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A long-term forecasting and simulation model for strategic planning of hospital bed capacity[☆]

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ABSTRACT

Growing healthcare needs leverage the potential savings of using resources efficiently. To that end, ProMoBed is a comprehensive model that supports strategic planning of bed capacity in inpatient hospitals. The model consists of an extrapolation and simulation component, the former supplying input for the latter. The extrapolation model forecasts admission rates and the average Length of Stay for pathology groups, and corrects for demographic changes. Subsequently, the simulation model emulates the demand for bed capacity, and makes service-level based bed capacity suggestions. Additionally, the model uses the Shapley value principle to disaggregate the effects on demand for inpatient days due to different causes. Results from the extrapolation model are applied to regions in Belgium, showing expected divergence in inpatient day demand evolution.

1. Introduction

In the Belgian healthcare landscape, hospitals play a central role, with general hospitals alone covering 18.2 billion of healthcare expenses in 2017 [1]. Consistently growing costs have forced governments to cut healthcare budgets and find ways to make the system more efficient. An apparent option is to reduce inefficiencies in how demand for care is met, by reducing overcapacity and exploiting economies of scale where possible. In hospital beds, for instance, a report by KCE [2] found that a general overcapacity existed in Belgium in 2017, except in geriatrics and rehabilitation, for which a shortage was found. The authors expect these imbalances to continue to grow in the future. Additionally, the report recommends that healthcare authorities consider merging healthcare facilities or specific wards to meet cost and quality objectives.

Given the long-term nature of infrastructure capacity decisions, consequences of under or overdimensioning hospitals can be long-lived. Overcapacity leads hospitals to incur costs on underutilized resources, and shortages can harm patients due to delays in care or sub-optimal hospital accommodations.

Consequently, when a new hospital is built, or a renovation is considered, it is crucial that capacity is thoughtfully examined. Practically, that implies some challenges. Forecasting required bed capacity is challenging because of the extensive set of factors that influence demand. A large set of predictors reinforce or counteract one another, directly and indirectly, while few of them are known in advance. For example, ageing, combined with population growth might induce admission growth, while the elderly also stay in the hospital for longer periods of time. All the while, medical science is improving procedures, reducing the average stay length and moving some treatments from the inpatient hospital to daycare. In addition, epidemiological changes, such as declining obesity can impact the incidence of particular diagnosis. Aside from the complexity of interacting predictors, translating inpatient hospital day demand into a capacity decision is subject to its own difficulties, as described in the literature section.

Currently, Belgian practitioners involved in this research indicate that the primary sources of data to support bed capacity decisions are peer benchmarking tools and straightforward business intelligence dashboards. What analyses often lack is the impact of demographic evolution, epidemiological transitions, and governmental decisions. When studies are available that include those factors, they are usually national studies that exclude regional parameters that affect outcomes for specific hospitals differently than the average. Examples are market shares and the local demographic distribution.

The ProMoBed model (Projection Model for Bed capacity planning) supports hospital administrators in forecasting the future need for bed capacity in their hospital, taking into account and

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disentangling effects from a wide set of variables that affect it. It is a model that primarily addresses the need for insights into how longer-term changes impact bed capacity requirements, though it could be applied to explore potential capacity optimizations with immediate effect, for example, by merging bed capacity for complementary wards.

This paper describes how hospital stay data can be used to model future demand for hospital beds and to support bed count decisions, and illustrates it with an application to an anonymized example hospital. First, a review of the literature shows how modelling hospital activity has been tackled in other work and what can be learned from those research efforts with respect to the objectives of this paper. Second, the methodology is explained, along with the evidence that justifies it. Concretely, it contains a discussion of how admissions, the LoS (Length of Stay), seasonality, and relevant factors that impact model parameters are derived and used to achieve the output of the model. In addition, it is shown how the output can be used to obtain the results that hospital administrators require in order to make decisions.

2. Literature overview

As Pitt et al. explain [3], a diverse array of quantitative model types has been deployed to study health services in general, each of which suitable for analyses with particular objectives and challenges. An initial distinction is made between analytical models and numeric simulation models. Analytical models include techniques such as optimization [4,5], Queuing Theory [6,7], Markov modelling [8,9], and Data Envelopment Analysis [10]. Numeric simulation models include Discrete Event Simulation models [11–15], System Dynamics [16,17], or Agent-Based Simulation [18–20]. Analytical models are generally used to address problems that are mathematically well-defined; the structure of the problem needs to be clear enough in order to be modelled with the restrictive assumptions that this type of model requires [3]. Comparatively, simulation models are generally flexible.

It is relatively rare for studies to predict the need for bed capacity for the wards of an entire inpatient hospital. More common is research that covers a specific department, with emergency room studies as the most extensive branch. Cochran et al. [21] is one of the exceptions that tackled capacity estimates for an entire hospital. The author divided the hospital in four capacity-carrying units, and used a queueing model, with the average LoS and admission numbers per patient group as input. The model targets a specific occupancy level, as is common practice [22]. These methods have been criticized as being too simplistic and general [23], however. Furthermore, the daily admission arrival pattern does not take into account seasonal patterns or consider differences in arrival pattern types between pathologies. The work of Mallor et al. [24] partially addresses this issue by introducing empirical admission distributions for patient groups whose daily arrival pattern significantly differs from the Poisson distribution. The simulated patient day demand distribution significantly differs from the observed distribution, as shown by a Kolmogorov–Smirnov test, until a set of management decisions, such as discharging rules, are included in the model.

The Strategic Bed Analysis Model (StratBAM) [25] is a holistic model with some degree of operational detail. A high-level process flow, of patients transferring between departments and units, is constructed. Four primary units, according to the required level of care, are identified. As output, it includes patient wait times as well as occupancy information, such that cost and benefit trade-offs can be evaluated. Patients' pathologies are not modelled explicitly. Rather, transfer probabilities largely capture the relative volume of required care for patients, along with department-specific Length of Stay (LoS) figures. A crucial advantage of this methodology is that the effort required in different parts of the patient journey can be simulated. If a further distinction had been made according to the pathology of the patient, it is likely that the confidence in transfer probability estimates would have fallen below acceptable levels, except for particularly large facilities. Nonetheless, that also implies that pathology-related factors, such as growth in the prevalence of orthopedic surgeries due to an ageing population, cannot be explicitly taken into account. In other words, the authors leaned towards explicit operational representation in the trade-off between modelling pathology details and operational ones.

Harper and Shahani [26] developed a broadly applicable model to plan hospital capacity down to the specialism level. The authors closely examine the effects of variability of demand on bed capacity requirements, especially in the context of planned as opposed to unplanned admissions. Accordingly, daily and monthly seasonality patterns are included. The model strikes a balance between operational and strategic decision-support, allowing the user to apply aggregated trends on the data by adjusting input parameters at the specialism level.

