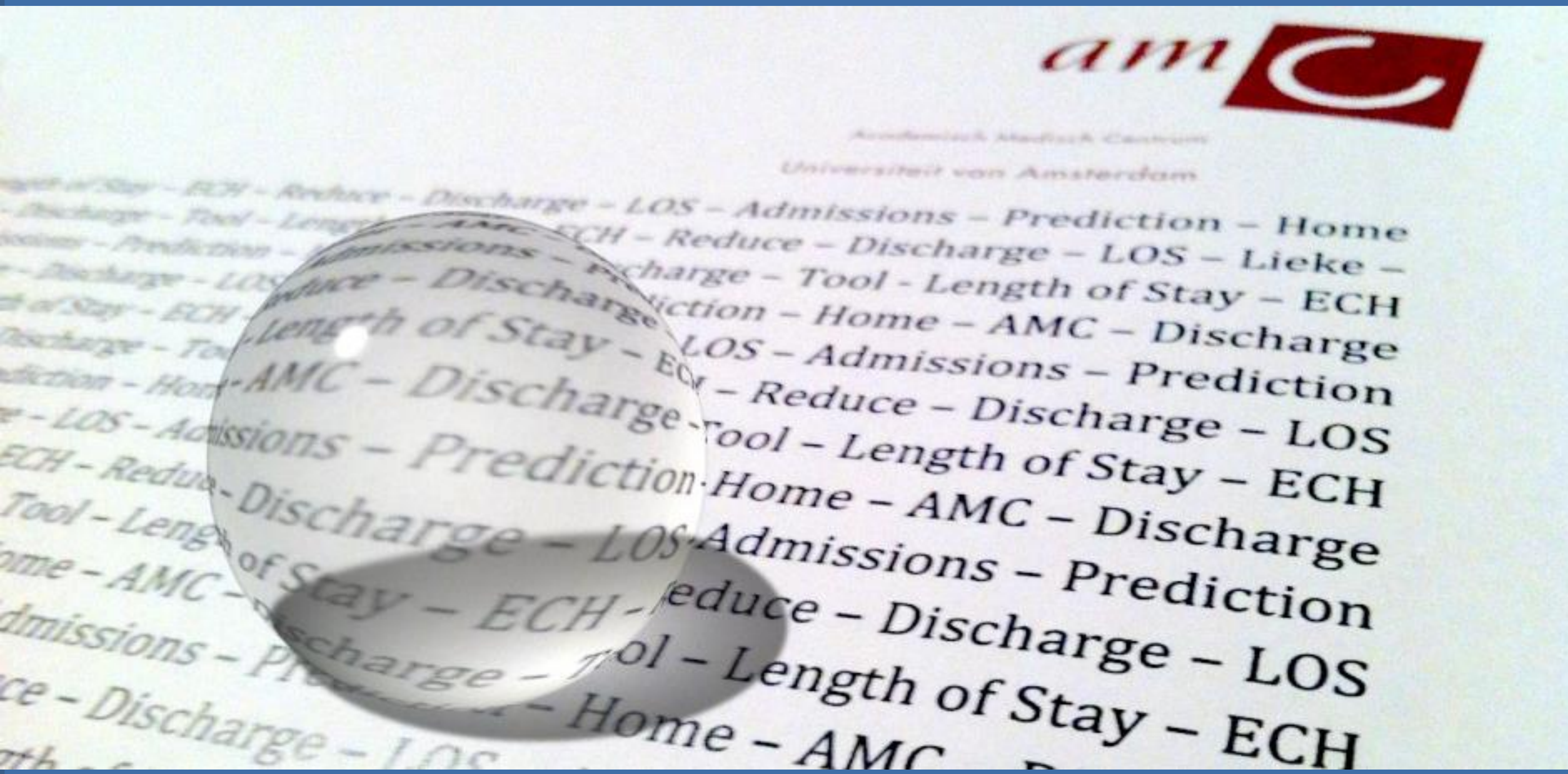
Your LOS(S), Your Gain

Prediction tool for the hospital Length of Stay

MSc. Thesis



Lieke van den Brandt, 11th of December, 2013

UNIVERSITY OF TWENTE.

"Prediction is very difficult, especially if it's about the future"

- Niels Bohr, Nobel laureate in Physics

Study	Industrial Engineering & Management
Track	Healthcare Technology & Management
Faculty	School of Management & Governance
University	University of Twente
Student #	s0177504
Examination	Dr. Ir. M.E. Zonderland (University of Twente)
Committee	Dr. N. Kortbeek (University of Twente)
	R.N.M. Vollebregt, MSc. (AMC Amsterdam)
	D.K. Bosman, MD (AMC Amsterdam)

Management Samenvatting

Achtergrond

Nederlandse ziekenhuizen worden gedwongen om hun beperkte middelen zo efficiënt mogelijk in te zetten. Een van deze middelen is de beddencapaciteit van ziekenhuizen. Een optimale opnameplanning gebruikt de beddencapaciteit zo efficiënt mogelijk. Om een dergelijke planning te krijgen, zijn vroege voorspellingen van het verwachte ontslagmoment van patiënten nodig. Verwachte ontslagmomenten kunnen worden voorspeld wanneer de verwachte duur van opnames bekend is. Met andere woorden, voorspellingen van de verwachte ligduur bij opname zijn nodig. In deze studie is de ligduur gedefinieerd als het aantal (halve) dagen dat een patiënt is opgenomen in het ziekenhuis gedurende een opname. Het nauwkeurig voorspellen van ligduur bij opname is een uitdaging door de grote variantie in ziekteverloop.

Het Emma Kinderziekenhuis (EKZ) wat onderdeel is van het Academisch Medisch Centrum Amsterdam (AMC) ervaart problemen met het voorspellen van ligduur bij opname. Interviews met het management van de afdelingen van het EKZ hebben uitgewezen dat ligduur momenteel niet consequent wordt voorspeld en geregistreerd. Wanneer de ligduur voorspeld wordt, is deze gebaseerd op de medische ervaring van de arts. Artsen geven aan dat zij 20% van de opnames onvoorspelbaar achten door de grote variantie in ziekteverloop. In dit onderzoek is daarom een prototype van een generiek voorspelmodel ontwikkeld dat de verwachte ligduur nauwkeurig voorspeld op basis van historische data. Daarnaast is de nauwkeurigheid van ligduur voorspellingen die door artsen gemaakt worden, gemeten.

Methode

Het voorspelmodel is gebaseerd op multiple regressie. Regressieanalyse bepaalt het verklarend vermogen van onafhankelijke variabelen op een afhankelijke uitkomstvariabele. Regressieanalyse heeft homogene groepen van voldoende grootte nodig om statistische significantie van onafhankelijke variabelen aan te tonen.

