “operates under the CRS assumption, which implies that all DMUs operate at an optimal scale. In contrast, the VRS model avoids this assumption, considering potential scale efficiencies” [26]. When adopting the VRS assumption, an additional constraint, $N1'\lambda = 1$, is incorporated into the CRS linear programming problem. This extra constraint is introduced to quantify scale efficiency effects, thus partitioning technical efficiency into pure technical efficiency and scale efficiency for each DMU [24,26].

The MPI represents an extension of DEA tailored to measure productivity changes over time for each DMU while dissecting these changes into those stemming from alterations in technical efficiency and those attributed to advancements or declines in technology levels [24]. MPI DEA is ideally suited for panel data, eliminating the need to select between the CRS or VRS approach since they yield equivalent results. In MPI DEA estimation, both the CRS and VRS approaches are employed to compute the diverse distances forming the foundation of Malmquist indices [26,32].

The MPI DEA method offers two orientations: input and output orientations. In the input orientation, production is characterized by calculating the minimal proportional decrease in the input vector, considering the output vector. Conversely, in the output orientation, production is defined by computing the maximal proportion increase in the output vector, given the input vector [33].

In this study, panel data spanning four years (2019–2020–2021–2022) were examined, forming three distinct periods, comparing years from t to $t + 1$ (2019–2020, 2020–2021, and 2021–2022). The computation of the MPI entailed estimating the distances for each of these three periods. A DEA analysis, incorporating both the CRS and VRS assumptions, was carried out for each of the four years (2019, 2020, 2021, and 2022) to evaluate the efficiencies of the DMUs to estimate the Malmquist indices for the three periods examined. It is important to note that while the efficiencies of the DMUs for the year 2019 were computed, Malmquist indices could not be estimated due to the unavailability of data for 2018, and thus no comparison between 2018 to 2019 could be made.

The Malmquist index, introduced initially in 1970 using Shephard’s distance function, has found extensive applications in various domains where the assessment of efficiency with panel data is required. Färe introduced an output-oriented MPI in 1994 [32]. However, in this paper, we employ the input-oriented MPI approach [24,32,34].

The MPI for a specific period (t to $t + 1$) signifies the productivity at the production point (x_{t+1}, y_{t+1}) relative to the production point (x_t, y_t) for each DMU, as defined by the following formula [26]:

$$M(y_{t+1}, x_{t+1}, y_t, x_t) = \{[dt + 1(x_{t+1}, y_{t+1})/dt(x_t, y_t)] \times [(dt(x_t, y_t)/dt + 1(x_t, y_t)) \times (dt(x_{t+1}, y_{t+1})/dt + 1(x_{t+1}, y_{t+1}))]^{1/2}\}$$

The MPI equation consists of two fractions, each with distinct interpretations. The first fraction represents the change in technical efficiency over the period (t to $t + 1$) whereas the second fraction captures the change in technology during the same period [24,26,32,34]. Furthermore, the change in technical efficiency can be dissected into components related to pure technical efficiency and scale inefficiency. Notably, a total productivity growth exceeding one indicates positive productivity growth from time t to time $t + 1$ [35].

To calculate the MPI equation, the four aforementioned distances must be computed using linear programming methods, which are expressed as follows [26]:

$$\begin{aligned} [dt(x_t, y_t)]^{-1} &= \min \theta, \lambda \theta, \text{ subject to: } -y_{it} + Y_t \lambda \geq 0, \theta x_{it} - X_t \lambda \geq 0, \lambda \geq 0 \\ [dt + 1(x_t + 1, y_t + 1)]^{-1} &= \min \theta, \lambda \theta, \text{ subject to: } -y_{i,t+1} + Y_{t+1} \lambda \geq 0, \theta x_{i,t+1} - X_{t+1} \lambda \geq 0, \lambda \geq 0 \\ [dt(x_t + 1, y_t + 1)]^{-1} &= \min \theta, \lambda \theta, \text{ subject to: } -y_{i,t+1} + Y_t \lambda \geq 0, \theta x_{i,t+1} - X_t \lambda \geq 0, \lambda \geq 0 \\ [dt + 1(x_t, y_t)]^{-1} &= \min \theta, \lambda \theta, \text{ subject to: } -y_{i,t} + Y_{t+1} \lambda \geq 0, \theta x_{i,t} - X_{t+1} \lambda \geq 0, \lambda \geq 0 \end{aligned}$$

It is worth noting that this paper involves the calculation of $N(3T-2)$ linear programming equations [33,36].

2.3. Data

The dataset employed in this study, encompassing both inputs and outputs, spans the years from 2019 to 2022. Out of the 58 OST units under the operation of OKANA across Greece, this study's focus was centered on 54 of these units, with four units being excluded due to constraints related to data availability and quality. This exclusion was to prevent arbitrary estimations and reduce the potential for bias within the analysis. The selected 54 healthcare facilities represented a significant majority, accounting for 93.10% of the total units. Furthermore, these units were distributed across various regions in Greece. This comprehensive approach was intended to bolster the robustness of the evaluation process [37,38].

This study adhered to established criteria governing the execution of MPI DEA, thereby safeguarding the comparability and validity of efficiency measurements for OST units. Specifically, it is important to highlight that all 54 OST units within this analysis employed identical categories of inputs and generated identical categories of outputs. Variability only existed in terms of the quantities utilized. Additionally, each input and output category was included for all 54 Decision-Making Units (DMUs). Within this sample, every DMU effectively utilized at least one input while simultaneously producing at least one output [34,39].

The analytical framework incorporated three distinct outputs to assess the domains of technical efficiency, technology, and overall productivity for each OST unit. Collectively, these outputs spanned the comprehensive spectrum of services delivered by each OST unit. In addition, the analysis incorporated four input variables, which reflected the aggregate staffing levels and resources requisite for the operational functions of OST units. These inputs were vital in facilitating patient therapy, psychosocial support, and various other essential healthcare services.

The dataset provided below encompasses measurements of all 54 OST units, documented on an annual basis to facilitate the subsequent MPI DEA analysis. The variables considered for both inputs and outputs are as follows:

Outputs:

Number of Patients receiving therapy, psychosocial support, and healthcare services—output 1

Total Number of exams conducted for parallel drug use—output 2

Total Number of psychosocial support sessions—output 3

Inputs:

Total number of staff occupied—input 1

Total expenses for payroll—input 2

Total expenses to cover the operational costs of the OST unit—input 3

Total expenses for medication costs (methadone and/or buprenorphine) necessary for providing therapy—input 4

It is important to emphasize that all inputs and outputs considered in this paper were measured for the years spanning from 2019 to 2022. The summary statistics presented in Table 1 encompass key metrics such as the minimum, maximum, mean, and standard deviation for each input and output variable incorporated in the analysis.

Table 1. Descriptive statistics of inputs and outputs for the years 2019, 2020, 2021, and 2022.

Variables	Statistics	2019	2020	2021	2022
Number of Patients (monthly average)	Mean	138.796	134.611	133.981	127.574
	St. Dev.	71.035	71.213	70.258	66.604
	Min	34	30	33	30
	Max	342	322	313	312
Exams for Parallel Drug Use	Mean	5033.333	4048.055	5157.203	4440.203
	St. Dev.	2423.231	2308.128	3137.907	2646.900
	Min	15	276	136	182
	Max	10,393	12,913	18,335	12,220
Psychosocial Support Sessions	Mean	3211.166	2125.944	2328.555	3074.962
	St. Dev.	2149.564	1385.723	1994.245	3034.302
	Min	590	491	346	308
	Max	8520	7051	9728	17,883
Total Staff	Mean	8.851	10.259	9.962	9.5
	St. Dev.	3.935	4.084	4.220	4.364
	Min	1	3	2	2
	Max	21	22	22	23
Payroll	Mean	197,386.306	210,642.243	212,365.632	210,583.136
	St. Dev.	119,920.836	117,467.833	114,525.735	114,597.159
	Min	19,450.6	28,956	26,543	28,148.9
	Max	552,969.59	564,191.56	576,690.62	595,531.12
Operating Costs	Mean	31,829.728	49,463.625	46,670.727	42,703.714
	St. Dev.	16,472.947	25,931.021	24,947.269	24,210.411
	Min	11,496.46	10,908.69	11,608.04	5677.18
	Max	89,750.01	135,110.77	129,696.47	123,675.11
Medicine Costs (Normalized Costs)	Mean	1.020405927	1.018518519	1.018518519	1.018518519
	St. Dev.	0.439889694	0.414488071	0.420808803	0.380470204
	Min	0.101920058	0.114757665	0.153171942	0.145834726
	Max	1.890265396	1.861751428	2.381074881	1.921010149
Valid N (listwise)	54				

3. Results

The measurement of productivity and efficiency for each of the 54 OST treatment units was conducted through input-oriented MPI DEA using DEAP ver2.1 [26].

This analysis evaluated the performance of 54 OST units in Greece across three periods: 2019–2020, 2020–2021, and 2021–2022, using MPI DEA methodology, comparing each year with the next. Key metrics analyzed included efficiency change (Effch), technological change (Techch), pure technical efficiency change (Pech), scale efficiency change (Sech), and total factor productivity change (Tfpch) [17]. Each metric provided insights into shifts in OST unit productivity change from one year to another.

For each period, indicators are summarized in Table 2, with indices over 1 indicating progress and values below 1 indicating declines, while a value of 1 reflects no change comparing one year to the next. The table details the number of DMUs that experienced increases, declines, or stability in productivity across the studied periods. Moreover, overall results for all three periods have been compiled to present a comprehensive view of OST unit performance during these years, which is critical for understanding the change in technical efficiency and technology, as well as for identifying potential areas for improvement in addiction treatment services.

Table 2. Summary scores and number of OST treatment units that progressed, regressed, or remained constant from year to year.

Mean	2019–2020	2020–2021	2021–2022	Total (2019–2022)
Effch	1.026	0.908	0.953	0.961
Techch	0.649	1.209	1.118	0.958
Pech	1.000	0.952	0.980	0.977
Sech	1.026	0.954	0.972	0.984
Tfpch	0.666	1.099	1.065	0.920
DMUs that progressed (tfpch > 1)	4 (7.4%)	39 (72.3%)	36 (66.7%)	11 (20.4%)
DMUs that regressed (tfpch < 1)	50 (92.6%)	15 (27.7%)	18 (33.3%)	43 (79.6%)
DMUs remained constant (tfpch = 1)	0	0	0	0

In the first period (2019–2020), only four OST units demonstrated an improvement in total productivity, while fifty units experienced a decline. During the second period (2020–2021), 39 units showed productivity gains whereas 15 units saw declines. In the third period (2021–2022), 36 OST units saw productivity growth, with 18 units reporting reduced productivity. When assessing productivity across all three periods combined, 11 DMUs achieved an overall increase in productivity while 43 DMUs faced an overall decline.

In Table 3, the OST units that progressed, regressed, or remained constant in terms of technical efficiency change, technological change, and productivity change were examined.

As shown in Table 3, OST units displayed fluctuating trends in technical efficiency, technological change, and overall productivity across the three periods. The analysis indicated that productivity declined significantly in the initial period (2019–2020) but showed improvement in the subsequent years (2020–2021 and 2021–2022). To assess these changes, the difference between technical efficiency change and technological change was calculated for each unit. Positive values for this difference suggested that productivity changes were primarily driven by technical efficiency improvements while negative values indicated that changes were primarily due to technological shifts for the DMU [40,41].

Table 3. Summary results: number of OST treatment units that progressed, regressed, or remained constant.

PERIOD (Comparing Years)	2019–2020	2020–2021	2021–2022	Total (2019–2022)
Change into Effch				
Prog. (effch > 1)	23 (42.6%)	9 (16.7%)	19 (35.2%)	15 (27.8%)
Reg. (effch < 1)	21 (38.9%)	33 (61.1%)	24 (44.4%)	29 (53.7%)
Constant (effch = 1)	10 (18.5%)	12 (22.2%)	11 (20.4%)	10 (18.5%)
Change into Techch				
Prog. (techch > 1)	1 (1.9%)	50 (92.6%)	38 (70.4%)	14 (26%)
Reg. (techch < 1)	53 (98.1%)	4 (7.4%)	16 (29.6%)	40 (74%)
Constant (techch = 1)	0	0	0	0
Change into Tfpch				
Prog. (tfpch > 1)	4 (7.4%)	39 (72.2%)	36 (66.7%)	11 (20.4%)
Reg. (tfpch < 1)	50 (92.6%)	15 (27.8%)	18 (33.3%)	43 (79.6%)
Constant (tfpch = 1)	0	0	0	0

Between 2019 and 2022, productivity shifts among OST treatment units were attributed mainly to technological changes for 23 units while 31 units experienced changes primarily due to variations in technical efficiency.

Productivity drivers varied by period. In the first period (comparison between 2019 and 2020), productivity levels declined due to technological changes that affected the production frontier, resulting in generally low productivity among DMUs. In contrast, during the second and third periods, technology expanded the production frontier, boosting overall productivity despite reduced technical efficiency in many OST units. These gains suggest that technology, rather than efficiency, was the primary driver of productivity in these years.

Overall, technology demonstrated considerable volatility across the observed periods, significantly impacting OST units' productivity. Units that displayed high volatility in productivity also showed marked technological fluctuations, underscoring that productivity changes were largely driven by shifts in technology. During this period, the COVID-19 pandemic likely contributed to the initial decline in productivity observed in the first year of the study. However, the introduction of take-home therapy helped mitigate this trend by expanding the production frontier, leading to improved OST unit productivity in the following years. Similarly, the introduction of generic buprenorphine further expanded the production frontier, enhancing both the technological capabilities and productivity of OST units. Regarding efficiency, the decline in the number of OST unit clients was likely influenced by the rising prevalence of synthetic opioids and stimulants, a global trend that underscores the urgent need to develop and integrate OST treatments for these substances. Adapting OST units to meet this emerging challenge is crucial to ensuring comprehensive care for affected populations [2–4,8].

4. Discussion

The 2019–2022 period was chosen to capture major external influences on OST treatment units, such as the COVID-19 pandemic in 2020, along with the emerging global trend of stimulant and synthetic opioid use [2,8,9]. These factors were successfully incorporated

into the study, with the technology decline observed among DMUs comparing 2019 with 2020 likely influenced by the pandemic-related lockdowns in Greece, along with other challenges affecting OST units. In the subsequent periods, productivity and technological capabilities improved as OST units adapted to new challenges by offering take-home therapy during the lockdowns for individuals facing addiction [1].

Following the pandemic, take-home therapy continued to be an option for patients in OST programs. Research by O'Connor et al. aimed to identify factors that contribute to patient retention in OST and the risks that lead to treatment dropout [42]. Their findings did not establish take-home therapy as a key determinant of retention. However, they emphasized that many OST patients experience isolation, a lack of social support, and restricted access to technology, all of which can hinder treatment adherence and outcomes. Additionally, individuals struggling with mental health issues reported that the isolation caused by lockdowns further deteriorated their well-being [42]. Similar difficulties were observed in Scotland and other parts of the UK, particularly in rural areas where transportation challenges created additional barriers to accessing treatment [43]. A separate study by Adams et al. [44] analyzed the effects of loosening restrictions on take-home doses during COVID-19. This systematic review incorporated 40 studies, primarily from North America and the UK. The quantitative data hinted at a possible correlation between take-home doses and improved retention, though no link was found between take-home doses and increased illicit substance use or overdose risk. The qualitative analysis revealed that take-home doses helped minimize patients' exposure to unregulated substances and stigma while reducing conflicts between work and treatment. While some individuals faced difficulties in managing their medication, the majority reported reduced anxiety, increased autonomy, and a stronger sense of control over their lives [44]. Overall, keeping take-home therapy available could offer significant benefits to patients, but additional supportive strategies should be explored. Enhancing long-term treatment outcomes may require integrating take-home therapy with alternative service delivery models [44], such as telehealth consultations and virtual support systems, to provide more comprehensive care.

In 2021, the adoption of generic medications (generic buprenorphine) further reduced treatment costs per person [1], contributing to technological and productivity advancements, as well as expanding the efficiency frontier and overall treatment capabilities. However, the technical efficiency of DMUs was still limited, possibly due to a reduced number of patients who were shifting to new substances (stimulants and synthetic opioids), reflecting decreased resource utilization. Although productivity levels improved in 2021 and 2022, some OST units have yet to reach their pre-2020 efficiency and productivity levels.

The findings of this study underscore the urgent need for evidence-based policy interventions to improve the efficiency and accessibility of opioid substitution therapy (OST) units. The correlation between substitution therapy and opioid-related adverse events further reinforces this imperative [45–48]. Additionally, the increasing prevalence of synthetic opioids and stimulants presents new and complex challenges, which have become critical and require urgent attention more than ever before [2–4,8]. Globally, opioid addiction treatment has increasingly relied on medications such as methadone, buprenorphine, and buprenorphine/naloxone, which have demonstrated effectiveness in reducing opioid-related harm [49]. However, to optimize treatment outcomes, policy frameworks must prioritize the allocation of resources to ensure that patients receive comprehensive care that addresses not only their addiction but also their broader needs such as mental health care, housing, and employment support [50].

Improving the operational efficiency of OST units requires more effective resource allocation guided by evidence-based decision-making. Policymakers should invest in robust monitoring and evaluation systems to track key performance indicators, including

patient retention, treatment adherence, and the impact of external factors such as the rise of synthetic opioids and stimulants. Such data can highlight service gaps and inform targeted improvements. In addition, reducing the stigma associated with OST programs is essential as stigma remains a major barrier to patient engagement and retention. Public awareness campaigns and training for healthcare professionals can help create a more supportive treatment environment, ultimately improving patient outcomes [51].

A significant challenge in the global context is the increasing prevalence of synthetic opioids and stimulants, which have introduced new complexities to addiction treatment. Research indicates that the use of these substances is rising, and global health organizations, such as the EMCDDA, WHO, and United Nations, have called for the development of targeted treatment options for these drugs [2–4,8]. Given the rapid rise of these drug trends, there is an urgent need to move beyond harm-reduction strategies and develop effective treatment options [2,8]. The introduction of new treatment protocols for synthetic opioids and stimulants is essential to keep OST programs responsive and effective amid changing trends in drug use.