This paper takes an approach to patient demand modelling that leans towards representing pathologies in relative detail, such that the origins of changes due to pathology prevalence can be modelled explicitly. It thus forgoes more detailed insights into effects of changing operational parameters, such as transfer rates between bed types, and it assumes local operational conditions that affect admission timing or stay duration, such as holiday periods or operating room planning schedules, to remain identical.

One study that does not model operational conditions at all is Van de Voorde et al. [2]. They focus on forecasting inpatient days per Diagnosis Related Group in Belgium by applying a trend analysis and by reweighting according to changes in age distributions and population growth or decline. Further, results of a set of scenarios, such as accelerated ageing or higher-than-expected substitution of inpatient by ambulatory care, are evaluated. Although the objectives of Van de Voorde et al. are to forecast on the national level and this study focuses on individual hospitals, a comparison of the forecasting results on the national level will be provided for benchmarking purposes (Section 4.3).

A lot of recent literature has focused on forecasting the short-term need for bed capacity and other healthcare resources related to the covid-19 pandemic [27,28]. This research distinguishes itself from that branch of the literature because it operates on a different timescale. Given predictions across various timescales, different types of context variables can or cannot reasonably be assumed to remain unchanged and have to be modelled explicitly. While short-term capacity models might focus on disease transmission and its immediate inhibitors and accelerants, requirements for this research are support for demographic shifts, epidemiological changes, and other factors that change more slowly over time.

3. Material and methods

The objectives of the ProMoBed model are to forecast future bed requirements, and to support hospital capacity planning decisions. In order to achieve these goals, the model must mimic the frequency distributions of demand levels, in terms of daily occupied beds, as reliably as possible. Additionally, it is required that pathology-related factors that affect admissions and the average LoS can be taken into consideration when constructing those frequency distributions. Subsequently, frequency distributions of inpatient bed demand per ward or specialism can inform refined bed capacity decisions based on desired service levels.

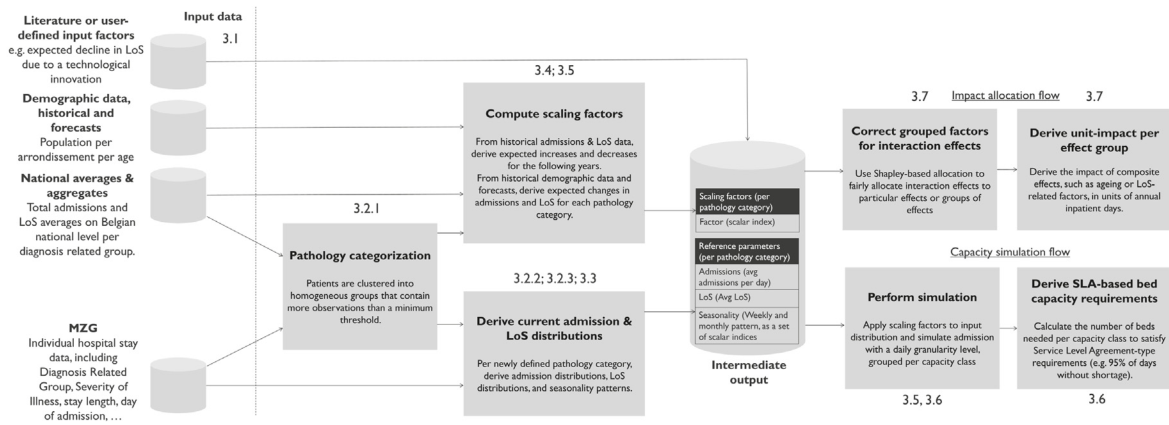

Fig. 1. ProMoBed model.

The ProMoBed model reproduces the expected demand pattern in a hospital given a particular set of input parameters. Additionally, in order to better support decision making, it allocates changes in total inpatient day demand compared to the status quo to different causes, such as demographic redistribution. The latter allocations are primarily based on the same input parameters as the hospital bed demand pattern, but are processed separately. Fig. 1 shows this distinction. The upper right part of the figure shows the part of the process that leads to the calculation of the allocations of demand differences, while the lower part of the figure is dedicated to the simulation of the daily inpatient bed demand pattern.

In order to characterize the evolution of the number of admissions and the LoS, two categories of factors are distinguished: those showing general trends applicable nationwide, and those capturing environmental conditions that are hospital-specific. The first category contains trends derived from historical data on the national level (3.7) and epidemiological and other forecasts based on literature research. The second one contains effects due to changes in demography or market share (3.6) and optionally, factors that depict scenarios in which administrators are interested, such as the implementation of new technology.

In the following sections, the components of the model are elaborated on. First, the data and cases used in the context of this paper is described (3.1). Subsequently, the representation of admission patterns in the model is discussed (3.2), followed by the Length of Stay implementation (3.3). A set of factors that capture change over time of the core parameters, admissions and LoS, are endogenous to the model. Concretely, these are the impact of changes in demographics and market shares. The computation method for the relevant factors is elaborated on in Section 3.4. Additionally, the methodology applied to derive trend-related factors is discussed in Section 3.5.

What follows in Section 3.6 is a discussion of how capacity requirements are derived from raw simulation output. Lastly, the allocation method that attributes inpatient day demand changes to various causes is described.

3.1. Application and input data

The ProMoBed model itself is generic, and could ingest pathology data from different types of sources. In this research, it is applied to Minimal Hospital Data (MZG), a data standard compulsory for Belgian hospitals [29] which contains pathology and stay duration information. Though the model has been applied to diverse hospitals in Belgium, the output described in this paper is anonymized to protect sensitive hospital and patient information. Concretely, a random subselection of MZG stays was sampled from a set of hospitals and aggregated to form a new dataset, from which the analyses in this paper are derived. Nonetheless, each methodological step and test in this paper has been replicated with data from individual hospitals, exhibiting consistent results in terms of occupancy distribution accuracy.

Aside from MZG data, the results in this paper rely on regional demographic forecasts by the Federal Planning Bureau [30] and national pathology data from the Federal Public Service of health, food chain, and environment [31]. The latter contains the relative prevalence of and average LoS for pathologies in Belgian regions on the arrondissement level and among age cohorts.

3.2. Admissions

3.2.1. Pathology categorization

Admission numbers are derived from the amount of observed admissions with a particular pathology in a given reference year. In order to ensure accurate estimates of admission numbers, pathologies for which few patients are admitted are grouped together. Assuming that admissions are Poisson distributed, more than 170 observations must correspond with a pathology group in order to estimate the admission figure with 95% confidence within confidence bounds of 15%, as in $\hat{\lambda} \pm 1.96\sqrt{\hat{\lambda}/n}$. This minimum is applied throughout the paper. Pathologies are grouped together based on the characteristics that they have in common and within a specialism. Pathologies with a similar LoS, severity of illness, and historical evolution of the national amount of admissions and LoS are clustered through a hierarchical clustering method [32]. The resulting groups of pathologies are referred to as *pathology categories*.