Het voorspelmodel bestaat uit een ligduur verklarend model en een toepassing op prospectieve data. Het verklarend model bestaat uit vier stappen. Ten eerste worden de opnames in de dataset gegroepeerd op diagnose. Ten tweede worden de groepen samengevoegd in klassen wanneer ze statistisch vergelijkbaar zijn om aan minimale groepsgrootte voor regressieanalyse te kunnen voldoen. Ten derde voert het model regressieanalyse uit op alle gevormde klassen. Ten vierde wordt voor elke klasse een ligduurformule gecreëerd op basis van de door regressie aangetoonde voorspellende variabelen. De toepassing op prospectieve data voorspelt de ligduur van nieuwe opnames door de opname te koppelen aan de juiste ligduurformule.

Resultaten

Niet alle voorgestelde voorspellers van ligduur uit de literatuur waren beschikbaar in de EKZ dataset (bijv. het gewicht van de patiënt en de aanwezigheid van een nevendiagnose). Dit kwam door moeilijkheden wat betreft het koppelen van verschillende databases in het EKZ. De locatie waarvandaan de patiënt is opgenomen (bijv. vanuit huis, ander ziekenhuis of spoedeisende hulp) en het opnamespecialisme bleken het grootste voorspellende vermogen voor ligduur te hebben in de EKZ dataset. Geslacht en opnamedag (weekdag of weekenddag) waren de slechtste voorspellers van ligduur.

Het voorspelmodel kon 40.7% van de opnames uit de test set voorspellen. De overige opnames waren niet te voorspellen omdat er te weinig opnames per diagnose in de training set zaten. De gemiddelde absolute afwijking tussen de voorspellingen van het model en de geobserveerde ligduur was 91.7%. Dit is een verbetering ten opzichte van de gemiddelde absolute afwijking tussen de voorspellingen van artsen en de geobserveerde ligduur. Deze was 147.6%.

Conclusie

Het ontwikkelde voorspelmodel kan de ligduur van patiënten die opgenomen zijn in het EKZ nauwkeuriger voorspellen dan dat artsen dat kunnen gebaseerd op hun medische ervaring. Desalniettemin is het aantal opnames wat te voorspellen is met het model gelimiteerd.

Aanbevelingen

Vanwege de grote gemiddelde absolute afwijking tussen de voorspellingen van het model en de geobserveerde ligduur wordt het nog niet aanbevolen om de opnameplanning in het EKZ te baseren op de ligduurvoorspellingen van het model. De dataset moet eerst meer opnames bevatten en meer voorspellende variabelen voor de ligduur. Daarmee kan de nauwkeurigheid van de voorspellingen vergroot worden. Door het generieke karakter van het voorspelmodel is het gemakkelijk om nieuwe of aangepaste datasets te analyseren.

Management Summary

Background

Hospitals in the Netherlands are forced to use their scarce resources as efficient as possible. One of these resources is the hospital bed capacity. An optimal admission planning uses hospital bed capacity as efficient as possible. In order to achieve such a planning, early predictions of the expected discharge moment of patients are needed. Expected discharge moments can be predicted if the expected duration of admissions is known. In other words, predictions of the expected length of stay (LOS) at admission are required. In this study, LOS is defined as the number of (semi-) days a patient is admitted to the hospital during an admission. Due to large variety in clinical course, it is a challenge to accurately predict LOS at admission.

The Emma Children's Hospital (ECH) of the Academic Medical Center Amsterdam (AMC) experiences difficulties in predicting LOS at admission. Interviews with the management of the ECH wards showed that LOS is currently not consequently predicted and registered. Prediction, when possible, is based on the physician's medical experience. Physicians stated that they perceive 20% of the admissions as unpredictable due to large variation in clinical course. This research therefore aims to develop a prototype of a generic prediction tool that accurately predicts expected LOS based on historical data. Additionally, the accuracy of the LOS predictions made by physicians is measured.

Method

The prediction tool developed in this study was based on multiple regression. Regression analysis determines the predictive capacity of independent variables on a dependent outcome variable. It requires homogenous groups of sufficient size to prove statistical significance of the independent variables.

The prediction tool consists of an LOS explanatory model and an application to prospective data. The explanatory model consists of four steps. First, admissions in the dataset are grouped on diagnosis. Second, groups are aggregated into classes when statistically comparable to meet minimally required class sizes for regression analysis. Third, the model performs regression analysis on all formed classes. Fourth, an LOS formula for each class based on the proven predictor variables resulting from regression analysis is created. The application to prospective data predicts the LOS for new admissions by matching the admission with the correct LOS formula.

Results

Not all proposed LOS predictor variables in literature were available in the ECH dataset (e.g. the weight of the patient and the presence of a secondary diagnosis). This was due to difficulties in combining various databases in the ECH. The location from where the patient was admitted (e.g. home, other hospital, ER) and the admission specialism had the highest predictive power on LOS. Gender and admission day (weekday or weekend day) were the poorest predictors of LOS.

The LOS prediction tool was able to predict the LOS of 40.7% of the admissions in the test set. The rest of the admissions were not predictable since too few admissions per diagnosis were available in the training set. Average absolute deviation between the tool's predictions and observed LOS was 91.7%. This is an improvement in comparison to the average absolute deviation between the physician's predictions and observed LOS, which was 147.6%.

Conclusion

The developed LOS prediction tool can predict the LOS of patients admitted to the ECH with higher accuracy than physicians can based on their medical experience. However, the number of admissions for which the tool can predict LOS, is limited.

Recommendations

Due to the large average absolute deviation between the tool's predictions and observed LOS, it is not yet recommended to base the admission planning of the ECH on LOS predictions made by the tool. The dataset first needs to be enlarged and more influencing LOS variables need to be included in order to increase the accuracy of the predictions. Due to the generic character of the prediction tool, new or enlarged datasets are easily analyzed.

Preface

In April 2013 I started this graduation project in the AMC to finish my masters in Industrial Engineering and Management. The AMC turned out to be a great choice; the experience of working in a hospital has been very informative and enjoyable and has confirmed my wish to work in health care. No matter how far away the patient sometimes seems, I only dealt with patients in numbers during this project, the ultimate goal always aims to benefit the patient in some way.

After a rocky start with a lot of trial and error and conceptual thinking, I am very proud that the prediction tool is finished. This would not have happened without the support of all people involved in this study. Maartje, thank you for keeping me on track. Your structured approach and experience helped me to deliver this thesis. Ronald, thank you so much for the endless time you invested in me and this research. Without your Excel tips and tricks the tool would be far from finished. I hope you can get the tool implemented in practice; "ehhh good luck with that"! Diederik and Lieke, thank you for opening the doors to practice and your contagious enthusiasm. Our Monday morning meetings were a great way to start the week. Lastly, I would like to thank Nikky for the dual role he played during my research. I enjoyed and valued our supervisor meetings and appreciated your constructive feedback.

Besides all the people directly involved, I would like to thank my AMC colleagues and fellow graduates. Whether you introduced me to the wonder world of statistics, read and commented on far from finished chapters, spent hours helping me with the model or just being there and supporting me: it all helped, thank you so much!