One promising strategy for improving OST accessibility and efficiency is the implementation of low-threshold units. These units have shown positive outcomes in enhancing patient engagement and treatment retention. By lowering barriers to entry through reduced eligibility criteria and offering immediate access to treatment, low-threshold units increase efficiency and help meet the demand for OST services, particularly among underserved populations [52].

5. Limitations

The dataset was provided by the Organization Against Drugs (OKANA), the largest public organization focused on addiction prevention and treatment in Greece, and covered the years 2019 to 2022. Data were collected from nearly all OST treatment units operating in Greece, though four units had to be excluded due to missing data. These missing data may have affected the frontier and led to bias; moreover, the robustness and reliability of the analysis could also have been impacted [53]. While this may have slightly affected the generalizability of the findings to all OST units in Greece, the selected dataset remained representative. Furthermore, while the study relied on data provided by OKANA, no specific evidence suggested systematic bias in the reporting process. A limitation of the data was the absence of quality-focused measures beyond patient numbers, such as treatment retention or patient and staff perspectives. This highlights the need for improved monitoring to collect higher-quality data and for further research that incorporates these crucial variables.

Additionally, data collection was limited to 2022 as a restructuring process in 2023 led to the closure and merging of some treatment units [1]. This limitation highlights the need for future research to incorporate post-restructuring data to better understand how structural changes impact the efficiency and productivity of OST units. Despite these constraints, this study provided valuable insights into the operational dynamics of OST units from 2019 to 2022, laying the groundwork for further research.

6. Conclusions

This paper has employed the non-parametric MPI DEA method to assess changes in productivity, efficiency, and technology among OST units in Greece from 2019 to 2022. The results have provided valuable insights into the performance and contributions of each OST unit in delivering therapy, psychosocial support, and primary healthcare services to individuals facing addiction. This research aims to improve decision-making and policy development regarding resource allocation to OST units and the outcomes they

achieve. It highlights the need for interventions to address new challenges and advance OST treatment in Greece. The goal is to enhance services and better meet the needs of individuals struggling with addiction.

The study's findings offer a deeper understanding of the technical efficiency and productivity levels achieved by OST units during the examined period. The analysis showed a decrease in productivity during the first period, followed by an increase in productivity levels during the next two periods, mainly driven by technological changes. External factors such as COVID-19, new drug trends, and responses like take-home therapy and the supply of generic buprenorphine as a treatment substance influenced the analysis, providing valuable insights.

Future research should focus on comparing different treatment approaches, particularly the operational efficiency of OST units in the post-pandemic context. Further studies are also needed to explore the impact of rising synthetic opioid and stimulant use on OST treatment effectiveness. The rise in stimulant and synthetic opioid use presents new challenges for treatment programs, suggesting the need for complementary approaches alongside existing opioid substitution therapies [2,8]. Research that focuses on patient retention and adopts a more patient-centered approach—prioritizing the quality of care over operational efficiency—would be valuable. Moreover, complementing quantitative findings with qualitative data through interviews with staff and clients of OST units could provide a more holistic evaluation of the treatment experience. This would offer a deeper understanding of the challenges and successes within OST programs.

In conclusion, while the implementation of OST in Greece has made significant progress, ongoing policy adjustments and operational improvements are necessary to meet the evolving demands of addiction treatment. By enhancing data-driven decision-making, lowering treatment thresholds, and expanding access, the efficiency and effectiveness of OST programs can be improved. Additionally, addressing the needs of individuals using synthetic opioids and stimulants should be a priority in future research and treatment development. This will ensure that OST remains a comprehensive and sustainable solution for individuals seeking treatment for addiction in the future.

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Abbreviations

The following abbreviations have been used in this manuscript:

OKANA	Organization Against Drugs
EMCDDA	Europeans Monitor Center for Drugs and Drug Addictions
EUDA	European Union Drugs Agency
OST	Opioid Substitution Treatment
DEA	Data Envelopment Analysis
DMU	Decision-Making Units
CRS	Constant Return to Scale
VRS	Variable Return to Scale
MPI	Malmquist Productivity Index

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The Role of Sustainability in Telemedicine Services: The Case of the Greek National Telemedicine Network

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Abstract: Background: Sustainability in healthcare has gained increasing importance due to its impact on environmental, financial, and social strategies, as well as on public health, and therefore, relevant policies and actions can also play a significant role in telemedicine services. The establishment of a sustainable telemedicine network at a country level is important to improve access to healthcare, reduce costs, increase convenience, and ensure the continuity of service delivery. However, there are significant environmental, social, technological, human, and governance challenges to meet the sustainability conditions for these networks. **Methods:** Thus, a narrative literature review was conducted to investigate the telemedicine implementation aspects and the sustainability dimensions in a unified approach and integrated strategy in order to develop a more resilient and equitable healthcare solution, ensuring its long-term integration into healthcare systems. **Results:** This paper aims to identify critical factors related to the proposed governance model for the National Telemedicine Network in Greece (EDIT) that influence sustainability requirements and interdisciplinary strategies to address relevant challenges. **Conclusions:** By examining these factors, the paper seeks to propose the fundamental pillars of a sustainable telemedicine framework and the methodology for developing a sustainability plan that will enhance EDIT's capacities toward a sustainable and resilient operation of telemedicine as a standard practice within the Greek healthcare system.

Keywords: e-health; telemedicine; sustainability; healthcare; Greek national telemedicine network

1. Introduction

Concerns about climate change have intensified in recent years, aligning with a global shift toward sustainable development and a growing consumer preference for eco-friendly products and services [1–3]. Sustainability has become a key priority for organizations across both the public and private sectors. Recently, it has gained notable attention in the healthcare industry, particularly within hospitals [4–6], which serve a vital role in society [7,8]. As providers of essential medical services, hospitals bear the responsibility of

ensuring high-quality healthcare for patients [4,9,10], especially for remote areas such as distant islands or other rural and mountainous areas that are difficult to access.

The impact of healthcare activities on environmental degradation and the environmental conditions' critical role in public health have intensified discussions to enforce sustainable environmental and social strategy, worldwide [11,12]. Healthcare organizations (HCOs) must navigate the challenges of resource management, cost control, technological advancements, and the integration of environmentally sustainable practices that balance social, economic, and ecological considerations [13–15].

Hospitals and healthcare organizations are major consumers of essential resources, including energy, water, and raw materials. The healthcare sector is responsible for an estimated 4–5% of global greenhouse gas emissions, underscoring its pivotal role in promoting sustainability, particularly from an environmental perspective [16]. Significant reductions in CO₂ emissions are expected over time while also enhancing patient care, increasing staff satisfaction, and achieving cost efficiencies [7]. Additionally, the operations of healthcare organizations contribute to advancing the 17 Sustainable Development Goals (SDGs), particularly in areas such as good health and well-being, gender equality, clean water and sanitation, and access to affordable, clean energy [17].

The need for a shift to circularity and sustainability strategies is recognized and addressed by, among others, the Circular Economy Action Plans introduced by the European Commission [18] and the United Nation's Sustainable Development Goal (SDG), the EU Green Deal (reach zero GHG emissions and carbon neutrality and protect human health by 2050) [19,20]. Over the years, different strategies to reduce or even minimize the environmental impact of healthcare have been suggested toward waste management, energy–water consumption, GHG emissions, etc. [21–24]. The adoption of telemedicine services seemed a proper approach and strategy, especially when it comes to the reduction in GHG emissions in the healthcare sector [25–27].

Telemedicine has positively impacted global healthcare and the environment in recent years [5]. In order to comply with the constantly growing demands for healthcare resources without exacerbating climate change [28], the provision of healthcare services must be built on sustainable and low-carbon systems and work models [29]. Sustainability in telemedicine refers to the ongoing ability of digital health systems to provide fair and high-quality healthcare services across diverse regions and populations while taking into consideration environmental, social, governance, and ethical considerations, ensuring lasting effectiveness in clinical, economic, and organizational terms.

It is proven that information and communication technology (ICT) is a solution to reduce the carbon footprint [30]. Moreover, the proper adoption and implementation of telemedicine services would be an answer to greener healthcare systems and for the protection and preservation of the environment [31]. In addition, several measures to reduce the carbon footprint of the healthcare sector have been identified in the framework of telemedicine [24], such as the use of reusable devices [32], reducing waste [33], and one-stop diagnostic solutions [34].

Based on the reviewed literature, it is acknowledged that in the implementation of telemedicine services, given the underlying challenges and the outcoming benefits, a framework establishing sustainability principles must be considered. Thus, in the present work, we attempt a first approach to investigate and propose a proper sustainability framework in the governance models of telehealth. Consequently, the main research question that follows our paper is as follows:

RQ: “How can the Greek national telemedicine network apply sustainability principles under the proposed governance model and what is the methodology to develop a suitable sustainability plan?”

Thus, we performed a narrative literature review in order to investigate the telemedicine implementation aspects and the sustainability dimensions in a unified approach and integrated strategy. The main research objectives that this paper is trying to answer, but are not limited to, are as follows:

- What is the current theoretical background that arises from the literature review regarding telemedicine and sustainability?
- What are the potential challenges?
- Can a mutual conceptual framework be created with respect to the characteristics of the current governance model of telemedicine?

This research is structured as follows: In Section 2, the theoretical background and a brief presentation of the methodology of this paper are presented along with the challenges and expected opportunities of telemedicine services. In addition, the structure and components of the national telemedicine network in Greece (EDIT) are briefly presented.

In Section 3, the findings of our research, also based on the author's experience, are presented, including the proposed fundamental pillars of a sustainable telemedicine governance framework, and in addition, the proposed methodology for developing a sustainability plan for telemedicine services in Greece with the respective steps to be followed.

Finally, Section 4 presents the concluding comments and remarks, along with the research gaps, the potential need for future academic research development, and the implications of this paper.

2. Theoretical Background

2.1. Methodology of Our Research

Our purpose was to conduct comprehensive research, and thus, the systematic literature review's guidelines were followed according to Yu and Watson [35] and Tranfield and Smart [36] and our methodology is presented in Figure 1. The first step, after defining the research questions and proposed objectives, was to develop the relevant review protocols and methods with all the necessary inclusion and exclusion criteria. A committee of experts was appointed, consisting of the following review authors/experts: three in the field of telemedicine, one in the field of sustainability in the healthcare sector, three healthcare professionals, and two academics with experience in the aforementioned fields as coordinators. The review authors performed a parallel independent assessment of the articles and reports, and in case of a disagreement or dispute, the coordinator was responsible for giving a solution. For our search, we used the online databases of Google Scholar and PubMed, which contain journal articles as well as "grey literature", such as conference proceedings and reports, and reviewed the first 19 pages of search results from the last two decades. The search was performed using the following terms, keywords, abbreviations, and combinations of e-health, telemedicine, telehealth, sustainability in telemedicine, digital health, sustainability in healthcare, Greek national telemedicine network, and ESG in healthcare, and only publications written in English.

At the first stage, we identified and selected the initial group of 1181 studies that were screened through their titles, the context of the abstracts (for papers), and the table of contents (for reports and non-academic publications) in order to investigate the relevancy of the papers based on the research question and relative objectives. The next step was to select the papers, publications, and reports that were close enough to answer them. A total of 197 studies were deemed relevant, and we obtained the full-text article for quality assessment. Then, we skimmed through the full-text articles to further evaluate the quality and eligibility of the studies. After careful review, a total of 89 studies were excluded, and altogether, we included a total of 108 studies in this research that meet our inclusion and exclusion criteria.

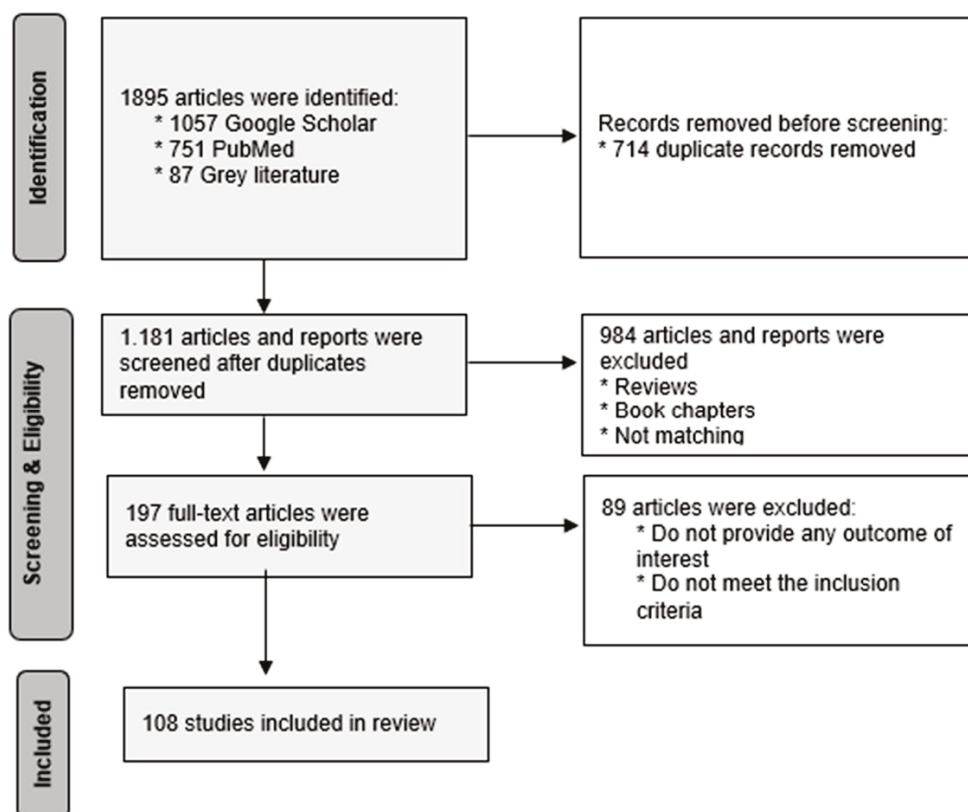


Figure 1. Methodology based on PRISMA principles. Source: Derived from our research.

After analyzing and synthesizing the existing information from the selected studies, we codified it into specific concepts, such as the challenges and benefits of telemedicine with regard to sustainability aspects, and then presented our findings. Afterward, we concluded with the suggestion of a conceptual model for the governance model of the Greek national telemedicine network. The implications of this research are quite significant for all healthcare actors and stakeholders (e.g., patients, healthcare providers, health institutions, academia, healthcare experts and executives, governments, etc.) because it presents an updated version of the current operating telemedicine system in Greek toward the sustainability principles and the modern philosophy of governance in digital healthcare services.

2.2. Challenges and Expected Positive Outcomes of Telemedicine

In the field of telemedicine, a lot of crucial challenges have been identified by different researches [37,38]. Pan et al. [38] refer to behavioral and operational aspects and the unwillingness to change during the implementation of telemedicine services, especially on the part of clinicians and non-clinicians in terms of smart healthcare systems' adoption [39]. Moreover, Rubbio et al. [40] and Martínez-Caro et al. [41] highlight the adoption difficulties and resiliency to change when it comes to implementing digital health technology platforms. Furthermore, Cobelli et al. [42] have identified ethical challenges such as privacy and security issues, the lack of autonomy, and other legal implications and liabilities [43], while other researchers present the high technological costs and the technical aptness of the staff [44,45]. From the patient's perspective, the lack of adaptation to the new technological tools [46,47], the limited broadband access [48], and the language barriers [48], the lack of trust and acceptance, as well as the digital literacy, are major challenges in the adoption of telemedicine services [45,48,49], in addition to other critical financial and infrastructural deficiencies [48–52].

Nevertheless, the positive impact of telemedicine services has been proven over the last decades and has the potential to greatly contribute to sustainability and support the development of an eco-friendly and socially based healthcare system [48]. Adopting telemedicine not only benefits the environment because of the reduction in transportation but also enhances access to care and improves patient specialized management through distance consultations, timely interventions, and individualized treatment options, ultimately improving health outcomes. By implementing these practices, healthcare practitioners and telemedicine platforms can greatly contribute to the battle against climate change, the preservation of natural resources, and the establishment of a more sustainable future [48]. Telemedicine is considered a beneficial and suitable approach toward sustainable healthcare [37,53]. In fact, telemedicine also has multiple benefits that should be mentioned with regard to society and the health systems [54]. Research has shown that telemedicine services can improve the overall performance of the healthcare systems [55], enhance patients' satisfaction [56], and increase the quality of services [57] by reducing the patients' waiting time [58]. In the same direction, telehealth services mitigate geographical barriers and increase access to healthcare services [30], reduce the emissions from patients' medical travel [58], reduce the overall healthcare emissions [59], minimize transportation and traveling time and costs [28,60], and contribute to a more efficient healthcare system because of the reduction in unnecessary hospital admissions [28,61]. The patient-centered experience due to the real-time communication with healthcare providers through video-conferences [62] enables continuous documentation of medical data [62] and provides easier follow-up and monitoring processes by healthcare professionals [62]. Moreover, it is imperative that competencies in ICT tools, virtual platforms, and applications must be enhanced both from the healthcare providers' and the end-users' sides [63,64]. The introduction and implementation of telemedicine services with their respective supportive systems and tools should be a responsibility [37] and, in some cases, the obligation of healthcare policy decision-makers at the micro level (e.g., in healthcare entities) and at the macro level (e.g., healthcare ministry) [42]. In the next section, a methodological approach to the governance of telemedicine networks in Greece, with sustainability as the main purpose, is presented.

2.3. The National Telemedicine Network in Greece (EDIT)

In response to ongoing challenges, the Greek Ministry of Health has been expanding the National Telemedicine Network to enhance healthcare services, particularly in remote islands, mountainous rural regions, and other inaccessible locations. This initiative aligns with Greece's constitutional commitment to ensuring equal healthcare access for all citizens, regardless of their place of residence. Currently, the Greek national telemedicine network (EDIT) includes [65,66] the following:

- Sixty-six Patient-Doctor Telemedicine Stations (PDTs), situated in hospitals, health centers, and multipurpose regional clinics.
- Twenty-one Consultant Telemedicine Stations (CTS), located across 12 regional and tertiary hospitals in the 2nd Greek Health Region (HR), as well as in the National Emergency Centre (NEC).
- Over 170 Home Care Stations (HCS) installed in patient homes or social care facilities within the 2nd Greek HR's jurisdiction.