3.2.2. Planned and unplanned admissions

In the model, patients are assumed homogeneous per pathology category, meaning that admissions and the LoS are sampled from common probability distributions. Nonetheless, other options were considered. As discussed by [26], considerable differences in the admission patterns between planned and unplanned hospitalizations can be observed. It is expected that planned admissions show less variability than unplanned admissions, given the operational incentive to spread out workloads. Therefore, a set of different admission modelling methods were considered.

Method A proposes that the admission pattern, defined as the number of patients per day, follows a Poisson distribution, regardless of whether admissions are planned or unplanned. Method B considers that unplanned admissions reflect a Poisson process, while an empirical frequency distribution is used to model planned admissions. Both are probability distributions of

Table 1
Arrival modelling method accuracy comparison on CHI-square test (95%). 49 categories are tested.

Method	Description	Pass rate
A	Poisson	38.9%
B	Hybrid: Poisson and empirical	5.6%
C	Seasonality-adjusted Poisson	77.6%

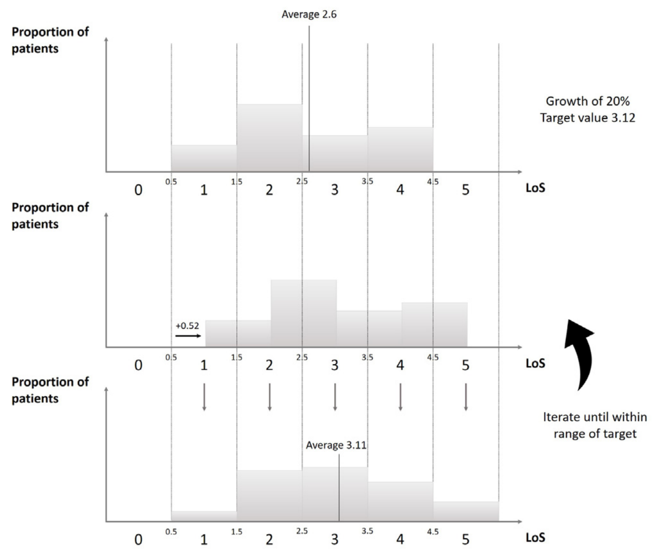

Fig. 2. LoS empirical distribution scaling.

the number of patients per day. Alternatively, method C presumes all admissions follow a Poisson distribution corrected for seasonality patterns. This means the probability distribution of daily admissions is also a function of the day of the month, and the day of the week. Method C assumes that operational conditions, such as personnel and operating quarter availability on weekdays, significantly affect admission rates, especially for planned admissions. Its performance is discussed here in comparison with other methods. A more detailed description of the mechanism is found in Section 3.2.3.

A CHI-square test is used to evaluate the quality of the different methods [33]. The observed arrival pattern in a reference year is compared to the expected distribution used in the different methods. For methods B and C, a large number of simulations is performed to accurately estimate the frequency distribution. Table 1 shows that method C outperforms the other methods, and yields results that are statistically indistinguishable from the observed pattern 77.6% percent of the time on the test data, with 95% confidence.

3.2.3. *Seasonality*

As described in Section 3.2.2, seasonality patterns are included in the best performing admission generating process. Concretely, a regression model derives the coefficients that determine seasonality effects. The effects are calculated on the pathology category level as modelled below:

$$\mathrm{AdmissionsOnDay_i} = \hat{\alpha} + \sum_{\mathrm{d}=1}^{6} \hat{\beta}_{\mathrm{d}} \times \mathrm{isDayOfWeek_{di}} + \sum_{\mathrm{m}=1}^{11} \hat{\beta}_{\mathrm{m}} \times \mathrm{isMonthOfYear_{mi}} + \hat{\varepsilon}_{\mathrm{i}}$$

Thus, admission estimates are made per day, taking into account the day of the week and month. Still, the ProMoBed model includes the possibility to apply multiplication factors to admission numbers. In order to achieve this, the model stores the coefficients in a standardized way. First the coefficients are transformed such that the results are relative to the average instead of the intercept by adding *intercept* − *average* to all DayOfWeek coefficients, and by adding a coefficient for Mondays that equals *intercept* − *average*. Subsequently, the coefficients are divided by the average. When the model uses the coefficients, they are multiplied by the applicable overall daily average admission rate. The result is a scaled seasonality pattern.

3.3. *Length of stay*

Mallor and Azcárate [24] observe that common distributions, such as lognormal, Weibul, or Gamma distributions, used to model the LoS, are often not suitable. The authors addressed this issue by developing non-normal regression models. For this work, the required variables to build such regression models were not available. The lack of fit to the usual fat-tailed distributions is confirmed in this work. Using the Scipy Python package, LoS samples per pathology category were fitted to Weibull, Lognormal, and Gamma distributions. Only the lognormal fitted distributions were sufficiently credible to pursue. Even then, only 5.9% of the fitted distributions passed a CHI-square test. That is why empirical frequency distributions are used in this work.

In order to scale the empirical frequency distributions accordingly with the applicable factors, a scaling heuristic is developed. Its objective is to conserve the shape of the frequency distribution as much as possible, while ensuring that the resulting average LoS is achieved with high accuracy. Fig. 2 illustrates the developed process and algorithm 1 shows related pseudocode. The observed frequency distribution is discrete with a granularity of days. The assumption is made that these distributions behave as concatenated uniform distributions between *days* ± 0.5. In order to scale the distribution, it is transformed horizontally with a constant, the difference between the target average, and the original average. The average of the transformed distribution is then re-evaluated and the procedure, with the same target average is repeated until the resulting distribution's average is within 1×10^{-5} of the target.

Algorithm 1: LoS Scaling algorithm

Input: Original volume distribution V = Array with volumes for each stay length, where the stay length corresponds with the index
Input: Displacement factor d = number by which the distribution needs to be transformed
Input: New frequencies F = zero-filled array
Input: New bin limits $L = [(i - 0.5) + d$ for i in *range*(*length*(V))]

foreach *for i in range(length(L))* **do**
  $mlb = L[i]$
  $mub = L[i+1]$
  $v = V[i]$
  foreach *for j in range(round(mlb),round(mub)+1):* **do**
    $lb = j - 0.5$
    $ub = j + 0.5$
    $L[j] += (min(mub, ub) - max(mlb, lb))/(ub - lb) * v$

Output: V = scaled volume distribution
Repeat: Repeat until difference of average LoS of V and target is $< 1e^{-6}$