Finally, I would like to thank my friends and family for their unconditional support and trust.

Lieke

Amsterdam – December 11, 2013

Contents

1 Introduction

The demand for health care continuously rises due to demographic developments and improved access to health care. Due to these developments and changes in the Dutch financial reimbursement system, hospitals are forced to use their scarce resources as efficient as possible. One of these resources is the hospital bed capacity.

An optimal admission planning uses hospital bed capacity as efficient as possible. Early predictions of the expected discharge moment of patients are needed to achieve such a planning. Expected discharge moments can be predicted if the expected duration of admissions is known. In other words, predictions of the expected length of stay (LOS) at admission are required. In this study, LOS is defined as the number of (semi-) days a patient is admitted to the hospital during an admission. Due to large variety in clinical course it is a challenge to accurately predict LOS at admission.

Besides enabling efficient admission planning, prediction of LOS at admission could lead to LOS reduction. LOS prediction would provide an incentive to work towards a patient's discharge. Literature has shown that this could already lead to a reduction in LOS [1]. Additionally, discrepancies between expected and actual LOS can be mapped with LOS predicted. By removing or modifying the causes of these discrepancies, LOS reduction could be realized. LOS reduction leads to a higher number of treated patients and therefore an increase in the average income for each bed per day [2]. Additionally, it can improve the quality of care (assuming that the patient's medical condition allows discharge) and patient satisfaction [3, 4]. Caminiti et al. and Panis et al. concluded that over 20% of hospital bed use in the studied hospitals was unnecessary due to organizational delay; implying a waste of resources and an increase of patient iatrogenic risk[1] [3, 4]. The different research contexts of the studied hospitals give rise to the expectation this phenomenon applies to many hospitals and that therefore part of LOS with organizational cause can be reduced. An expected disadvantage of LOS reduction could be the raise in number of undesired readmissions. Literature does not confirm this disadvantage [5, 6].

Additionally, LOS predictions can be used to better prepare patients for their discharge. Communicating a predicted discharge date to patients has proven to have a positive influence on their hospital experience [7]. Highly valued hospital experiences are desirable as they are increasingly recognized as a pillar of quality in healthcare [8].

Since hospitals currently experience difficulties with predicting expected LOS, this research aims to develop a prototype of a generic prediction tool that accurately predicts LOS based on historical data.

1.1 Research context

The overall objective of this research is to develop a prediction tool that is generically applicable. However, to limit the scope of this research and to evaluate

[1] inadvertent adverse effect or complication resulting from medical treatment or advice

the usefulness of the tool, the tool is primarily developed for and tested in the Emma Children's Hospital (ECH) of the Academic Medical Centre Amsterdam (AMC).

1.1.1 Academic Medical Centre Amsterdam (AMC)

The AMC was founded in 1983 after a merger between two hospitals from the Amsterdam city center and the medical faculty of the University of Amsterdam (UvA). The ECH was incorporated five years later. The AMC is one of the eight academic medical centers in the Netherlands; besides the treatment of patients, it also carries out a great deal of medical research and provides medical education. Currently, the AMC has ten divisions supported centrally by corporate staff and facility services. The total number of employees is approximately 7.000 [9].

In 2011, almost 390.000 patients received treatment in the outpatient department, around 31.000 patients received treatment in the day care unit and 30.000 patients were admitted in the clinic. The average LOS was 6,7 nursing days[2] [11].

In 2011, the AMC started an improvement program called SLIM to achieve quality improvements and cost reductions. One of the AMC's targets for 2013 was to reduce the LOS by 10% compared to 2012 [12]. The SLIM program is executed by the departments Finance & Control and KPI (Kwaliteit en Proces Innovatie). KPI acts as an internal consultant department and aims to redesign and improve the hospital's processes while maintaining or improving the quality of care.

1.1.2 Emma Children's Hospital

The ECH has an outpatient department with a daycare unit and an inpatient department. The inpatient department consists of six nursing wards. There are three age-related wards: Infants (<1 year), Older Children (1-12 years), and Teenagers (> 12 years). Additionally, there are four specialized wards: Pediatric Oncology, Pediatric Intensive Care, Neonatal Intensive Care and Pediatric Surgery.

1.2 Problem statement

For this research, the following problem statement is formulated:

The lack of knowledge concerning the expected LOS at patients' admission results in unnecessary prolonged stays in the hospital. This is accompanied by possible reduced quality of care, negative influence on the patient's experience and unnecessary costs.

1.3 Framework for Planning and Control

To demarcate the scope of this research, the framework for planning and control of Hans et al. is used [13]. The framework is build up by four managerial areas and four levels of hierarchical decomposition which results in sixteen areas of planning and control, see Figure 1.

[2] A nursing day is a charged calendar day that pertains to the period between admission and discharge of a hospital stay. Both the admission day (under the restriction that admission occurred before 8PM) and the discharge day are marked as a charged calendar day. [10]

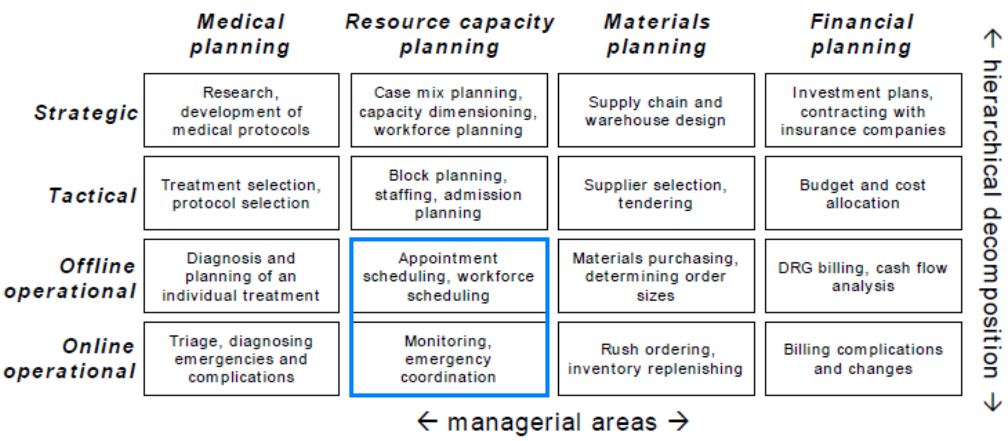


Figure 1: Example application of the framework for health care planning and control to a general hospital [13], with in blue the focus of this research highlighted.

Resource capacity planning addresses the dimensioning, planning, scheduling, monitoring and control of renewable resources. LOS prediction, and indirectly LOS reduction, influences the admission, discharge and overall bed planning and is therefore located in the area of resource capacity planning.

