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Developing a predictive model for resource allocation in healthcare: A case study from an Italian Hospital

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ABSTRACT

The sustainability and efficiency of healthcare systems remain a global challenge, particularly in resource allocation for elective surgeries. This study examines the case of the Rizzoli Orthopedic Institute, a specialized Italian hospital facing significant waiting list imbalances, with approximately 24,000 patients awaiting surgery. The research employs a predictive modeling approach to optimize hospital resource allocation, particularly operating rooms and inpatient beds, to improve surgical scheduling efficiency. By leveraging statistical and computational methods, including historical data analysis and simulation modeling, this study aims to identify an optimal strategy to balance surgical demand and capacity. Over a sequence of 1811 total hip replacement surgeries, our mean calculated operating time was 74.31 min (SD: 19.41), and the estimate of resource demand calculated 1635 total operating hours (or 258 shifts) and 19 bed spaces to clear the current waiting list. Our model indicated potential for 30 % capacity-demand mismatch for this procedure alone. These findings indicate the need for strategic realignment of hospital resources. Key findings indicate that the existing operating-room capacity and bed assignments are insufficient to handle even a single high-volume surgery procedure (total hip replacements) without delays. In real-life practice, hospital managers can use these findings to inform scheduling policy, make staffing assignment priorities, and maybe even plan temporary capacity boosts or off-site sites for surgery.

1. Introduction

The stability and sustainability of the healthcare system is one of the biggest focuses of governments all over the world. In addition to being one of the most sensitive areas of life for populations in both developed and developing countries, healthcare is one of the most costly areas of public expenditure. The European Union countries alone spent around €1.6 trillion in 2021, or 10.9 % of GDP (according to Eurostat), and considering this amount of expenditure, the key question is always how effectively this funding is spent. Times of uncertainty and external shocks only exacerbate the situation. This was the case with COVID-19. In Italy in particular, over the 2 years of the pandemic, the number of people on waiting lists for elective surgery increased by 27 % (according to Istat). Moreover, according to Istat's BES 2022 report, at the end of 2022, about 7 % of the Italian population (approximately 4 million people) will have dropped out of healthcare services due to long waiting times. And this figure is still higher than in 2019, before the pandemic, which was 6.3 %. And the issue tends to worsen due to a snowball effect, with more urgent patients being prioritized and a disproportionate increase in the number of patients receiving services out of time. As a result, at the same time as dealing with the consequences of the pandemic, further work is needed to improve the accessibility of medical

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services for the population. To tackle this complex challenge, it is not enough to scale up capacity (+ 25,000 hospital beds in Italy between 2020 and 2021, Statista). It is also necessary to dig deeper into processes and apply new methods to optimize and improve efficiency. This research is performed at the Rizzoli Orthopedic Institute, a highly specialized hospital and research institute in the field of orthopedics and traumatology. It serves more than 150.000 patients' visits and carries about 15.000 admissions. The disposed resources are 344 beds (of which 18 at the Bentivoglio Hospital and another 40 at the Argenta Hospital (Argenta - Ferrara) and more than 1.400 personnel. A predictive model of the resource demand was developed at the Rizzoli Orthopedic Institute to be able to assess beforehand the balance between surgical supply and demand and the equilibrium point at which supply can guarantee the consumption of patients accumulated on the waiting list. At Rizzoli, there are two critical issues related to waiting lists:

- The institute has got a waiting list of about 24,000 patients (hereafter according to IOR data).
- There is an imbalance between the number of operations performed (approximately 15,000 per year) and the number of new patients on the waiting list (about 17,000 per year), which emphasizes the urgent need for efficiency.

1.1. Background

The focus on efficiency and optimization of clinical-organizational pathways within health care has grown increasingly over the past 15–20 years. For instance, Lowery (1998) emphasized the role of simulation in making 'analytic' decisions under uncertainty, crucial for comparing systems and optimizing resources. Moreover, Brailsford and Hilton (2001) laid the groundwork in healthcare systems modeling by comparing discrete event simulation and system dynamics, showcasing their effectiveness through case studies. Granja et al. (2014) advanced this by applying a simulated annealing algorithm to patient admission scheduling in diagnostic imaging, achieving a 5 % reduction in completion time and a 38 % decrease in patient waiting times. This highlighted the efficacy of simulation in healthcare management. In addition, Molina-Pariente et al. (2018) introduced a stochastic approach to operating room scheduling, using a Monte Carlo method combined with a greedy local search and simulation, effectively reducing costs and managing uncertainty. These studies collectively demonstrate the significant impact of simulation methodologies in enhancing healthcare efficiency and decision-making.

