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E-HOSPITAL – A Digital Workbench for Hospital Operations and Services Planning Using Information Technology and Algebraic Languages

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Abstract

In this paper, we describe the development of a unified framework and a digital workbench for the strategic, tactical and operational hospital management plan driven by information technology and analytics. The workbench can be used not only by multiple stakeholders in the healthcare delivery setting, but also for pedagogical purposes on topics such as healthcare analytics, services management, and information systems. This tool combines the three classical hierarchical decision-making levels in one integrated environment. At each level, several decision problems can be chosen. Extensions of mathematical models from the literature are presented and incorporated into the digital platform. In a case study using real-world data, we demonstrate how we used the workbench to inform strategic capacity planning decisions in a multi-hospital, multi-stakeholder setting in the United Kingdom.

Keywords:

Models, Theoretical; Decision Making; Hospital Administration

Introduction

The rapidly growing patient population worldwide and the increasing demand for high-quality healthcare services are imposing severe capital, resource and human capacity constraints on hospitals. For example, one in every five Medicare beneficiaries in the United States is hospitalized at least once or multiple times per year. On the supply-side, almost 5,000 inpatient, acute-care hospitals exist nationwide that treat these beneficiaries. Of the approximately $300 billion dollars spent on the Medicare program per year, almost $100 billion is spent on inpatient services [1].

Given limited budgets, hospitals seek to treat patients efficiently and effectively in order to stay profitable. Adapting inpatient services that aim to improve the planning of hospital-wide workflows using information technology (IT), operations management (OM), and advanced data analytics (DA) techniques are some of the recent developments that we observe in healthcare delivery [13, 15, 16, 28, 29].

In this paper, we demonstrate this convergence by proposing a unified digital workbench to help multiple stakeholders to improve the planning and allocation of scarce hospital resources to improve transparency and efficiency of inpatient services. Additionally, we demonstrate the feasibility of the proposed workbench by applying it to capacity planning decisions at a multi-hospital site using a preliminary prototype implementation.

Hierarchical Modelling of Organizational Decision Making

We draw on the classical hierarchical management decision levels [2] to delineate different stakeholders' objectives for a using our workbench at each decision-making level. A framework to break down business decisions into strategic, tactical and operational decision levels are illustrated in Figure 1 [2]. Its essential aim was to assess the environment of an organization and to adjust internal resources accordingly [11]. The model is depicted by the regular triangle shown in Figure 1.

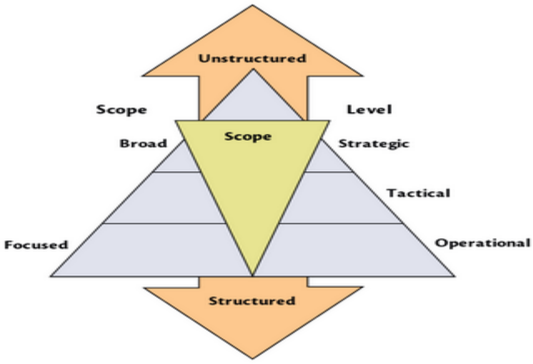

Figure 1 – Hierarchical Decision Levels [2]

The figure reveals that the strategic decision level covers a broad scope of unstructured problems while operational level decisions are more focused and structured. This is a clear approach to show how healthcare management decisions can be organized. When strategic decisions are performed, decision makers focus on, for example, patient groups, rather than an individual patient which is the focus of operational scheduling decisions. Despite its development more than 50 years ago, the framework presented in [2] is still widely accepted in decision support systems (DSS) research, as demonstrated in [3]. By breaking down DSS research literature into the classical hierarchies, their work reveals that the majority of business problems in DSS design science research have focused on the operational level. In contrast, our E-HOSPITAL workbench combines all levels in one digital platform.

Stakeholders in the Decision-Making

Figure 2 provides an overview of different stakeholders and their objectives, aiming to understand inefficiencies in hospitals, improve resource utilization, or to maximize profit.

