How to juggle priorities? An interactive tool to provide quantitative support for strategic patient-mix decisions: an ophthalmology case

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Abstract An interactive tool was developed for the ophthalmology department of the Academic Medical Center to quantitatively support management with strategic patient-mix decisions. The tool enables management to alter the number of patients in various patient groups and to see the consequences in terms of key performance indicators. In our case study, we focused on the bottleneck: the operating room. First, we performed a literature review to identify all factors that influence an operating room's utilization rate. Next, we decided which factors were relevant to our study. For these relevant factors, two quantitative methods were applied to quantify the impact of an individual factor: regression analysis and computer simulation. Finally, the average duration of an operation, the number of cancellations due to overrun of previous surgeries, and the waiting time target for elective patients all turned out to have significant impact. Accordingly, for the case study, the interactive tool was shown to offer management quantitative decision support to act proactively to expected alterations in patient-mix. Hence, management can anticipate the future situation, and either alter the expected patient-mix or expand capacity to ensure that the key performance indicators will be met in the future.

1 Introduction

1.1 Motivation

The increasing demand for health care and, at the same time, the pressure to restrict budgets, is putting more and more pressure on hospitals to perform. However, it might not be enough to just improve efficiency, especially where demand significantly exceeds supply over the course of multiple successive months or even years. The question often comes down to deciding either way: to reduce demand in general, or to make more specific decisions about certain patient groups. However, to make the right decision, the medical management of a teaching hospital has to juggle different priorities, namely, constraints from the medical perspective (research and education), from the legal perspective (the obligated care region and last resort[1]), capacity usage, and financial feasibility. This paper will focus on the first three aspects.

1.2 Description of the problem

In the case presented in this paper, the ophthalmology department at the Academic Medical Center (AMC) in Amsterdam was dealing with a restricted budget and long queues. This department had a waiting list of over 1 year for elective surgical procedures, a list that was steadily growing because for the past few years, demand had

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[1] Last resort indicates that patients can not be treated in other hospitals and the AMC is the last option for these patients.

exceeded supply by approximately 30%. Seeing that the access times for a consultation at the outpatient department (OPD) were stable, and the nursing ward had sufficient capacity, the AMC ophthalmology department's main bottleneck was the operating room capacity. Therefore, we focused primarily on the operating room, rather than on the outpatient department or the nursing ward.

To reduce the waiting lists for elective ophthalmologic surgery, we first optimized the capacity usage. Unfortunately, this optimization was not enough to solve the problem completely. Even with the maximum feasible expansion of capacity, the waiting lists would not be reduced to a satisfactory level. Therefore, we were forced to reduce the workload and thus the number of patients to ensure that the waiting time target for surgical procedures would be met in the future. To decide upon a feasible patient mix, medical management had to make sure all patients in the obligated care region could be treated, and that, as part of their training, the resident physicians could see a sufficient number of secondary level of care patients. The remaining capacity could be used for research purposes. In conclusion, the aim of medical management was to maximize the number of surgeries performed on preferred patients while meeting the key performance indicator (KPI) targets for the operating room.

Currently, management lacks the proper decision support for determining the consequences of their decisions and therefore for making good choices. Because of this, we wanted to build an interactive tool to quantitatively support management with these difficult strategic patient-mix decisions. By using the tool for various patient groups, management is able to set the targets for the KPIs, and observe the resulting capacity requirements of the OPD, the operating room, and the nursing ward.

1.3 Literature review for interactive decision-support tool for strategic patient-mix decisions

In the majority of operations research studies in health care, decision support was provided by solving a specific problem. Few studies described a decision-support tool that made medical management self-supporting and able to solve similar problems on a regular basis. Kusters and Groot [1] developed a decision-support tool for admission planning for elective patients on a waiting list to optimally utilize the available beds, nursing staff, and operating room in the short term. Multiple studies reported on the use of a "balanced scorecard," which helps medical management meet financial goals [2–5].

Vissers et al. [6] addressed the patient-mix optimization problem of cardiothoracic surgery at the tactical level. Although Vissers et al. modeled the capacity usage of both

the operating room and the nursing ward, waiting times or other performance targets were not explicitly taken into account. Ma et al. [7] described a methodology for determining the optimal case mix for maximizing hospital profits with the given resource capacity. The hospital in our case is a teaching hospital, where research and education play prominent roles and maximizing profit is not the main objective. In addition, we wanted management to decide upon the best patient mix directly, rather than specifying the weights for all patient groups and therefore indirectly optimizing the patient mix. Blake and Carter [8] described a methodology for strategic resource allocation in hospitals. Similar to Vissers et al. and Ma et al., Blake and Carter assumed the available operating room time and total number of bed days available to be independent of the patient mix. Therefore, KPIs such as a waiting time performance target, a maximum risk of overtime, or a maximum percentage of cancellations were not explicitly taken into account.

In summary, we found no articles describing an interactive tool for supporting medical management with patient-mix decisions and linking these strategic decisions explicitly to the preferred KPIs such as waiting times. Previous research on patient-mix decisions has used rules of thumb to predict the effect of alterations in patient mix on KPIs. For example, the maximum utilization rate of an operating room was assumed to be a certain percentage (e.g., 85%), without taking a specific surgical case mix into account (e.g., the distribution of case durations and the percentage of urgent procedures). This assumption is in direct conflict with studies that reported the dependency of surgical case mix and an operating room's utilization rate on the one hand and the resulting performance in terms of waiting times [9] and accepted risk of overtime on the other [10].