Further advancing the scope of resource planning in healthcare, Stefanini et al. (2020) introduce a data-driven methodology using process mining for cancer treatment, highlighting the role of advanced analytics in healthcare resource planning. Thomas et al. (2001) examines the impact of random demand fluctuations on healthcare capacity, emphasizing the necessity of surplus capacity to maintain low waiting times, especially in specialized areas. Guinet and Chaabane (2003) propose a medium-term planning heuristic for operating theaters, focusing on patient satisfaction and resource efficiency, using a model with capacity and time-window constraints that proves effective in various scenarios. Lotfi and Behnamian (2022) develop a model to optimize OR scheduling in hospital networks, aiming to balance resources, minimize surgery times and costs, and address both emergency and elective patients' needs. de Castro Lobo et al. (2022) explore post-pandemic hospital recovery using concept maps and quantitative data envelopment analysis, introducing a productivity frontier function for scenario planning and advocating for temporary human resource contracts. Aringhieri et al. (2022a) employ matheuristic algorithms for OR planning, combining workload balance and patient priority maximization in a hierarchical multi-objective optimization, improving operational efficiency in OR scheduling.

In a meta-analysis of the literature, Brailsford et al. (2009) offer a multi-dimensional categorization of simulation and modeling research in healthcare, providing a systematic framework for operational research modeling applications in this field. Fone et al. (2003) conduct a systematic review of 182 papers on computer simulation modeling in population health and healthcare delivery, revealing diverse applications and variable quality, and highlighting the need for further research to assess its value in healthcare policy. Jacobson et al. (2013) discuss the evolution of discrete-event simulation in healthcare systems over four decades, emphasizing its role in resource optimization, patient flow enhancement, and cost minimization. May et al. (2011) review surgical scheduling literature, categorizing it into six areas and proposing future research directions, offering insights for surgical scheduling studies. Sobolev et al. (2011) review 34 publications on computer simulation modeling of patient flow in surgical care, noting that most studies lack sufficient relevance for policymakers, underlining the need for involving health system managers in simulation studies. Samudra et al. (2016) classify OR planning and scheduling literature, providing guidelines to enhance clarity and relevance for both researchers and practitioners. Guerriero and Guido (2011) extensively review the application of Operational Research in surgical planning and scheduling, highlighting the complexity of operating theater management and the importance of quantitative techniques. Cardoen et al. (2010) provide a comprehensive review of operational research in OR planning and scheduling, offering insights into problem settings, technical features, and future research areas in OR management.

1.2. Objective

The objective aims to build the basis for the development of the dynamic simulation model in order to achieve the efficient optimization of the limited resources allocation to deliver the surgery services in time for elective surgery patients. To achieve the inception of the model, the following process will be applied: estimate the number of resources needed in terms of beds and operating rooms to cover the current patients on the waiting list, compared with the existing selection process without adjustment.

The calculation takes in considerations only the elective pathway and not the urgent pathway because the model is set with the waiting list (elective patients), so consider only patient that are waiting the surgery in the waiting list. The urgent pathway cannot be considered in the model because it does not follow a standard schedule. That is, there is no waiting list for urgent patients with which to plan resources, because the flow of urgent patients, even if it sometimes has a cyclical flow, cannot be planned in advance, except by means of historical data.

2. Methods

The proposed method for answering the research question is based on the calculation of statistical means of the duration of surgical operations and inpatient days, for the different types of operations and for the reference operating units, in order to be able to assess and express the waiting list in terms of the operating theater resources and hospital beds that each patient will consume. This mean-based, linear approach was favored over more complex machine-learning or simulation alternatives for several reasons. First, hospital managers value a readily interpretable and rapidly updateable model that aids communication. Second, resource constraints (time, computing resources, personnel expertise) favor approaches that can be put into practice rapidly. Third, transparent, linear models foster credibility with clinical staff, as all concerned can observe how inputs (patient volumes, procedure durations) translate into outputs (bed or OR hour demand). Finally, in case of absence of any prediction models, linear approximation is a useful first step to have a first instrument in resource planning and monitoring.