The hierarchical decomposition level of the research is more difficult to define, considering LOS prediction can be used on all four levels. On the strategic level, a prediction can be made of the expected number of patients in the upcoming year and their respective LOS, based on historical data. This influences the decisions taken regarding the case mix of the hospital and/or the capacity dimensioning. With the expected LOS known, the necessary amount of staff can be predicted. This corresponds to the tactical level on which LOS predictions can be used. On an operational level, the tool influences discharge planning of the patient and overall patient planning of the ward [14].

To define the scope of this research, the choice to focus on the level of operational planning is made. Operational planning involves short-term decision making related to the execution of the health care delivery process [14]. Considering that the tool will predict LOS at admission, the time horizon of the tool is short. This corresponds with the operational level of the framework. The timing of the prediction immediately influences the patient planning of the ward, which corresponds to the online operational level. In addition, LOS predictions influence the offline operational process of discharge planning. Therefore, the tool is both located at the offline and online operational level, as highlighted in Figure 1.

1.4 Research objective and research questions

Based on the problem stated in section 1.2, the following research objective is formulated:

Development of a generic prediction tool prototype which accurately predicts the individual hospital LOS, based on patient characteristics and organizational factors known at admission.

Six research questions are formulated to attain this objective. The sequence of the research questions forms the outline of this thesis.

Chapter 2 — How is LOS currently predicted at the AMC and at other Dutch hospitals?

a. How is LOS currently predicted at the AMC?
b. How accurate are the current LOS predictions of the AMC?
c. How is LOS currently predicted at other hospitals?

Chapter 3 — What prediction models and influencing variables of LOS are known in literature?

a. What models are known in literature to predict LOS?
b. What variables found in literature influence LOS?

Chapter 4 — How can an LOS prediction tool be developed?

a. How is LOS predicted based on available influencing variables?
b. How are LOS predictions translated in a tool for practice?

Chapter 5 — How can the developed prediction tool be applied to the ECH?

Chapter 6

a. Which variables influence the LOS of patients admitted to the ECH?
b. How effective is the tool in practice?

Chapter 7 — What can be concluded from this research?

a. What are recommendations for future research?
b. What adjustments need to be made in the current processes at the ECH to implement the tool in practice?

2 Current Length of Stay prediction

To identify the current state of LOS prediction, both the AMC (section 2.1) and two other Dutch hospitals (section 2.2) are analyzed by means of interviewing personnel.

2.1 LOS prediction at the AMC

To describe current LOS prediction in the AMC, two departments are evaluated: the ECH (section 2.1.1) and the Geriatrics department (section 2.1.2). The ECH is chosen considering that it is the target group in this research; Geriatrics is analyzed since it already performed research on LOS prediction.

2.1.1 LOS prediction in the Emma Children's Hospital

Interviews with the management of the ECH wards showed that the expected LOS is currently not consequently predicted and/or registered. The admission planner stated that patients are currently scheduled based on a fixed number of admissions, independently of the expected LOS of present patients. Predictions are rarely used for planning purposes and the discharge process is not based on expected LOS.

Physicians state that they can predict the LOS for around 80% of admissions, at admission. Current LOS prediction usually takes place in the physician's mind by considering the age and weight of the patient, (primary and secondary) diagnosis, required treatment and the patient's history. The predictions are often not registered on paper. The accuracy of the physicians' predictions is therefore unclear. The other 20% of the admissions is perceived as unpredictable due to the large variety in clinical course.

Different opinions regarding LOS prediction tools exist. Multiple wards would like to use a tool, in order to help predict the "unpredictable" group of admissions and to achieve consequent LOS registration. The counterargument most commonly stated relates to the opinion that physicians can already predict LOS, based on their medical experience. To measure the added value of an LOS prediction tool, the accuracy of LOS predictions made by physicians needed to be evaluated. See the next paragraph for the setup and results of this measurement.

Setup physicians' predictions

In response to the results of the interviews, a retrospective study concerning the accuracy of physicians' LOS predictions was performed. Physicians predicted LOS retrospectively to allow for a large number of admissions predicted in a relative short timeframe. Also, this setup required minimal time investment of the participating physicians. Justification for this setup was confirmed by an AMC clinical epidemiologist.

Case descriptions of historic patients were developed to predict LOS retrospectively. Presented data in the case descriptions included the patient's gender, age and diagnosis, admission day, code and ward, and whether an acute or elective admission was concerned. The inability to assess the patient in person and having restricted information complicated the prediction of LOS; hence participants were asked for rough estimates of LOS.

A power analysis [10] was conducted to determine the number of required cases (admissions to be predicted) to achieve statistical significance. The minimum number of participating physicians was set to three by weighing the influence of the number of physicians in relation to the number of required cases. Other input values were chosen in collaboration with the clinical epidemiologist. The power analysis resulted in a required number of 31 cases (See Appendix B for the input and output values of the power analysis).

A collaborating pediatrician proposed 31 frequently occurring diagnoses in pediatric patients. With these diagnoses, specific admissions were selected from data. One case for each diagnosis was chosen based on having an LOS around the average and showing logical values for the other parameters (e.g. admission from the Emergency Room always corresponds with an acute admission). In this way, 'average' cases were selected to enhance the feasibility of prediction.

Physicians were selected by the collaborating pediatrician. Selection was based on the level of experience and willingness to participate. Physicians who regularly act as attending physician were invited to participate as they are responsible for LOS predictions in practice.

Results physicians' predictions

Five attending physicians participated in the study. The assumption was made that all participants had a similar amount of medical experience. The results show that the average absolute deviation between predicted and observed LOS was 147.6%, see Table 1. The lowest absolute average deviation of a physician was 83.9% while the highest absolute average deviation was 256.9%. These results are compared with the prediction tool's results in section 6.2.

Physician	Average absolute deviation
1	83,9%
2	99,1%
3	150,4%
4	256,9%
Total average	147,6%

Table 1: Average absolute deviation between observed LOS and physicians' predictions.

2.1.2 LOS prediction at Geriatrics

In 2011 Geriatrics set up a project to safeguard the provision of high quality care around discharge [15]. The goals of this project involved (1) improving the healthcare process around discharge, (2) increasing patient safety around discharge, and (3) increasing patient satisfaction around discharge.

One way to achieve these goals involved predicting the expected discharge date for 80% of the patients within 48 hours after admission. The expected discharge date is formed by the admission date plus the expected LOS. To support LOS prediction, a discharge matrix was developed, see Table 2. This matrix includes five diagnostic groups[3] which cover 80% of the diagnoses of admitted patients. The expected LOS for each of these groups, expressed as the median[4] LOS, is calculated for three age groups and is based on 640 patients admitted in the period between 2006 and 2008. The majority of patients had multiple co-morbidities [15].