To further enhance telemedicine capabilities, the Greek Ministry of Health is implementing significant upgrades, including additional infrastructure and subscription-based services. The planned improvements include the following:

- Three hundred and fifty-five new Patient-Doctor Telemedicine Stations (PDTs) to be deployed in selected healthcare facilities across the country.

- Thirty-five additional Consultant Telemedicine Stations (CTS), strategically placed based on healthcare facility capacity and operational needs.
- Five Telemedicine Training Centers, equipped with both CTS and PDTs technology, to train healthcare professionals in university hospitals nationwide.
- Three thousand Home Monitoring Systems (HCS), integrated with EDIT and its supporting software, to improve remote patient monitoring.
- Three new regional Control Centers and a centralized Command and Control Center at the Ministry of Health to oversee telemedicine operations.

Between 2016 and 2023, Greece witnessed a substantial increase in teleconsultation services, particularly in mental health [65,66]. Telepsychiatry sessions emerged as the most common form of telemedicine consultation, followed by pediatric telepsychiatry, diabetology consultations, and chronic disease management services. The continuous evolution of telemedicine in Greece demonstrates its vital role in improving healthcare accessibility, particularly for individuals living in isolated or underserved areas who face barriers to traditional medical services. To maximize the effectiveness of EDIT, it is essential to implement clear regulations and standards that uphold quality care and ensure optimal clinical outcomes [65,66].

Expanding telemedicine, particularly in Greece's remote and mountainous regions, for prompt response to cover the needs of chronic patients or for health problems consultations represents a strategic and necessary approach to fulfilling the constitutional obligation of universal healthcare access. But, in order to be sustainable and take into consideration the necessary aspects of the ever-changing environment, a proper framework and methodology should exist to verify the continuous existence and improvement in terms of meeting the needs and expectations of the end-users and the stakeholders [65,66].

3. Results

Our study is based on literature review and on experience in the telemedicine field. The purpose of this section is to present a proper framework based on the principles and philosophy of sustainability that will support and improve the governance model of EDIT so as to meet the challenges and risks that organizations are currently facing.

3.1. Fundamental Pillars of a Proper Sustainable Telemedicine Framework

Telemedicine services in the healthcare sector are using various tools and applications, such as information and communication technology (ICT) platforms, to deliver the necessary and expected healthcare support and services [37,67–69]. It is interesting to mention that Chauhan et al. [37] have identified 37 key success factors concerning the delivery of the proper telemedicine services, with under seven major dimensions (criteria): social, environmental, economic, technological, legal and regulatory, ethical, and organizational. In this study, and more specifically in Figure 2, we present a conceptual model where the fundamental pillars of a proper sustainable telemedicine framework for the governance of the Greek national telemedicine network should consist of the following: environment (E), social (S), governance (G), economic (E), digital transformation and innovation (DTI), the legal framework (L), quality assurance (QA), and finally, the ethical considerations (EC).

Our research indicates that these pillars are complementary, mutually dependent, and supportive and should be considered as a holistic model in terms of successful implementation.

Each pillar consists of specific factors to be identified, considered, measured, evaluated, monitored, and revised. Appendix A presents the table of the proposed factors per pillar. In addition, this study tries to make a first attempt to show the correlation between the above-mentioned factors based on the authors' empirical research. In Figure 3, it is clearly

demonstrated that all factors are interlinked and have a mutual influence in an undeniable manner. In any case, our findings are based on empirical application and experience, thus, not conclusive.

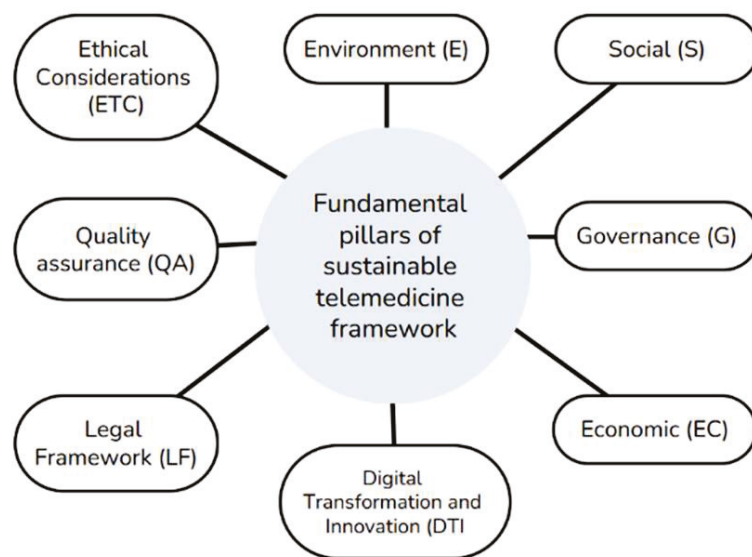


Figure 2. Fundamental pillars of sustainable telemedicine framework Source: Derived from our research.

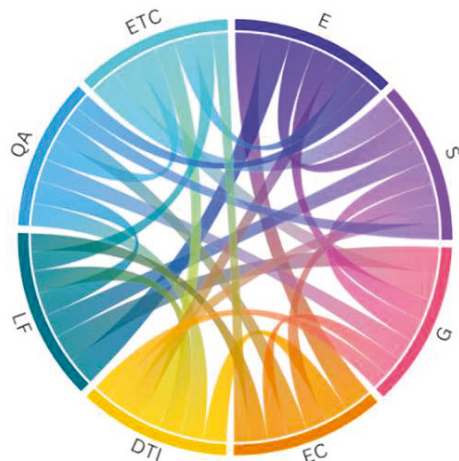


Figure 3. Correlation of the fundamental pillars of sustainable telemedicine framework Source: Derived from our research.

Further research needs to be carried out due to the promising findings presented in this paper, and the work on the remaining issues is continuing and will be presented in future papers.

3.2. The Proposed Methodology for Developing a Sustainability Plan in Telemedicine Services in Greece

Sustainability has become vital for the protection of society and the environment. Although telemedicine is facing challenges, it is still considered an appropriate method to deliver and provide qualitative healthcare services in remote areas or even in developing countries where there are persistent shortages of specialization and healthcare resources [70]. Various studies have proven that the existence of a proper framework should be available in telemedicine implementation, and many researchers have presented different methodologies [70–74], but the interesting fact is that sustainability does not

appear as an aspect or action dimension. In Greece, a governance framework has been recently proposed for the national telemedicine network to ensure alignment with regulatory requirements, quality dimensions, stakeholder expectations, and compliance with ethical and technical standards, while promoting innovation and excellence in the practice of telemedicine [66]. One of the key principles of the governance model is sustainability so that the network can adapt to the environmental, social, technological, financial, or any other needs and developments that affect the healthcare ecosystem.

This study suggests the key factors that concern the sustainability of telemedicine and the relevant methodology for their adoption consist of the following steps and relevant targets (Figure 4):

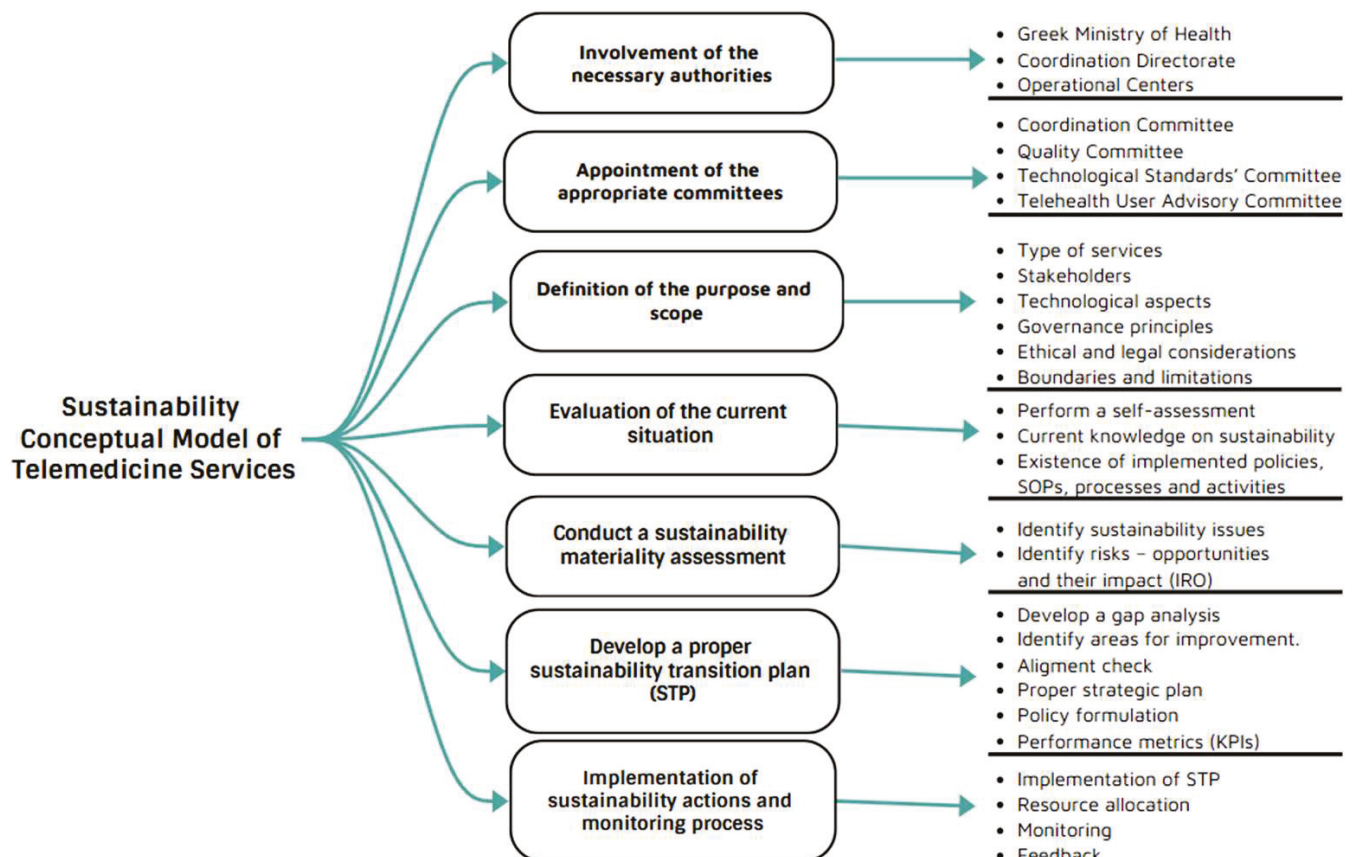


Figure 4. Proposed steps of the methodology for developing a sustainability plan in telemedicine services in Greece Source: Derived from our research.

Involvement of the necessary authorities: In the proposed governance framework, the Greek Ministry of Health is the authority that sets the strategic plan. This includes the allocation of necessary resources and the needed directions, policies, and guidelines for the implementation of telemedicine services at the seven healthcare regions by the coordination of the Operational Centers of the regions.

The Coordination Directorate is accountable for the operational management. This is supported by three newly established units: the Business Operations Department, the Technological Infrastructure and Innovation Department, and the Communication, Publicity, and Digital Media Department. These departments are responsible for coordinating, guiding, and assisting the Operational Centers located in the regions to ensure seamless daily operations through the application of a well-defined framework of actors and standardized procedures.

Appointment of the appropriate committees: In this governance model, three significant committees are defined that will operate under the Greek Ministry of Health. The first one is the Coordination Committee which will be responsible for the overall application of the Greek national telemedicine program and will be deemed a high-level advisory and decision-making body. The Quality Committee will be responsible for implementing safety guidelines and telemedicine protocols, enhancing the quality of the telemedicine services toward continuous quality improvements. The Technological Standards Committee will be responsible for the establishment of technical protocols and respective standards related to the infrastructure, interoperability, and security. Finally, a Telehealth User Advisory Committee is proposed to ensure that patients and community members have a voice in the design, implementation, and assessment of the telemedicine program.

Definition of purpose and scope: The first step is to establish a clear understanding of the key elements, such as the need, purpose, and goal of a conceptual model in telemedicine services toward sustainability. In addition, it is necessary to define a summary of the structure, the type of telemedicine services to be included, the key stakeholders and other interested parties, the technological aspects, the requirements' framework for quality and safety assurance, the basic governance principles including ethical and legal considerations, and the boundaries and limitations within which it operates [66].

Evaluation of the current situation: A healthcare entity should perform a self-assessment for identifying the status of the sustainability approach of its operations, especially at the Top Management level. Specifically, the healthcare entity should identify critical aspects such as the level of knowledge regarding sustainability and the existence of already implemented policies, Standard Operating Processes and activities for sustainability.

Conduct a materiality assessment: Oll et al. [75], Gerwanski et al. [76], and Kara-
giannis et al. [77] claim that materiality can enhance quality, transparency, and integrity and is considered a key tool for identifying the sustainability issues in corporate strategy and risk management processes [78]. To this end, a proper materiality analysis should be performed to specify the criteria and principles of the international sustainability standards that are important for the major stakeholders of the network [75,79,80]. Studies claim the importance of materiality as a fundamental concept by highlighting how materiality determines the importance of issues [75,81,82] and is linked to sustainability issues' value relevance [75,83–90]. In addition, through the materiality process, the risks and opportunities and their impact on the fundamental pillars of the sustainable telemedicine framework are identified. That is considered an important tool for strategic planning for the decision-making process, with application in telemedicine services [84,85].

Develop a proper transition plan: Based on the findings of the self-assessment and the materiality assessment, a gap analysis should be performed in order to identify, analyze, and perform the proper actions toward sustainability requirements and then identify areas for improvement. It is vital that the applied policies, SOPs, processes, targets, and KPIs are aligned with sustainability aspects in order to create the sustainability transition action plan. The sustainability plan should also include the resources needed for the system to be designed, individual stakeholder capabilities, system characteristics aligned to the organizational strategy, and the applicable standards. In addition, the impact–risk and opportunities (IRO) should be taken into account, and sustainability alternatives should be defined in prior [70,91,92].

Implementation of sustainability actions and monitoring process: After the sustainability transition plan is defined and approved, the implementation phase begins with specific timeframes and accurate planning to improve the sustainability aspect of the telemedicine network. This process is vital because it requires a lot of resources and changes to the already established philosophy. Another essential element is the monitoring of the whole

process and the implementation of sustainability initiatives and the respective progress in terms of continuous improvement. More specifically, regularly tracking progress toward sustainability goals using the identified metrics should be performed through internal audits to ensure adherence to the reported goals and identify areas for improvement. Moreover, maintaining open channels for stakeholder feedback is critical to ensure that the hospital's sustainability practices evolve in line with stakeholder expectations and global trends.

4. Discussion

The progression and long-term viability of telemedicine in Greece have been significantly influenced by both European Union digital health directives and the country's own strategic health plans. Initial steps toward adoption were facilitated through EU-backed initiatives like TALOS and FEST during the 1990s, which allowed island-based clinics to transmit ECG data to mainland hospitals. Later, projects such as Hygeia-Net, launched in 1998, reflected Greece's ongoing efforts to expand healthcare access in geographically isolated areas. Between 2006 and 2015, the national eHealth roadmap—developed in alignment with broader EU digital priorities—formally acknowledged the importance of telemedicine in reducing regional health disparities. Despite this, progress was constrained by challenges including insufficient legal frameworks, the absence of structured reimbursement systems, and disjointed digital infrastructure. A notable advancement came in 2011 with the creation of the National Telemedicine Network (EDIT), which has since expanded, especially with financial support from EU cohesion programs and post-pandemic recovery plans. Currently, EDIT plays a central role in delivering healthcare remotely, particularly to hard-to-reach populations. However, its continued success relies heavily on harmonizing with EU-level policies such as the European Health Data Space (EHDS) and on strategic investments in areas like system interoperability, healthcare provider training, and digital competence. Greece's journey underscores the critical influence of transnational policy coordination on ensuring the durability and scalability of digital health systems.

Moreover, in other European countries like the Netherlands [93], Norway [94], Sweden [95], Estonia [96], Spain [97], and France [98], the existing telemedicine models are taking into account ESG considerations along with economic aspects and have very strong governance frameworks. In Greece, the EDIT network is still under development in terms of the governance structure. Implementing a national telemedicine network is very challenging, and its sustainability is significant. Requirements to be included and considered are the financing and resources [24,37,39] (e.g., procurement and contracting framework), technology and infrastructure [39,43,44] (e.g., reliable and secure connectivity, equipment), leadership and governance [46–53] (e.g., safety and quality standards), staff management and training [28,59–64], beneficiary management (patients and caregivers) [25,28,59–64] (e.g., accessibility), evaluation and research [65–69] (e.g., risk assessments and information utilization), and innovation [28,43–47] (e.g., integration of innovations). These elements are crucial in terms of sustainability for the successful development of a national telehealth system.

The healthcare sector needs to rely on a sustainable and resilient operational model, and the respective investments have become an important tool that concerns both public and private stakeholders seeking to achieve health-related goals [16,70,99–102], achieve financial sustainability, and meet the needs and expectations of the interested parties, especially for society in terms of social impact [103–105]. Applying a sustainable healthcare model that considers environmental, social, and governance (ESG) factors in its operations will ultimately address business challenges [16] and align with the Sustainable Develop-

ment Goals (SDGs) [106–109]. ESG integration not only enhances the long-term viability of investments but also strengthens stakeholder trust and social license to operate [110–113].

5. Conclusions

According to our literature review, we found evidence and references to support the proposed fundamental pillars of the sustainable telemedicine framework. Gray [114] and Oliveira et al. [115] mention the importance of the environment and also the need for environmental impact assessment to ensure that the developed system works in harmony with the environment and also to have evidence so as to reduce the negative effects in terms of emission, waste, energy and water consumption, etc. Kituyi et al. [70], Chetty et al. [116], and Carcary [117] claim that telemedicine has a social sustainability component and highlight the importance of considering and involving the local community and society in general so as to equalize the healthcare system due to catholic and overall access from all patients [118].