1.4 Objective

The objective of this study was to develop an interactive tool to quantitatively support the management of the AMC ophthalmology department with their strategic patient-mix decisions while taking the KPIs into account. This interactive tool will enable management to alter the number of patients in various patient groups and to see the consequences in terms of the KPIs of the OPD, the operating room, and the nursing ward. Iteratively, they will be able to decide upon a future patient mix with a balance between supply and demand that will allow the targets for the KPIs to be met.

To be user-friendly, we developed the interactive decision-support tool in MS Excel. To decide upon the appropriate level of detail, we applied two quantitative methods: regression analysis and computer simulation.

2 Study setting

To develop our interactive tool, we studied the AMC ophthalmology department. Because the AMC is a teaching hospital, the ophthalmology department offers both secondary and tertiary level medical care. Nearly all the secondary level of care patients are seen by resident physicians as part of their professional training, and they are supervised by attending physicians. In addition, the department has three tertiary groups of surgeons focusing on various subspecialties: the front segment of the eye (cornea and glaucoma patients), back segment of the eye (medical retina, surgical retina, diabetes, and uveitus patients), and the outer segment of the eye (orbital and pediatric ophthalmology patients. During our study each group (called a segment) consisted of five or six physicians specialized in one or two subspecialties each.

In 2008, more than 6,000 new patients and almost 28,000 follow-up patients were seen at the OPD. Furthermore, in the same year, the ophthalmology department performed almost 2,400 surgical procedures. As the majority of the surgical procedures were performed in an outpatient setting, the nursing ward of the AMC ophthalmology department was relatively small.

At the start of our study in August 2008, the access times[2] for multiple subspecialties varied between 4 and 8 weeks. Furthermore, the department had a waiting list of over 1 year for several elective surgical procedures. Although the access times at the OPD were stable for all subspecialties, the waiting list for surgical procedures was growing steadily because demand have exceeded supply for the past few years. The AMC ophthalmology department set the access time target at 90% of patients within 2 weeks, and the waiting time target for surgical procedures at 80% of patients within 5 weeks.

Because we focused primarily on the operating room, we will describe how the available capacity was used within the AMC. The total operating time was allocated specifically to the AMC ophthalmology department at the start of the year. All elective patients (inpatients as well as outpatients) were scheduled for surgery by a specific surgeon in an operating session dedicated to that particular surgeon. Consequently, each surgeon had his or her own waiting list for elective patients. Given that the AMC is a teaching hospital, resident surgeons usually perform some part of each surgery under supervision of an attending surgeon. Furthermore, shortly before the day of surgery, the semi-urgent and urgent patients were scheduled in reserved urgent time slots that were not surgeon-specific. To limit the

number of cancellations due to prioritizing urgent patients, management needed to reserve enough urgent time slots to deal with the fluctuating number of urgent patients.[3] At the same time, management also wanted to use the scarce operating time efficiently, and did not want to reserve too many urgent time slots since they may remain idle. Note that operating time that becomes available due to late, unexpected, cancellations could be used for urgent patients as well. To limit overtime, management also had to make sure that a scheduled operating session included enough slack time to deal with unexpected events during the day (e. g., a late start or fluctuations in sedation time or turnover time). It should be noted that the AMC ophthalmology department has a case mix with predominantly short case duration and is thus at greater risk of cancellations due to overruns.

3 Study design

The patient population was divided into various patient groups to enable management to alter the numbers of patients per patient group and experiment with different patient mixes. To make it easier to integrate capacity and financial decisions, each patient group consisted of several related "diagnosis-treatment codes" (in Dutch, "diagnose behandel combinaties," or DBCs, which are similar to diagnosis-related groups, or DRGs). As a result, most of the groups represented a single subspecialty. The secondary level of care patients[4] were all gathered into one group, and the remaining DBCs were gathered into another group. We assumed that with this partition, the average capacity usage of the OPD, the operating room, and the nursing ward would be independent of a group's size.

3.1 Appropriate level of detail

Before we describe the modeling of the OPD and the operating room, we first have to elucidate the appropriate level of detail for the nursing ward. We assumed that as long as the capacity demand for the nursing ward did not exceed the previous year's production, the capacity would be sufficient in the future. The capacity demand per patient group was calculated by multiplying the number of patients in a patient group by the capacity usage per patient. The total capacity demand was the sum of all the patient groups.

With regard to the OPD, we added more detail and compared the capacity demand and the previous year's

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[2] In this article we use the term access time for the number of days a patient has to wait until the first appointment at the OPD and we use the term waiting time for a surgical procedure.

[3] Note that almost all urgent surgeries had to be performed in the operating time specifically allocated to the ophthalmology department.
[4] Secondary level of care patients are referred by general practitioners, in contrast to third line-patients, who are referred by other hospitals to an academic hospital.

production per segment. At strategic level, it was sufficient to compare the capacity per segment: because multiple physicians within a single segment were specialized in more than one of that segment's subspecialties, they were able to treat patients from other subspecialties within that segment.