Diagnostic group \ Age	65-74 years	75-84 years	≥ 85 years
Infection	6	8	10
Malignancy	8	8	*
Water and electrolyte disturbance	10	7	9
Gastrointestinal problems	4	6	6
Cardio Vascular condition	5	7	8

Table 2: Discharge matrix Geriatrics, translated from Dutch [15]. The numbers express the median expected LOS in days.
* no reliable median due to small number of patients

Since the second half of 2011, LOS is predicted using the discharge matrix. The LOS predictions are daily discussed and adjusted if needed, during the physicians' rounds.

Results Geriatrics LOS predictions

Preliminary evaluation of the results showed that around 80% of the predicted discharge dates were achieved. The LOS of patients admitted after the introduction of the discharge matrix (posttest) seems to be longer than the LOS of patients admitted before the introduction (baseline measurement). The Geriatrics researcher expects this to be due to the fact that patients with an LOS shorter than 48 hours are excluded from analysis[5]. If using the discharge matrix results in LOS reduction, more patients have an LOS shorter than 48 hours. As a result, more admissions are excluded from the analysis. The average LOS is then excessively influenced by the longer LOSs. Further analysis must be performed to substantiate this statement.

Improvements in the discharge process due to LOS predictions are experienced by the Geriatrics staff. There is more awareness regarding a patient's discharge and corresponding required actions if LOS is predicted. Nevertheless, a peak in workload on the day of discharge is still experienced. An area for improvement therefore includes spreading out the work across the patient's stay. This is addressed by using the available checklists for discharge [15].

[3] These groups were formed at the discretion of the Geriatrics researcher.
[4] Geriatrics researcher's choice to account for skewed LOS data.
[5] The boundary was set to 48 hours since the discharge moment needed to be predicted within 48 hours after admission.

2.2 LOS prediction at other Dutch hospitals

To determine various ways of LOS prediction, two Dutch hospitals were visited. During these visits, LOS prediction and its effects were discussed. The findings from the visit to the Albert Schweitzer Hospital in Dordrecht (ASZ) are stated in section 2.2.1, while the results from the visit to the Isala Clinics situated in Zwolle are described in section 2.2.2.

2.2.1 Albert Schweitzer Hospital (Dordrecht)

The ASZ in Dordrecht was contacted in response to a news article that stated a significant LOS reduction at the ASZ due to implementation of a new system based on the Theory of Constraints (ToC) [16]. This theory states that constraints determine the performance of a system. A constraint is defined by Goldratt as "anything that limits the performance of a system relative to its goal" [17]. In the ToC system, constraints are translated into focus points around which a business can be organized or improved. The focus points for the ASZ concerned the alignment of different departments within a patient's logistical path.

The ToC system was implemented in the ASZ three years ago and resulted in an average LOS reduction of 2,9 days between 2009 and 2012 [16]. With ToC focus lies on LOS by monitoring the logistical process during a patient's stay. The system sends out signals the moment the expected discharge date is exceeded. Reasons for delayed discharge must be specified to analyze and dissolve bottlenecks.

The ToC system requires LOS prediction at patient's admission. Predicting LOS is not perceived as a problem; LOS predictions are based on physicians' medical experience. The predictions are considered to be accurate; research into the accuracy is not performed.

The ToC system has led to an increase in the number of patients treated due to reduction in LOS. This is accompanied by a more equally distributed workload during the patient's stay considering the acts needed for discharge are planned in advance based on the expected discharge date.

2.2.2 Isala Clinics (Zwolle)

Since four years, the Isala Clinics predicts LOS for each patient, based on diagnosis. The prediction is retrieved from a table containing all diagnoses and their expected LOS. The proposed LOS represents the LOS belonging to the 70th percentile[6] of the data for a specific diagnosis. The Isala Clinics chose this percentile by weighing the expected number of prediction adjustments and the accuracy of the LOS prediction (for planning purposes).

During admission planning, the predicted LOS is used to optimally utilize hospital capacity. This implies the importance of up-to-date LOS predictions. The LOS is adjusted if needed during the daily physician's rounds. Reasons for adjustment are logged to evaluate the causes of prolonged stays.

[6] Definition 70th percentile: 70% of the historical patients with the diagnosis had an LOS shorter or equal to the proposed LOS

This system is gradually becoming more appreciated by the users considering the importance to improve capacity utilization of the wards. It is valued highest at wards that experience a shortage of beds as LOS is used to predict the required number of personnel.

This chapter showed that the inconsistent prediction and registration of LOS, and the inaccuracy of the current predictions in the ECH elicit the possible added value of an LOS prediction tool. The chapter also provided possible methods and input parameters for the tool. Since these methods and parameters are not comprehensive, additional LOS prediction models are reviewed in the next chapter.

3 Literature

This chapter reviews current scientific literature on the prediction of LOS in order to gather input for the LOS prediction tool developed in this study. Only literature expected to be relevant for this study (estimated by the researcher) is presented.

Literature mainly focuses on LOS explanatory models instead of LOS predictive models. The difference between these models concerns the moment of analysis [18]. LOS explanatory models aim to explain historical LOS based on variables that are available before, during and after discharge. These variables are defined in this study as ex-post[7] available explanatory variables and LOS analysis proceeds retrospectively. LOS predictive models are explanatory models where only variables that are known at admission are taken into account. The variables in these models are defined as ex-ante[8] available explanatory variables and LOS analysis proceeds prospectively. Ex-ante available variables are therefore a subset of ex-post available variables, see Figure 2. Some variables are not consequently ex-post or ex-ante available explanatory variables (e.g. number of disciplines involved). Additionally, ex-post available variables that are not ex-ante available variables can sometimes be estimated. For example, research concerning the prediction of complications at patient level is currently conducted at the AMC [19]. The methods used in explanatory and predictive models can be equal, but input and output differs.

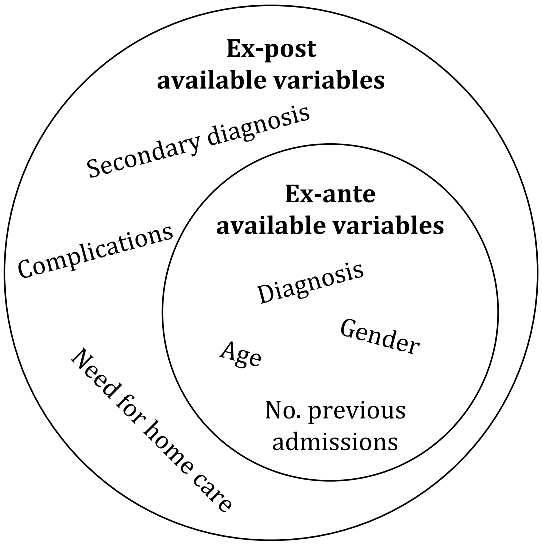


Figure 2: Illustration of ex-post and ex-ante available variables. The stated variables are not exhaustive and are categorized dependent on the admission.

The relation between LOS explanatory models and LOS prediction tools is illustrated in Figure 3. An LOS prediction tool consists of an LOS explanatory model with an application to prospective data.