Moreover, the governance aspect plays a crucial role in the adoption of telemedicine services [48,119,120] and can significantly influence their sustainability. The economic aspect is found to have a very strong connection with telemedicine services, mostly regarding economic policies on funding models and reimbursement strategies surrounding telemedicine and the reduction in costs [121]. Digital transformation can play a fundamental role in the provision and improvement of the whole telemedicine structure [122,123] and in achieving universal health coverage and health-related goals [124,124,125]. Furthermore, in the proposed governance framework for the national telemedicine network in Greece [65,66], the legal framework, quality assurance, and ethical considerations are deemed imperative concepts and elements for the successful and efficient implementation of telemedicine services in order to align with stakeholder expectations.

Due to limited resource availability, immediate and radical actions are not easy to implement. It is important to highlight that sustainability in telemedicine services presents several challenges that must be carefully addressed to ensure long-term viability and effectiveness. One major concern is the financial sustainability of telemedicine infrastructure, as the initial investment in technology, equipment, and network expansion can be costly, requiring ongoing funding for maintenance, updates, and training. Additionally, disparities in digital access and technological literacy, particularly in rural and underserved areas, can hinder widespread adoption and equitable service delivery. Regulatory and legal challenges, including data privacy, cybersecurity, and compliance with healthcare standards, also pose significant barriers to sustainable telemedicine implementation.

Furthermore, the integration of telemedicine into existing healthcare systems requires careful planning to avoid disruptions in service continuity, ensure interoperability between platforms, and maintain high-quality patient care. Moreover, sustainability in telemedicine services should extend beyond financial and technological challenges to include environmental, social, and governance (ESG) concerns, as well as the impact of climate change, and the digitization of healthcare services is able to promote sustainable practices in the healthcare sector.

Finally, this paper aims to be a beacon for future research on sustainability in the provision of telemedicine services. The limitations of our paper are the outlined principles and research methodology that require further in-depth investigation based on a systematic literature review, and there may also be more factors that influence telemedicine than those investigated and theoretically introduced. Although various factors have been demonstrated per category, more field research needs to be carried out. So, the intent is to pilot-test and validate the proposed governance model empirically, based on the factors and KPIs for the fundamental pillars of the sustainable telemedicine framework, by applying

it to selected case studies in EDIT, evaluating their structures, stakeholder engagement mechanisms, and policy frameworks. The analysis will examine how these components support the long-term sustainability of telemedicine services in Greece, employing both qualitative evaluation methods and quantitative performance indicators.

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Abbreviations

The following abbreviations are used in this manuscript:

EDIT	National Telemedicine Network in Greece
HCOs	Healthcare organizations
SDGs	Sustainable Development Goals
ICT	information and communication technology
PDTS	Patient-Doctor Telemedicine Stations
CTS	Consultant Telemedicine Stations
HR	Health Region
DTI	Digital Transformation and Innovation
QA	Quality assurance
SOP	Standard operating procedure
IRO	Impact—risk and opportunities
KPIs	Key performance indicators
ESG	Environmental, Social, and Governance

Appendix A

Table A1. Proposed factors and KPIs for the fundamental pillars of sustainable telemedicine framework. Source: Derived from our research.

Environment (E) Aspect		
Code	Factor	Proposed KPI
EC001	Energy Efficiency and Renewable Energy	Percentage of total energy from renewable sources.
EC002	Waste Management and Reduction	Percentage of medical waste recycled or safely treated.
EC003	Water Conservation and Management	Volume of water used per patient per day.
EC004	Transportation and Mobility	Percentage reduction in fuel-based transportation emissions.
EC005	Reduction in Hazardous Chemicals	Percentage of non-toxic, biodegradable cleaning products used.
Social (S) Aspect		
Code	Factor	Proposed KPI
SC001	Patient Safety and Quality of Care	Number of adverse events per 1000 patients.
SC002	Health Equity and Accessibility	Percentage of underserved patients receiving care.
SC003	Community Engagement and Public Health Programs	Number of community health initiatives per year.
SC004	Ethical Patient Treatment and Informed Consent	Percentage of patients receiving informed consent before procedures.
SC005	Patient Rights and Complaint Handling	Average resolution time for patient complaints.
Governance (G) Aspect		
Code	Factor	Proposed KPI
GC001	Regulatory Compliance	Number of compliance violations per year.
GC002	Patient Safety and Quality Care	Hospital-acquired infection rate (HAI) per 1000 patient days.
GC003	Data Governance and Security	Percentage of staff trained on data security protocols annually.
GC004	Stakeholder Engagement and Transparency	Patient satisfaction score (measured via surveys).
GC005	Patient Experience and Engagement	Patient engagement index or satisfaction scores.
Economic (EC) Aspect		
Code	Factor	Proposed KPI
EcC001	Cost Efficiency and Resource Allocation	Cost per patient treated (cost per session).
EcC002	Operational Budget Management	Percentage of budget variance (actual vs. planned).
EcC003	Cost-Effectiveness of Interventions	Amount of money that was saved due to the intervention
EcC004	Financial Risk Management	Percentage of revenue protected through risk management strategies
EcC005	Return on Investment (ROI) for Healthcare Services	ROI of preventive health programs.

Table A1. Cont.

Digital Transformation and Innovation (DTI) Aspect		
Code	Factor	Proposed KPI
DTI001	Return on digital investments	$\text{RODI} = \text{Net Benefits from Digital Investments} / \text{Total Digital Investment Cost} \times 100$
DTI002	Revenue from new digital channels	$\text{Revenue from New Digital Channels} = \sum \text{Sales} / \text{Revenue from New Digital Platforms}$
DTI003	Adoption and performance metrics	$\text{User Adoption Rate} = \text{Active Users} / \text{Total Target Users} \times 100$
DTI004	Revenue from digital technology	$\text{Revenue from Digital Technology} = \sum \text{Revenue from Digital Products, Services, and Platforms}$
DTI005	Actions performed to address digital illiteracy of patients	$\text{Patients Trained} = \sum \text{Patients Who Completed Digital Literacy Programs}$
Legal Framework (LF) Aspect		
Code	Factor	Proposed KPI
LF001	Regulatory Compliance	$\text{Compliance Rate} = (\text{Telemedicine Services Compliant with Regulations} / \text{Total Telemedicine Services}) \times 100$
LF002	Licensing and Credentialing	$\text{Licensing Compliance Rate} = (\text{Licensed Providers} / \text{Total Providers}) \times 100$
LF003	Reimbursement and Payment Compliance	$\text{Reimbursement Rate} = (\text{Reimbursed Claims} / \text{Total Claims Submitted}) \times 100$
Quality Assurance (QA) Aspect		
Code	Factor	Proposed KPI
QA001	Clinical Quality and Effectiveness	$\text{Diagnosis Accuracy} = (\text{Correct Diagnoses} / \text{Total Diagnoses}) \times 100$
QA002	Patient Satisfaction and Experience	$\text{PS} = (\text{Positive Responses from Patients} / \text{Total Responses}) \times 100$
QA003	Patient Outcomes and Follow-Up Care	$\text{Follow-up Rate} = (\text{Scheduled Follow-up Appointments} / \text{Total Consultations}) \times 100$
Ethical Considerations (ETC) Aspect		
Code	Factor	Proposed KPI
ECN001	Patient Privacy and Confidentiality	$\text{Privacy Compliance Rate} = (\text{Compliant Systems} / \text{Total Systems}) \times 100$
ECN002	Informed Consent	$\text{Informed Consent Rate} = (\text{Patients Who Signed Consent} / \text{Total Patients}) \times 100$
ECN003	Accountability and Transparency	$\text{Documentation Transparency Rate} = (\text{Consultations Documented Clearly and Accurately} / \text{Total Consultations}) \times 100$
ECN004	Cultural Sensitivity and Respect for Diversity	$\text{Training Rate} = (\text{Providers Who Received Cultural Sensitivity Training} / \text{Total Providers}) \times 100$

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Article

A Cost Analysis of Diabetic Hand Infections: A Study Based on Direct, Indirect, and One-Year Follow-Up Costs

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Abstract

Background: Diabetes mellitus is a chronic metabolic disorder that increases mortality and morbidity rates. Infections of the hand can easily cause long-term morbidity and dysfunction, but despite their associated high morbidity, diabetic hand infections are more neglected than diabetic foot infections. **Objectives:** This study was conducted over a one-year follow-up period, considering the total costs of treatment over one year post discharge for patients with diabetic hand infections that required surgery. A Monte Carlo Simulation was used in this study as a sensitivity analysis of all the cost calculations. **Materials and Methods:** A total of 62 out of 75 patients were diagnosed with Type 2 diabetes; 11 were female, and 64 were male. Out of all the patients, 15 visited outpatient clinics 30 times or more, and due to their recurrent visits, the outpatient treatment costs reached USD 5162.41 ± 3838.55. The total cost incurred over the period from the patients' first hospitalization to the completion of all treatments and the end of the one-year follow-up was USD 24,602.22 ± 5257.15. **Conclusions:** The cost of hospitalization was the most important factor affecting the total expenses. Therefore, taking precautions before a diabetic hand infection occurs, or when one does occur, performing treatment without delay is expected to reduce the economic burden.

Keywords: diabetes mellitus; complications; economic; burden; healthcare

1. Introduction

Diabetes mellitus is a chronic metabolic disorder that increases mortality and morbidity rates. Its incidence is likely to double between 2005 and 2030, according to the World Health Organization, which estimates that 346 million people worldwide have diabetes [1]. According to the International Diabetes Federation Diabetes Atlas (2025 Edition), approximately 537 million adults aged 20–79 years are living with diabetes globally, and this number is projected to rise to 783 million by 2045 [2].

Diabetic hand lesions, while less frequently studied than diabetic foot ulcers, pose a significant health burden. Their incidence is estimated to be approximately 0.37–1.0% among patients with diabetes. These infections are commonly associated with poor glycemic control, peripheral neuropathy, and immunosuppression. The clinical outcomes can range from superficial cellulitis to deep-space infections requiring surgical intervention. Recent studies have highlighted the role of delayed presentation and a lack of early surgical consultation as key contributors to morbidity and prolonged hospitalization [3].

In patients with diabetes, infection could be simply described as the result of the balance between host resistance and microorganisms being disrupted in favor of the latter,

microorganisms' evasion of the immune system, and their proliferation in the system [4]. Even a simple skin infection can go as far as osteomyelitis, as the ability to heal decreases.

Infections of the hand can easily cause long-term morbidity and dysfunction [5]. Despite their associated high morbidity, however, diabetic hand infections are more neglected than diabetic foot infections [6]. Consequently, the treatment of diabetic hand infections is often delayed, owing to a lack of knowledge of the possible risk or a reliance on conventional treatments [7]. Although joint mobility limitations, Dupuytren's contraction, and trigger finger are the most common ailments in the hands of patients with diabetes, ulcers due to diabetic infections can easily cause serious complications that can lead to amputations [8].

Diabetes is one of the most costly and burdensome chronic illnesses ever recorded [9]. In 2014–15, the economic burden of diabetes in England was approximately USD 1.4–USD 1.6 billion, and it is expected to be USD 14.7 billion higher in 2030 [10]. Hand infections are an important cause of health expenditures. Even if diabetic hand infections are treated appropriately, both the expenditures associated with the treatment process and scar tissue, joint contractures, stiffness, chronic pain, amputation, and the subsequent loss of labor after treatment can contribute to the economic burden.

Several studies in the literature record the incidences and outcomes of diabetic and/or non-diabetic hand infections [11,12]. However, none of them describe the economic burden of diabetic hand infections. Thus, our study aimed to raise awareness of this economic burden and draw attention to the importance of preventive medicine by showing the economic consequences of diabetic hand infections and their complications, which are absent in the literature or less emphasized than diabetic foot infections.

2. Material and Methods

After obtaining ethical approval from local ethics commissions, a prospective, open-label, non-randomized observational study (i.e., case series) was conducted over one year. Data (sourced from the Hospital Information Management System) was collected descriptively and cross-sectionally on all the diabetic hand infections surgically treated in our diabetic foot and chronic wound care clinic from November 2015 to November 2020. Prior to their enrollment, all the patients provided informed written permission, and the research was performed in compliance with the Helsinki Declaration's principles.

Patients were included if they met all of the following criteria: (1) infections located in the fingers, thumb, hand, wrist, or forearm that required surgical intervention; (2) wound cultures obtained at the time of diagnosis; (3) the initiation of antibiotic therapy prior to surgery; and (4) a minimum follow-up period of one year after the diagnosis of diabetes mellitus and/or a diabetic hand infection, with complete medical records kept. The exclusion criteria included infections located above the elbow joint and postoperative infections. In addition, patients with incomplete medical records or those lost to follow-up were excluded from the analysis.

Preoperatively, we recorded the patients' name, age, sex, file number, dominant hand, type of diabetes, glycated hemoglobin (HbA1c), white blood cell (WBC) count, sedimentation level, and C-reactive protein (CRP) level, along with the side operated on, the location and anamnesis of the hand infection, the type of diabetes, co-existing morbidities, and the date of surgery. Perioperatively, we recorded the type of surgical intervention (ray amputation, open amputation, drainage, vacuum-assisted closure (VAC), fasciotomy), complications and their treatments, the gram culture, the length of the hospital stay, and follow-up data for at least one year. Also, the total cost of treatment and the costs immediately and at a follow-up one year post discharge were calculated. All the costs were converted to their equivalent in the last quarter of the year 2022 according to the European

Central Bank foreign exchange reference rates. Furthermore, a Monte Carlo Simulation was performed to conduct a sensitivity analysis in this research.

A Monte Carlo Simulation (MCS) was conducted to estimate the long-term economic burden associated with diabetic hand infections and to model the impact of variable clinical and economic parameters on the overall cost. This simulation was not used to analyze retrospective clinical data but was implemented as a complementary tool to project future cost scenarios under uncertainty. The primary aim of the MCS was to explore how the variations in key input parameters—such as the hospitalization rates, recurrence of infection, antibiotic therapy duration, surgical intervention rates, and unit healthcare costs—affected the total direct and indirect costs over a one-year follow-up period. The key input variables were identified from both our dataset and the relevant literature. Where available, empirical distributions were derived from the observed data. Otherwise, expert opinions and published estimates were used [13]. The following probability distributions were applied:

- Hospitalization cost: A triangular distribution (min: TRY 8000; mode: TRY 12,000; max: TRY 18,000).
- Surgical intervention cost: A normal distribution (mean: TRY 6500; SD: TRY 1200).
- Antibiotic therapy duration (days): A uniform distribution (range: 10–21 days).
- Re-infection rate: A beta distribution ($\alpha = 3$, $\beta = 20$), based on recurrence observations.
- Lost workdays: A triangular distribution (min: 7; mode: 14; max: 28 days).

A total of 10,000 iterations were run for each scenario by randomly sampling from the assigned distributions. The results were summarized as the mean total costs with 95% confidence intervals. A probabilistic sensitivity analysis was also performed to assess the robustness of the findings across a range of input uncertainties. We chose to perform an MCS due to its ability to incorporate parameter uncertainty and provide a probabilistic range of expected outcomes. Compared to deterministic models, this approach provides more realistic scenario analysis and policy-relevant insights, especially in the context of healthcare cost forecasting, where the input variability is high, and was designed according to established principles in probabilistic modeling [13].

The primary outcomes of this study were defined as (1) the direct treatment costs; (2) indirect productivity losses due to an incapacity for work; and (3) cumulative one-year follow-up costs.

The cost analysis included multiple categories of medical and non-medical expenses. These were costs associated with hospitalization (ward and ICU stays), medications (antibiotics, insulin, and analgesics), surgical procedures (debridement and amputation), outpatient clinic visits, imaging and laboratory tests, and rehabilitation sessions, as well as indirect costs associated with a loss of work productivity due to treatment or disability.

The cost analysis in this study was conducted from a healthcare payer perspective using a bottom-up costing approach, while also incorporating the indirect costs of lost productivity through a human capital approach. Although a societal perspective is implied by the inclusion of productivity losses, it was not comprehensively adopted by this study. The indirect costs were estimated by applying the national average wage loss to the number of missed workdays [14].

All the cost data were converted to US dollars using the European Central Bank's average annual exchange rates and adjusted for inflation using the US Consumer Price Index (CPI) for the last quarter of 2022. This method was consistently applied across all the direct and indirect cost categories.

The cases in this research were analyzed over a span of ten to fifteen years, and the expenses were presented in terms of the cost/patient/year in Euros and British Pounds. In addition, invoices from the Turkish Social Security Service with amounts in Turkish Lira

were used to perform the present research. To enable comparisons, these expenses needed to be converted into a consistent currency. As an accessible methodology, the authors decide to convert all the expenses analyzed and reported in this study into US dollars. For this purpose, the steps below were followed:

- i. Using the European Central Bank's (<http://www.ecb.europa.eu>, accessed on 23 July 2025). annual average foreign exchange rates, a multiplicative factor for converting the cost to the corresponding year's US dollar value was calculated.
- ii. The cost was then multiplied by the conversion factor to obtain a USD amount.
- iii. According to the US Annual Inflation statistics, this amount was converted to its equivalent in the final quarter of 2022 (https://www.bls.gov/data/inflation_calculator.htm, accessed on 23 July 2025).

In this study, a sensitivity analysis was carried out through the use of a Monte Carlo Simulation (MCS). MCS is an approach that uses formulas in favor of random number generation and iterative trial and error. Due to its statistical modeling capabilities, an MCS is able to offer a rough estimate of the range of probable expenditures. Concurrently, the cost distribution variables are obtained. This simulation approach is not a theory but rather a tool for finding answers to difficult questions. Problems can be tackled in a variety of ways using this method, all of which are dependent on the specifics of the system and the model that will be built from it. An observational distribution of the variance is used to produce a sample during the simulation procedure, and random numbers are used to represent improbable circumstances. An MCS is capable of giving all the parameters and variables random values in line with the probabilities. It is this random number generation that forms the basis of the simulation. For instance, the probability distribution, based on values randomly picked from a normal distribution, looks like this for a 66% chance that treatment will be needed for osteomyelitis: if the patient's random number is between 00 and 66, they will receive osteomyelitis therapy, and if it is between 67 and 99, they will not require any special care for their condition. In this research, the distribution parameters were calculated at the diabetic hand infection diagnosis, treatment, and follow-up stages. As part of this study, we simulated every conceivable scenario five thousand times and used the data to produce distribution values with a one-year horizon.

