Decision Support for Patient Discharge in Hospitals – Analyzing the Relationship Between Length of Stay and Readmission Risk, Cost, and Profit

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Abstract. Determining the optimal time for patient discharge is a challenging and complex task that involves multiple opposing decision perspectives. On the one hand, patient safety and the quality of healthcare service delivery and on the other hand, economic factors and resource availability need to be considered by hospital personnel. By using state-of-the-art machine learning methods, this paper presents a novel approach to determine the optimal time of patient discharge from different viewpoints, including a cost-centered, an outcome-centered, and a balanced perspective. The proposed approach has been developed and tested as part of a case study in an Australian private hospital group. For this purpose, unplanned readmissions and associated costs for episodes of admitted patient care are analyzed with regards to the respective time of discharge. The results of the analyses show that increasing the length of stay for certain procedure groups can lead to reduced costs. The developed approach can aid physicians and hospital management to make more evidence-based decisions to ensure both sufficient healthcare quality and cost-effective resource allocation in hospitals.

Keywords: Machine learning · Length of stay · Unplanned readmissions · Patient discharge

1 Introduction

The increasing demand for healthcare services as well as the change from a fee-for-service to a prospective payment system in many countries force hospitals to increase their case rate and reduce hospital length of stay (LOS) for patients. According to these payment systems, patients are classified into so-called Diagnosis-Related Groups (DRG). These groups provide a clinically meaningful way of relating a hospital's casemix to its resources, where patients with similar clinical conditions requiring comparable hospital resources are categorized into groups and priced accordingly (Fetter *et al.* 1980). This means, that hospitals are reimbursed for a patient episode with a fixed amount of money that is defined for the specific DRG independent from the duration of the patient stay. Only if the LOS exceeds or falls below the average boundaries for this DRG

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(i.e., so-called "low outliers" or "high outliers"), hospital reimbursement is adjusted. Thus, hospitals are motivated to shorten LOS and release patients as close to this lower boundary as possible. Studies show, that this reduction can result in higher unplanned readmission rates (Oh *et al.* 2017) that can, in turn, lead to penalty fees or reduced compensation for hospitals. Several initiatives have been introduced worldwide to tackle the issue of preventable readmissions. Most prominent are the Hospital Readmission Reduction Program (HRRP) in the US (CMS 2016) and the Australian National Healthcare Agreement for Unplanned Hospital Readmission Rates (AIHW 2018). These programs aim at identifying, monitoring, and reducing hospital readmissions according to different criteria. The starting point of these interventions lies in the screening of individuals at high risk of discharge failure (Scott 2010). By identifying high-risk patients, hospital resources can be allocated accordingly and interventions and discharge planning can be adapted. Multiple factors associated with a higher risk of readmission have been identified in research, including health factors (e.g., co-morbidities (van Walraven *et al.* 2011; Kumar *et al.* 2017)), social factors (e.g., marital status (Hasan *et al.* 2010)), clinical factors (e.g., hospital utilization (Shadmi *et al.* 2015), length of stay (Heggestad 2002)), or effective discharge management (Ohta *et al.* 2016). While some of these influences cannot be directly controlled, especially the time and management of patient discharge is a modifiable factor. While some studies suggest a longer LOS to be beneficial (Horney *et al.* 2017), others state the importance of an early release (Morris *et al.* 2011; Hasan *et al.* 2010) to avoid hospital-related issues such as infections or bed sores. While the impact of an increased LOS on the quality of healthcare services and thus, the readmission risk is still debated, the resulting costs for a prolonged stay are apparent. With each additional day of hospitalization, incurred costs for accommodation, personnel, as well as opportunity costs for the occupied hospital bed, continuously increase. These opposing views result in a complex optimization problem of finding a suitable time for patient discharge that leads to both the maximum profit for the hospital while also reducing the rate of unplanned readmissions. Therefore, the main goal of this paper is to investigate the relationship between patient LOS and readmission risks and the respective costs that need to be considered in this context and provide recommendations on determining the optimal time for patient discharge based on these factors. For this purpose, episode data from an Australian private hospital group is utilized to estimate the readmission risk for individual patients across multiple DRGs. The remainder of this paper is structured as follows: Sect. 2 gives an overview of the theoretical and conceptual foundations that are required to calculate the respective costs and outcome measures for a patient episode. Section 3 subsequently aggregates these findings into three different perspectives on the optimal time of patient discharge, namely from a solely cost-centered view, an outcome-centered view, and a balanced view. Finally, the conceptual views are tested with actual episode data and critically reflected to identify limitations and future research potentials of this work.