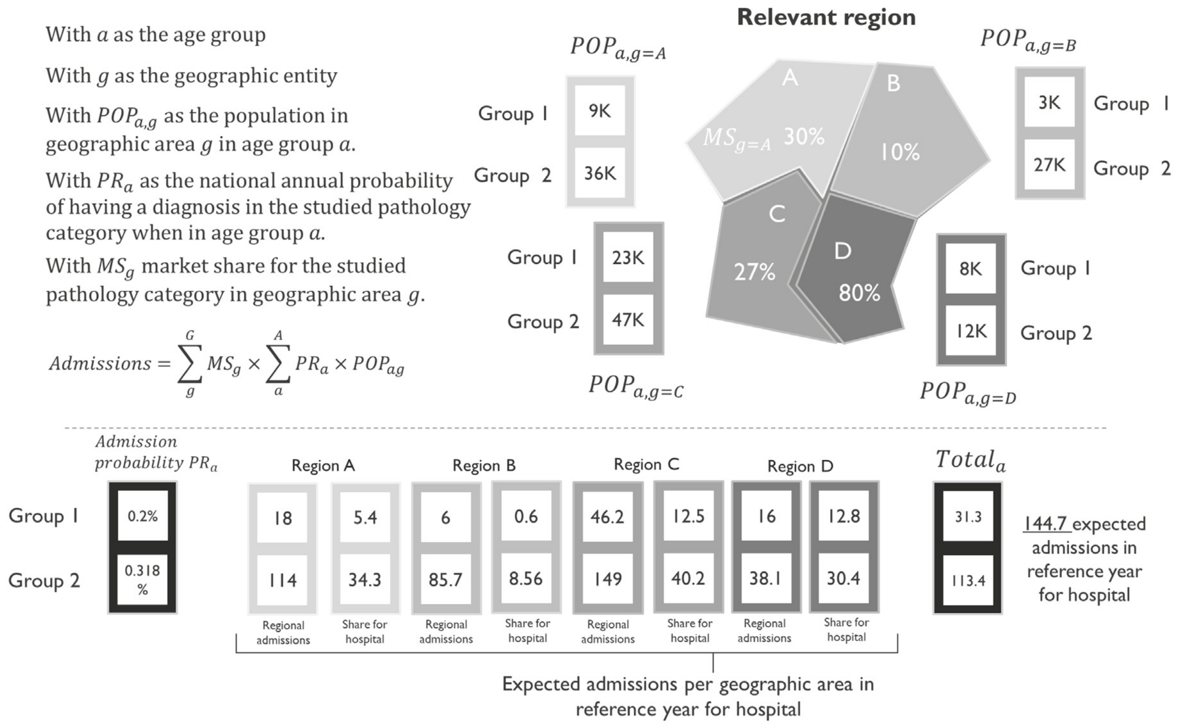

Fig. 3. Illustration of derivation market share and demographic impact.

3.4. Impact of demographic and market share evolution

An important driver of inpatient day demand evolution is demographic change. In many countries, ageing impacts demand for healthcare resources through a higher prevalence of many pathologies, and the longer average LoS required in treatment. The ProMoBed model estimates the impact of demographic evolution on admissions and LoS. Since the model targets individual hospitals rather than the entire health system, it takes into account local demography, insofar as the considered hospital's patient population is localized. Concretely, market shares in different geographic regions per pathology category are derived by taking together hospital and regional admissions data. Market shares in different geographic areas are not known per age group and therefore assumed to be identical across age groups. Consequently, the combination of market shares in different regional populations is taken to reflect the demographic profile of a hospital's constituency. In other words, a demographic profile weighted according to market shares is used, rather than the demographic profile of the region a hospital is based in. Thus, the impact of demographic evolution is entwined with that of a hospital's market shares in different regions. Fig. 3 illustrates the process of deriving expected admissions given a particular demographic context, which forms the basis for the derivation of demographic impact factors. In essence, a proportional system is used, in which national admission probabilities per age group and the LoS per age group are assumed to be constant locally and over time. Expected admissions and average LoS are calculated for the current demographic context, and subsequently for the projected demographic context. The fraction of future and current expected admissions is the demographic impact factor applied in the model. Optionally, projections of shifting market shares are included in these calculations. Importantly, the assumption that admission probability is constant over time is only used here to isolate the studied effects. Other model components (3.7) account for shifting admission probabilities and LoS evolutions over time not related to demography. The calculation of LoS factors requires an additional step as compared to the admission factors because the average LoS is weighted according to the expected admissions. By themselves, these calculations yield some interesting insights, as discussed in the results section.

3.5. Historical extrapolation

Historical extrapolations are performed on timeseries data from the Belgian Technical Cell for hospital data [34] extending from 1997 until 2017. The data is aggregated according to pathology category on the national level and corrected for demographic changes matching the methodology in the previous section.

Some issues exist with the input data. While admissions are identified by APR-DRG-code [35] and severity of illness, the APR-DRG classification system has been modified several times since 1997, leading to an inconsistent time series for some pathologies. The pathology categories for which these changes are relevant are modelled differently than others.

The standard modelling method is as follows: for admissions, a linear trend is assumed, and a maximum of two dummy variables, covering the changes in APR-DRG grouper version, are included in an OLS regression model. If a CHOW-test with 2012 as assumed transition point indicates that a structural change in the series exists, only data from after 2012 is used in the OLS regression. If the trend coefficient is significant, the trend is used. Otherwise, a constant admission rate is assumed. Additionally, if the fit of the model to the data for specific pathologies is unsatisfactory, a stable admission rate is assumed. For the average Length of Stay, OLS regression models assuming a linear and a logarithmic trend are compared. For 88% of pathology categories, the model with the logarithmic trend has a higher adjusted R-squared. Consequently, a logarithmic trend is taken to represent the average LoS timeseries well, and applied for all pathology categories.

3.6. Simulation and capacity recommendations

In order to support the determination of capacity needs, clarification is required of which resource constraints are relevant

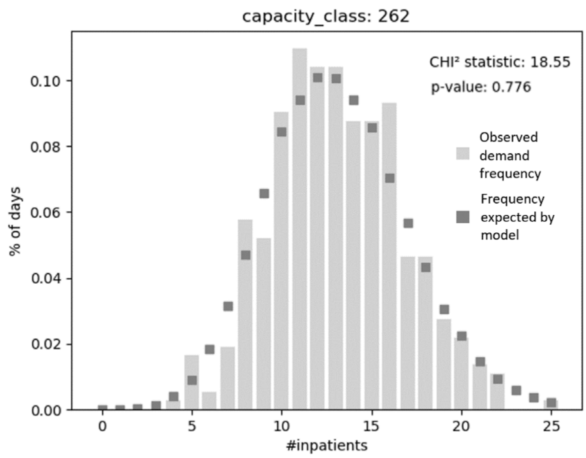

Fig. 4. Frequency distribution for capacity class 262.