3. Results

The research comprised 75 participants followed up for at least one year and complete data from 173 individuals who matched the inclusion criteria. A total of 11 were female with a mean age of 61.5 ± 8.12 , 64 were male with a mean age of 56.2 ± 11.3 , and 62 patients were diagnosed with Type 2 diabetes. Similarly, in the 75 patients included in the study, the infection-causing microorganism was isolated, and the majority of cases were caused by a mixed-type infection, as shown in detail in Figure 1.

Of all the patients, 59 were right-handed, and 48 of the right-handed patients and 6 of the left-handed patients had an infection in their right hand. While the dominant hand was infected in 58 of the patients, the non-dominant hand was infected in 17. The distribution of the infection locations is shown in Figure 2.

On a clinical examination at admission, the patients presented with various signs of infection, including purulent discharge (52%), erythema (68%), localized or diffuse swelling (74%), gangrene (29%), and limited joint motion (35%). These findings helped to characterize the severity and extent of the diabetic hand infections evaluated in this study.

The primary metabolic blood test results at the time of diabetic hand infection diagnosis are shown in Table 1, and the diagnoses in all the cases according to their ICD-10 (International Classification of Diseases, Tenth Revision) codes are shown in Figure 3.

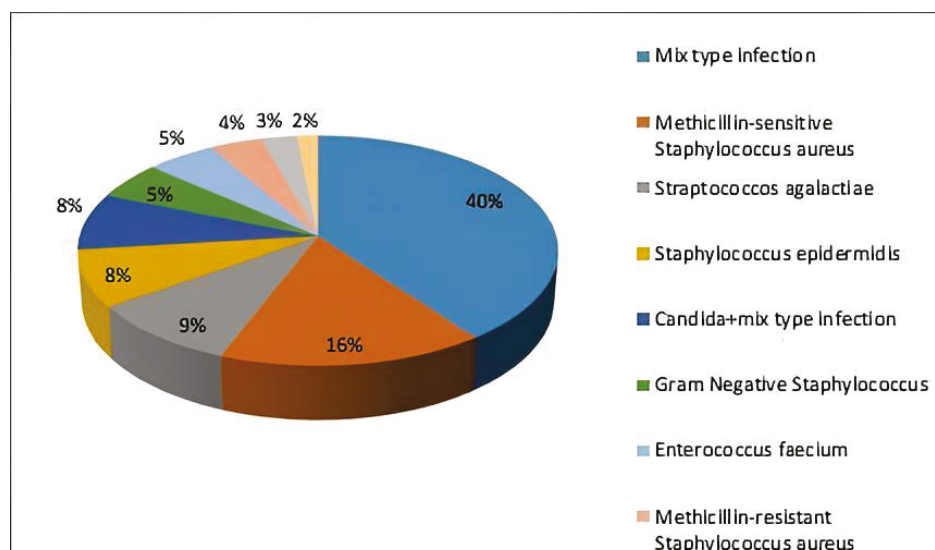


Figure 1. Distribution of isolated microorganisms.

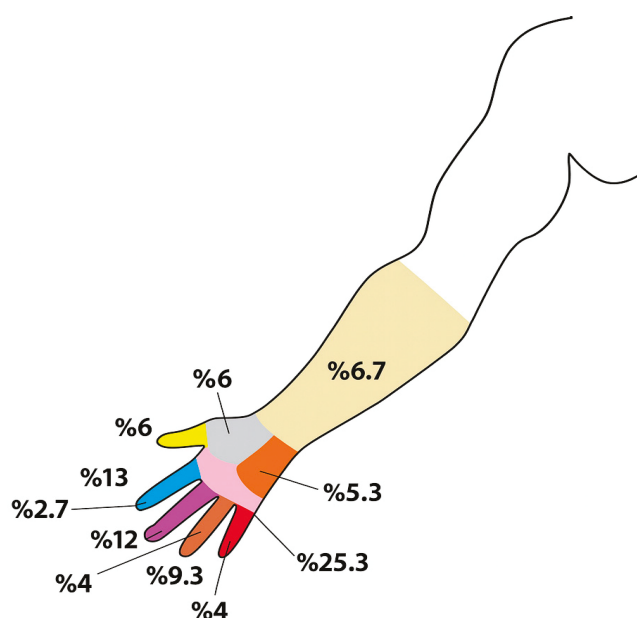


Figure 2. Distribution of diabetic hand infection locations at time of diagnosis.

Table 1. Parameters regarding the primary metabolic blood test results at the time of diabetic hand infection diagnosis.

Parameters	$\bar{x} \pm SD/Average (Min-Max)$
Age	57.01 $\pm$ 11.09/62 (28–68)
Pre-infection HbA ₁ C (mmol/mol)	8.20 $\pm$ 1.33/8.10 (6–12)
Follow-up period (months)	19.13 $\pm$ 10.48/17 (1–44)
Blood sugar level at the diagnosis (mg/dL)	335.81 $\pm$ 88.14/324.0 (216.0–365.0)
At diagnosis HgA ₁ C value (mmol/mol)	8.27 $\pm$ 1.15/8.30 (6–13)
Sedimentation rate at the diagnosis (mm/h)	33.75 $\pm$ 10.16/34.00 (16–65)
CRP at the diagnosis (mg/L)	49.83 $\pm$ 15.72/50.00 (25–102)
WBC at the diagnosis (#/mcL)	11,440.80 $\pm$ 3151.65/11,440.00 (2400–19,820)
Period of hospitalization (days)	22.68 $\pm$ 13.89/22.00 (0–65)

Abbreviations: SD, standard deviation; min, minimum; max, maximum. #/mcL: Number of cells per microliter.

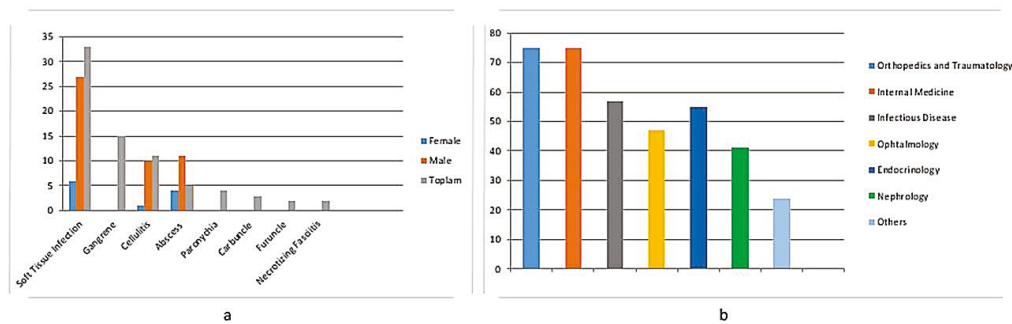


Figure 3. (a) Diagnoses in all the cases according to the ICD-10 codes and sex. (b) Number of outpatient clinic visits according to the clinic.

The total cost for the treatment of the patients in this study included the costs incurred during their 1-year follow-up period and whole hospitalization duration. The components that constituted this cost were the outpatient clinic visit costs, public health insurance report fees, test/examination and radiology costs, and antidiabetic drug costs. In Table 2, detailed costs for every step of the treatment process are given.

Table 2. Subtotal and total costs of diabetic hand infection treatment.

Parameters	$\bar{x} \pm SD/Average (Min-Max)$
Drug cost ^Ψ (US dollar)	5542.426 ± 3519.60/4473.00 (1006.00–19,873.00)
Length of stay in the clinic (days)	19.36 ± 10.45/21 (0–48)
The clinic stay cost ^Υ (US dollar)	6222.64 ± 4377.76/5534.00 (0–18,473.00)
Length of stay in the ICU (days)	3.31 ± 6.80/0 (0–30)
The ICU stay cost ^Θ (US dollar)	2256.09 ± 388.44/1842.5 (0–18,567.00)
of outpatient clinic visits	22.29 ± 11.01/20 (7–59)
Outpatient clinic visit cost ^Φ (US dollar)	5162.41 ± 3838.55/4382.00 (384.00–15,635.00)
Subtotal without surgical treatment	6228.20 ± 4570.48/4982.00 (498.00–21,116.00)
Surgical treatment cost (US dollar)	3607.33 ± 5290.70/521.00 (21.00–19,407.00)
of Days to report incapacity for work (days)	7.85 ± 21.69/0 (0–102)
Incapacity for work cost (US dollar)	745.53 ± 203.32/0 (0–1002.00)
Total cost including whole treatment process (US dollar)	24,602.22 ± 5257.1523/21,155.00 (3166.00–68,975.00)

^Ψ Including all medication costs during hospitalization and the one-year follow-up period. ^Υ Including consultations and surgical and non-surgical interventions performed by departments other than Orthopedics, such as Ophthalmology and Nephrology. ^Θ Some, but not all, patients were admitted to the ICU not because of surgical complications but due to metabolic reasons. ^Φ Including all follow-up costs, such as those for orthosis and prosthesis devices, laboratory tests, imaging, hyperbaric oxygen treatment, physical therapy and rehabilitation, and percutaneous transluminal angioplasty.

A total of 15 patients visited outpatient clinics 30 times or more, and the outpatient treatment costs increased due to the recurrent visits of these patients. The total cost incurred from the patients' first hospitalization to the completion of all treatments and the end of their outpatient clinic visits is also shown in Table 1. On one hand, the relationship between the number of outpatient clinic visits and the surgical procedure type was not statistically significant ($p = 0.151$), as shown in Table 3. On the contrary, a statistically significant

relationship was found between the type of surgical intervention and the outpatient clinic visit costs ($p = 0.004$), as shown in Table 4.

Table 3. Cross-tab of number of outpatient clinic visits by type of surgical intervention.

# of Outpatient Clinic Visits	Types of Surgical Interventions	#	$\bar{x} \pm SD$ Average (Min–Max)
	Drainage	24	18.91 $\pm$ 11.13 17.00 (7.00–59.00)
	Drainage + VAC	4	18.75 $\pm$ 2.98 18.00 (16.00–23.00)
	Open Amputation + VAC	5	27.80 $\pm$ 11.94 16.50 (10.00–41.00)
	Ray Amputation	18	22.83 $\pm$ 11.28 20.50 (12.00–58.00)
	Fasciotomy + VAC	7	21.71 $\pm$ 8.57 22.00 (10.00–35.00)
	Fasciotomy + Ray Amputation	10	21.90 $\pm$ 9.42 19.50 (10.00–41.00)
	Amputation + Flap Reconstruction	6	33.50 $\pm$ 13.32 31.50 (16.00–54.00)
	Fasciotomy + VAC + Flap Reconstruction	1	21.00
	K-W		10.728, $p = 0.151$

indicates the number of patients undergoing each surgical intervention. Kruskal–Wallis test compares the number of outpatient visits across different surgical intervention groups. Abbreviations: SD, standard deviation; min, minimum; max, maximum; VAC, vacuum-assisted closure.

Table 4. Cross-tab of cost of outpatient clinic visits by type of surgical intervention.

Cost of Outpatient Clinic Visits (US Dollars)	Types of Surgical Interventions	#	$\bar{x} \pm SD$ Average (Min–Max)
	Drainage	24	3256.45 $\pm$ 3250.38 2273.00 (384.00–12,584.00)
	Drainage + VAC	4	6489.00 $\pm$ 4541.81 7611.50 (498.00–10,235.00)
	Open Amputation + VAC	5	5434.20 $\pm$ 4095.99 4872.00 (1804.00–12,390.00)
	Ray Amputation	18	529.33 $\pm$ 229.38 457.50 (192.00–1584.00)
	Fasciotomy + VAC	7	6289.71 $\pm$ 5044.81 4409.00 (2009.00–15,635.00)
	Fasciotomy + Ray Amputation + VAC	10	4065.30 $\pm$ 2394.61 4434.50 (845.00–8943.00)
	Amputation + Flap Reconstruction	6	1010.00 $\pm$ 504.76 1291.00 (387.00–1034.00)
	Fasciotomy + Flap Reconstruction	1	1329.00 $\pm$ 204.06 1953.00 (237.00–1034.00)
	K-W		21.162, $p = 0.004$

indicates the number of patients undergoing each surgical intervention. Kruskal–Wallis test compares the number of outpatient visits across different surgical intervention groups. Abbreviations: SD, standard deviation; min, minimum; max, maximum; VAC, vacuum-assisted closure.

4. Discussion

This study analyzed the direct and indirect healthcare costs associated with diabetic hand infections over a one-year period. The primary findings indicate that hospitalization

and delayed treatment were the main contributors to the total cost, while the type of surgical intervention and the clinical severity of the infection influenced the cost variability. These outcomes directly fulfill the research objective outlined in the Introduction: to quantify the economic burden of diabetic hand infections and identify potentially modifiable cost drivers that can inform early intervention strategies.

Although it is known that foot ulcers are often related to diabetes due to neuropathy and ischemia, the number of hand ulcers is likely to increase as the number of diabetic patients is expected to double over the next decade, reaching approximately half a billion. It is fairly unusual for a superficial infection to lead to amputation in this patient population, but the risk is still at least eleven times higher [15–17]. Therefore, the process of treating diabetic hand infections, unlike other complications of diabetes, should begin at the moment of diagnosis and even be performed prophylactically.

Diabetic hand lesions are not formally classified as chronic complications of diabetes by most professional organizations (e.g., the ADA and EASD) but are instead considered acute conditions that require urgent medical intervention due to their potential for rapid progression and severe outcomes [18].

In the region where this study was conducted, admission to the nearest health institution for blood glucose level regulation in patients with diabetes is unfortunately very rare [17]. In fact, eleven patients in our study were unaware that they had diabetes before the infection developed in their hands. In the literature, late presentation to a health institution is reported as a poor prognostic factor in upper extremity infections related to diabetes [19].

The economic burden of diabetes and its complications, especially the impact of foot ulcers on healthcare systems and the individuals affected, is significant [20–24]. However, the current literature does not provide any information about the economic burden of diabetic hand infections. Our study is the first to reveal this over a five-year period.

The situation has been highlighted by recent studies regarding the economic burden on healthcare systems and individuals with diabetes caused by foot-related complications, including the cost of both outpatient and inpatient treatment. Some examples of studies from all over the world include the following. Firstly, in England, the National Health Service (NHS) cost for the year 2014–2015 was USD 1.4–1.6 billion. This represented over 1% of the health budget, or USD 1.25 of every USD 175 spent by the NHS [10]. Despite the fact that about 90% of this expense was due to foot ulcers, there is no available data for diabetic hand infections, ulcers, and/or amputations. In England, the total cost of care, including outpatient and inpatient treatments, for a cured foot ulcer was estimated to be USD 2645; for an unhealed ulcer to be followed up, it was USD 10,865, and for an amputation due to an ulcer, it was USD 20,955 [25]. Infections of foot ulcers during outpatient treatment markedly raised the costs in England to USD 16.075 [26].

According to a study conducted in Russia, the average expenditures to treat patients admitted to a hospital with foot ulcers based on their Wagner Classification were as follows: USD 2600 for grade 1, USD 2995 for grade 2, USD 4179 for grade 3, and USD 5668 for grade 4. Similarly to our results, the length of the hospital stay, foot surgery, and vascular surgery had the highest impacts on the cost [27]. Similar results demonstrating that the average cost increased as the Wagner Classification grade of an ulcer worsened were also shown by Acar et al. [28].

This economic burden is even worse in the USA. Between 2006 and 2010, 1,019,861 patients with diabetic foot ulcers were submitted to emergency departments, representing 1.9% of the total 54.2 million cases of diabetes. The national cost for the emergency departments was USD 1.9 billion to 8.78 billion per year (USD 2014) for 81.2% of the admitted patients, including inpatient expenses. The clinical outcomes included death in 2.0% of

cases, sepsis in 9.6% of cases, and amputation in 10.5% of cases (a major–minor amputation ratio of 0.46) [29]. The cost of diabetic foot management in the USA between 2007 and 2011 was approximately USD 9–13 billion. An additional USD 11,710–16,833 might have been added to a patient's yearly healthcare expenses due to diabetic foot ulceration, doubling the cost of providing diabetes treatment [30]. There were also large indirect costs, such as the loss of individual wages, the impact on patients' careers, and the repercussions of absenteeism for employers. In 2017, diabetes treatment directly cost the United States USD 237 billion, with one-third of these expenses attributable to diabetic foot ulcers [31].

Lastly, in a systemic review conducted by Tcherro et al. comparing the diabetic foot infection costs in five European regions, it was reported that although all the expenses were substantial and varied considerably across Europe due to disparities in the provision of and access to healthcare, it was certain that the economic burden of diabetic foot infection had increased in the last few decades and will increase much more over the next two decades [32]. The literature published up to now shows the presence of diabetic hand infection cases, not just diabetic foot infection cases, in the invisible part of the iceberg and the associated high health expenditures that awaits healthcare systems.

An observational study conducted in Turkey was published in 2016 and was similar to ours regarding the average total cost of a diabetic foot ulcer per patient, USD 14,146.8. Also, in 2014, the health expenses per person in Turkey were USD 1045, and the average annual per-patient cost to treat diabetic foot ulcers was 14 times that amount [33]. Ten years later, we found that the economic burden, not of diabetic foot ulcers but of diabetic hand infections, at this time and their complications reached USD 24,602, 24 times the health expenses per person in 2014.

The results of this study are congruent with those of previous ones on the cost analysis of diabetic foot ulcers and their complications. In Turkey, the largest proportion of expenditures related to diabetic hand infections and their complications have arisen from inpatient clinic treatments. This should encourage the implementation of preventive approaches. The distinguishing characteristic of the current study is that the expenditures per patient were approximately the same for diabetic hand infections and their complications as for diabetic foot ulcers.