We embed multiple mathematical models and its solution approaches from the literature to support these objectives in an integrated decision-making environment. End users such as hospital administrators, healthcare analytics specialists and other decision makers can use the proposed workbench to demonstrate/explore how mathematical models can improve resource planning and allocation decisions in hospitals. Furthermore, we illustrate the use of the workbench in a Continuous Improvement Unit (CIU) of a health board, described as a case study later in this paper.

	Stakeholder		
Decision making level	Board of Directors of Care Providers	Nursing/ Operating Room Manager	End Users such as Healthcare Analytics Researchers, Faculties, Members of Continuous Improvement Units
Strategic	Resource planning decisions	Staffing decisions	Demonstration of planning problems on all decision-making levels, teaching operational excellence for members of staff in the health service
Tactical	Identification of bottlenecks in shift or other tactical planning decisions	Shift scheduling	
Operational	Identifying which elective patients may be responsible for increasing or decreasing profit margins for day-by-day planning	Appointment scheduling	

Figure 2 – Stakeholders on Each Decision-Making Level

Related Work on Decision Support Tools

An early review of evaluation studies of clinical decision support tools in medical informatics was performed by Kaplan [21], while a more recent review focused on multi-morbid patients is provided by Fraccaro et al. [12]. More recently, Meulendijk et al. [22] presented a clinical decision support tool for physicians to optimize the patient's treatment plan and to avoid over-prescriptions.

Solving healthcare analytics and operations management problems in hospitals by means of a mathematical programming-based decision support tool has also been addressed in the literature. However, much more limited research is available as compared to decision support tools which focus on the clinical or medical perspective. In what follows, we provide an overview of, in our opinion, the four most relevant decision support tools that integrate DA, IT and OM for solving important and complex decision problems in healthcare delivery.

Joustra et al. [24] introduced a strategic decision support tool for patient mix decisions by enabling the management to alter the number of patients in various patient groups. Using sensitivity analysis, the impact of changing input parameters on key performance indicators can be studied. The authors presented a case study of the tool's application but did not provide details on its software implementation.

A tactical decision support tool for cyclic master surgery scheduling (MSS) implemented in Visual C++.NET was developed by Beliën et al. [5]. The system visualizes the impact of the MSS on the demand for various resources throughout the rest of the hospital. This system displays the impact of switching two physicians on the expected resource consumption pattern and additionally, it supports decisions made on the tactical level.

Another software system that was successfully applied on an operational decision level in a hospital is called ORSOS [9]. ORSOS is an enterprise-wide surgery scheduling and resource management system that automatically manages all surgical staff, equipment, and inventory using an engine that considers all of the clinical, financial, and operational criteria that must be addressed for each surgical event. Scheduling specific tasks, this tool supports decisions on the operational level.

Finally, Cayirli et al. [10] develop an appointment scheduling model that is also located on the operational decision level. It is implemented in an open-source online decision support tool and therefore not limited to a specific operating system.

We note that the systems which were published in the literature so far only support one of the three hierrchical decision-making levels, focusing either on the strategic, tactical or operational level. None of these applications integrate all three levels in one decision support tool. This ability will eventually allow opportunities to link solutions across the interfaces of these levels. To summarize, the main innovations of our E-HOSPITAL platform are two-fold: i) A unified, flexible and extensible workbench that combines different mathematical models of hospital resource planning problems by combining three classical hierarchical decision-making levels; ii) Formal, algebraic specifications of extensions of existing mathematical models are provided, implemented, and can be solved to optimality using sample instances, thus combining IT, operations and healthcare analytics in a single platform.

The remainder of this paper is structured as follows. We describe the workbench implementation and how we consider features that are highly relevant for practice by illustrating the use of the tool. Following this, we demonstrate the application of the workbench in a case study based on demand and capacity planning for hip fracture patients using real-world data from two hospitals. Lastly, we conclude with ideas for future work to extend the workbench, specifically highlighting opportunities linking the multiple levels.

Methods

When implementing the workbench, we focused on widely acknowledged theoretical concepts from the decision sciences literature that break down planning problems into different decision levels. When developing our modelling extensions, we incorporated practitioner's feedback into the existing models.