The time period for historical data is set between December 2022 and January 2024.

The necessary data are obtained from the Rizzoli Orthopaedic

Institute's internal management system in which it is possible to view the computerized Operating Registry, observe the times of utilization of the Operating Block, and from a basic set of data related to the patient's medical history. The data is structured and standardized, but there are potentially several problems with its use. Firstly, some of the data is not collected automatically. Secondly, there is no simple log system by which to track what changes have been made to the data (number of transfers, changes in the planning of the operation, etc.). The operating register is the official record of every surgical procedure and for this reason, forms an integral part of the clinical documentation.

All patient information used in this study were anonymized across the board and treated in line with institutional review board (IRB) directives and relevant European data-protection legislation (e.g., GDPR). Personal identifiers were stripped from every record before analysis. Electronic data were stored on password-protected, secure servers that were solely accessible to the research team. All these measures maintained patient confidentiality at every stage of data gathering and modeling.

The data to be collected provides detailed information on the business activities, the patients and the operations performed. These form the basis for the development of the dynamic simulation model.

- Type of main procedure applied with ICD-9-CM code.
- Operative unit that performed the intervention.
- Start and end time of surgical time in hour/minute format.
- Time of entry and exit from the operating room.
- Time of anesthesia.
- Hospitalization days.

Historical data is used to calculate the mean operation time and the mean stay time in hospital (hospitalization time) for each type of procedure with respect to the operational unit responsible for the procedure conducted. After these calculations, the values are used to predict the requested capacity to serve all current patients in the waiting list. The resulting table contains the following information:

- TOT hhso, this column shows the total number of operating theater hours required to consume the patients on the waiting list for each operating unit.
- TOT slots, from the previous column it was possible to calculate the total number of slots into which to divide the operating theater hours to consume the patients on the waiting list, by dividing the total number of hhso by 6 h and 20 min.
- TOT inpatient days, this value represents the total number of inpatient days required for the patients currently on the waiting list for each operating unit.
- Beds, the inpatient days are translated into the bed resource, in one year, needed for the patients currently on the waiting list, by dividing the total number of inpatient days by 365 days.
- Patients Enrolled, represents the number of patients who were enrolled, i.e. placed, on the Waiting List for each operating unit

Before applying our model, we cleaned the dataset by removing or imputing missing data where critical patient variables (e.g., exact operation times) were unavailable. For the proposed method, based on the mean calculations, we need to make a basic descriptive analysis of operations duration time with a normality distribution check. As the means could not be used without at least approximate normal distribution. Otherwise, we will need to make notes and justifications, which consequences may arise.

During this analysis we will focus on one of the most common surgery type in the Rizzoli hospital: Total hip replacement (the ICD9CM code 8151), which contribute 14.66 % (3851) of all operations in historical data.

In order to achieve the data about mean of surgical time and hospitalization time, we followed procedure as follows:

1. We did the mean and variance of operating room time and inpatient days of all patients who had total hip replacement surgery (code 8151).
2. To test whether the data sample was usable in its entirety, i.e., using data from all operating units treating hip replacement, the test of equal means and variance homoscedasticity within pooled data was used. The test was used to find out whether the averages and variances of surgical time and hospital time are similar or different between operating units. Specifically, this time was used because, if the results showed similarity in the data, records from all operating units could be used, otherwise, an operating unit driver that more closely reflected the characteristics of hip replacement surgeries would be used.
3. Through the test, it could be seen that the business units had different statistics from each other (mean and variance). As could be seen from the results for equality of means (Tables 1 and 2) and variance (Table 3), we cannot consider the aggregate data for research because the assumptions for equality of means and variances are rejected.

Therefore, an operating unit (OU 1) was chosen for the modeling project because it best matched the mean and variance of both surgical and inpatient times, as well as the sample size.