To accurately predict whether a future patient mix would meet the waiting time target and other operating room KPIs, we had several alternatives for the level of detail. A first alternative was to use a rule of thumb for the maximum allowed utilization rate for the operating room (e.g., 85%), and thus the maximum workload for a specific patient mix. Unfortunately, this was not sufficiently accurate. A second alternative for determining the maximum allowed utilization rate was to use the previous year's actual utilization rate. This utilization rate already implicitly incorporated all departmental aspects such as patient-mix characteristics, aspects related to personnel and organization, and the previous year's achieved KPIs. However, if we were to use the previous year's utilization rate, we would be implicitly assuming that none of the departmental aspects would change in the future. The patient mix in particular will change, because the medical management of the AMC ophthalmology department has to reduce the total capacity usage of the operating room, and so consequently, the number of patients. Furthermore, management was not satisfied with the achieved KPIs.

To calculate the maximum allowed utilization rate, we performed a literature review to identify all the factors that influence an operating room's utilization rate. Next, we decided which factors were relevant to our study, and thus should be included. Finally, we quantified the effect of the included factors on the maximum allowed utilization rate of the operating room and incorporated these results into the interactive decision-support tool.

3.2 Definition of the operating room utilization rate

Several alternatives were available for determining the operating room utilization rate. In our study, we defined the operating room utilization rate according to the definition commonly used within the AMC: the sum of all surgeries scheduled within an operating session that were not cancelled during the day divided by the total session time.

Note that this definition of the utilization rate includes unforeseen overtime. In contrast, unscheduled urgent patients were not included in this, nor were turnover times. It should be noted that because the AMC has emergency operating rooms, we excluded emergency patients in the analyses of the maximum allowed utilization rate of the operating rooms that are dedicated to elective and semi-urgent and urgent patients.

3.3 Literature review to identify factors that influence an operating room's utilization rate

To identify all factors that might influence an operating room's utilization rate, we performed a literature review. We divided the factors into several categories, and explored each of these categories:

1. Management decisions
2. Patient-mix characteristics
3. Organizational factors
4. Personnel-related factors
5. Cancellations due to other reasons

3.3.1 Management decisions

Management decisions regarding KPIs influence an operating room's utilization rate. For instance, a stringent target (e.g., 80% of patients must have surgery within 5 weeks) requires more operating time to deal with fluctuations to the number of patients [9]. Furthermore, as Van Houdenhoven et al. [10] show, there is a link between accepted risk of overtime and utilization rate: if management accepts a higher risk of overtime, the utilization rate will increase as well. A strongly related management decision is the maximum allowed percentage of cancellations due to overrun of previous surgeries [11]. For an ophthalmology department with a majority of relatively short surgical case durations, a stringent cancellation target will lead to a defensive scheduling strategy, and thus a lower utilization rate. Another management decision concerning cancellations is the maximum allowed percentage of cancellations due to prioritized semi-urgent and urgent patients. Although dedicating more urgent time slots will reduce the number of cancellations, these urgent time slots are at greater risk of remaining idle than regular time slots due to a lack of urgent patients on a specific day [12]. Consequently, more urgent time slots will decrease the overall utilization rate of the operating room. The final management decision that influences the utilization rate is the target for the accuracy of a surgery's starting time [13].

3.3.2 Patient-mix characteristics

The second category of factors is patient-mix (or surgical case-mix) characteristics. The distribution of the case durations has a significant impact on the operating room utilization rate. Therefore, we incorporated two specific aspects of the distribution of case durations, namely, (1) the average case duration and (2) the percentage of case durations shorter than 1 h. The first is a measure of the average number of turnovers between succeeding surgeries. Please recall that because turnover times were not included

in the operating room utilization rate, it is plausible that more surgeries per day result in a lower utilization rate. The second is a measure of the ability to fully schedule the available operating time, due to the bin-packing effect. Therefore, we expected that a higher percentage of short durations results in a higher utilization rate.

Another patient-mix characteristic is economy of scale: a large department may be able to use the available operating time more efficiently than a small one [14].

Finally, the percentage of urgent patients combined with the urgency level may influence the utilization rate as well [15]. A higher percentage of urgent patients requires more urgent time slots to ensure that the percentage of cancellations due to urgent patients will not increase. Please recall that more urgent time slots will decrease the utilization rate. Furthermore, the degree of fluctuations in the daily and weekly numbers of urgent patients will affect the number of urgent time slots, and therefore also the operating room utilization rate, according to the definition used at AMC. The same holds for the fluctuations in the weekly number of regular patients: the more this weekly number fluctuates, the larger the chance a time slot will not be used, and thus lower the utilization rate [16]. The same reasoning holds for seasonal patterns in demand.

3.3.3 Organizational factors

The third category included organizational factors. The first organizational factor is the division of operating time among various specialties. In general, a more flexible use of capacity among various specialties results in a higher operating room utilization rate. Consequently, the degree of subspecialty is also relevant to the utilization rate. In general, the more the available capacity is subdivided among subspecialties (or even among individual physicians), the lower the utilization rate [17]. Note that flexible usage among specialties does require fully equipped operating rooms.

Also, the scheduling algorithm is an important organizational factor affecting the efficient use of operating room capacity. Various studies [18–21] reported efficiency improvements with alternative scheduling algorithms.

Moreover, fluctuations in the availability of operating time (e.g., due to public holidays and vacation periods) tend to reduce the utilization rate [22].

Another organizational factor is the turnover time. Both the average and the variation in the turnover time are relevant to the operating room utilization rate [23]. If the variation in turnover time is high, more slack time is required to limit the risk of overtime. A related factor is the availability of a separate sedation room to limit the time between two surgical procedures.

The final organizational factor we found in the literature was the availability of surgical materials and surgical trays.

Obviously, if availability is well organized, the utilization rate is higher. In contrast, if materials or surgical trays are often unavailable or incomplete, surgery may take longer and the utilization rate may become lower.