Implementation of the Different Decision Levels

Using the design objective of [2], seven approaches were selected from the literature that apply mathematical programming methods to provide decision support for healthcare OM problems. We also took into account the planning matrix of Hans et al. [19] who provided a similar classification of problems on the strategic, tactical and operational decision-making levels.

Strategic Decision Level

The strategic planning involves decision processes related to allocating resources, controlling organizational performance, establishing broad policies, and evaluating capital investment or merger proposals [26]. Decision support tools at this level need to help decision makers envision the future and negotiate with stakeholders by examining multiple scenarios [26].

These analyses are exactly what our workbench is aiming to provide: On the strategic level, Busse et al. [8] and Blake et al. [6] were selected. Both papers decide on the case mix of patients in hospitals while capacity constraints are considered. The difference between the two models is that Blake et al. [6] had target levels of physicians for treating patients and target revenue of the hospital, among others. In contrast, Busse et al.[8] followed an aggregate planning level to decide how many cases a hospital can support, given constrained resources. As a consequence, analyses can be run such as: Given operating room and bed capacity, what is the feasible number of patients to be treated within hospital budget limits?

Another scenario analysis is to examine the impact on revenue and the number of patients to be treated, given an increase or decrease in capacity.

Tactical Decision Level

Our workbench's tactical decision level consists of the tactical admission problem devised by Hans et al. [27]. Moreover, we include Master Surgical Scheduling (MSS) problems into that decision level, selecting the approaches of Blake et al. [7] and [25]. The difference between the two MSS papers is that Van Oostrom et al. [25] incorporate uncertainty into the planning while the approach in Blake et al. [7] is entirely deterministic.

Operational Decision Level

On the operational decision level, the operational shift scheduling problem in Beaulieau et al. [4], as well as an extension of the hospital-wide patient flow problem in Gartner at el. [14], were implemented.

Model Extensions

Before implementing the different models, we extended them to improve their applicability. On the strategic level, we extended the work of Busse et al. [8] on a temporal dimension. This allows users to insert expected values for different time periods for demand broken down by different diagnosis-related groups (DRGs). Another extension was the tactical planning problem of Vissers et al. [27] in order to capture demand for physical therapists and therapy rooms in the admission planning of patients. On the operational planning level, we extended the model of Gartner et al. [14] in order to capture admission decisions of patients, among others. The extensions are described in more detail on the workbench's repository: https://github.com/drdanielgartner/ehospital.

An Illustration of the Workbench

Figure 3 provides a specific example of the digital workbench. As can be seen, it separates the strategic, tactical and operational decision level using three tabs that are arranged vertically in the graphical user interface (GUI). Then, in each of the different planning levels, tabs are arranged horizontally, which separate the different approaches from each other.

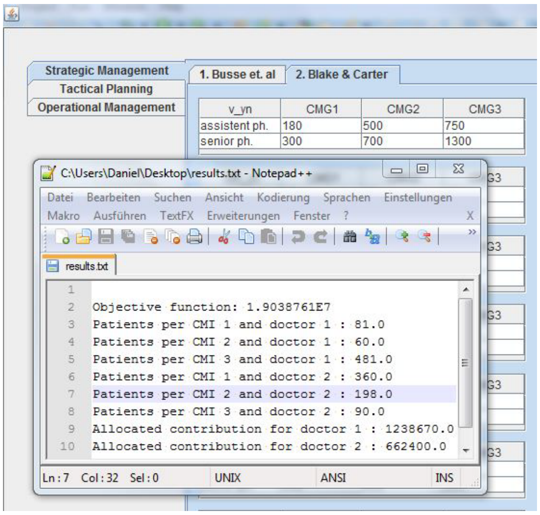

Figure 3 – Strategic Planning [6]

The illustration selects and solves the case mix planning problem of Blake et al. [6]. The GUI shows pre-specified default values e.g. for the number of case mix groups desired for each physician or the hospital capacity (e.g. beds and operating room time). After solving the problem instance, the user can store the output in a text file, which provides information about the generated solution which also includes the objective function value and the cases assigned to each physician.