As a result, we obtain our dataset with 1811 observations, 74.31 mean and 19.41 standard deviation (Table 4).

Normality and skewness transformations are required to ensure that simple mean-based models accurately capture resource demands. In short, raw surgery duration data contained extremes that can distort mean estimates. By applying methods like logarithmic transforms and Box–Cox transformations, we reduced these extremes and thus made our final mean estimates more trustworthy. In practice, this process enables hospital administrators to avoid low-balling or overestimating true resource requirements because of some very long surgeries.

As the first step of distribution analysis, we obtained the density histogram of operation time in minutes (time_m) with kernel density curve estimation (KDE) and normal curve distribution as a benchmark (Graph 1).

Thinking about KDE as a function composed of building components is essential to comprehending it. KDE is unique in that it uses a single kind of brick called the kernel, or "one brick to rule them all." This brick's capacity to move and stretch/shrink is its primary characteristic (time_m). KDE is the total of all the bricks that are assigned to each datapoint. KDE is a composite function composed of a kernel function, which is a type of building component.

As could be observed, there is a significant left skewness from the benchmark, as well as variation difference, based on tails slope sharpness.

The first step of data normalization is a natural logarithm transformation to smooth the data. After new variable generation we run the data visualization again (Graph 2).

The logarithmic transformation led to less significant left skewness, but there is still a problem with tails distribution. As in the right tail there is a concentration point of extreme cases, which are in general are not in focus of or research. Moreover, those extreme observations

Table 1
Frequency statistics.

OU	Freq.	Percent	Cum.
OU_1	**1811**	**47.03**	**47.03**
OU_2	**933**	**24.23**	**71.25**
OU_3	**1**	**0.03**	**71.28**
OU_4	**608**	**15.79**	**87.07**
OU_5	**339**	**8.80**	**95.87**
OU_6	**148**	**3.84**	**99.71**
OU_7	**11**	**0.29**	**100.00**
Total	3851	100.00	

Table 2
Equality of means test results.

	Statistic	F(df1,	df2)	= F	Prob > F
Wilks' lambda	0.8210	4.0	3834.0	208.97	0.0000 e
Pillai's trace	0.1790	4.0	3834.0	208.97	0.0000 e
Lawley-Hotelling trace	0.2180	4.0	3834.0	208.97	0.0000 e
Roy's largest root	0.2180	4.0	3834.0	208.97	0.0000 e

e = exact, a = approximate, u = upper bound on F.

Table 3
Equality of variations test results.

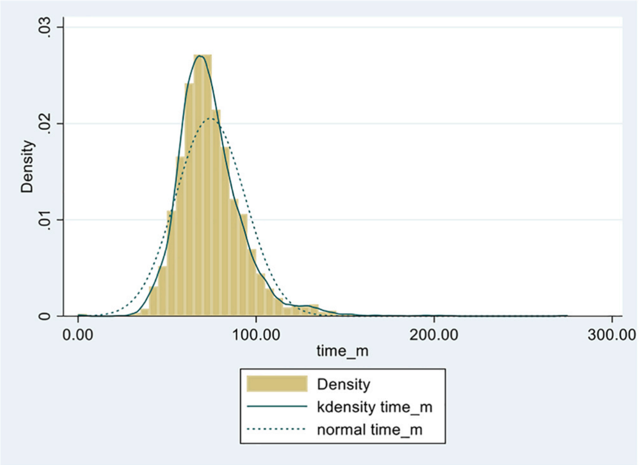
Summary of time_m

OU	Mean	Std. dev.	Freq.
OU_1	74.31	19.41	1811
OU_2	67.63	19.34	933
OU_4	93.26	31.86	608
OU_5	91.24	24.41	339
OU_6	106.33	35.85	148
Total	78.42	25.43	3839

W0 = 51.597551 df(4, 3834) Pr > F = 0.00000000. W50 = 45.090492 df(4, 3834) Pr > F = 0.00000000. W10 = 46.358798 df(4, 3834) Pr > F = 0.00000000.

Table 4
Descriptive statistics of operation time for OU1, Total hip replacement.