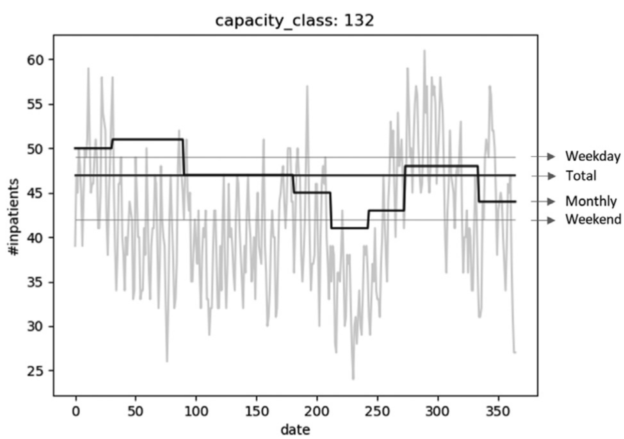

Fig. 5. Illustration capacity suggestions based on a service level of 80%.

in the considered hospital. The ProMoBed model enables the flexible mapping of pathology categories with what the authors dubbed *capacity classes*. Capacity classes are groups of pathology categories that access the same resource pool, primarily beds. Thus, a hospital can regroup pathologies according to the layout of a ward, or the resource that is examined.

A numeric rather than analytical approach is taken since existing analytical methods do not support the seasonality-adjusted Poisson admission process that this research, in Section 3.2.2, found to outperform a standard Poisson process.

The simulation process, corresponding to the bottom flow in Fig. 1, contains the following steps:

1. Collect input
   - Admission distributions $year_{ref}$
   - LoS distributions $year_{ref}$
   - Relevant impact factors $year_{sim}$
2. Preprocess
   - Scale admission distributions
   - Scale LoS distributions
   - Scale seasonality pattern
3. Simulate
   - Stochastically create demand pattern using seasonality, admission, and LoS distributions per capacity class.
4. Analyse
   - Construct demand frequency distribution from output
   - Derive decision support metrics.

In step 1, the required data, current admission distributions, LoS distributions, and relevant impact factors are fetched.

In step 2, preprocess, factors are applied to admission and LoS distributions of pathology categories with the information collected in step 1. Endogenously, the factors include those representing historical trends in admission numbers and LoS per pathology category, and demographic changes. Additional factors capturing expected or induced evolutions, such as the implementation of a LoS-reducing novel process or anticipating on short-term trends, are included at this stage.

Step 3 starts with the application of the seasonality pattern to the simulated year, resulting in an average number of admissions for each day of the simulated year for a pathology category. Subsequently, each day of the year is iterated over, using the encountered average values to initialize a Poisson distribution which is sampled to represent the effective simulated admission number. For each admission, the relevant empirical distribution is sampled to assign a LoS to each admission. The resulting pattern on inpatient days for each pathology category is combined within the relevant capacity classes, such that one stream of demand per capacity class is created. This process is repeated hundreds of times in order to be able to estimate the desired metrics of the model accurately.

In step 4, the inpatient bed demand frequency distribution is derived from the stochastically created demand pattern (refer to D in overview figure). Additionally, other derived metrics are calculated, such as the capacity required to achieve a particular service level. A set of filtered service level recommendations yields support for different policy questions. Here, the service level refers to the percentage of days on which there is sufficient capacity to fulfil demand.

Fig. 4 shows the demand frequency distribution resulting from step 4 for capacity class 262. Fig. 5 illustrates the results for a target year of capacity class 132. In order to offer a service level of 80%, it requires a capacity of 47 beds. Nonetheless, if capacity can be set more flexibly, capacity needs can be determined for more granular timeframes. For instance, a capacity level can be set for each month, or a different capacity can be set for weekends as opposed to weekdays.

3.7. Impact allocation

In the ProMoBed simulation model, many different *impact factors* can interact and compound each other, collectively affecting demand outcomes. In order to reduce the opacity of the model, the allocation analysis derives the causes of growth or decrease in inpatient day demand from the primary input (refer to C in overview figure). Concretely, the differences in demand are allocated to particular factors and groups of factors across types, pathology categories, capacity classes, or fields. The changes in average inpatient day demand are entirely driven by factors that impact the underlying parameters of LoS or admissions. Interaction effects between factors are allocated using the Shapley value principle [36], a fair allocation method used to divide common costs or benefits when causes are ambiguous.

Since the ProMoBed model supports strategic decision making, results are often aggregations of many underlying influences and factors. The allocation should enable decision-makers to review the causes of aggregated outcomes in a manner that is staged, deepening complexity and detail as more insight is required. In order to enable this type of drill-down analysis, input to the

Table 2
Optional input attributes for impact allocations.

Attributes	Attribute enumerations
Factor id	Unique id of impact factor
Field	Demography&Marketshare; Historical extrapolation; literature research
Type	Admission; LoS
Pathology category	Unique id of pathology category

allocation model determines the granularity of the output. Concretely, the attributes along which demand differences should be allocated are chosen by the user. The options are shown in Table 2. Concretely, the algorithm groups all impacts factors that share the values of the given attributes. For instance, if only the attribute *field* is submitted, the algorithm will yield the demand difference allocations to the three different fields, relating how much is due to demography and market share evolutions, how much is due to historical trends, and how much is due to factors added based on literature research. Alternatively, if the attribute *type* is also added as input, then the algorithm would yield six outputs, for each combination of the values of the attributes *field* and *type*. Thus, a decision-maker would not only be able to identify whether growth is due to demographic changes, but whether that effect is counteracted by the historical decline in the average LoS.

The algorithm calculates the allocated impact according to the following steps:

1. Group all factors f_{ipj} according to the input attribute values, but separated per pathology category, and take the product of each group. With i as a unique input attribute value combination, p as a pathology category, and j as a unique identifier for the factor.

$$\mathrm{f_{ip}} = \prod_{\mathrm{j}}^{\mathrm{J}} \mathrm{f_{ipj}} \quad \forall \mathrm{i} \in \mathrm{I}, \forall \mathrm{p} \in \mathrm{P}$$

2. Calculate the share of the total growth or decline in inpatient day demand that is allocated to each group using the Shapley value.

   A Construct sets $\mathrm{G_p}$ that contain all $\mathrm{f_{ip}}$.
   B Let set D_{ip} be the increment set for f_{ip}
   C For each permutation of $\mathrm{G_p}$:
   Set $value = 1$
   Iterate over each i
   $\mathrm{increment_{ip}} = \mathrm{value} - \mathrm{value} \times \mathrm{f_{ip}}$
   $value = value \times f_{ip}$
   Append $\mathrm{increment_{ip}}$ to $\mathrm{D_{ip}}$

3. Calculate difference in inpatient day demand δ_{ip} per grouped factor f_{ip}

$$\delta_{\mathrm{ip}} = \mathrm{Admissions_p} \times \mathrm{LoS_p} \times \mathrm{AVG}(\mathrm{D_{ip}})$$
$$\forall \mathrm{i} \in \mathrm{I}, \forall \mathrm{p} \in \mathrm{P}$$

4. If the grouping attributes excluded the pathology category option, then sum the inpatient day demand differences for the different groups over the relevant pathology categories.

$$\delta_i = \sum_{\mathrm{p}}^{\mathrm{P}} \delta_{\mathrm{ip}} \quad \forall \mathrm{i} \in \mathrm{I}$$

Thus, the allocated impact on demand is expressed in inpatient days. Allocation can be performed within a capacity class, or across capacity classes for the entire inpatient hospital. Fig. 6 shows an example of allocation results for different input attributes. Tile (a) results when only *type* is given as an attribute, while tile (d) shows a more granular subdivision of the effects based on attributes *type*, *field*, and *pathology category*.