2 Theoretical and Conceptual Foundations

2.1 Objective and Method

Since 2006, the Australian Institute of Health and Welfare has been tracking 28-day readmission rates (AIHW 2018). Here, readmission is defined as follows:

- The second admission has to follow a separation from the same hospital where the patient was either treated with a knee replacement (TKA), hip replacement (THA), tonsillectomy and adenoidectomy (TONADE), hysterectomy (HYS), prostatectomy (PRO), cataract surgery (CAT) or appendectomy (APP).
- The second admission has to occur within 28 days of the previous separation.
- The principal diagnosis of the second admission has to refer to a complication, sequelae of complications, or post-procedural disorders from the index admission.

As readmission rates are already widely used as a measure to indicate how well a patient is taken care of (Benbassat and Taragin 2000), the readmission risk curve is implemented to showcase the impact of the discharge decision and LOS on the quality of care. In addition, economic factors, such as hospital costs and reimbursements are contrasted against this measure to disclose the impact on both perspectives to the decision-maker. Thus, doctors can determine the optimal time of patient discharge both from an economical perspective as well as according to the patient status. From an economical perspective, the lower boundary for patient length of stay is deemed optimal due to the unvarying reimbursement rates (cf. Fig. 1(a)). However, considering the risk of readmission (cf. Fig. 1(b)), a longer LOS can be preferable, depending on the underlying strategy with regards to cost efficiency and quality of care. To be able to visualize the risk of readmission for an individual patient over time as well as the respective costs and reimbursements for a single episode, several measures need to be calculated beforehand.

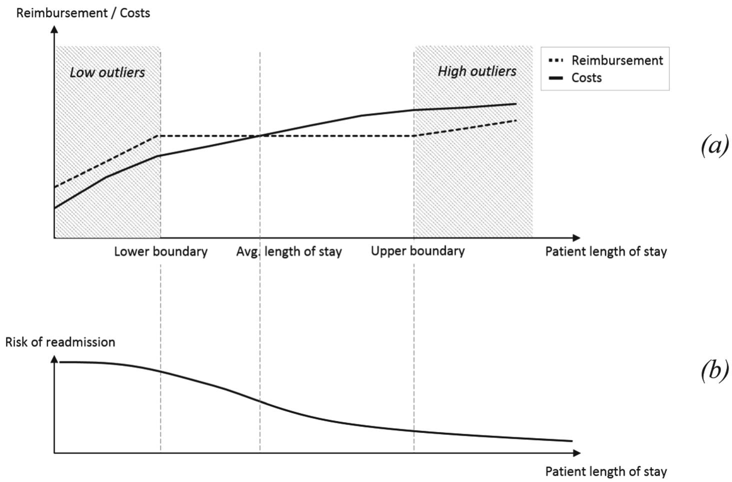

Fig. 1. Reimbursement, costs, and readmission risk for a patient episode over time

2.2 Readmission Risk Chart

To determine the readmission risk of a patient during his/her stay, historical patient episode data is utilized to develop prediction models for each of the AIHW procedure groups (Eigner *et al.* 2017; Eigner *et al.* 2018). Based on the predicted probability of readmission, the current risk is determined for the investigated episode. Thus, by understanding this risk in more detail, physicians and hospital personnel can make better-informed, more evidence-based decisions on patient discharge and additional treatment.

To realize this in practice, the most suitable prediction model is selected according to the presented diagnosis and the main performed procedure. This ensures that procedure-specific risk factors are considered in the readmission risk prediction, resulting in a higher prediction accuracy (Eigner and Cooney 2019). The model is applied to simulate the readmission risk when discharging the patient at the current point in time (i.e., for the current length of stay) as well as the following days with an increasing length of stay. This results in a readmission risk curve that determines the risk progression over time to indicate the optimal time of discharge from a quality point-of-view.