3.3.4 Personnel-related factors

The next category of factors is related to the operating room personnel. The first personnel-related factor concerns the punctuality of surgeons and anesthesiologists: many studies reported on late starts in the operating room or waiting times during the rest of the day [24]. Also, the accuracy of the predicted case durations impacts the utilization rate [25]. If surgeons are able to predict their case durations accurately, the actual durations will not differ much from the scheduled durations, and the schedule will be full more often without undue risk of overtime and cancellations due to overruns of previous surgeries. A related factor is the number of resident physicians: it is harder to accurately predict case durations if a resident physician performs all or part of the surgery [26, 27]. Using the same reasoning as for the previous factor, a higher number of resident physicians is likely to reduce the operating room utilization rate.

3.3.5 Cancellations due to other reasons

Having already discussed management decisions concerning cancellations, namely the percentage of cancellations due to overruns of previous surgeries or prioritized urgent patients, in this section we describe cancellations due to other reasons.

Several reasons for cancellations are patient-related: the patient cancelled the surgery or did not show up (specifically with outpatient surgery), there was a change in the patient's clinical status, the patient was not ready for surgery, or the preoperative screening was not performed (or was not performed properly).

In addition, some reasons for cancellations are hospital-related: there was no postoperative bed available, there was a lack of medical instruments or equipment, one or more members of the operating team were unavailable, there was an administrative cause, or a communication failure.

3.4 Selection of relevant factors

For our study, we had to select the relevant factors from an extensive list of factors that might influence operating room utilization rate (see Table 1). In this section, we clarify why we included or excluded specific factors from our study. If an alteration to the number of patients per patient group was not expected to have a significant impact on a specific factor, we excluded it. The reason for including or

Table 1 Overview of relevant factors

Description of category and corresponding factors	Relevant to our case study?
Management decisions	
Waiting time target for elective patients	Yes
Accepted risk of overtime	Yes
Maximum number of cancellations due to overrun of previous surgeries	Yes
Maximum number of cancellations due to prioritizing urgent patients	Yes
Accuracy of surgery starting time	No
Patient-mix characteristics	
Average case duration	Yes
Percentage of case durations shorter than one hour	Yes
Economy of scale	No
Percentage of urgent patients	Yes
Fluctuations in weekly number of urgent patients	No
Fluctuations in demand per week and seasonal pattern	No
Organizational factors	
Division of operating time among specialties	No
Degree of subspecialty	No
Flexibility in use of operating rooms	No
Scheduling algorithm	No
Fluctuations in availability of operating time per week and seasonal pattern	No
Average and variation of turnover times	No
Separate sedation room	No
Availability of materials and surgical nets	No
Personnel-related factors	
Specific surgeons	No
Number of resident physicians	No
Degree of accuracy of scheduled case durations	No
Late start in operating room and waiting for surgeon or anesthesiologist during the day	No
Cancellations due to other reasons	
Patient-related reasons	No
Hospital-related reasons	No

excluding specific factors is described in the same order as the categories in the previous section.

Because we wanted to enable medical management to experiment with different decisions, we included the waiting time target for elective patients, the accepted risk of overtime, and the maximum percentage of cancellations due to overrun of previous surgeries or due to prioritizing urgent patients. Only the accuracy of a surgery's starting time was excluded, because this was not considered a KPI in the AMC.

Our goal was that medical management would use the interactive tool to experiment with different numbers of

patients per patient group to see the consequences in terms of the operating room KPIs. As this alteration might significantly change the distribution of case durations, we decided to include the average case duration and the percentage of case durations shorter than 1 h. In the future the department most likely wants to keep using all available operating time and the department was not allowed to acquire significantly more operating time. For this reason it is not likely that the future capacity will deviate from the current capacity significantly. Therefore, changes in economy of scale will be relatively small and consequently, we excluded this factor. By contrast, we included the percentage of urgent patients. Our definition of urgent patients is "patients who need to have surgery within 8 days", because the elective operating schedule had to be fixed in the remaining period. The reasoning to include this factor is that the percentage of urgent patients differs substantially between the different patient groups and subsequently, an alteration in the number of patients per patient group is likely to change the overall percentage of urgent patients. The final patient-mix factors—namely, the fluctuations in the weekly number of urgent and elective patients and the seasonal pattern—were excluded, because we assumed these fluctuations will not change in the near future.

With regard to organizational factors, we assumed that no major alterations will occur in the near future. Therefore, we excluded all organizational factors from the rest of our study. We used the same reasoning for personnel-related factors and cancellations due to other reasons, and thus excluded all personnel-related factors as well.

4 Quantitative modeling

The second column of Table 1 shows whether we included or excluded a specific factor. Next, we wanted to quantify the impact of all included factors on the maximum allowed utilization rate of the operating room, and selected regression analysis for this purpose. With regression analysis, a number of actual utilization rates and actual realizations of the included factors were used to determine the respective coefficients of a regression model that can be used to predict the utilization rate with different values for the included factors. Unfortunately, the waiting times for elective patients achieved in the past could not be retrieved from any of the AMC information systems because the department only started to schedule patients in the operating room information system "OKplus" in June 2008. Before that, the department entered the scheduled patients in OKplus just 1 week

before the surgery date, and because the date the surgery was requested was not included, the actual waiting time could not be determined. Therefore, we interviewed the scheduler of the ophthalmology department and the waiting times for elective patients seemed to be more than 6 months during the past few years. We expected that a 6 month waiting time would not have had significant impact on the realized utilization rates. For these two reasons, we used computer simulation to quantify the effect of the waiting time target for elective patients on the maximum allowed utilization rate.