4. Results

In this results section, the reliability of the model is discussed first. Subsequently, its results are compared to other, publicly available studies. Finally, results concerning the substance of long-term inpatient day demand evolution are discussed.

4.1. Model reliability

The accuracy of bed capacity decisions is partially based on the truthful representation of the required beds frequency distribution. Accordingly, in order to evaluate the accuracy of this model, a comparison could be made of the frequency distribution of required beds that is generated by the model without projecting to a future date and the one that is observed in contemporary data. This can be problematic however, since capacity itself affects the Length of Stay through managerial actions taken by hospital administrators. Mallor and Azcárate [24] discuss this phenomenon and improve their own base model by introducing mechanisms that mimic management decisions, impacting the LoS distribution. Since this model is meant to be used to set capacity, it does not make sense to work analogously, and to attempt to improve the similarity between the generated and observed distribution by taking into account management decisions that are driven by capacity shortages or surpluses.

Applying a CHI-square test to compare the simulated frequency distribution of required beds with the one observed in the data, 63.2% of the 38 capacity classes are statistically indistinguishable on the 95% confidence level. Given the aforementioned expected differences, the metric should not be interpreted as a straightforward measurement of performance. An alternative approach is to evaluate the components of the required bed capacity distribution that are not affected by the managerial action issue. Since managerial actions act on the LoS distribution, that leaves the admission distribution component. As described in Sections 3.2.2 and 3.3, the methodology to generate admissions was chosen based on performance. Concretely, generated arrival frequency distributions per pathology category are statistically indistinguishable from observed ones 77.6% of the time on the 95% confidence level. Since insufficient historical data is available, it is not possible to evaluate the model's forward projections.

4.2. Application randomized hospital

As described in the methodology section, the model is applied to a fictional hospital containing a randomized subset of hospital stays from 5 different hospitals. As shown in Fig. 7, the total inpatient day demand in the hospital is expected to remain stable, though the isolated effects demographics and trends derived from historical data could significantly affect its trajectory. The curves show the aggregated effect of the impact allocated to one particular cause added to the total amount of inpatient days in 2017.

While in aggregate, the demand for inpatient days is expected to remain relatively stable, specific, individual specialisms are expected to grow or shrink significantly.

In terms of required bed capacity, a service level approach can be applied since the concrete daily required bed pattern is generated. The service level could be defined as the proportion of days on which a shortage is tolerated, or the relative number

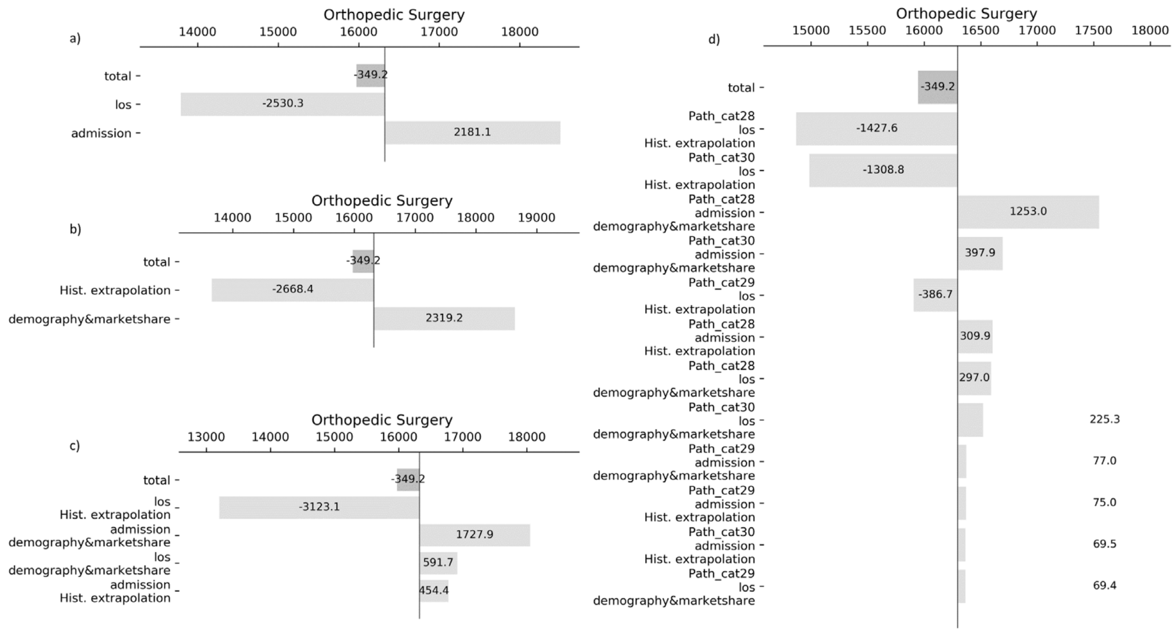

Fig. 6. Results of impact allocations applied to orthopedic surgery. The figures show the allocated delta in expected inpatient admissions in 2025 versus 2017. From (a) to (d), allocation is done more granularly. From allocation to changes in LoS or admissions (a), to allocations to changes related to a combination of field, type, and pathology category, e.g. demographics impacting the LoS of a particular pathology that results in more or fewer inpatient days for the capacity class (d).

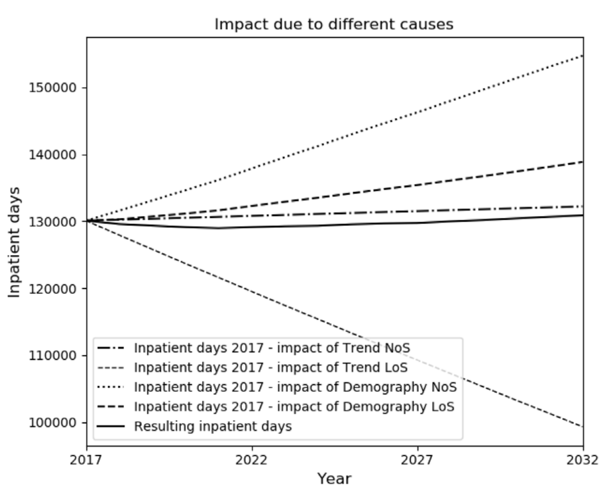

Fig. 7. Shows hospital-wide inpatient day evolution exclusively allocated to one source. A relatively stable inpatient days evolution is the result of other effects compensating each other: primarily a steep rise in admissions (NoS) due to demographic changes, and significant decline in average LoS.