Variable	Obs	Mean	Std dev.	Min	Max
time_m	1811	74.30977	19.41286	0	275

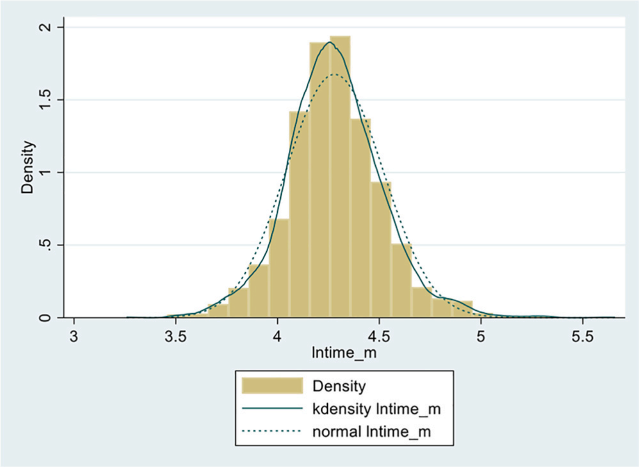


Graph 1. The operation time distribution for OU1, Total hip replacement.

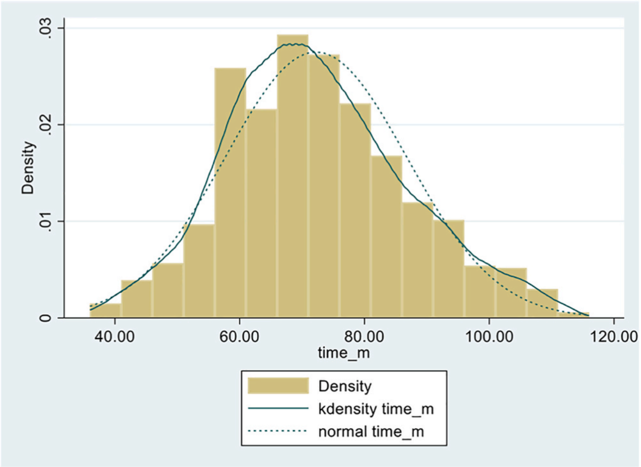
influence the total variation.

Thus, as the second step, we eliminate the outliers' observations based on the ± 2 standard deviations from the mean. That will be points 35,48405 and 113,135 based on information from Table 4. After the procedure 72 observations were dropped in total (7 were less than 35,48405, and 65 were more than 113,135), which is about 4 % of all observations. Based on visual analysis (Graph 3) we conclude that the tails distribution problem is almost solved. Also, we get the skewness and kurtosis test results (Table 5) as a justification of this statement.

The P-value for kurtosis normality hypothesis is about 19 %, thus we cannot reject the null that kurtosis is similar to normal distribution. But, as it was expected from data visualization, we reject the null that skewness is as in normal distribution. The joint test is also to reject the null about normal distribution of the data.



Graph 2. The operation ln time distribution for OU 1, Total hip replacement.



Graph 3. The operation time distribution for OU 1, Total hip replacement (adjusted).

Table 5
Skewness and kurtosis tests for normality results.

————Joint test————					
Variable	Obs	Pr(skewness)	Pr(kurtosis)	Adj chi2(2)	Prob > chi2
time_m	1739	0.0000	0.1851	26.91	0.0000

To test the data with skewness adjustment we use a Zero-skewness Box–Cox transformation. As visually we do not observe now the issues with tails distribution smoothness, there is no need for logarithmic transformation. The normality test results for generated transformed data are presented in Table 6.

Now we are not able to reject the hypothesis of normal data distribution, with a P-value around 35 %.

Taken together, these cleaning and transformation steps help ensure

Table 6
Skewness and kurtosis tests for normality results, Zero-skewness Box–Cox transformation.

————Joint test————					
Variable	Obs	Pr(skewness)	Pr(kurtosis)	Adj chi2(2)	Prob > chi2
bctime_mk	1739	0.9999	0.1467	2.10	0.3492

that the reported resource estimates more accurately mirror routine rather than extreme usage scenarios. At the same time, they may cause the model to underrepresent exceptionally long procedures if multiple complex cases occur close together. For hospital managers, this means the model's outputs should be understood as average-case or near-average-case scenarios, rather than absolute forecasts of every possible event. Nonetheless, these adjustments strike a practical balance: the dataset remains large enough to represent typical demand, and the resulting estimates are more stable for planning purposes, while minimizing the risk that poor-quality or anomalous data will distort outcomes.