[7] Latin for 'after the event'
[8] Latin for 'before the event'

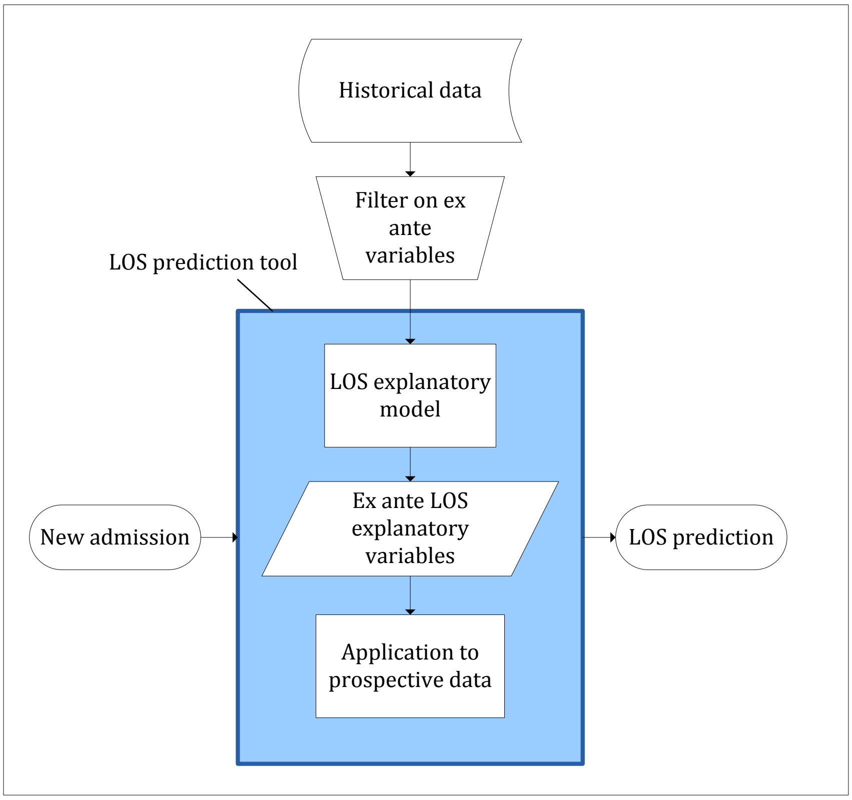


Figure 3: LOS prediction flow diagram. The LOS prediction tool is highlighted in blue. See Appendix D for the corresponding legend.

Different types of methods exist to determine the influence of ex-post or ex-ante available explanatory variables [20-23]. Various LOS explanatory methods are discussed in section 3.1. The ex-post available explanatory variables resulting from the described methods are presented in section 3.2. The chapter ends with section 3.3 that provides the research implications concerning the selected factors from the models in literature, applied to the LOS prediction tool developed in this study.

3.1 LOS explanatory methods

This section presents the methods used in LOS explanatory models found in literature. The section is based on the PhD thesis of M. de Lourdes Guzman Castillo [21] by reason of the elaborate systematic research on the topic most recently performed. Additional literature is added to extend the findings and to include literature applicable to the AMC's situation. For practicality, the categorization of models proposed in [21] is used. Each of these categories is described in the following sections.

3.1.1 Arithmetic methods

Arithmetic methods compute the average LOS by calculating the mean LOS or the median LOS of the log-transformed data to correct for the skewed nature of the LOS distribution [21]. The most prominent flaws of these methods concern the often overestimation of the average LOS in the case of the mean LOS and the underestimation of the average LOS when represented as the median of the log-transformed data [24]. Also, arithmetic methods assume that all included patients will have an identical LOS regardless of their personal characteristics.

The heterogeneity in the cohort under study assuredly implies that patient characteristics should be taken into account [25, 26]. Despite these flaws, arithmetic methods are still the most common methodology used at hospitals due to their ease of use [21].

3.1.2 Statistical methodology

Linear regression approaches are the most widely used modeling methods [20-22, 27-29]. As stated in [21], these approaches aim to predict an outcome variable based on several covariates. Covariates are defined in the context of LOS as the patient's characteristics and external factors which possibly predict LOS (i.e. medical condition, patient age, patient gender, pathological history, etc.). LOS data used in linear regression models needs to be log-transformed considering the assumption that the input data are normally distributed.

LOS distributions can best be modeled by a lognormal model [30]. Data analysis performed in [21] supported this finding and supplemented it with the advice to represent LOS data by a mixture model composed of two or three lognormal components combined.

Different truncation rules for the detection of outliers are compared. Cots et al. [31] concluded that the lower and upper boundary for outliers are most accurately formed by taking two standard deviations from the geometric mean. This truncation rule is supplemented with the advice to substitute the outliers by the accepted values closest to the lower and upper boundaries instead of eliminating the outliers [24, 30].

3.1.3 Finite mixture models

Quantin et al. [32] tried to find the best distribution to fit LOS data to explain LOS. They came to the conclusion that none of the distributions under study satisfactorily fit the data due to disparities in patient care and medical practice within a diagnosis related group (DRG). They therefore suggested that the observed distribution of LOS within a DRG may in fact represent a mixture of several different distributions. This type of model is commonly referred to as finite mixture models. In these models a continuous variable in a large sample consists of two or more clusters of observations (components) with different means and perhaps different standard deviations within each cluster. To define the clusters within each sample, analysis of covariates is performed to detect which covariate is linked to which cluster.

3.1.4 Data-mining techniques

Data-mining techniques aim to describe one or more of the variables present in data in relation to all the other variables. De Lourdes Guzman Castillo describes two types of data-mining techniques for the prediction of LOS: regression-type models and classification-type models. Regression-type models, such as regression trees, analyze the LOS as a continuous variable and do not assume that the underlying relationships between the covariates and LOS are linear. The latter forms the difference between the linear regression models described in the statistical methods above and this data-mining technique. Classification and regression trees (CART) are the most commonly used regression-type models and have proven to be effective in the prediction of LOS [33]. In classification-type models, the dependent variable in analysis is a discretized version of LOS. The originally continuous variable is split into different intervals according to specified criteria forming a number of categories. The aim of this method is to classify patients into these categories according to their characteristics. The challenge with this method is to choose an adequate classification algorithm, whose success relies on the particular nature of the data. An extensive study performed by Lim et al. concludes that the results between many algorithms predicting LOS are sufficiently similar suggesting that other criteria such as the interpretability of the data mining method needs to be taken into account [33].

Azari et al. proposed a multi-tiered data mining approach that employs patient clustering to create training sets to train different classification algorithms [23]. The criteria for clustering evaluated in [23] concerned the disease condition, Charlson index[9] and variation in sum of squared errors. The groups were utilized to predict LOS by multiple classifiers. Results show that using clustering as a precursor to form the training set is preferred over non-clustering based training sets. Clustering patients on disease condition and predicting their LOS with the JRip algorithm[10] resulted in the highest value for prediction accuracy. Berki et al. also state that patients need to be grouped before the influence of variables on LOS can be identified [36].

