Towards a fairer reimbursement system for burn patients using cost-sensitive classification

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1 INTRODUCTION

The National Health Service (NHS) serves a broad UK population with varied demographic and medical histories. An acceleration in medical advances has led to a greater scope of treating chronic illness [1]. In turn, this burden the NHS with rising costs and with limitation of access to funds, these have fuelled the popularity and the adoption of Prospective Payment System (PPS) over retrospective systems. PPS is a reimbursement method that allows for the predetermination of a fixed amount to be allocated to health providers for the treatment of patients with a specific diagnosis. The overall aim is to ensure an equitable and fair distribution of funds. It also acts as an instrument to understand the organisational activity, such as the type of patient cared for and treatment delivered. The system adopted in the UK is called Health Resource Groups (HRGs). HRGs are groupings of clinically similar patients which use comparable healthcare resources. Although these groups are generated using patient-level data, the grouping rules are typically generated by transcribing expert advice into if-else rules meant to capture differing patient severity and length of stay (LOS).

These HRGs should be clinically meaningful groups of diagnoses and interventions that consume similar levels of NHS resources. However, the aim of having homogeneous groups in terms of resource usage might not be met due to: (i) the methodology’s dependence on expert advice, which carries the risk of ignoring less established factors that account for specific patient subgroups’ complexity; (ii) the validation of identified groups using LOS only, an imperfect indicator of resource usage [2]; (iii) the determination of payment rate as an average of the cost of each HRG. This is, in essence, a generalisation that will exacerbate the effect of any non-homogeneous groups. Non-homogeneity in the resource usage of the identified groups may lead to a significant disadvantage to small and highly specialised services that, by necessity, operate at very high expenditure. Burn services are one such service – they are small, rely on specialist equipment and intervention, deal with various case complexity and stay open regardless of the number of patients admitted, with a minimum staff number constantly on the rota [3].

We investigate if the current burn HRG can be improved while remaining interpretable, by using a cost-sensitive decision tree model. Our approach aims to create a fairer system by identifying more homogeneous groups of burn patients, thus ensuring a consistent cost reimbursement for the provision of similar patient care. To validate the methodology, we use data of actual burn patients. We show that the proposed approach can identify more homogeneous patient groups, enabling a more equitable and fair reimbursement.
2 COHORT AND DATA DESCRIPTION
The current burn care pathway is designed to treat paediatrics separately from adults due to evidence of young age as a significant complicator of burn injury [4]. Further evidence was found in [5] that different factors and resource requirements characterise adult and young burn patients. Thus, any developed approach should be customised for adult and child patients. This paper focuses on identifying homogeneous groups of young (<16 years old) burn patients only, by using anonymised patient-level data from all burn services in England and Wales.

The information of patients that attended a burn service is collected by clinicians and nurses, from the first contact with a burn service to rehabilitation and any late reconstruction procedure [6]. The dataset excludes burn injury patients who died before reaching a burn service and those with minor injuries cared for in the community or hospitals that are not specialist burn services. The data covers 2003 to 2019, comprising just over 18,000 young patients and was extracted from the internal Burn Injury Database (iBID) [7]. An internal iBID patient-level costing methodology [8] is applied to generate the cost of the burn patients.

3 ANALYTICAL PIPELINE
In healthcare, adopted models are potentially responsible for human life and, thus, there is a need for high confidence from clinicians on the results of a model. Therefore, it is imperative that adopted models are explainable. An explainable model, such as a decision tree, allows result tracing, increases transparency and facilitates model improvement [9]. For instance, offering a clear explanation of why a specific burn patient is placed in a higher severity group than another would increase the trust level of clinicians. Thus, we propose a cost-sensitive decision tree model, trained and tested to evaluate model performance on unseen data.

A decision tree classifier was chosen as it allows the identification of rules generated for classification. To increase homogeneity, our paper introduces a key feature: the allocation of misclassification costs between classes. We chose a cost-sensitive decision tree that ensures that even with a misclassification, the predicted class is in close proximity (by cost, LOS and severity) to the expected patient class. This model enables model penalisation as the distance is identified by ranking classes by the average value across all LOS, TBSA and cost DT target classes as that reflects the average severity, cost and length of hospital stay. This distance is identified by ranking classes by the average value of LOS, cost and total burn surface area (TBSA). The classifier was implemented with the mlr [11] and rpart [12] packages in R, with a customised cost measure.

In summary, the analytical pipeline adopted to build this proposed model includes data preprocessing, identifying target features and variables of importance, and building the final model.

3.1 Data Preprocessing
With the need to compare our adopted model results to the current HRG groups, access to the HRG labels for each patient is needed. However, due to non-access to the Health Episode Statistics (HES) dataset typically used to create HRGs and thus the inability to directly merge the iBID dataset to the HES, it is essential to recreate the HRG burn methodology using the iBID dataset. This was done in close collaboration with the NHS National Casemix office. The first step was to replace all missing values with 0. The assumption is that fields are left empty when the value is 0, no or not applicable (also adopted by the current HRG methodology) [13]. The next step was the identification of iBID variables or a proxy to variables used in the HES dataset. The HRG replication was then done using if-else rules created by the Casemix team and adapted by an NHS Casemix expert to suit the iBID dataset. We expect 13 classes to be generated for the young burn patient subgroup, ranked from most severe to least severe.

The next data preprocessing step involves removing all cases grouped into the unclassifiable group, as these cases have no TBSA or depth of burn recorded for any of the 27 potential burn sites (parts of the body), which is a pre-requisite (as stated in the burn HRG methodology) for reimbursement as a burn case. Cases with LOS greater than 360 and cost greater than £1,000,000 are considered outliers by the iBID data administrators and thus removed. The data preprocessing also includes removing irrelevant variables (administrative variables, variables with high missing values, variables with unstructured data, variables with one unique value and variables which are duplicates of another).