To calculate the final prediction of the maximum allowed utilization rate, we adapted the utilization rate predicted by regression analysis with the results of the computer simulation.

4.1 Regression analysis

For the analysis, we collected monthly data points: one data point contained the actual utilization rate and the corresponding values of all included factors (see the next section for details).

To perform the regression analysis [28], we used SPSS. We applied the backward stepwise procedure to identify significant factors, and in each step the least significant factor was excluded from the model, but only if the p-value was larger than 0.05.

Subsequently, the regression equation $y = a + b_1x_1 + b_2x_2 + \ldots + b_nx_n$ was used to calculate the maximum allowed utilization rate, where y = the maximum allowed utilization rate, a = the model constant, and b = the regression coefficient (B_i) of factor(x_i).

4.2 Computer simulation

In the interactive tool, we used computer simulation [29] to quantify the effect of a more stringent waiting time target for elective patients on the maximum allowed utilization rate of the operating room. The waiting time target can be set per patient group to enable management to differentiate between the various groups.

We scheduled a patient in the first week with available capacity according to the First Come First Served principle. To limit the level of detail, we determined the waiting time in number of weeks. Then, both demand and capacity were specified in number of surgeries per week. To accurately predict the alteration in utilization rate, we incorporated the fluctuations in weekly demand and in weekly capacity into our simulation model. We assumed that physicians were not available a certain percentage of the weeks, and randomly selected a week with no demand and no capacity. Unfortunately, we did not have enough data to perform a proper data fit for the

fluctuating weekly demand. Therefore, we experimented with both a discrete uniform distribution and a Poisson distribution to check the sensitivity of the outcomes for different types of distribution. Finally, we selected the distribution with worst case outcomes. To be able to easily experiment with different weekly capacities (resulting in different utilization rates), we modeled the fluctuating weekly capacity with a Poisson distribution in all scenarios.

Next, instead of simulating each patient group, we simulated several categories with different average weekly numbers of surgeries (e.g., two or four surgeries). Within each category, we experimented with various threshold values for the waiting time (e.g., 5 weeks, 9 weeks, 3 months, and 6 months), and we determined the minimum weekly capacity (with a precision of 0.01) to ensure that at least 80% of the patients experienced less waiting time than the threshold value. Subsequently, the maximum allowed utilization rate per category for meeting a specific waiting time target was calculated by dividing the average weekly demand by this minimum weekly capacity. To select the corresponding category of a patient group, we rounded down the actual average weekly number of surgeries of the specific patient group.

We built the simulation model in Enterprise Dynamics Version 8. We constructed a confidence interval for the percentage of patients experiencing less waiting time than the threshold value. To obtain a 5% half-width for the 95% confidence intervals, the run length (excluding warm-up period) was set at 10 years and we ran the model for 300 replications per experiment. In addition, the warm-up period was set at 1 year. If the lower bound of the confidence interval was larger than 80%, the capacity was considered to be sufficient.

4.3 Interactive tool

For the interactive tool, we combined the results of the regression analysis and the computer simulation. Therefore, we adapted the utilization rate predicted by regression analysis for the effect of a more stringent waiting time target for elective patients. Formula (1) shows how we adapted the maximum allowed utilization rate predicted by regression analysis to incorporate the impact of a more stringent waiting time target. To calculate the department's overall utilization rate with the preferred waiting times, we determined the weighted average of the utilization rates corresponding to the preferred waiting time and the category of the specific patient group (see formula (2)). In addition, the department's overall utilization rate with the current waiting times was the weighted average of the corresponding

utilization rates of the individual patient groups (see formula (3)).

Let:

ρ_{final}	the maximum allowed utilization rate predicted by regression analysis and adapted by simulation
ρ_{MVA}	the utilization rate predicted by regression analysis
ρ_{pref}	the department's overall utilization rate with the preferred waiting times
ρ_{cur}	the department's overall utilization rate with the current waiting times
μ_n	the average demand of patient group n, $n = 1,..., N$
cat_n	the corresponding category of patient group n with $cat_n = \max\{1, \lfloor \mu_n \rfloor\}$
dur_n	the average duration of a surgery in patient group n
$\rho_{cat_n, Wpref}$	the simulation-based, maximum allowed utilization rate for the category of patient group n to meet the preferred waiting time W_{pref}
$\rho_{cat_n, Wcur}$	the simulation-based, maximum utilization rate for the category of patient group n that corresponds to the average waiting time of the past year W_{cur}

$$\rho_{final} = \rho_{MVA} \times \frac{\rho_{pref}}{\rho_{cur}} \qquad (1)$$

$$\rho_{pref} = \sum_{n=1}^{N} \left(\mu_n \times dur_n \times \rho_{cat_n, Wpref} \right) \Bigg/ \sum_{n=1}^{N} \left(\mu_n \times dur_n \right) \qquad (2)$$

$$\rho_{cur} = \sum_{n=1}^{N} \left(\mu_n \times dur_n \times \rho_{cat_n, Wcur} \right) \Bigg/ \sum_{n=1}^{N} \left(\mu_n \times dur_n \right) \qquad (3)$$

5 Data collection for the case study

In the following two subsections, we describe how we collected the required data to decide upon the appropriate level of detail and for the resulting interactive decision-support tool.