2.3 Cost Chart

To determine the cost development over time, the National Hospital Cost Data Collection (NHCDC) Australian Public Hospitals Cost Report is used to calculate the average costs per DRG (IHPA 2018). Here, costs are categorized according to various cost buckets that reflect certain cost pools within a hospital. Each bucket summarizes the costs for a particular function in a hospital (e.g., the operating room). Overall, sixteen cost buckets are differentiated. While certain buckets, for example, prosthesis and imaging, are assumed to be independent of the actual LOS and therefore constant for a certain procedure group, hotel costs continuously grow with an increased LOS. Following the approach by Arefian *et al.* (2016), costs of accommodation, medical treatment, laboratory procedures, materials and services, and physician and nursing care are included in the cost per bed day calculation. On-costs, operating room, prosthesis, depreciation and imaging costs are aggregated as procedure-specific costs that are independent of the LOS. Table 1 provides the average costs for each procedure group, including the LOS-independent procedure costs and the LOS-dependent costs per bed day.

Table 1. Average costs for each AIHW procedure group (in $)

	APP	CAT	HYS	PRO	THA	TKA	TONADE
Procedure costs	4,652	2,696	8,067	4,446	16,217	16,033	2,136
Cost per bed day	1,384	1,253	1,617	1,398	1,359	1,396	1,566

2.4 Reimbursement Chart

To calculate the reimbursement rate for each episode, the Victorian Weighted Inlier Equivalent Separation (WIES) is used. Episodes with a shorter or longer length of stay compared to an average range ("inliers") for each DRG are reimbursed according to different pre-defined weights. Each WIES is multiplied by a base price (b), namely the Australian National Efficient Price (NEP). For 2018–19, the NEP is valued at $ 5,012 (IHPA 2018). Inlier episodes with a LOS over one day use the standard multi-day inlier weight for that DRG. For a shorter hospital LOS, a low outlier per diem cost weight is used as a basis for reimbursement calculation. An extended LOS uses a high outlier per diem weight.

Additional weights are applied for one-day or same-day stays and hospital-in-the-home days as well as cost weights for co-payments to moderate financial risk for hospitals that provide special types of care (DHHS 2018). The WIES cost weight for same-day episodes, one-day episodes, and multi-day inliers are available directly in the WIES25 weights table (DHHS 2018). As reimbursement is determined based on the episode's DRG, which is assigned only post-admission, the most likely DRG must be identified in advance. To determine the DRG pre-discharge, a logistic regression model is applied. Based on the suggested DRG, the responding WIES weights are utilized to display the final reimbursement rate.

3 Optimal Time of Patient Discharge

To determine the optimal time of patient discharge, the presented measures are used to develop three perspectives from a profit-centered, a quality-centered and a balanced viewpoint. For the profit-centered perspective, only costs and reimbursements are considered to identify the most financially rewarding time for patient discharge. Figure 2 displays the recommendation for an average patient after a knee replacement with major complexity to discharge on the second day for a maximum profit.

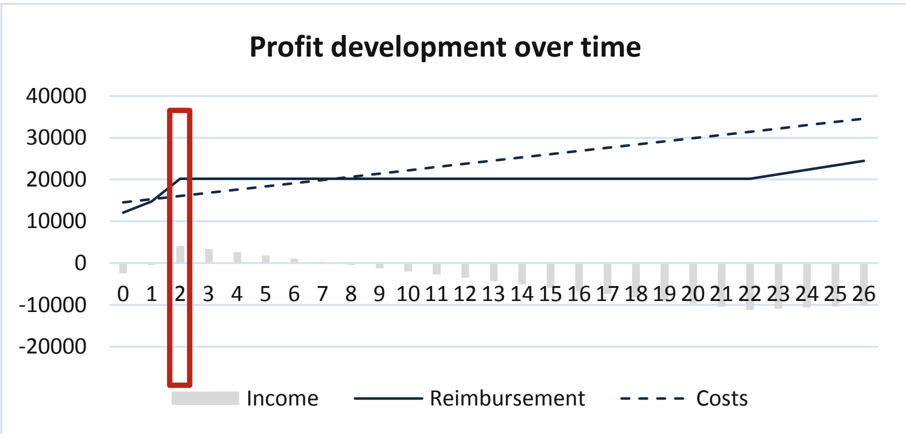

Fig. 2. Profit development over time for an average patient after a knee replacement with major complexity (DRG I04A)

The second perspective is based on the prospective readmission risk during the hospital stay. Figure 3 displays the average proportion of patients that were readmitted in the past according to their time of discharge. From a healthcare quality perspective, the ninth day is selected to be the optimal point of discharge with the lowest readmission risk. While this visualization only considers the length of stay as the influencing factor for readmission risk, the developed prediction models include additional risk factors specific to each procedure group. The increasing risk depicted in Fig. 3 is mainly due to the occurrence of complex cases with multiple complications. For episodes without any major incidents, an increased length of stay is associated with a higher quality of care and thus a reduced risk of readmission (cf. Fig. 1). However, as patients are usually released once they're sufficiently healed, this is not directly reflected in the historical data.