Installation Requirements

Before running the .jar file of the platform-independent environment which, again, can be downloaded at https://github.com/drdanielgartner/ehospital, IBM ILOG CPLEX [20] has to be installed. Also, at least version 6 of the Java Runtime Environment has to be installed.

Results

In this section, we describe how we incorporated a capacity planning model into the platform and how we carried out an analysis for a real-world project with a health board in the U.K.

Incorporating Capacity Planning into E-HOSPITAL – A Case Study

The objective of the case study is to show how the E-HOSPITAL workbench can be extended and used to support a real-world decision-making scenario. The task is to determine the optimal level of operating room and bed resource capacity required for treating hip fracture patients in a multi-hospital site in the United Kingdom. This problem is located at the strategic planning level. Rather than deciding on a narrow scope i.e. on individual patients at the operational level (e.g. patient scheduling decisions [18]), we decided on a broader scope, which is less structured and constrained [6]. Additionally, Busse et al. [8] models seem at first glance to be highly suitable. However, the board of directors who will use the decision support tool in future needs to determine the resource capacity level rather than the optimal number of patients given fixed capacities. Also, the board had specific usability requests e.g. to vary patient demand and length of stay.

Research Questions

The research questions which can be broken down into analytics and services planning are as follows:

Analytics-focused research questions

- How many patients require the service during a one-year planning horizon?
- What is the length of stay distribution of patients requiring hip fracture treatment in each of the hospital's catchment areas?

Strategic planning questions

- Fixing the catchment areas to the hospital sites, what are the total amounts of operating room time and bed capacity required?
- Pooling hospitals, what are the resource requirements for each of the hospitals?

Project Phases and Timeline

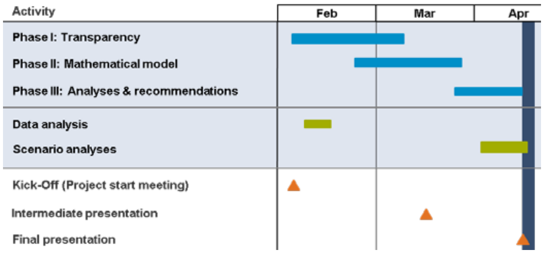

Figure 4 – Hip Fracture Demand and Capacity Planning

When carrying out the case study, we broke this project down into different phases as shown in Figure 4. In what follows, we will provide more details for each of the different project phases.

Transparency

In the first phase of the project which we called the "Transparency Phase", we evaluated the length of stay (LOS) distribution because, in healthcare delivery, this is a major source of uncertainty and costs. Our data analysis revealed that the two hospitals that we studied (henceforth denoted as hospital 1 and hospital 2) are faced with a large inter-quartile range of LOS. Moreover, the median LOS is 28 days for hospital 1 and 23 days for hospital 2.

A more detailed analysis of the LOS data using histograms and Gaussian Kernel Density Estimators (KDEs) is shown in Figure 5. It reveals a left-skewed shape of the LOS distribution, which is similar to LOS distributions that can be observed in previous research [17, 23].

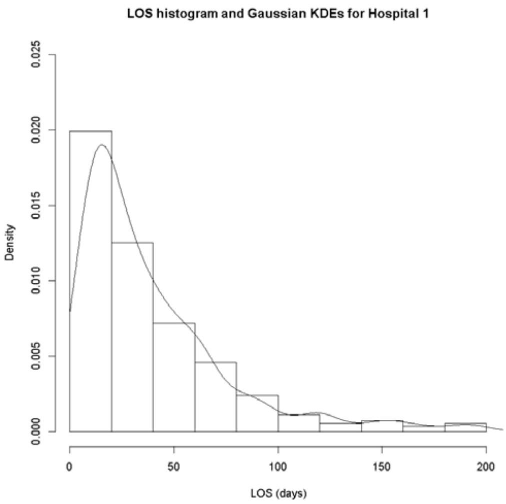

Figure 5 – Boxplots of LOS Distribution for Hospital 1

Mathematical Modelling

In the mathematical modelling phase, we used a model which is available in the workbench's github repository. The model was developed in collaboration with Orthopaedic physicians and the GUI in collaboration with the physicians and the Modelling Lead of the Aneurin Bevan Continuous Improvement Unit (ABCi). The result is shown in Figure 6.