5.1 Data collection to decide upon the appropriate level of detail

To apply the described quantitative methods, we had to collect the data for the regression analysis and the simulation model.

5.1.1 Data collection for the regression analysis

For the regression analysis, the average operating room utilization rate and the average values of the included factors were collected per month for the entire ophthalmology department, from January 2006 through September 2009.

The average operating room utilization rate was extracted from the AMC operating room information system OKplus. The average monthly utilization rate was 0.76; this utilization rate varied between 0.70 and 0.83.

Table 2 contains the average monthly values as well as the minimum and maximum monthly values per included factor. Please recall that the actual waiting times were not available, and therefore this included factor was not incorporated into the regression analysis.

The total monthly overtime, the number of cancellations due to overrun of previous surgeries, the number of cancellations due to prioritizing urgent patients, the average case duration, and the percentage of case durations shorter than 1 h could be extracted from OKplus. To determine the number of cancellations due to prioritizing urgent patients, we used cancellations within 24 h.

Table 2 Average, minimum, and maximum monthly values per included factor

Included factor	Average value	Minimum value	Maximum value
Waiting time for elective patients	n.a.	n.a.	n.a.
Total monthly overtime (in hours)	4.4	0.8	10.4
Number of cancellations due to overrun of previous surgeries	7.5	2	13
Number of cancellations due to prioritizing urgent patients	1.5	0	5
Average case duration (in minutes)	80	72	88
Percentage of case durations shorter than 1 h	0.33	0.25	0.42
Percentage of semi-urgent and urgent patients within 8 days	0.10	0	0.19

The data for the final included factor—the percentage of semi-urgent and urgent patients within 8 days—could only be extracted from OKplus after June 2008. Please recall that before June 2008, the date the surgery was requested was not entered in OKplus, nor was the urgency level. For this reason, we determined the percentage of semi-urgent and urgent patients per patient group based on the period from June 2008 through February 2009. To determine this percentage for the period before June 2008, we used patients' DBCs to classify all them into their corresponding patient groups, which were subsets of related DBCs. Subsequently, we used the number of patients per patient group in a specific month to calculate the weighted average of the percentage of semi-urgent and urgent patients in that month. See formula (4) for the described weighted average, with T the number of months and N the number of patient groups.

Let:

$X_{i,t}$ the number of patients per patient group i in month t

p_i the percentage of semi-urgent and urgent patients per patient group i

P_t the weighted average of the percentage of semi-urgent and urgent patients in month t

$$P_t = \sum_{i=1}^{N} X_{i,t} \times p_i \bigg/ \sum_{i=1}^{N} X_{i,t} \quad for \; t = 1, ..., T \quad (4)$$

5.1.2 Data collection for the computer simulation

Although the waiting times for elective patients achieved in the past could not be retrieved from any of the AMC information systems, we were able to extract the current waiting times for elective patients per patient group.

We decided to distinguish five categories: the first category with an average of one surgery per week, the second category with an average of two surgeries per week, and so on. In addition, we determined by analyzing the number of weeks

without either demand or capacity in the OKplus database, that physicians were not available 20% of the time.

5.2 Data collection for the interactive decision-support tool

To enable management to experiment with different numbers of patients per group, we collected the data for the interactive tool per patient group.

To make it easier to integrate the capacity perspective and financial perspective in the future, we used the same patient groups. Each patient group consisted of several related DBCs. Because of this, we also tried to collect as much of the required data as we could from the DBC database. In our study, we used closed and validated DBC records from the AMC ophthalmology department for the years 2006 through 2008. Because DBCs were automatically closed after 1 year, we decided to combine multiple DBC records with the same patient number and the same diagnosis code to create a care path for each patient. In addition, we only combined successive DBC records when the closing date of the first DBC record was exactly 1 day before the opening date of the second record. All DBC records that could not be combined were assumed to be independent, and were therefore used individually. To illustrate the data collection, Table 3 shows the required information for a limited number of patient groups. Although, the interactive tool incorporates all subspecialties of the AMC ophthalmology department, we choose to list just a limited number to provide a better overview.

To check whether the demand for the OPD did not exceed the previous year's production, we had to collect the average number of new consultations and follow-up consultations per patient and their corresponding durations for each patient group.

To check whether the capacity demand for the nursing ward did not exceed the previous year's production, we collected the average length of stay for each patient group. It should be noted that patients who were not admitted to the hospital counted as zero days in calculating the average length of stay.

Table 3 Required information per patient group

Type of data	Orbital	Surgical retina	Medical retina	Secondary
Avg number of new consultations	0.77	0.74	0.76	0.79
Avg duration of new consultations	15	10	15	20
Avg number of follow-up consultations	3.05	3.34	2.04	0.97
Avg duration of follow-up consultations	15	10	10	15
Avg length of stay on nursing ward	1.00	1.66	0.06	0.05
Percentage of patients needing surgery	28%	61%	5%	2%
Avg case duration per patient (in mins)	158	118	59	93
Avg case duration per surgery (in mins)	112	74	59	73
Percentage of case durations shorter than 1 h	7%	38%	54%	30%
Percentage of urgent patients within 8 days	7%	50%	10%	26%

For the operating room, we extracted the percentage of patients needing surgery and the average case duration for each specified group from the DBC database. Note that we distinguished two types of average case durations, namely, per patient (to calculate the total operating room demand per patient group) and per surgery (for the regression analysis). These numbers could differ if patients were operated upon multiple times, which happens relatively often in an ophthalmology department. In addition, the data extraction for the average case duration, the percentage of case durations shorter than 1 h, and the percentage of urgent patients within 8 days was explained in the previous section. Because the average weekly number of surgeries per patient group depended on the number of patients in the corresponding patient group, we calculated these numbers directly in the interactive tool.