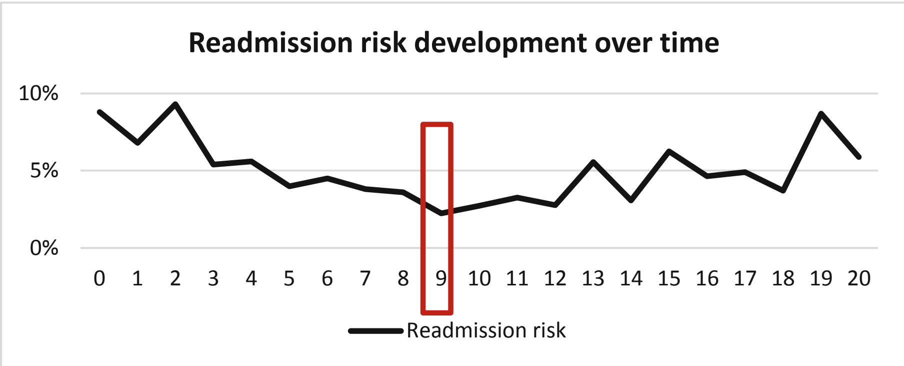

Fig. 3. Proportion of readmissions for patients after a knee replacement (DRG I04A)

To combine both perspectives into a balanced view that considers both economical as well as quality measures, both measures are combined into one visualization (Fig. 4).

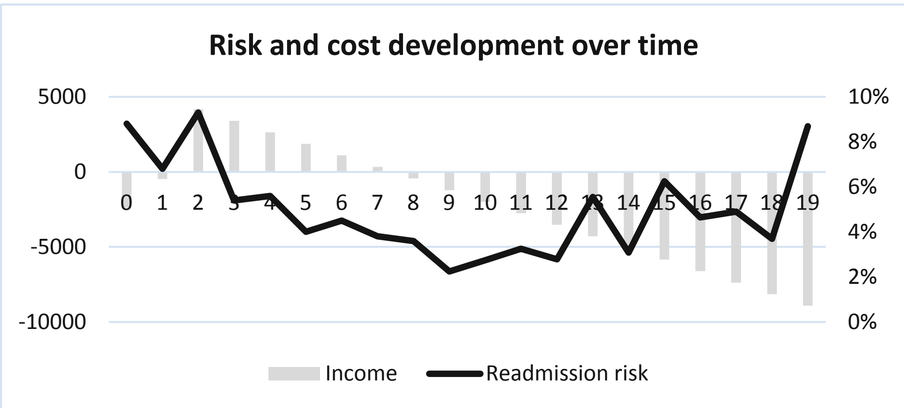

Fig. 4. Risk and cost development for an average patient after a knee replacement (DRG I04A)

To quantify the readmission risk to allow for better comparability, this measure can also be transformed into a cost factor. This is done by multiplying the current readmission risk with the average cost for a readmission episode. However, this approach neglects reputation damages.

4 Discussion and Conclusion

The increasing pressure on healthcare professionals to deliver high-quality patient care with restricted time and resources is forcing hospitals to find more efficient ways of providing healthcare services. To counter this issue, this paper presents a concept to support hospital personnel to consider both the economical as well as the quality-driven viewpoint in the patient discharge decision by analyzing previous patient episodes. The implications of this study are relevant to both research and practice. Considering the quality of care and regulatory penalties, the importance of identifying patients at high risk of readmission is apparent. Improved post-discharge care and support for self-care can help to abate potential readmissions of identified individuals, thereby reducing overall costs and increasing healthcare quality (Shulan *et al.* 2013). Thus, by aiding the identification of potential risk patients, hospital resources can be better allocated to critical patients, and health interventions are already possible in an early stage of the patient pathway.

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