Conclusion

In [21], literature regarding current LOS prediction models was reviewed using a number of guidelines. These included the ability of the model or method to: account for skewness and heavy tails, include covariates, handle small samples and the ease of implementation. Also, the clinical or operational meaning, the ability to model probabilistic relationships and whether the analytical approach had a patient grouping component, were taken into account as requirements.

Based on these criteria, the models with a case-mix analysis base – finite mixture models and data mining techniques – seem to be most suitable to predict LOS in public hospitals in Mexico. However, statistical methods are the most widely used modelling method due to their ease of use and broad application possibilities.

The four proposed methods formed input for the setup of the LOS prediction tool developed in this study. The feasibility of each of the methods when applied to the ECH was estimated. Substantiation regarding the used methods in this study's prediction tool is presented in section 3.3.

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[9] Charlson et al. proposed a formal generalization of the diagnosis codes in the form of a categorized comorbidity score [34]

[10] See [35] for a description of the JRip algorithm

3.2 LOS explanatory variables

This section describes the ex-post available explanatory variables influencing LOS found in literature. Most of the explanatory LOS variables discussed are based on research conducted by Tump et al. [20]. This study is chosen as starting point as it is the most recent study addressing influencing LOS factors and since it is also conducted at the AMC. Additional literature is added to extend the findings.

Tump et al. collected admission data by performing observations. They conducted uni- and multivariable statistical analyses to find significantly explanatory variables of LOS. The specific influence of each of the variables is expressed as a percentage by which the baseline untransformed LOS is increased or decreased. These percentages can solely be used for indicative purposes by reason of Tump's small study sample. The small study sample and an expert's opinion regarding the results ask for recalculation of the influence of LOS explanatory variables.

Literature [20, 36-39] shows that explanatory LOS variables can be divided into patient characteristics and organizational factors. Section 3.2.1 discusses the patient characteristics and medical factors, while section 3.2.2 presents the organizational factors.

3.2.1 Patient characteristics and medical factors

This section addresses patient characteristics that influence LOS. Medical factors, such as the diagnosis, are also considered. The first paragraph summarizes the explanatory variables found by Tump et al. while the second paragraph presents research that verifies these variables and summarizes additional literature.

Explanatory patient characteristics and medical factors found by Tump et al.

Tump et al. [20] concluded that the sex, age, associated specialism, risk of malnutrition, arisen complications and number of other disciplines involved are the patient characteristics that significantly contributed to a patient's LOS. These factors were all independently predictive; no significant interactions between factors were found.

Additional explanatory patient characteristics and medical factors

Literature confirms the age, gender, involved specialism and presence of complications as explanatory variables of LOS [22, 36, 39-41]. Malnutrition was confirmed twice [42, 43] and is complemented with sources that state high weight/BMI (Body Mass Index) as a prolonging factor of LOS [22, 37, 44]. Multiple articles state the severity of illness as one of the most influencing variables of LOS [23, 36, 37, 39, 45]. Tump et al. did not conclude this in their study as the diagnosis was excluded from analysis due to the small study sample.

Additional explanatory variables of LOS found in literature concerned the number of previous hospital admissions [22], the head circumference (in neonates) [45] and the presence of a secondary diagnosis (such as obesity, respiratory difficulties etc.) [22, 42, 44, 46].

3.2.2 Organizational factors

Literature shows that LOS is often prolonged due to organizational deficiencies instead of medical reasons. The first paragraph summarizes the explanatory variables found by Tump et al. while the second paragraph presents additional organizational factors that explained LOS.

Explanatory organizational factors found by Tump et al.

Tump et al. [20] concluded that the need for home care after discharge and the involvement of multiple (pediatric) disciplines significantly prolonged LOS. The involvement of multiple disciplines is interpreted both as a medical factor and an organizational factor. When multiple disciplines are involved, the diagnosis is expected to be more complex. Additionally, the involvement of multiple disciplines raises the need for organizational alignment between different departments which also influences LOS [47].

Additional explanatory organizational factors

The need for home care is confirmed as an explanatory variable of LOS in literature [38, 48]. Another explaining variable concerned the logistical problems in arranging a patient's transport to home or to another institution after discharge [43, 48].

Two articles state the time and type of admission as LOS explanatory variables [36, 49], where the type of admission describes whether a patient is acutely or electively admitted. The influence of the time of admission on LOS reflects in the fact that during weekends less medical procedures are performed.

Applied to LOS prediction at admission, the influencing LOS variables in predictive models are restricted. Only variables that are known at admission can be included. Therefore, not all independent variables found in explanatory models can be used in the LOS prediction tool developed in this study.

3.3 Research implications

Various LOS explanatory models are presented in section 3.1. These models cannot serve as an LOS prediction tool since they explain LOS with the use of ex-post available variables. Therefore, a generic LOS prediction tool with an application to prospective data is developed in this study. The presented models and explanatory LOS variables do serve as inspiration for the LOS prediction tool.

Two aspects from current LOS explanatory models apply to LOS data in general and are therefore relevant for this study. These include performing a natural log transformation of LOS data to account for skewness and heavy tails [21-23, 50] and substituting outliers [21]. Additionally, data clustering based on diagnosis is applied in this study by reason of proven performance in [23, 36] and the expected support base amongst users.

Multiple regression was estimated to be the most suitable method for the LOS prediction tool developed in this study regarding its proven performance in literature [20-22], expected suitability for automation, its ease of use and its applicability to the ECH data. The regression methodology is described in Appendix C.

Section 3.2 presented various ex-post available explanatory variables; see Table 3 for a complete overview. In models that predict LOS at admission, only ex-ante available explanatory variables can be used; a selection is therefore made in the second column of Table 3.

The ex-ante available explanatory variables form possible input for the LOS prediction model developed in this study.

LOS explanatory variable	Ex ante available variable?	Article
Sex	Yes	[20, 22, 39, 41]
Age	Yes	[20, 22, 39-41]
Weight/BMI	Yes	[22, 37, 44]
Associated specialism	Yes	[20]
Risk of malnutrition	Yes	[20, 42, 43]
Arisen complications	No	[20, 36]
Number of other disciplines involved	Sometimes	[20]
Severity of illness	Yes	[36, 37, 39, 45]
Number of previous hospital admissions	Yes	[22]
Head circumference (in neonates)	Yes	[45]
Presence of a secondary diagnosis	Sometimes	[22, 42, 44, 46]
Need for home care after discharge	Sometimes	[20, 38, 48]
Logistical problems in arranging a patient's transport to home or to another institution after discharge	Sometimes	[43, 48]
Time and type of admission	Yes	[36, 49]

Table 3: LOS explanatory variables derived from literature

4 Model

This chapter describes the development of the LOS prediction tool. The research implications presented in section 3.3 are incorporated in the tool. The model is developed in Microsoft Excel for its ease of use and availability of the program in the ECH. The built-in formulas in Microsoft Excel are assumed to be reliable.