Regarding the limitations of our study and future directions, the budget for diabetic foot and/or hand infection treatment and care is set by each country's government and strictly depends on the country's level of economic development. There are also certainly disparities in the methods that can be used for calculating the costs. The costs estimated here do not represent those for the treatment of all diabetes patients in Turkey, and this study was limited to analyzing the expenditures incurred within a one-year follow-up period and conducted in just one hospital. There is thus an urgent need for reliable and practicable national guidelines including uniformly calculated components of all the costs, which will aid in assessing the economic burden of diabetic hand infections and their complications. Further, this will aid in the identification of high-value resources whose consumption may be reduced using cost-effective healthcare strategies.

Although a post hoc power analysis was initially considered, the retrospective design and sample size limitations of this study did not allow for a robust statistical power calculation. Therefore, the possibility of Type II errors in the subgroup comparisons remains a relevant limitation.

Additionally, data on confounding variables, such as patients' socioeconomic status and delays in treatment, were not systematically available for all the patients. Therefore, an adjustment for these variables could not be conducted in the analysis. This limitation should be addressed in future multicenter studies through structured data collection and multivariable statistical modeling. Additionally, although a statistically significant relation-

ship was observed between the surgical intervention types and outpatient costs ($p = 0.004$), this study was not powered or designed to permit a formal cost-effectiveness comparison. Future prospective studies should be conducted to evaluate the comparative economic value of different surgical strategies. Finally, cost comparisons between the treatment of diabetic hand infections and diabetic foot ulcers across countries must be interpreted with caution. Due to variations in healthcare systems, cost-reporting standards, and economic conditions, these comparisons are meant to be illustrative rather than inferential. This limitation has been noted to avoid overgeneralization in cross-national cost interpretation.

5. Conclusions

The main factor that increased the cost was the treatment applied during the period prior to the need for surgery and the duration of its implementation. To mitigate future increases in the economic burden of diabetic hand infections and their complications, the most realistic and conclusively evidenced approach will be to consult a surgeon where surgical necessity is suspected and for surgeons to perform the most appropriate and radical surgical intervention without delay. This study highlights the role of hospitalization as the main cost driver in diabetic hand infections, with treatment delays contributing to significantly higher costs. While this does not constitute a formal cost-benefit analysis, the findings suggest that early surgical referral and intervention may reduce the economic burden. We emphasize this as a policy-relevant recommendation and encourage further studies to investigate the health-economic impacts of preventive and timely care strategies in this patient population.

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Abbreviations

The following abbreviations are used in this manuscript:

HbA1c	Glycated hemoglobin
WBC	White blood cell
CRP	C-reactive protein
VAC	Vacuum-assisted closure
SPSS	Statistical Package for the Social Sciences
ICD-10	International Classification of Diseases, Tenth Revision
NHS	National Health Service

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Article

Systemic Population Segmentation Based on the Unified Care Model: An Approach to Health System Transformation

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Abstract

Context: Population segmentation is a critical health system planning activity that enables more integrated, needs-responsive, and sustainable care. This paper describes the development and evaluation of a Systemic Health System Population Segmentation Model based on the person-centred and needs-based Unified Care Model by Yishun Health, a regional population health system in Singapore. We highlight three implications to enhance health systems operational relevance: (i) psychosocial factors as key determinants of outcomes, (ii) accountability and resource allocation across differentiated segments, and (iii) integration of lifelong and episodic care needs. **Methods:** Three interdependent models were developed, a Lifelong Care Segmentation Model, a Needs-Based Sub-Segmentation Model, and an Episodic Care Segmentation Model, all underpinned by the Unified Care Model. These models systematically stratify residents into mutually exclusive and collectively exhaustive population groups based on biopsychosocial needs across different health system levels. An expert-driven design process was used, supported by integrated administrative and clinical data. Model evaluation examined the ability to stratify patients into distinct risk groups using healthcare utilisation, costs, and readmission outcomes. **Findings:** In 2022, 78,810 residents were segmented into seven lifelong care segments, with 43,473 residents with chronic conditions further stratified into sub-segments reflecting varying complexity and psychosocial needs. Additionally, 14,335 emergency admissions were categorised into six episodic care segments. Healthcare utilisation and annual healthcare costs differed significantly across needs-based sub-segments ($p < 0.001$). Higher episodic care needs were associated with longer hospital stays, higher rates of emergency readmissions, and admission costs ($p < 0.001$). Psychosocial issues consistently emerged as a key determinant of poorer outcomes, underscoring implications for more systemic and systematic accountability assignment and more deliberate resource planning, especially for care integration horizontally. The integration of lifelong and episodic care needs further enabled operational redesign for vertically integrated health systems. **Conclusions:** By incorporating psychosocial drivers, focusing on clarifying accountability and resource allocation, and lifelong-episodic care integration, our Systemic Health System Population Segmentation Model strengthens the operational utility of segmentation as a foundation for population health system transformation and provided a robust framework for health systems governance and leadership system redesign globally.

Keywords: systemic design; population segmentation; needs-based segmentation; health system transformation; unified care model; integrated care

1. Introduction

1.1. Population Segmentation in Health and Healthcare Systems

Population segmentation is a critical planning and development activity in health systems aimed at enabling more efficient system functioning. It forms a core component of value-driven strategies for improving outcomes and value in health and healthcare systems.

Segmentation uses defined criteria representing specific characteristics of the population to design “segmentation models”. The aim of segmentation models is to distribute the population into homogenous “sub-populations” with similar characteristics [1]. These defined criteria or specific characteristics are usually chosen based on their potential impact on the health systems’ outcomes-of-interest, and inability to address or intervene on these specific characteristics therefore, in effect, represents a risk of “non-attainment” of the outcomes-of-interest.

Effective segmentation models enable stratification of the population into smaller sub-populations based on different levels of risk. This stratification allows for the design of more targeted “segment-specific interventions” that can address specific characteristics more appropriately and efficiently, thereby mitigating the risks of poor outcomes [1]. Consequently, the use of segmentation models enables more targeted services planning and resource allocation, increasing overall health services and system efficiency.

Population segmentation can be implemented at the macrosystem, mesosystem, or microsystem levels of a health system, optimising different outcomes depending on the system level [1,2]. Macrosystem segmentation models are typically applied at the level of the whole population enrolled with a health system and are usually designed by the governance and leadership system of health systems. Macrosystem segmentation models are focused on forming mutually exclusive and collectively exhaustive subgroups based on differential levels of overall risk for key outcomes such as healthcare utilisation and overall healthcare costs [1]. For example, macrosystem segmentation might stratify the entire resident population into mutually exclusive groups, identifying a high-risk segment of residents living with multiple, advanced chronic diseases. This enables health system leaders to more effectively plan financing models, allocate resources, and set accountability structures for this segment, as for all segments, across the population health system.

In contrast, mesosystem and microsystem segmentation models focus on specific sub-populations within the health system. These models aim to improve outcomes relevant to specific providers, programmes, or organisations, often for specialised programme redesign [3,4]. Additionally, microsystem segmentation models may employ disease-, discipline-, and/or profession-based clinical or specialty criteria to generate patient segments with different disease/sub-specialty severity, to facilitate the design of disease- or site-based care paths for provider teams. The primary goals are to optimise condition-specific outcomes and efficiently allocate specialised resources. In relation to the aforementioned high-risk segment of residents living with multiple, advanced chronic diseases, depending on the residents’ unique disease conditions or the provider’s services criteria, each resident would belong in multiple mesosystem or microsystem segmentation model segments.

It is important to note that while mesosystem and microsystem segmentation models serve a valuable purpose, they often have considerable overlaps and gaps in their specific

characteristics and outcomes of interest. Unlike macrosystem segmentation models, they are usually neither mutually exclusive nor collectively exhaustive of the whole population.

1.2. International Context

With population ageing and increasing chronic disease burden [5], health systems worldwide are experiencing escalating costs and facing challenges in ensuring sustainable access to quality healthcare services. As a result, health system financing mechanisms are increasingly moving away from “fee-for-service” towards “bundled funding”, or other population-based funding mechanisms such as “capitation”, to sustain patient care outcomes within more constrained financial resources [6,7]. These financing policy changes effectively pass the financial risks of healthcare provision, from the level of whole health systems down to subsidiary systems or organisations, such as provider systems (e.g., integrated care organisations or hospital systems) or third-party organisations (e.g., accountable care organisations or health insurers).

This shift in financial risk has significant implications for population health systems’ planning and delivery of healthcare. As subsidiary provider systems and healthcare organisations take on this financial risk, they must consider macrosystem healthcare utilisation and overall cost-of-care as key outcomes that their mesosystem and microsystem levels ultimately contribute towards. This shift necessitates a rethinking and redesign of segmentation models commonly used by these entities for mesosystem and microsystem services and resource planning and allocation, especially in relation to how they work together systemically to enable macrosystem populations’ segment outcomes more effectively.

1.3. Local Context

In response to these changes, we have observed a trend in Singapore where hospital systems are exploring the use of macrosystem population segmentation models for patients within their geographical catchment areas. The primary aim is to reduce the utilisation of expensive hospital care and, consequently, costs-of-care [8]. The expectation to manage financial risks has also driven Singapore hospital systems to initiate “upstream” macrosystem population segment-specific interventions to reduce healthcare costs and mitigate financial risks [9].

In 2017, the National Healthcare Group (NHG), reorganised Khoo Teck Puat Hospital (a 795-bed acute hospital), Yishun Community Hospital (a 428-bed sub-acute, rehabilitative, and palliative care hospital), and Admiralty Medical Centre (an ambulatory care centre) into Yishun Health (YH) as an integrated care organisation serving 320,000 residents within the Yishun Zone Regional Population Health System in Northern Singapore. YH’s role expanded beyond mere healthcare service provision to collaborating with care partners to enhance residents’ health and well-being and integrate care [10]. Plans were also developed for Yishun Health to manage age-specific healthcare utilisation, cost-of-care outcomes, and value, to assume a significant portion of the financial risk of healthcare services provision for residents living within the Yishun Zone.

Operating within this context, YH initiated numerous health system and services transformation initiatives to accelerate the development of a people-centred, integrated, and value-driven regional population health system. A key initiative was the development and adoption of a set of design principles for the Unified Care Model (UCM) with its subsidiary lifelong care and episodic care services models to guide the development of the YH future-state integrated and value-based Service Delivery System.

The UCM incorporates several key features that influence population segmentation. First, it aims to meet population health needs, measured by resident health-related experience, quality-of-life, and protective health factors. Second, while individual provider

outcomes are important, they are considered subsidiary components of broader population health outcomes. Third, the system measures costs across all providers to optimise resident and patient value. Fourth, integrated care models—lifelong care and episodic care—address the totality of health needs within the Yishun Zone population. The lifelong care subsystem focuses on ongoing health maintenance and chronic disease management, while the episodic care subsystem addresses acute crises and complex elective medical events. These subsystems collectively cover all residents with health needs in the Yishun Zone. Finally, both systems have microsystems representing smaller sub-populations with distinct needs, such as people living well and those with advanced chronic illness in lifelong care and patients requiring acute stroke and pneumonia care in episodic care.

1.4. Care Model Implications for Health System Population Segmentation Models

Population segmentation models are increasingly utilised to optimise outcomes across various levels of the health system [11]. However, the rationale behind selecting specific criteria for population segmentation are often not immediately apparent or transparent. It is also unclear how the different population segment-specific interventions that help to achieve outcomes for their respective population segments, whether and how they are vertically integrated with segment-specific interventions at the macrosystem level, and systemically, whether they come together effectively and efficiently in generating whole-health-system outcomes.

For instance, instead of focusing on characteristics directly impacting a person's lifelong functional health outcomes in spite of their acute disease condition, a hospital provider system may deploy microsystem and mesosystem segmentation models based upon provider-centric criteria such as medical subspecialty or disease-specific criteria only, and then try to improve patient function and experience outcomes only within the context (and competencies) of a medical specialty or disease treatment pathway. In other words, coordination of continuing care to attain person-centred functional outcomes is beyond the ambit of particular medical subspecialty or disease-specific pathways and becomes left to other, often less resourced, care providers elsewhere in the health system (macrosystem).

The result, therefore, is that there can be different degrees of disconnection between a health system's stated goals of person-centred outcomes and the actual criteria used for population segmentation at the microsystem, mesosystem, and macrosystem levels. Indeed, the causal relationship between selected characteristics for population segmentation and the health system's desired outcomes can be complex and, in some instances, insufficiently examined and tenuous, or even wrong. This does not mean that desired person-centred health system outcomes are unattainable. However, segmentation-specific interventions based on population segmentation models that are not needs-based or systemically linked to macrosystem segmentation models are unlikely to be effectively designed and even less likely to be efficient in improving person-centred whole-health-system outcomes and how this can be achieved is a key research gap in the literature. While existing segmentation models at the mesosystem and microsystem levels remain relevant, especially for subsidiary systems and provider organisations, there is an increasing need to ensure that mesosystem and microsystem outcomes align with the desired outcomes at the macrosystem level given the context of broader prevention strategies and sustainable health system cost management. New approaches to population segmentation at the mesosystem and microsystem levels must address these tensions while maintaining operational efficiency and avoiding excessive cost-cutting or care rationing. This situation therefore demands a comprehensive and systemic design approach to population segmentation.

1.5. Systemic Health System Population Segmentation—Singapore Case Study

In a well-defined health system, changes to the context and therefore the definition of the health systems' macrosystem outcomes and its macrosystem population segmentation model will have cascading effects. The criteria for mesosystem (e.g., cohorts) and microsystem (e.g., high-risk populations) segmentation models and their interdependencies with each other within the broader macrosystem framework will each require re-definition or clarification to ensure their distinctiveness and efficiency across different levels of the health system.

The changing local context of YH has therefore driven us to embark on systemic redesign and comprehensive redefinition of our population segmentation criteria and models spanning the macrosystem, mesosystem, and microsystem levels of our regional population health system's service delivery model based on the UCM.

We adopted population needs-based criteria [8] to understand health determinants across the entire population to facilitate more effective delivery of person-centred health services to sub-populations or segments with similar health needs, regardless of individual disease status [12,13]. Recognising the continued importance of mesosystem and microsystem segmentation models within a macrosystem population health system, we therefore also propose a clear relationship and interdependency between population needs-based segmentation models at the macrosystem level and programme-criteria based (utilisation-based) or disease-treatment based models or at the mesosystem and microsystem levels. This paper aims to

1. Introduce a novel person-centred and needs-based Systemic Health System Population Segmentation Model approach to enable whole population health system redesign.
2. Describe the Lifelong Care Segmentation and the Needs-Based Sub-Segmentation Models for the macrosystem and mesosystem levels of the Service Delivery System of a health system, based on the UCM.
3. Describe the Episodic Care Segmentation Model for the mesosystem and microsystem levels of the Service Delivery System of a health system, based on the UCM.
4. Illustrate the operational relevance of such a systemic segmentation model for integrated care delivery by highlighting the implications of psychosocial determinants of health outcomes and the accountability and resource allocation considerations at different system levels, as well as the vertical integration of lifelong and episodic care within health systems.
5. Illustrate the evaluation results of these models.

These clarifications will clarify how various population segmentation models can work together to provide a systemic approach to health system design, enabling more systemic services planning and resource allocation to enhance care integration, outcomes, and value at the whole population health system level. Such an approach will facilitate more effective segment-specific integrated care delivery and service planning [14] and provide insights that may be valuable to other health systems facing similar challenges in population health management and integrated care delivery.

2. Materials and Methods

The National Healthcare Group (NHG) had developed a River of Life (ROL) framework to meet health needs for the entire population segmented to five segments of care covering both lifelong care needs—living well, living with illness, living with frailty, and leaving well—and episodic care needs—crisis and complex care [15]. However, biological conditions, e.g., presence of chronic disease and/or frailty status alone, do not fully reflect

the lifelong needs of the population [16]. Also, the disease and/or frail groups could have very diverse needs, which warrants further sub-segmentation to enable more targeted interventions. Furthermore, episodic care needs are often triggered in the form of an escalation, rather than in isolation, from the base lifelong needs. Yishun Health (YH) enhanced the ROL segmentation model by 1. incorporating the stage of disease trajectory and population psychosocial needs into the lifelong segmentation (LS) model; 2. further sub-segmenting population with chronic diseases and/or frailty into the Needs-Based Sub-Segmentation (NBSS) model; and 3. incorporating sporadic needs into lifelong base needs to develop an Episodic Segmentation (ES) model [17].

There are two major approaches to population segmentation tool development: an expert-driven approach and a data-driven approach [8]. YH adopted an expert-driven approach in the interim to ensure segmentation criteria aligned with the Unified Care Model (UCM)'s person-centred philosophy and incorporation of established clinical knowledge about disease progression and psychosocial complexity. Internally, this expert-driven approach facilitated greater acceptance amongst our clinicians to use these segments for services planning while initiating the collection of more comprehensive population needs and outcomes data through our Yishun Health Population Health Survey 2022. A multi-disciplinary team of internal experts was assembled, comprising clinicians, public health and health system and services planning consultants, and data scientists and data analysts. This diverse group collaboratively selected and defined both the population inclusion and exclusion criteria and the segmentation criteria, ensuring a holistic perspective in the development process.

2.1. Lifelong Care Segmentation (LS) Model Development

The development of the LS model was underpinned by the following key guiding principles: (1) Instead of using a provider-centred approach such as disease condition- or healthcare utilisation-based criteria, we adopted a set of person-centred and needs-based segmentation criteria. This means that the model must consider the entire population and the full spectrum of needs that influences an individual's health outcomes. Based on a literature review [18–23] and inputs from our team of experts, we selected segmentation criteria that consider an individual's holistic needs across their bio-psycho-social spectrum. These criteria encompass the stage of chronic illness, the presence of mental health conditions, and social issues [17]. (2) Segments must be sufficiently discriminatory and mutually exclusive, ensuring that the population within each segment shares similar health needs. Conversely, across each segment, people should have systematically well-differentiated healthcare needs. (3) Additionally, segments must collectively be exhaustive of all residents in Yishun Zone. By adhering to these criteria, the LS aims to assist policy makers in planning services, evaluating outcomes, and tracking progress.