As a result, we should consider in the resource demand estimation outcomes that those numbers are biased due to skewness, but at the same time, as variance is close enough to normal distribution, we can assume consistency.

3. Results

Table 7 represents the results of resource demand prediction. The required operation room total time is 1.635 hours which corresponds to 258 working shifts and 19 bed places. The working load allocation is not equal, and it should be considered in the process of resource distribution and planning.

Our results are in line with other resource-allocation investigations (e.g., Brailsford and Hilton, 2001; Aringhieri et al., 2022a, 2022b), which call attention to the persistent mismatch between operating-room capacity and patient demand. As in these studies, we found that a simple modeling approach brings quick dividends to operational planning. Yet, unlike more complex simulations, our model enjoys the benefit of interpretability and quicker update assets particularly valuable to institutions grappling with fluctuating patient loads.

The problem statement defines an urgent necessity to reduce unacceptably long waiting times for elective orthopedic procedures, here against the background of an overwhelmed healthcare system. The worth of our study addresses this shortcoming directly with the presentation of a lean, mean-based predictive model. Through the translation of waiting-list data into concrete operating hours and bed forecasts, the model offers a practical solution for resource planning that can be updated at regular intervals and understood by both technical staff and decision-makers also in consideration with the characteristics of patients placed on waiting lists and production constraints.

4. Discussion

The model is an example of estimating the workload of a hospital's work capacity (shifts, operating room hours, beds) for one type of procedure for specific operations unit. If we look at the results in terms of shares that the type 8151 (total hip replacement) in OU 1 takes up about 7 % of the waiting list of the total number of patients. At the same time, in terms of the required resource inputs, the full processing of this number of patients would take up 30 % of the available operating slots for the clinics where this procedure is performed and 8 % of the available beds. As can be seen from this comparison, there is a clear imbalance between the demand for a particular type of surgery and the available supply of resources on the part of the hospital. In addition, it must be remembered that we have considered the case of only one type of operation and the available resources must be shared with other areas of activity of the Rizzoli Hospital.

Table 7
The working load estimation to serve all patients currently enrolled in the waiting list for the Total hip replacement.

	TOT hhso (h)	TOT slot	TOT inpatient days	Posti letto	ARRUOLATI
OU1	1635:12:17	258	7050	19	7050

As a follow-up to these results, we see a clear future potential in studying the efficiency of available resource allocation and improving the optimization of resource utilization through a predictive model, since physical capacity expansion seems to be an unlikely scenario. A wide range of tools can be used for this purpose, from linear projections and systems of differential equations to ML and AI models.

The main challenge in this task, apart from adequate model selection itself, will be to consider all constraints and target functions that are within the hospital's field of responsibility. Thus, the main target functions will be:

- The goal, according to government benchmarks, is 70 % of patients operated on within 180 days of being placed on the waiting list
- Reducing the length of the waiting list queue

In addition, it is necessary not to forget about the basic constraints that will be imposed in the optimization problem:

- The hospital's financial budget for future periods. We need to assess how realistic it will be to organize slots at external operating sites (both in terms of rent and staff costs).
- Medical staff workload. It is important to consider both financial and physical and psychological constraints on the ability to provide additional workload for current staff.
- Dynamics of incoming patient flow both in terms of first visits and waiting list dynamics. The intersection of operational activities and consulting services obviously causes an imbalance in the distribution of doctors' working hours.
- Distribution of patient classes by type of surgical urgency. In addition to the state benchmark, there are standards for waiting times for surgery based on the class assigned to patients. The hospital should aim to minimize the number of patients with wait times that exceed the established limits.
- Capacity of logistics and storage facilities. It is necessary to keep in mind the process of preparatory work, where the increasing volume or frequency of operations may cause problems in continuous and efficient business processes.
- Operational capabilities of preoperative and postoperative patient care. It will also be necessary to address the optimization processes for the accommodation and care of patients, since most of the operations at Rizzoli involve the provision of a bed for the patient