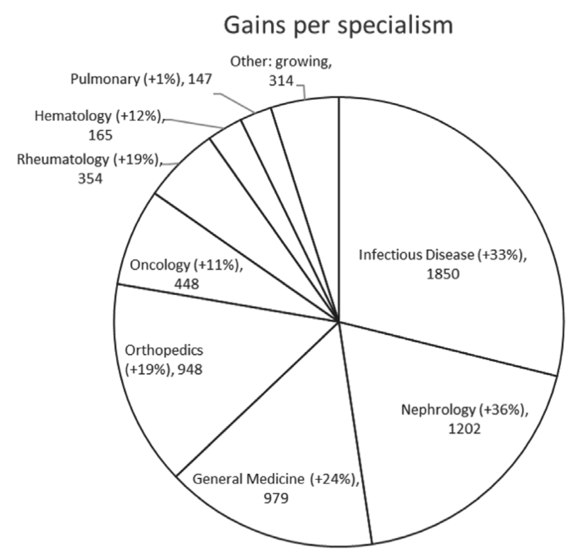

Fig. 8. Sources of inpatient day growth by 2027 for test hospital.

of inpatient days for which capacity unavailability is tolerated. Aside from setting a service level-based capacity, optimizations of which wards or specialities should share capacity can be based on the care pattern analysis. Different capacity classes can be merged virtually and a lower safety capacity, i.e. capacity on top of what is required on average, could be achieved by merging capacity classes with more complementary demand patterns.

Fig. 6 zooms in on a particular capacity class, which corresponds to Orthopedic Surgery. It shows to which causes the difference in demand, in terms of inpatient days, can be allocated. The graphs in the figure contain the results for different combinations of impact factor attributes *type*, *field*, and *pathology category*. In (a), (b), (c), and (d), factor impact is grouped according to *type*; *field*; *type* and *field*; and *type*, *field*, and *pathology category* respectively. This dissection allows administrators to trace and critically assess the origins of particular growth or decline estimates.

Figs. 8 and 9 illustrates the type of output that the model generates by showing in which specialisms the largest gains and declines are expected for the test hospital.

4.3. Application: Belgian regional differences

The extrapolation and inpatient day demand impact allocation part of the model, as represented by the top lane in Fig. 1, can be also applied to entire regions. In that case, regional admission figures and national average LoS numbers are extrapolated according to national trends and corrected for local demographic conditions. Consequently, divergence in results between regions is due to demographics and the relative prevalence of different pathologies.

Fig. 10 shows how expected growth or declines are distributed across the Belgian regions on the administrative arrondissement

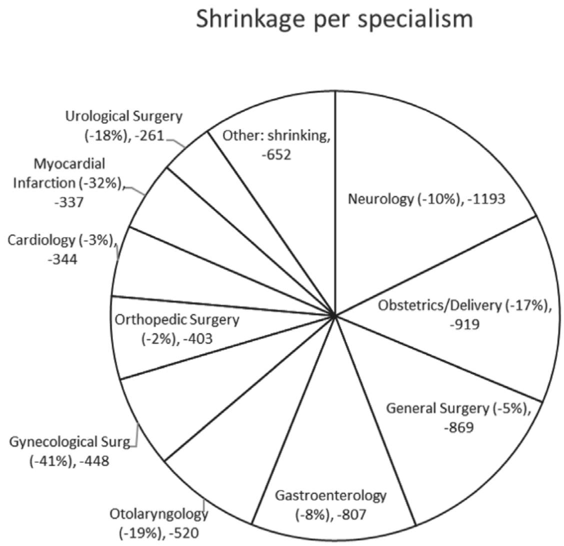

Fig. 9. Sources of inpatient day declines by 2027 for test hospital.

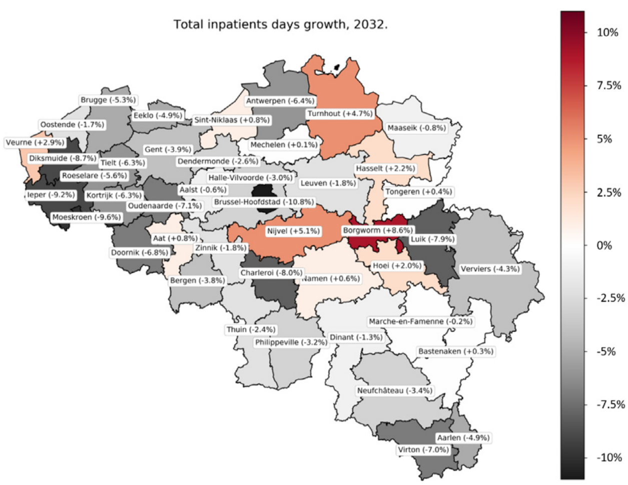

Fig. 10. Aggregated expected inpatient day growth per arrondissement by 2032 as compared to 2017.

level, which are identified by the two most significant digits of the NSI code [37]. The largest increase by 2032 is expected to occur in Borgworm, 8.6%, the largest decline by 2032 is expected in the Brussels capital region, −10.8%. Additionally, Figs. 11 and 12 show the difference in inpatient days expected in 2027 as compared to 2017, per arrondissement and per capacity class. The results are dissected and allocated to different causes.

These results show that a decline in inpatient days is expected in most of the country. In those arrondissements where growth is expected, the effects of an ageing population on inpatient days is stronger than those in others. The decline in average LoS trend is consistently responsible for a decline in inpatient days by 2027 of approximately 14% in most arrondissements. As expected, declines in average LoS are observed in almost all specialisms, with exceptions where it remains constant. Nationally, the effects of ageing and population growth inflate the number of inpatient days for all specialisms, including those that typically treat younger people, such as obstetrics and neonatology. In some specific arrondissements, however, the local effect is a reduction in inpatient days, as shown in Fig. 13.

These results aggregated on the national level are largely in line with the results found in the 2017 study by Van de Voorde et al. [2]. The work cites an overall decrease in inpatient days of −5.4% for the period of 2014 to 2025, consisting of a growth in admissions of 11.8% and average LoS decreases of between 10 and 20%. For the period of 2017 to 2028, the ProMoBed model forecasts overall decrease of −3.4%, consisting of the following components: −0.5% due to the admission rate trend, −15.7% due to the trend in the LoS, +9.3% due to the demographic effect on admissions, and +3.53% due to the demographic effect on the average LoS.

5. Conclusion

The ProMoBed model does not address all challenges concerning hospital capacity predictions, but it innovates in ways that help the authors achieve long-term bed capacity planning objectives. It provides a pathology-driven method to forecast inpatient days and the need for bed capacity that is adaptable to the context of individual hospitals. By focusing on pathology rather than operational details, pathology-specific predictions and hospital layout can be taken into account. It furthermore offers considerable transparency as a rule, without which it might be perceived as a black box. These attributes, pathology-driven, flexible, and transparent, capture the primary contribution of this methodology to the literature.