We first identified the total number of residents living in the Yishun Zone Planning Area based on census data from the Singapore Department of Statistics (2022) [18], including Singapore citizens or permanent residents who reside in the catchment area of Yishun Zone. Next, using the existing and readily available data points that reflect or serve as surrogates for the segmentation criteria mentioned above, we identified residents who visited YH in 2022 for lifelong segmentation. These data points were found within YH's Central Data Repository (CDR), a comprehensive data repository that integrates administrative, clinical, and financial data from multiple IT source systems within the organisation. A list of 38 chronic illnesses and their corresponding ICD-10 codes was used to identify if a resident had prior chronic disease diagnoses (Appendix A). These chronic conditions were selected based on the NHG's established chronic disease list, with additional input from YH clinicians to ensure relevance to the local population's disease burden and care

delivery priorities. All past historical primary and secondary ICD-10 diagnosis codes of the residents were included in the analysis. To ascertain if the chronic illnesses were “early” or “advanced” in terms of disease progression, we referred to the resident’s Diagnosis-Related Groups (DRGs), ICD-10 codes, and SNOMED codes of their chronic disease diagnosis. If the chronic disease diagnosis codes indicated the presence of complications or complications were identified by clinician’s review, we defined such residents to be at an advance stage of chronic illness. In addition, patients with Clinical Frailty Score (CFS) statuses with a cut-off score >7 were classified under the “Leaving Well” segment.

Next, the evidence of psychosocial complexity impacting healthcare needs and outcomes necessitated the operationalisation of relevant psychosocial needs criteria into our models. As there were significant administrative data limitations within our existing systems, we used available proxy indicators within our CDR to initiate the process i.e., “just get started”. We defined psychosocial issues as the presence of mental health conditions, social issues, or both. Mental health issues were identified through ICD-10 diagnostic codes for mental and behavioural disorders (F00–99 categories) from residents’ historical primary and secondary diagnoses. This included conditions such as depression, anxiety disorders, bipolar disorder, and schizophrenia documented during clinical encounters. Social issues were identified through two proxy indicators: documented visits to medical social workers, indicating psychosocial needs requiring professional intervention, and residence in public rental housing as a proxy for low socioeconomic status, since such housing is allocated to very-low-income households in Singapore. After applying the above segmentation criteria, seven lifelong care segments with increasing complexity of lifelong care needs were derived forming our needs-based Lifelong Care Segmentation Model. The seven lifelong care segments (LSs) are: LS1. Living Well, LS2. Living Well with Social Issues, LS3. Early Disease, LS4. Early Disease with Psychosocial Issues, LS5. Advanced Disease, LS6. Advanced Disease with Psychosocial Issues, and LS7. Leaving Well.

2.2. Further Needs-Based Sub-Segmentation (NBSS) Model Development

To facilitate the design of more targeted, sub-segment-specific services, for segments with more intense needs, the NBSS model further stratifies residents with chronic diseases (LS3–LS6) into ten sub-segments based on disease complexity and psychosocial needs. The NBSS model creates a matrix structure with two main dimensions: disease stage (early versus advanced) and complexity level. Sub-segments range from residents with single chronic diseases only (A1, B1) to those with multiple chronic diseases combined with both mental health issues and social problems (A5, B5). The intermediate categories capture residents with multiple chronic diseases alone (A2, B2), multiple chronic diseases with mental health issues (A3, B3), and multiple chronic diseases with social issues (A4, B4). This granular sub-segmentation aims to enable the development of horizontally integrated services models that facilitated more targeted care planning for residents with differing levels of medical and psychosocial complexity within the broader chronic disease population. (Detailed segmentation criteria are provided in Appendix B.)

2.3. Episodic Care Segmentation (ES) Model Development

Whilst lifelong care segments represent the ongoing, base needs of a resident living in the community, when crisis and complex care needs occur, there is an escalation of care needs. Under the UCM, this is termed episodic care needs and leads to, e.g., urgent acute hospital admissions. Therefore, the ES model was developed as a systemic extension of the LS model specifically for residents admitted to YH through the emergency department. This model incorporates different levels of episodic care needs, as quantified by the Patient Acuity Category Scale (PACS) value. By layering acute care needs over the existing LS

model, the ES model provides a more comprehensive yet systemic view of differing patient person-centred needs during their acute episodes, facilitating vertically integrated and more systemic care delivery for the whole health system. With reference to average length of stay (ALOS) as the key outcome, six ES segments were derived based on Lifelong Segment and ED PACS Value, namely, ES1. Low Resource Intensity, ES2. Low Acuity, ES3. Low Acuity with Psychosocial Issues, ES4. High Acuity, ES5. High Acuity with Psychosocial Issues, and ES6. Leaving Well (Figure 1).

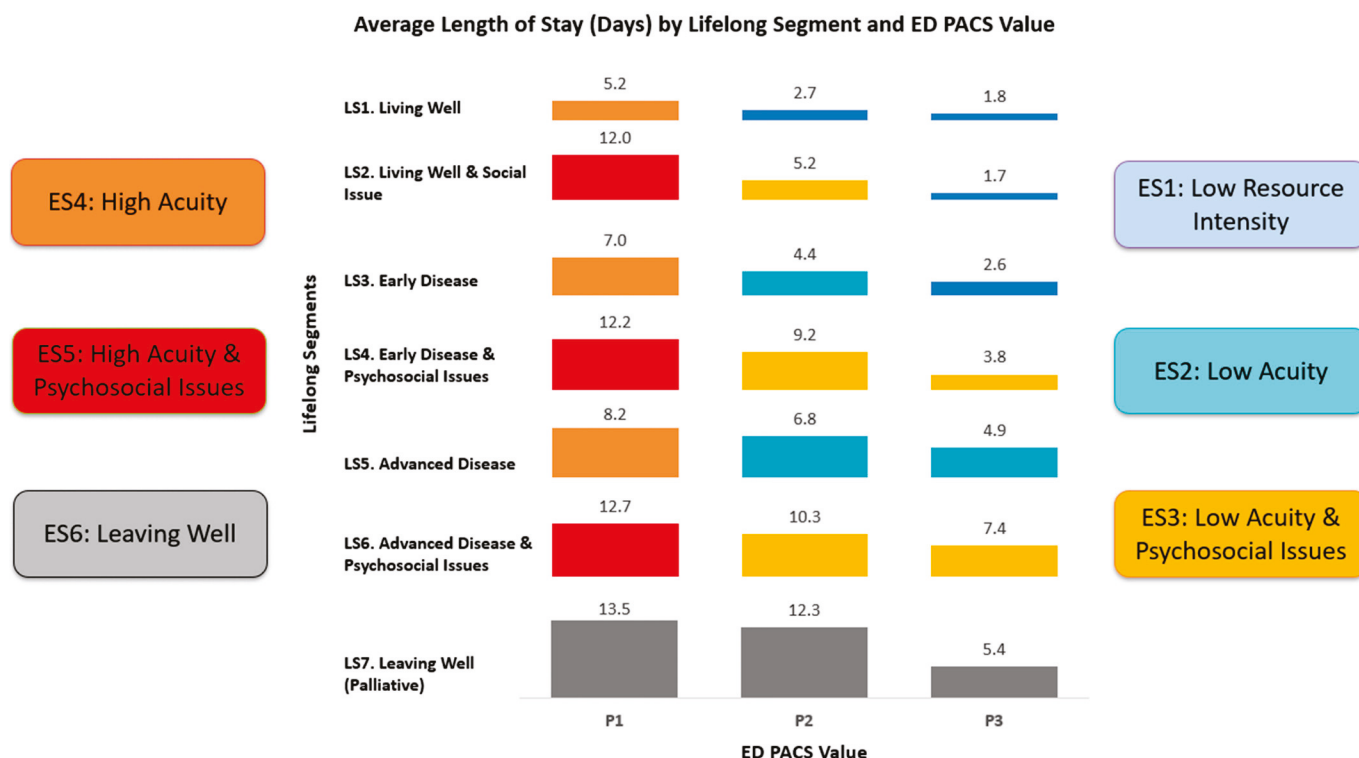


Figure 1. Yishun Health Episodic Care Segmentation (ES) Model and criteria.

2.4. Health System Population Segmentation Model Evaluation

Operationally, our Systemic Health System Population Segmentation Model is meant to allow health system stewards to create additional accountability structures by segments that highlight the disproportionate effect of psychosocial factors on utilisation and outcomes, assigning responsibility for outcomes to providers across the care continuum systemically. Accordingly, evaluation was aimed at understanding the respective segmentation model's ability to segment Yishun Zone residents into mutually exclusive groups that are relatively homogenous in terms of lifelong and episodic healthcare needs, and that these groups were meaningfully distinct—crucial in rationalising the customisation of care plans and the dedication of resources to each segment.

To evaluate whether our NBSS model was able to generate segments of people with uniquely distinct needs, we correlated the segments to various population health outcomes [19–24] or surrogates, starting with readily available data in our CDR, including healthcare utilisation and cost in the latest year that residents visited YH, i.e., number and cost of visits and admissions to our hospital's emergency department, specialist outpatient clinics, and inpatient ward, and the annual hospitalisation bed days. The statistical distinction and difference between population segments across the outcome measures was also studied.

To evaluate the ability of our ES model to generate groups of patients with distinct level of episodic care needs, statistical differences between the ES segments were ex-

amined using available outcome data, i.e., ALOS, inpatient admission cost, and 30-day emergency readmission.

Administrative data from the electronic medical record system were used, with minimal missing values due to systematic data collection. Residents with incomplete essential segmentation data were excluded. Data preparation was conducted using the Konstanz Information Miner (KNIME) Analytics Platform version 4.6.3 (Switzerland). Statistical analyses were performed with SPSS version 27. Chi-square tests were used for categorical variables to assess associations between segments and demographic characteristics. One-way ANOVA was applied to compare continuous outcome variables (e.g., utilisation, costs, length of stay) simultaneously across multiple segments while controlling for error. Linear regression was used to examine associations between segmentation variables and continuous outcomes, adjusting for potential confounders. Parametric tests were selected given the large sample size and approximate normality of the outcome distributions. Statistical significance was set at $p < 0.05$. AI software was used for proofreading (Pair Chat, Open Government Products, Singapore; ChatGPT (GPT-5), OpenAI, USA).

3. Results

In the year 2022, a total of 78,810 residents known to Yishun Health were segmented into seven lifelong care segments using our Lifelong Care (LS) Segmentation Model (Figure 2).

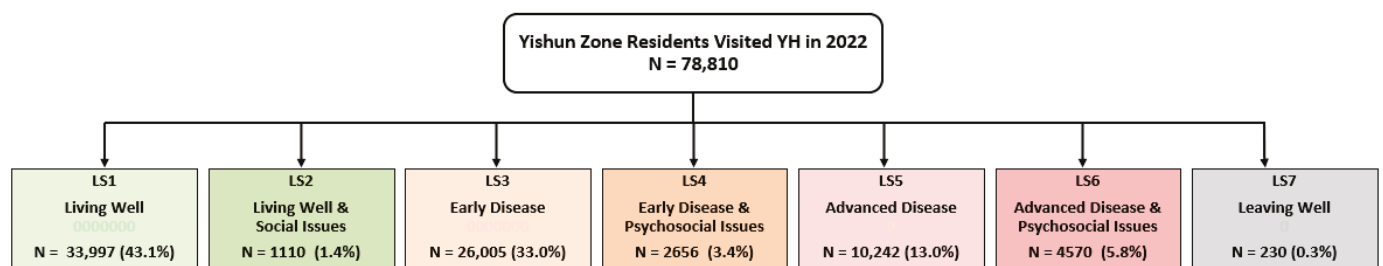


Figure 2. Population size in Yishun Health Lifelong Care (LS) Segmentation Model.

The majority of residents were classified as Living Well (43.1%) or Living with Early Disease (33.0%), representing relatively healthy populations without significant psychosocial complexity. As expected, age and comorbidity burden increased progressively across lifelong care segments (LS1–LS7), with mean age rising from 38.9 to 76.9 years and Charlson Comorbidity Index scores increasing from 0.4 to 8.8, reflecting the clinical logic of the segmentation model (Table 1). The CCI is the most widely used index used to determine survival rates in patients with multiple comorbidities [25].

Table 1. Profile of Yishun Zone residents by lifelong care segments.

	LS1	LS2	LS3	LS4	LS5	LS6	LS7	<i>p</i> -Value
Mean Age (Years)	38.9	37.2	56.7	61.4	63.7	67.6	76.9	<0.001
Gender								
Female %	49.3%	49.9%	50.3%	56.9%	44.6%	49.6%	46.7%	<0.001
Ethnicity								
Chinese, %	59.9%	30.3%	68.8%	65.9%	62.2%	60.6%	69.6%	<0.001
Malay, %	11.5%	39.0%	11.9%	16.3%	16.5%	18.8%	13.1%	
Indian, %	11.9%	14.5%	10.5%	10.7%	13.3%	12.7%	7.0%	
Others, %	16.7%	16.2%	8.8%	7.1%	8.0%	7.9%	10.3%	
Average CCI score	0.4	0.4	2.2	3.1	5.1	6.4	8.8	<0.001

The Needs-Based Sub-Segmentation (NBSS) Model further sub-segmented 43,473 residents with chronic disease (Figure 3). Most residents were at early disease stages without psychosocial needs (A1 and A2), while fewer had mental and/or social issues (A3–A5 and B3–B5). Residents with complex needs were older with higher Charlson Comorbidity Index scores (Table 2), following expected clinical patterns.

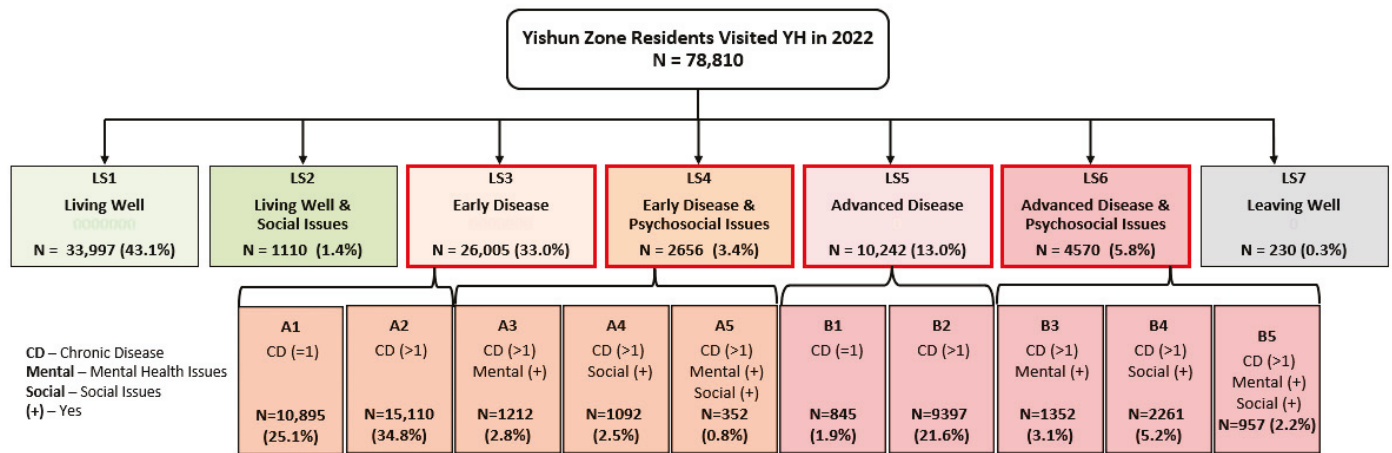


Figure 3. Population size in Yishun Health Needs-Based Sub-Segmentation (NBSS) Model.

Table 2. Profile of Yishun Zone residents by needs-based sub-segments.

	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5	p-Value
Mean Age (Years)	49.3	62.1	58.2	63.5	65.4	47.0	65.2	68.6	65.2	71.6	<0.001
Gender											
Female %	52.6%	48.4%	57.1%	51.4%	65.3%	48.3%	43.9%	57.9%	42.5%	54.4%	<0.001
Ethnicity											
Chinese, %	65.5%	71.9%	72.4%	58.5%	67.3%	56.6%	62.9%	68.7%	53.6%	64.6%	<0.001
Malay, %	13.0%	11.0%	10.5%	22.1%	13.1%	17.5%	16.0%	11.1%	24.8%	15.4%	
Indian, %	11.0%	10.0%	9.8%	11.8%	12.5%	13.4%	13.7%	13.6%	12.7%	14.2%	
Others, %	10.5%	7.0%	7.3%	7.6%	7.1%	12.5%	7.3%	6.6%	8.9%	5.9%	
Average CCI score	1.2	2.9	2.7	3.3	3.7	1.8	5.4	6.1	6.2	7.3	<0.001

Table 3 demonstrates that the NBSS model effectively predicts healthcare outcomes, with sub-segments showing progressively higher utilisation and costs corresponding to increased complexity. Residents with multiple chronic diseases, mental health issues, and/or social problems had significantly higher emergency department visits, specialist consultations, inpatient admissions, hospitalised bed days, and annual healthcare costs. Notably, mental health and social issues emerged as stronger predictors of poor outcomes than did medical complexity alone.

Next, our Episodic Care Segmentation (ES) Model classified 14,335 emergency admissions into six segments (ES1–ES6), with most categorised as low acuity with or without psychosocial issues (ES1–ES3). Higher-acuity segments and those with mental/social issues demonstrated significantly longer length of stay, higher costs, and increased 30-day readmission rates (Table 4). Notably, psychosocial issues were the primary driver of poor outcomes even among patients with similar medical acuity levels.

A critical finding across all segmentation models was the profound impact of psychosocial issues on healthcare outcomes, which consistently emerged as a stronger predictor of poor outcomes than medical complexity alone. In the NBSS model, residents with psychosocial issues (mental health and/or social problems) demonstrated significantly

higher healthcare utilisation and costs compared to those with similar medical complexity but without psychosocial issues. For example, residents with early disease and psychosocial issues (A3–A5) had higher emergency department visits (0.9–1.6 vs. 0.4–0.6), longer hospitalisation stays (2.3–9.5 vs. 0.7–0.8 days), and substantially higher annual costs (SGD 3981–SGD 10,682 vs. SGD 1941–SGD 2538) than those with early disease alone (A1–A2).