6 Results

In this section, we present the quantitative results of the regression analysis and the computer simulation. Furthermore, we demonstrate the use of the interactive tool for our case study, including the results of the regression analysis and the computer simulation.

6.1 Results to decide upon the appropriate level of detail

6.1.1 Results of the regression analysis

We performed an ANOVA-test to check if the regression model is valid (significance level=0.018).

The regression analysis indicated that the percentage of case durations shorter than 1 h, the total monthly overtime in hours, and the number of cancellations due to overrun of previous surgeries were significant factors (see Table 4). The resulting R was 0.58. The other included factors—namely, the number of cancellations due to prioritizing urgent patients, the average case duration, and the percentage of urgent patients—were not significant.

We expected that a higher average case duration would result in fewer turnovers, and thus in a lower utilization rate. In addition, we expected that a higher percentage of case durations shorter than 1 h would result in a higher utilization rate, because these short cases could be used to fill the remaining operating time on a specific day. Remarkably, the B coefficient of the percentage of case durations shorter than 1 h was negative, so a higher percentage resulted in a lower utilization rate. Apparently, this factor was not a good indicator for the ability to fully schedule the available operating time. In contrast, this factor seemed to be an indicator for the number of turnovers, and so had a negative impact on the operating room utilization rate.

Therefore, we experimented with a regression model without the percentage of case durations shorter than 1 h. This model indicated that the average case duration and the number of cancellations due to overrun of previous surgeries were significant factors (see Table 5). The resulting R of this model was 0.48, so slightly worse than the first model.

6.1.2 Results of the computer simulation

To check the sensitivity of the outcomes for the type of distribution, we first used a discrete uniform distribution for the weekly demand, and subsequently we used a Poisson distribution to randomly select the weekly number of requested surgeries. For this comparison, we experimented with an average of two and four surgeries per week with a 20% chance of no demand at all for surgery during a week. Therefore, the discrete uniform distribution was between one and four per week and between one and nine per week respectively. For the Poisson distributed demand, we used an average value of 2.5 and 5.0 per week. Per type of distribution, we experimented with all possible combinations of the average weekly number of surgeries and the different threshold values for the waiting time target, namely, 5 weeks, 9 weeks, 3 months, and 6 months.

We concluded that the difference in maximum utilization rate between two threshold values is slightly higher with a Poisson distributed demand than with a uniformly distributed demand. Because we preferred to obtain worst-case outcomes, we continued our experimentation with a Poisson distributed demand.

Table 6 shows the maximum utilization rate with a Poisson distributed demand for an average of one, two, three, four, or five surgeries per week and the different threshold values.

Table 4 Results of the first model of multivariate analysis

Significant factor	B coefficient	B Standard error	Beta coefficient	p-value
Model constant	0.814	0.038		0.000
Percentage of case durations shorter than one hour	-0.300	0.105	-0.395	0.025
Number of cancellations due to overrun of previous surgeries	0.004	0.002	0.324	0.025
Overtime (in hours)	0.005	0.002	0.293	0.040

Table 5 Results of the second model of multivariate analysis

Significant factor	B coefficient	B Standard error	Beta coefficient	p-value
Model constant	0.490	0.111		0.000
Average duration of operations (in minutes)	0.003	0.001	0.349	0.029
Number of cancellations due to overrun of previous surgeries	0.005	0.002	0.375	0.020

Clearly, a more stringent waiting time target has a significant impact on the maximum utilization rate of the operating room. Moreover, the negative impact is larger for a small number of surgeries per week (i.e., one or two) than for a larger number of surgeries (i.e., four or five). The next conclusion is that with a threshold value of 26 weeks, the maximum utilization rate is almost 100% in all situations except for one surgery per week.

Finally, to adapt the utilization rate predicted by regression analysis, we calculated ρ_{cur} and ρ_{pref} with the utilization rates of the Poisson distributed demand.
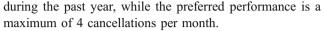
6.2 Results of the interactive decision-support tool

For the interactive tool, we used regression analysis and computer simulation to quantify the impact of all included factors on the operating room utilization rate. To demonstrate the use of the interactive tool, we give an illustrative example with a limited number of patient groups, namely, orbital, surgical retina, medical retina, and secondary level of care patients. These are the same subspecialties we used to illustrate the data collection in Table 3. The actual tool incorporates all subspecialties of the AMC ophthalmology department.

Before discussing the scenarios, we will first describe the current performance and the preferred performance (see Table 7). For example, in the current situation, at least 80% of the elective medical retina patients experienced a waiting time of less than 9 weeks, while the preferred threshold value for this patient group is 5 weeks, based upon the so-called Treek norm which was set by the Dutch government. Furthermore, the maximum number of cancellations due to overrun of previous surgeries was 7.5 per month on average

during the past year, while the preferred performance is a maximum of 4 cancellations per month.

For the first scenario, we determined the maximum allowed utilization rate for the current situation with the current performance and calculated the total demand for the OPD, the nursing ward, and the operating room (see Table 8).

Next, we determined the maximum utilization rate and the total operating room demand with the original number of patients and the preferred performance (see Table 7). Because the maximum utilization rates drops from 75.6% to 70.0%, and the number of patients per patient group remains equal to the current situation, the total operating room demand increases by more than 5,000 h.