In feedback sessions, hospital administrators confirm their interest in capacity forecasts. The transparency provided by contextual information, such as the impact allocation and regional comparisons, offers an added value. Shortcomings that are expressed include the policy-driven nature of inpatient demand. Governments consider adopting hospital financing schemes that can thoroughly affect the expressed number of inpatient days. Additionally, experts contend that additional technological progress should be more explicitly taken into account, which was not part of the current phase of the research project. Although the model for the most part does not endogenously account for these trends, it is well-equipped to adopt exogenous input figures that quantify them. Lastly, physical units of beds do not generally mirror specialisms, except in large hospitals. Capacity classes in the model should be defined in a way that reflects the physical units that are present in a hospital, which is not a trivial task.

6. Future work

Several avenues for improvement to the model exist. First, the accuracy of the current output could be improved by increasing the confidence in estimates of the current admission amount per pathology. Concretely, multiple years of data could be used to compute that figure. Additionally, multiple scenarios depicting potential policy interventions could be studied. An evident example is moving treatments from inpatient hospitals to daycare facilities. The impact of that shift could be made explicit, and outpatient clinics themselves could similarly be modelled. The latter is planned within the scope of the ProMoBed project.

Further, the mapping between patients and treatment units could be refined. In the context of this application, predefined bed indexes could be used for that purpose. This expansion is also planned as future work.

Given the current convention of using occupancy rates to translate the number of inpatient days to capacity requirements, it would be interesting to analyse the current practical service levels offered in hospitals and especially the difference between them in different facilities. A related inquiry could quantify the consequences of capacity deficits or surpluses by unravelling the relationship between occupancy and the Length of Stay in different types of wards or units, as has been applied in emergency rooms [38].

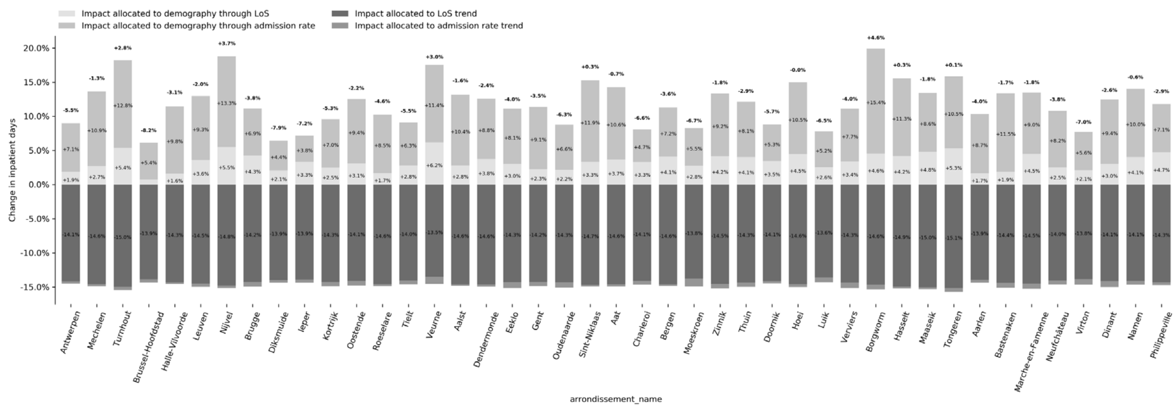

Fig. 11. Aggregated change in inpatient days per arrondissement in 2027 as compared to 2017. The figure shows the impact on inpatient days allocated to 4 categories of impact sources. The expected net impact for the arrondissement is indicated above the bars.

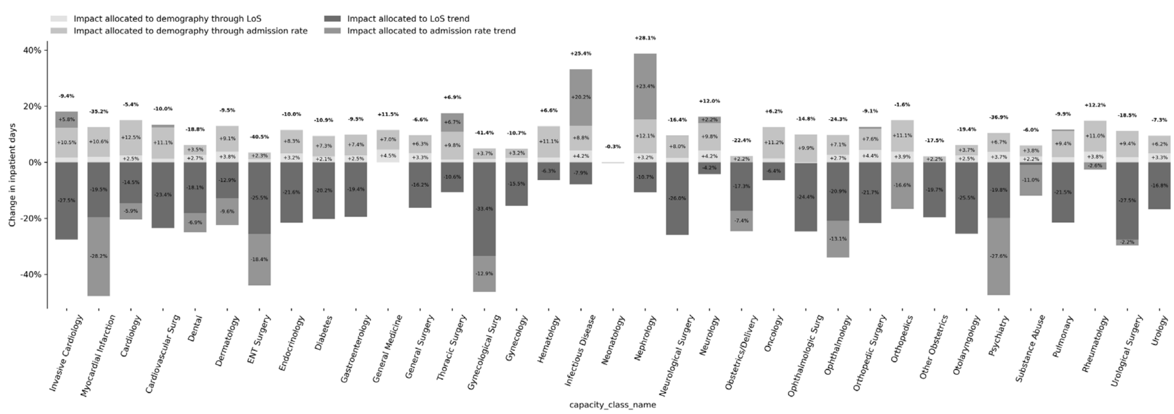

Fig. 12. Aggregated change in inpatient days per capacity class in 2027 as compared to 2017. The figure shows the impact on inpatient days allocated to 4 categories of impact sources. The expected net impact for the capacity class is indicated above the bars.

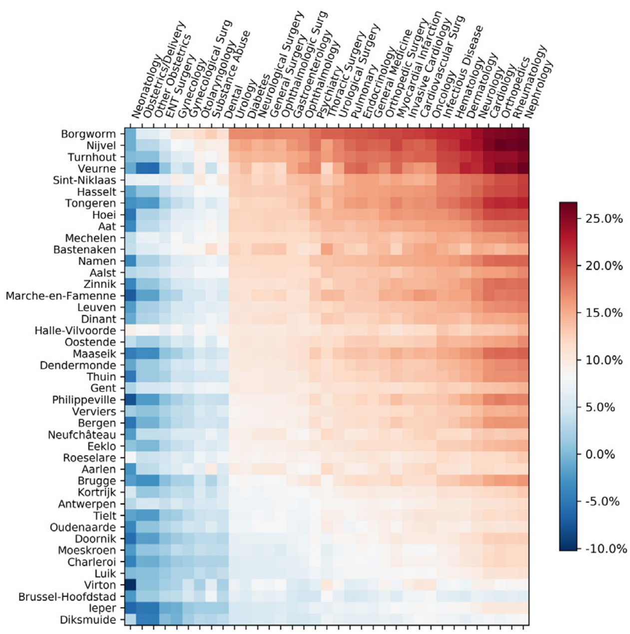

Fig. 13. Isolated impact of demographic changes on inpatient days per arrondissement and specialism in 2027 as compared to 2017.

CRediT authorship contribution statement

Timo Latruwe: Conceptualization, Methodology, Software. **Marlies Van der Wee:** Supervision. **Pieter Vanleenhove:** Conceptualization, Validation. **Joke Devriese:** Methodology. **Sofie Verbrugge:** Supervision, Writing – review & editing. **Didier Colle:** Supervision, Writing – review & editing.

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.

Data availability

The authors do not have permission to share data.

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