Table 3. Healthcare utilisation and cost outcomes of Yishun Zone residents by needs-based sub-segments.

	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5	<i>p</i> -Value
Average No. of ED visits	0.6	0.4	0.9	0.9	1.6	0.7	0.7	1.3	1.1	2.1	<0.001
Average No. of SOC visits	2.0	2.7	3.0	3.5	3.7	2.6	3.4	3.5	4.9	4.8	<0.001
Average No. of inpatient admission	0.3	0.4	0.5	0.7	1.0	0.6	0.7	1.1	1.3	2.0	<0.001
Average annual hospitalisation bed days	0.7	0.8	2.3	4.8	9.5	2.8	2.7	8.1	9.9	22.6	<0.001
Average annual overall healthcare cost (SGD)	\$1941	\$2538	\$3981	\$6955	\$10,682	\$5432	\$6018	\$10,399	\$14,524	\$23,356	<0.001

Table 4. Healthcare utilisation, cost, and patient outcome by episodic segments.

	ES1	ES2	ES3	ES4	ES5	ES6	<i>p</i> -Value
Number of cases (%)	1966 (11.7%)	5807 (34.6%)	4215 (25.1%)	1274 (7.6%)	722 (4.3%)	351 (2.1%)	
Average length of stay (Day)	2.2	4.3	8.2	6.7	11.8	10.7	<0.001
Average inpatient admission cost (SGD)	\$3283	\$5571	\$8384	\$14,314	\$17,298	\$10,655	<0.001
30-day emergency readmission rate	1.4%	5.3%	16.3%	6.8%	16.1%	29.9%	<0.001

Similarly, in the ES model, the presence of psychosocial issues was the key differentiator of outcomes within similar acuity levels. Patients with low acuity but psychosocial issues (ES3) had dramatically higher 30-day readmission rates (16.3% vs. 5.3%) and longer stays (8.2 vs. 4.3 days) compared to those with low acuity alone (ES2). This pattern persisted across all acuity levels, with psychosocial issues consistently associated with poorer outcomes regardless of medical complexity.

These results emphasise that psychosocial factors, more than medical complexity alone, drive poor outcomes. This has immediate implications for health system planners to redirect resources towards social and mental health support within community and hospital care.

4. Discussion

Population segmentation models, operating at different levels of a health system, are designed for various legitimate purposes but lack systemic focus and coordination across system levels to achieve a common, integrated whole-health-system goal. In essence, macrosystem segmentation models can be thought of as “demand-sided” segmentation models representing the needs of residents and patients that can be used to align or harness the care by different “supply-sided” segmentation models and their integrated services models focusing on meeting the needs of specific cohorts of interest to a profession/specialty, a disease type, or an institution and the services they provide, e.g., acute care services.

Supply-sided mesosystem- or microsystem-level patient segmentation models can generate “mutually exclusive sub-segments” that exhaustively include all patients meeting the service model’s inclusion criteria. These models may individually lead to more patient-centric care for specific disease-based patient populations. However, from a systemic perspective, when taken together at the level of the macrosystem or population health system, these numerous supply-sided mesosystem and microsystem-level segmentation models cease to be mutually exclusive. Since patients are cared for by providers and processes designed for multiple overlapping patient segments, supply-sided patient segmentation models paradoxically undermine the patient-centricity they aim to create. Ultimately, this undermines the ability to achieve genuine integrated and value-driven care. [26]. In addition, disease- and healthcare utilisation-based criteria appear to have been used by provider-oriented systems to design segmentation models that are actually meant for their macrosystem or their population health systems [8,14,27]. We posit that this is a fundamental misunderstanding of the criteria driving the type and quantity of risks to outcome attainment at the macrosystem level versus at lower levels of the system, such as at the mesosystem and microsystem levels of a population health system.

Clarifying these distinctions—as we did using a systemic cascade of models in our whole-health-system population segmentation model—is essential and will be beneficial for improving the person centricity and the value of population health systems.

4.1. Psychosocial Factors as Determinants of More Systemic Outcomes

First, our findings mirror a growing body of international literature highlighting that psychosocial determinants, including mental health conditions, social isolation, and socioeconomic disadvantage, often exert a greater influence on healthcare utilisation and outcomes than medical complexity alone [28–30]. Macrosystems should therefore adopt psychosocial factors as key determinants for more person-centred outcomes, moving beyond a narrow focus on cost and utilisation as segmentation criteria. By prioritising these factors, health system stewards can also better align with individual and community needs and meet rising public expectations. Mesosystems and microsystems, which have traditionally focused on specialty or disease-based or utilisation-based criteria for segmentation so as to improve the same outcomes, can in turn incorporate psychosocial factors into their segmentation criteria to align services design towards more person-centric and value-based outcomes that add up more systemically to whole-system, macrosystem outcomes. Such services development can be guided using person-centred, whole system models of care such as the Unified Care Model (UCM) [10], to ensure effectiveness at all system levels.

4.2. Accountability and Resource Allocation for All Population Segments

Second, once we have a systemic cascade of person-centred and needs-based population segmentation models, i.e., Lifelong Care Segmentation (LS), Needs-Based Sub-Segmentation (NBSS), and Episodic Care Segmentation (ES), the purpose of care improvement, integration, and health system transformation—which is thought of as the pursuit of services redesign and resource allocation that more effectively address these specific characteristics to enhance outcomes or mitigate the risks of poor outcomes for different population segments or sub-populations [11,31]—can now be pursued systemically, at scale, potentially enabling more efficient whole-system allocation of resources. Health systems and services design can prioritise policy to encourage primary healthcare providers to be more accountable to manage the health and medical conditions of these residents over a specified duration, e.g., annual or longer “cycles” of care and therefore resident health outcomes. For example, we can use the NBSS model to assign residents with similar needs to respective Primary Coordinating Doctors (PCDs) and their care teams to be accountable

for their lifelong health outcomes [32]. This model enables PCDs to estimate workload, plan resources, and design horizontally integrated segment-specific interventions to meet residents' needs.

Indeed, after applying the NBSS model, we found that most residents have lower health needs, with no or early-stage diseases. PCDs can emphasise primary prevention and routine chronic disease management as necessary. A smaller number of residents have multiple or complex medical conditions that involve mental and/or social issues driving significantly higher healthcare utilisation and costs. For this segment, it may be possible to commission PCDs to lead a multi-disciplinary, multi-institution team of more skilled professionals to be accountable for integrated services models that incorporate more personalised care and support processes that address mental, social and medical risk factors together to improve patient outcomes.

4.3. Vertical Integration of Lifelong and Episodic Care

Third, beyond horizontally integrated care teams, the Systemic Health System Population Segmentation Model can also provide guidance for vertical integration of services models across different health system levels that together enable more coherent whole-health-system planning to meet residents' needs and improve population health outcomes.

As explained, LS and NBSS models operationalised by PCDs and their teams aim to bring about care that is more horizontally integrated. However, the ES model is also derived from the LS and NBSS models and therefore advocates for the bringing of lifelong person-centred perspectives into episodic care to improve episodic care design and outcomes. For acute hospitals, this offers an innovative approach to patient care and resource allocation, e.g., operational bed/ward management. By segmenting patients upon admission, patients from different NBSS segments can be immediately assigned to the appropriate ES care team with the necessary bed/ward resources, such as generalists, specialists, or medical social workers, to treat and manage different levels of acuity and social issues. Service managers can consider coordinating this care with the patients' PCDs. Such an approach can promote new and vertically integrated services models to come into being that consider the patients' sporadic crisis care needs during their acute hospital stay alongside their lifelong needs so as to improve the resident experience of acute care while shortening unnecessary patient stays in acute hospitals due to the patients' psychosocial determinants of health, thereby improving operational efficiency. Transitions of care back to the PCD within the community are also more continuous and coordinated, potentially lowering financial risks for both the hospital system and patients ultimately.

4.4. Comparison with International Models, Equity and Ethical Considerations

Our approach builds upon and goes beyond other validated or well-established international segmentation models [4]. For example, the Bridges to Health framework similarly proposed eight population groups based on health states (e.g., healthy, maternal, frail elderly, end-of-life), providing conceptual clarity for service design [1] but with less emphasis on linking segmentation to operational accountability structures across the health system. The Kaiser Permanente Risk Pyramid segments populations primarily by clinical risk of utilisation to assign patients into tiers for improved chronic disease management [33] and is therefore more operationally anchored. While the British Columbia Health System Matrix [34] expands this to the whole population, neither of these sufficiently integrates psychosocial or equity-related determinants and none aim to provide systemic guidance for integrated care operationalisation. In contrast, our Systemic Health System Population Segmentation Model—anchored using the UCM—explicitly incorporates psychosocial and socioeconomic factors; by integrating lifelong and episodic needs both horizontally and

vertically, our approach extends beyond descriptive segmentation to provide a pragmatic governance framework for accountability and resource allocation for whole-health-system integrated care service redesign.

Population segmentation raises equity and ethical concerns, especially regarding resource allocation and potential stigmatisation. By incorporating socioeconomic proxies like public rental housing status, our model potentially identifies residents at higher risk of poor outcomes due to social disadvantage. These equity-sensitive criteria, when brought into services design in the form of NBSS segments, can potentially help health systems improve health equity. Last, our segmentation categories are meant to be system and services planning tools; this lessens the chance of potential patient stigma, but we acknowledge that adequate clinical and operational governance processes must ensure transparent ethical trade-offs during care to protect individual residents/patients. Future iterations of our systemic segmentation models can include richer self-reported measures of health literacy, functional status, and social support to enable more precise needs and other mental health and social criteria, including inequity identification.

5. Limitations and Generalisability

5.1. Operational Feasibility and Implementation Challenges

Front-line clinician involvement was integral to our design and refinement of the segmentation models in our lived experience. Multidisciplinary clinicians participated in defining segmentation criteria and psychosocial indicators, and their feedback through iterative patient case discussions exemplified how we manage the criteria and operationalisation of the cascade of systemic population segmentation models. Specific services development forums shaped ongoing services design and refinements to aid implementation. While many clinicians welcomed the clarity segmentation brought to patient outcomes accountability and coordination, concerns arose about workload as we transition from disease-based to bio-psycho-socially integrated segmentation approaches. For example, the LS and NBSS models faced manpower constraints in specialist care and agreement issues in primary care, while the ES model was challenged by incomplete data at the emergency department. These required significant continuous service model and organisation adaptations, which are still ongoing.

Cultural change was critical—we attempted to move clinicians and managers from viewing population systemic segmentation as an alternative to disease-based models to embracing it as a complementary, system-enabling ‘AND’ approach. Overcoming these challenges required iterative dialogue, alignment with changing institutional priorities, and demonstration of tangible value through service evaluation, and many of these efforts and organisational adaptations remain ongoing. Our experience suggests that success strongly depends on adequate resourcing, data readiness, and cultural commitment to achieving person-centred, integrated care as one whole system.

5.2. Outcome Attribution

Establishing systemic accountability is essential to ensure that improvements in outcomes are meaningfully linked to segmentation-enabled strategies. Yet, a persistent challenge lies in delineating accountability across multiple sites and care teams that jointly deliver vertically and horizontally integrated care and in measuring it efficiently. Our current approach anchors accountability to defined population segments—such as assigning higher-need sub-segments to specific Primary Coordinating Doctors (PCDs) and care teams—thereby allowing LS/NBSS derived segment-level measurement and tracking of utilisation, costs, and outcomes. In addition, we have also developed ES derived segment-level measurements and dashboards. However, as integration deepens, clarification of

shared accountability across teams and settings will be complex. A promising direction may involve developing multi-tiered accountability frameworks that align shared outcomes with distributed responsibilities both horizontal and vertically, supported by interoperable data systems and common health systems and subsystem metrics. Ultimately, advancing this work will require future research into governance structures and measurement frameworks that can operationalise shared accountability within systemically segmented and systemically designed health systems.

5.3. Data and Model Validation

Our models rely predominantly on administrative data from our electronic medical record system, which excludes important psychosocial and functional measurements such as health literacy, detailed health behaviours, functional status, caregiver availability, and comprehensive social determinants of health. To address these data constraints, we incorporated available proxy indicators including medical social worker visits and public rental housing status as socioeconomic markers, utilised Clinical Frailty Scale scores where available, and engaged multidisciplinary clinical experts to ensure appropriate interpretation of administrative data. We acknowledge that we may still have underestimated the true prevalence of biopsychosocial needs, as our data only captures formally diagnosed conditions and documented social needs, missing undiagnosed or undocumented psychosocial issues. Moving forward, Yishun Health has conducted a Population Health Survey in 2022 to systematically collect resident-reported functional needs, social circumstances, and quality of life measures, which will be linked with administrative data and data from our electronic medical record system to enhance segmentation accuracy and comprehensiveness.

In addition, while our expert-driven approach to model development is clinically rational and contextually appropriate, the lack of external validation or comparison with data-driven models (e.g., clustering algorithms, latent class analysis) may limit the robustness and generalisability of our segmentation framework. To mitigate this concern, we conducted comprehensive internal validation using healthcare utilisation, cost, and readmission outcomes to demonstrate the discriminatory ability of our segmentation models across different population groups. For future enhancement, we plan to compare our expert-driven approach with data-driven segmentation methods such as machine learning clustering algorithms and latent class analysis to assess model robustness and identify potential improvements. Additionally, we are developing partnerships with other health systems to enable external validation of our segmentation framework.

5.4. External Validity, and Next Steps for Adoption

Notwithstanding the above challenges and our segmentation innovation being within Singapore's urban and regional population health system context, our approach to the segmentation using the Systemic Health System Population Segmentation Model can be adapted to other health systems. Its design principles—needs-based, psychosocially informed, and integrating lifelong with episodic perspectives—can be applied to populations with differing demographics and disease burdens. In rural settings, proxies may shift toward geographic access or service availability; in younger populations, toward behavioural and preventive factors; and in systems with differing morbidity profiles, toward locally salient conditions.

Successful implementation elsewhere will require significantly different enabling conditions than those in Singapore that we have discussed above. However, the need for interoperable data infrastructure linking clinical and social domains, clear governance frameworks assigning outcome accountability to care teams, investment in multidisciplinary workforce capability, and staged piloting to iteratively refine the models are clearly areas that remain similar and needed by every health system.

Our Systemic Health System Population Segmentation Model approach not only advances academic understanding but also provides health system leaders with pragmatic levers to redesign services, allocate resources, and strengthen accountability in pursuit of integrated, person-centred care. Embedding segmentation into routine strategic planning and resource allocation cycles will help all health systems to sustain system-level impact. Future work should focus on evaluating how such systemic population segmentation models perform across diverse governance and financing contexts.

6. Conclusions

Yishun Health's Systemic Health System Population Segmentation Model successfully stratified residents into distinct groups with predictable health outcomes and resource needs. The models' key insight—that psychosocial factors drive healthcare outcomes more than medical complexity alone—has profound implications for health system design and resource prioritisation.

Beyond methodological innovation, the models' operational value lies in clarifying the impact of psychosocial drivers, strengthening accountability and resource allocation frameworks, and integrating lifelong with episodic care needs. These models function as structural mechanisms for health system transformation, enabling targeted resource allocation, clear accountability frameworks, and coordinated, integrated care delivery across the care continuum and the whole health system. By embedding these segmentation approaches within value-based care frameworks, health systems can achieve more effective population health management and improved outcomes.

Our systematic and systemic approach offers a replicable framework for other health systems seeking to transition from fragmented, provider-centred care to integrated, person-centred population health models. For adoption beyond our setting, health systems should prioritise integrated data systems, governance alignment, workforce readiness, and phased implementation as critical next steps.

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Appendix A. Chronic Diseases and Corresponding ICD-10 Codes Used for Yishun Health Lifelong Care Segmentation (LS) Model

ICD-10	Disease Description	ICD-10	Disease Description
B18, K70–K77, Z94	Chronic liver disease	H53, H54, Z44, Z97	Visual impairment and assistive devices
C00–C75	Cancer	H90–H91, Q16	Hearing impairment and congenital ear disorders
C76–C80	Tumour	I10–I13, I15, O10, 011	Hypertension
C81–C90, C96	Lymphoma	I20–I25	Ischemic heart disease
C91–C95	Leukaemia	I48	Atrial fibrillation
E10–E14, O24	Diabetes	I50	Heart failure
E78	Hyperlipidaemia	I60–I64, I67, I69	Stroke
F00–F03	Dementia	I70–I74, I77, I79	Peripheral vascular disease
F20	Schizophrenia	J41–J44	COPD
F30, F31	Bipolar	J45, J46	Asthma
F32–F34, F38–F39	Depression	K25–K28	Peptic ulcer disease
F40–F45	Anxiety	L40	Psoriasis
G04, G11	Neuroinflammatory and degenerative disorders	M05, M06, M08	Rheumatoid arthritis
G20	Parkinson	M15–M19	Osteoarthritis
G30	Alzheimer’s disease	M30–M36	Connective tissue
G40–G41	Epilepsy	M80–M82	Osteoporosis
G45, I65, I66	Cerebrovascular insufficiency	N02–N08, N11, N14–N16	Nephritis
G46	Vascular syndromes of brain	N18, N19, N25, Z49, Z99	Renal failure
G81–G83	Paralytic syndromes	N40	Hyperplasia of prostate

Appendix B. Yishun Health Needs-Based Sub-Segmentation (NBSS) Model and Criteria

	A: Early Disease	B: Advanced Disease
1 Single Chronic Disease or Frail only	A1) 1 chronic disease only, or - No chronic disease, but CFS = 6–7	B1) 1 chronic disease only
2 Multiple Chronic Diseases	A2) >1 chronic disease	B2) >1 chronic disease
3 Multiple Chronic Diseases + Mental Health Issues	A3) >1 chronic disease, and ≥1 mental health issue	B3) >1 chronic disease, and ≥1 mental health issue
4 Multiple Chronic Diseases + Social Issues	A4) >1 chronic disease, and - With social issues	B4) >1 chronic disease, and - With social issues
5 Multiple Chronic Diseases + Mental Health Issues + Social Issues	A5) >1 chronic disease, and ≥1 mental health issue, and - With social issues	B5) >1 chronic disease, and ≥1 mental health issue, and - With social issues

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