One solution to compensate for the increased demand is to expand operating room time. If this is not possible, the number of patients has to be reduced.

Scenario 3 (see Table 8) contains an overall reduction of 8.9% for all patient groups to ensure that the total future demand of the operating room will not exceed the current demand. In scenarios 4, 5, and 6, there has only been a reduction in a single patient group per scenario: secondary level of care patients (-65.1%), orbital patients (-23.0%), and surgical retina patients (-15.1%) respectively. Note that we did not show a reduction in medical retina patients because the total operating room demand of this group is not enough to compensate for the increased demand. The final scenario contains a reduction in orbital patients and surgical retina patients (-11.4%) and an increase in medical retina patients (+43.0%). These numbers result in an equal demand for the OPD and the operating room compared with the current situation.

In all scenarios, because the capacity demand for the OPD and nursing ward does not exceed the previous year's production, there will be sufficient capacity in the future.

7 Discussion

To determine which level of detail best supports the medical management of the AMC ophthalmology department with their strategic patient-mix decisions and takes the KPIs into account, we focused on the department's bottleneck; the operating room. For the OPD and nursing ward, we assumed that as long as the capacity demand does not

Table 6 Results of the computer simulation

Avg no of surgeries	Threshold values of waiting time target			
	5 weeks	9 weeks	13 weeks	26 weeks
1	0.735	0.828	0.880	0.969
2	0.814	0.890	0.933	0.996
3	0.858	0.921	0.949	0.997
4	0.867	0.931	0.958	0.998
5	0.887	0.940	0.969	0.998

Table 7 Current and preferred performance for the operating room

Performance	Threshold values of waiting time targets				Max no of cancellations due to overrun prev surgeries
	Orbital	Surgical retina	Medical retina	Secondary	
Current	26 weeks	5 weeks	9 weeks	9 weeks	7.5
Preferred	5 weeks	5 weeks	5 weeks	9 weeks	4

exceed the previous year's production, there will be sufficient capacity in the future.

For the operating room, we determine the maximum workload, taking the preferred levels for all KPIs into account. We started with a literature review to identify all factors that influence an operating room's utilization rate. Next, we decided which factors were relevant to our study, and thus should be included. We included four KPIs and three patient-mix characteristics. Finally, we quantified the effect of the included factors on the maximum allowed utilization rate of the operating room with a combination of regression analysis and computer simulation.

The regression analysis indicated that the percentage of case durations shorter than 1 h, the total monthly overtime in hours, and the number of cancellations due to overrun of previous surgeries were significant factors. Surprisingly, the average case duration was not. By contrast, the percentage of case durations shorter than 1 h was significant, but with an unexpected impact: a higher percentage results in a lower utilization rate, and vice versa. It seemed that the latter factor was a better indicator for the number of turnovers than the average case duration. Therefore, we chose to experiment with a model that excluded the percentage of case durations shorter than 1 h. This model indicated that although the average case duration was significant, the fit of the regression dropped. Nevertheless, we selected the latter model for incorporation into our interactive decision-support tool.

To quantify the effect of a more stringent waiting time target for elective patients, we used computer simulation. We determined the maximum utilization rate for different threshold values: 5 weeks, 9 weeks, 3 months, and 6 months. The simulation confirmed that a more stringent waiting time target has a significant impact on the maximum utilization rate of the operating room. Moreover, the negative impact is larger for a small number of surgeries per week than for a larger number of surgeries.

Finally, we adapted the department's overall utilization rate from the regression analysis with the results from the computer simulation. By incorporating these results into the interactive decision-support tool, we enabled the management of the AMC ophthalmology department to alter the number of patients in various patient groups and to see the consequences in terms of the KPIs.

7.1 Final conclusions

Clearly, it is not enough to apply a rule of thumb for the maximum allowed utilization rate of an operating room that does not account for all specific departmental aspects. Also, the previous year's utilization rate does not account for future alterations in patient mix and the possible gap between preferred and current performances, and so is also not entirely satisfactory. Even at strategic level, it is necessary to incorporate management decisions concerning

Table 8 Various scenarios of the interactive tool

Scenario	Number of patients per patient group per year				Total demand OPD (in hours)	Total demand nursing ward (in days)	Max utilization rate operating room	Total demand operating room (in hours)
	Orbital	Surgical retina	Medical retina	Secondary				
1. Current situation	461	411	346	3,168	2,506	1,322	77.6%	73,331
2. Preferred performance	461	411	346	3,168	2,506	1,322	72.2%	78,774
3. Overall reduction	422	376	317	2,899	2,293	1,210	71.0%	73,301
4. Less secondary	461	411	346	900	1,358	1,209	71.8%	73,324
5. Less orbital	361	411	346	3,168	2,410	1,222	71.6%	73,272
6. Less surgical retina	461	353	346	3,168	2,466	1,226	71.9%	73,282
7. Less orbital, less surgical retina, and more medical retina	410	366	495	3,168	2,505	1,206	70.8%	73,242

KPIs and future patient-mix characteristics to determine the maximum workload of the operating room.

The interactive tool offers medical management quantitative decision support to enable them to act proactively instead of reactively to expected alterations in patient mix. When acting proactively, management can anticipate the future situation, and either alter the expected patient mix or arrange for new equipment and retrain physicians in a related subspecialty to ensure that the KPIs will be met in the future.

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