3.2 Identification of Target Features and Variables of Importance
The proposed model is a decision tree (DT) classifier, a supervised model that requires ‘true’ labels. Thus, the target classes (true labels) were generated using three critical factors in burn care – LOS, cost and TBSA. These factors were identified from previous analysis and the literature and represent the aim of HRGs to create clinically meaningful groups (burn severity) that have similar resource usage (LOS and cost of treatment). These factors were first log-transformed to reduce skew, followed by k-means cluster analysis to segment each factor into 13 target classes. The identified classes were ranked from most severe/costly to least severe/costly (to allow for adequate comparison with the current HRGs). With these, three cost-sensitive DT models (LOS, TBSA and cost DT) were built using the ranked classes to identify the variables of importance from each model. The target class ranking is necessary to enable comparison with the ranked HRG and the incorporation of a cost-sensitive model.

3.3 Final Decision Tree (DT) Model
Here, we describe the final model for comparison with the current HRG and extraction of classification rules. The 13 target classes for this model are derived using k-means cluster analysis. The feature space for the cluster analysis is computed by calculating the average rank across all LOS, TBSA and cost DT target classes as identified using the approach described in Section 3.2. Adopting the mean rank of each case allows for the identification of the classes that reflect the average severity, cost and length of hospital stay.

The independent variables are those identified as important from the LOS, TBSA and cost DT. The dataset is then split into a train and test set. These subsets are oversampled independently by duplicating cases in the minority classes. The oversampling is needed to ensure the adopted model has enough samples to learn the decision boundary effectively.
The model used is a cost-sensitive DT model, trained and tested to evaluate model performance on unseen data. The cost-sensitive DT model is used to increase model penalisation as the distance of the class predicted compared to the actual class increases.

4 RESULTS

This section presents the results of the data-driven model generated using a cost-sensitive DT. We first evaluate the engineered target classes generated to ensure it reflects homogeneity in severity and resource usage. Figure 1 shows a scatterplot of LOS, TBSA, and Cost DT model ranked target classes, where class 1 depicts least severe/costly, and class 13 depicts most severe/costly, against that of the Final DT target classes (also ranked). The plotted Final DT target classes reflects, as expected, homogeneity in severity and resource usage. It shows that the target classes have a decreasing LOS, cost, and TBSA as its severity (reflected by the Final DT ranked classes) decreases.

Figure 1: Spread of ranked LOS, Cost and TBSA model target classes - each dot represents a patient’s LOS, cost and TBSA group and the colour represents the Final DT group.

Comparing the HRGs with the generated target classes, we show histograms of intra-group variance (in terms of cost, TBSA and LOS) of the DT and HRG model to evaluate how much homogeneity can be found. Figure 2 illustrates a lower intra-group variance in the DT groups than to the HRG groups for the train data. In particular, we found that, on average, the cost intra-group variance (0.4) for DT groups is three times lower than the HRG groups cost intra-group variance (1.5). This pattern is seen for the LOS intra-group variance - 0.8 for DT groups and 1.7 for HRG groups. As expected, a lower difference when we compare the average severity (TBSA) intra-group variance of DT groups at 0.5 and that of the HRG groups at 0.6. Evaluating these intra-group variances on the train data is needed to ensure the engineered classes meet the homogeneity criteria. These evaluations indicate that the new target classes provide higher intra-group similarity in terms of the three critical factors than the HRGs. Thus, these target classes are adopted.

Figure 2: DT and HRG intra-group variance - LOS, Cost and TBSA - on train data. The value on each legend is the average Cost, LOS and TBSA intra-group variance for the DT and HRG groups.

With these promising results, it is imperative to understand the rules that allow the classification of cases into each engineered class and evaluate the model’s performance on unseen cases. This is done by identifying the feature space, which are the variables of importance identified from the TBSA, LOS and Cost DT classifiers. Then the creation of a cost matrix for penalisation. The cost matrix is shown in Figure 3, with the rows indicating true and the columns predicted class labels. The diagonal zero values indicate a cost of 0 for accurate prediction, with an increase in cost as predicted class deviation from the true class increases. This is added to the Final DT model pipeline with a train and test split to evaluate performance.

The confusion matrix shown in Figure 4 reveals good classification of unseen cases (test data). The confusion matrix shows that
most of the cases are predicted as the precise class. Where the classification is wrong, the misclassified class is in close proximity to the true class. Except for class 8, with most cases predicted as class 9 and some cases misclassified three classes away. This higher misclassification of class 8 suggests the likely need to reduce the total number of classes in the young patient subgroup. The model identifies class 8 and 9 as both made up of cases with TBSA >=5 but differentiated by the LOS. Class 8 are those with LOS < 2.5 while class 9 are patients with LOS >= 2.5 (see Figure 7).

Figure 5: DT and HRG groups by LOS, Cost and TBSA on test data. Ordered in decreasing order of injury severity.

Figure 7: Classification tree showing explainable classification rules generated from the cost-sensitive DT model.

5 CONCLUSION AND FUTURE WORK

The adopted model creates a classification rule that is easy to explain and less complex than the current HRG methodology. This meets the HRG requirement that groups are clinically relevant to allow for organisational activities. Additional, our adopted model meets the requirements of group homogeneity in terms of resource usage and severity. The resultant groups from the adopted DT model evidenced increased homogeneity across the three critical factors – length of hospital stay, cost to the hospital and severity of burn, compared to the current HRG. Thus, our identified groups are better suited for cost reimbursement.

Our future work includes the customisation of the cost matrix to reflect a non-linear and non-monotonic penalty (e.g., actual monetary cost) for misclassification and applying this analytical pipeline to adult burn patients.
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