Although our model of forecasting does have some limitations inherent in it that readers should be aware of. First, it only accounts for elective procedures and not emergencies, which can abruptly derail planned operations and skew planned utilization of resources. Second, we are taking the assumption that normality approximations (after transformations) would be sufficient for mean-based resource estimates; in reality, highly skewed data or a handful of outliers might reduce accuracy. Third, the model estimates a steady rate of inflowing patients, which may not be the case in the case of external shocks (e.g., a new pandemic). Noting these limitations highlights the requirement for continuous updates and cautious inference when extrapolating findings outside of the Rizzoli Orthopedic Institute.

As a result, based on the results of the work, we showed that even using the example of one type of operation, an imbalance in supply and demand is visible. As a result, it is impossible to optimize the operational activities of the hospital without further, more comprehensive modeling. Through the implementation of a predictive model, based on the initial empirical evidence provided by this study, which considers not only the resources required to dispose of the waiting list, but which also allows organizational constraints and production and performance objectives to be taken into account within a hospital structure, it will be possible to obtain as an output of the same model, the optimization of surgical scheduling, improve the allocation of resources and favor a more efficient disposal of waiting lists.

Our analysis shows that other hospitals looking to improve elective-surgery throughput can adapt this forecasting approach by:

- Using a formalized system for collecting data (similar to the Operating Register) to feed the model with real-time utilization of resources information.
- Collaborating with policymakers to set performance goals (e.g., best acceptable waiting times) and link them to changes in capacity production.
- Having a regular review process whereby managers check model output and adjust bed allocations, operating-room capacity, and staffing requirements.
- Recalculate waiting-list figures from time to time, in order to keep their projections of capacity current.
- Setting tiered priority levels for procedures, to satisfy high-demand operations and more specialized, low-frequency ones.
- Integrating predictive modeling requirements into performance-measurement systems, where data-driven approaches become the standard in hospitals.

By applying these suggestions systematically, hospitals with comparable patient influxes can expect resource pressures and manage staff and bed availability in advance.

5. Conclusion

Our study shows that even when examining a single high-volume procedure, such as total hip replacement, there is a substantial mismatch—up to 30 %—between available hospital resources (i.e., operating-room slots, inpatient beds) and patient demand. Specifically, clearing the backlog for this single procedure alone could require 1635 total operating hours (equal to 258 shifts) and 19 beds, demonstrating that the current operating-room and bed capacity are insufficient for tackling the waiting list effectively. These findings highlight the broader problem of strained hospital resources, making clear the need for timely, data-driven resource planning.

From a hospital-management perspective, these results underscore the importance of systematically applying predictive modeling to optimize scheduling policy, bed allocation, and staffing. Our simple, mean-based approach can be readily integrated into existing workflows and updated with new data on a rolling basis, allowing managers to anticipate bottlenecks and make more proactive decisions. At the policy level, encouraging healthcare institutions to adopt dynamic forecasting tools can reduce waiting times, better align resources with local patient needs, and limit the snowball effect that long queues can generate.

More comprehensive or advanced simulation and optimization models (e.g., agent-based or AI-driven approaches) could extend this framework to incorporate urgent cases, improve forecast accuracy, and further strengthen hospital resilience against unexpected surges in demand. Ultimately, investing in robust predictive tools, coupled with supportive policies and real-time data infrastructures, will empower hospital managers and policymakers to maintain more responsive, efficient, and patient-centered care.

CRediT authorship contribution statement

Beatrice Ricci: Conceptualization. **Virginia Gulino:** Writing – original draft. **Edoardo Gallerani:** Writing – original draft. **Marco Nigro:** Writing – original draft. **Peter Perger:** Writing – original draft. **Elena Lombardo:** Writing – original draft. **Anselmo Campagna:** Writing – original draft. **Emanuele Padovani:** Writing – original draft. **Stanislav Russo:** Writing – original draft. **Matteo Buccioli:** Writing – original draft. **Sergey Zhitikhin:** Writing – original draft.

Ethics

None

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Conflict of interest

The authors have no conflicts of interest.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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