The upper part of the workbench revealed that patient demand reached 271 and 278 patients in the catchment area of hospitals 1 and 2, respectively, with the median LOS at 28 and 23 days. Manipulating the slider below the "#Patients" label and the slider below the "LOS quantile", we observe that, for example, we can run our analysis for up to 50% more patients as compared to the baseline demand. Also, we can select any quantile for the LOS distribution. This reflects risk sensitivity for practitioners while ensuring that enough bed and operating room capacity is determined by the mathematical model since demand is fluctuating.

Assumptions, Analyses & Recommendations

For our analyses, we assumed that the average duration of a hip fracture surgery is 2.5 hours. To determine the demand, we selected patients admitted to the Accident and Emergency Unit (A&E) in 2014 and patients who were discharged from the hospital in 2014. We set up two scenarios as follows: Scenario 1 consisted of a run where we used the median (50% quintile) for length of stay. Also, we focused on actual patient demand observed in 2014. Moreover, we ran the model with a fixed assignment of patients to hospitals. This means that patients who arrive from hospital 1's catchment area are exclusively treated in that hospital. The same holds true for hospital 2. In the second scenario, we include a third hospital (hospital 3) which will be built in the near future within the health board. In this scenario, the objective is to level bed capacity.

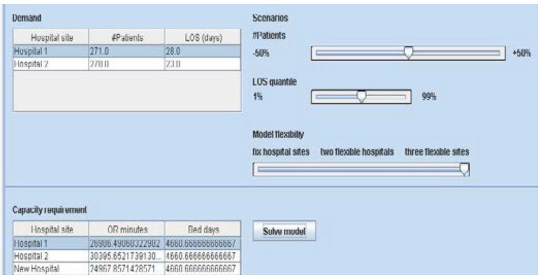

Figure 6 – Model integration in the E-HOSPITAL workbench and results of the fully-flexible model

The results of the scenario analysis revealed that using the fixed model, approximately 7,588 and 6,394 bed days are required for hospital 1 and 2, respectively. The results using the flexible model for three hospital sites (Figure 6) revealed that 4,661 bed days are required for each of the hospital sites. However, one can observe that the operating room capacity is different across the hospital sites which is attributed to the different patients' LOS. Fewer patients are admitted to hospital 1, but have the same total bed days due to their longer LOS, but lower total OR capacity requirement.

Discussion

Compared with the current state of the art, the proposed platform can be considered as the first that unifies multiple models in one platform and extends it to increase the acceptability in health care. Another contribution that extends current state of the art is that multiple decision levels can be tackled by using this platform. One limitation, however, is that the commercial solver CPLEX has to be installed with the platform.

In the scenario analysis that we provided in the results section, we employed realized patient demand as a predictor for future demand. In other inpatient settings and especially for elective patients, the size of waiting lists has to be accounted for as well. Also, there are many more factors that determine length of stay such as quality of care, hospital discharge policies, and so on. However, many of these can be incorporated as site-specific parameters into the mathematical models and solved for varying scenarios of parameter values.

Conclusion

In this paper, we described the development of a unified digital workbench for hospital resource planning that is based on a well-accepted, multi-level decision-making framework. The platform leverages information technology, operations management, and data analytics to support not only healthcare decision makers but also healthcare analytics and information systems specialists as well as educators of these topics. The tool combines the three classical hierarchical decision-making levels in one integrated environment. At each level, several decision problems can be chosen. Extensions of mathematical models from the literature are presented and incorporated into the workbench. In a case study using real-world data, we demonstrated how we used the workbench to inform capacity decisions in a multi-hospital site.

Future work will address the intersection between the different decision layers. Although the intersection between the strategic and the tactical layer have not yet been covered extensively due to computational complexity, our aim is to provide computationally tractable, heuristic methods to evaluate the intersection between multiple decision layers when optimal approaches are not feasible.

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