Based on the definition of prediction models provided in Chapter 3, the prediction tool is based on an explanatory model with an application to prospective data. The explanatory model in this study is defined as the computational model and is based on multiple linear regression. Regression analysis on historical data produces the explanatory LOS variables. For practicality, the explanatory variables are called predictors in the model description. The computational model creates LOS formulas with these predictors. The application to prospective data is defined as the user interface that uses the LOS formulas in order to calculate the expected LOS of a new admission entered in the interface. The relation between the two parts of the prediction tool is illustrated in Figure 4.

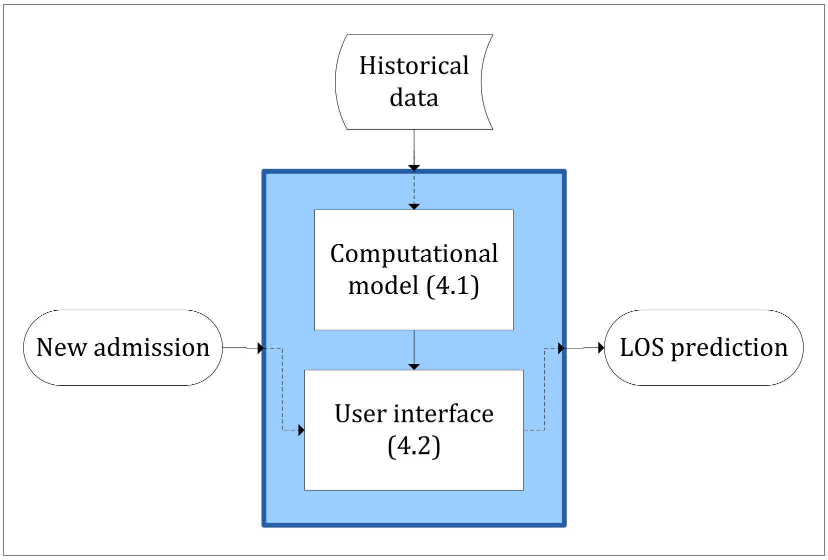

Figure 4: Illustration of the LOS prediction tool. See Appendix D for the corresponding legend.

This chapter discusses both parts of the prediction tool: section 4.1 describes the computational model while section 4.2 addresses the user interface.

4.1 Computational model

The computational model equals the LOS explanatory model in Figure 3. Data containing historical admissions form the input for the computational model. The dataset needs to be preliminary prepared by the user. This preparation includes performing a natural log transformation of LOS. Additionally, desired filters can be applied at the user's discretion.

The computational model consists of four steps; see the flowchart in Figure 5. The first step concerns data preparation performed in the model. In the second step, admissions are aggregated into classes to allow regression analysis. The third step includes the performance of regression analysis on all formed classes. Fourth and finally, LOS formulas based on the results of the regression analyses are created. All steps are described in the following sections.

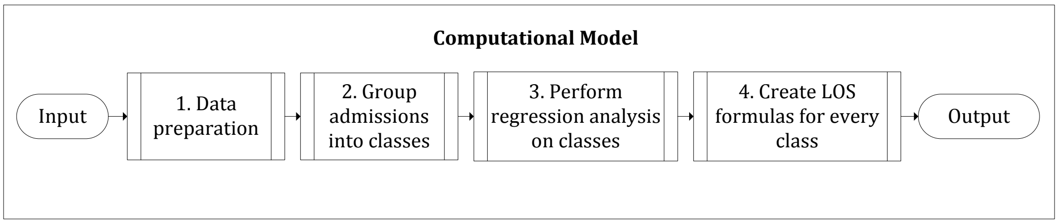

Figure 5: Flowchart of the computational model. See Appendix D for the corresponding legend.

4.1.1 Data preparation

The first step in the computational model involves data preparation. This step consists of four sub steps, see Figure 6. The dataset variables are prepared for admission aggregation and regression analysis. The admissions are then initially grouped based on the chosen grouping criterion. With the set requirements for primary, secondary and unpredictable classes, the formed classes are typified. Finally outlier analysis is performed on the data be reason of proven performance in literature (see Chapter 3). All steps are discussed in the following paragraphs.

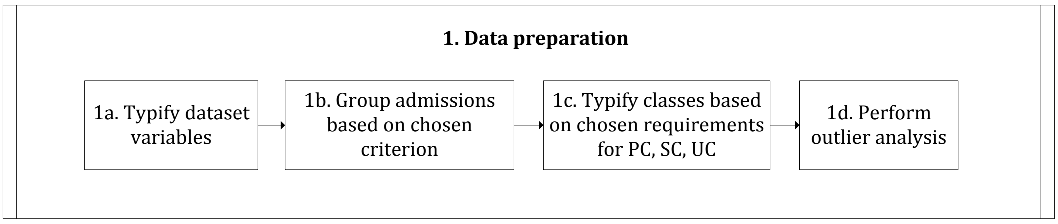

Figure 6: Flowchart step 1: Data preparation. PC: Primary Class, SC: Secondary Class, UC: Unpredictable Class. See Appendix D for the corresponding legend.

1a. Typify the dataset variables

In order to group the admissions and perform regression analysis, the user needs to typify all variables in the dataset. Variable types are: a negligible variable, the outcome variable, a basic variable, a predictor or the grouping criterion.

All variables typified as negligible variables are neglected by the model.

The outcome variable concerns the log transformed LOS.

The basic variables are formed by the admission year and the admission number. Combination of these values corresponds to unique admissions to ensure that each admission is traceable.

Predictor variables are the independent variables that will be used in multiple regression analysis. Different subtypes for predictor variables exist: dichotomous, categorical or continuous. Suggestions for predictor variables are given in Table 3 (section 3.3). Discontinuous variables need to be redefined in dichotomous variables or categorical variables with the smallest amount of option values possible. As a result, the smallest number of variables is formed.

This ensures that as many variables as possible can be incorporated in the model, which enlarges the chance of a better prediction model.

The grouping criterion forms the basis of the admission aggregation. To select the grouping criterion, the variance in LOS and the number of admissions within a group need to be analyzed. The ideal group criterion yields minimal variance within a group, maximal variance between groups and as many admissions per group as possible. With minimal variance and a maximal number of admissions within a group, the model can accurately predict LOS for new patients having the same group criterion value (e.g. diagnosis). With a maximal variance in LOS between groups, distinct classes are generated. This benefits the accuracy of the predictions. The choice for grouping criterion is based on the user's assessment. The group criterion should not be a continuous variable since every unique value will create its own group. This results in multiple groups consisting of only one admission. Group aggregation cannot occur with one admission per group. Few new admissions will then be predictable considering that the model only predicts LOS for groups with a minimal number of historical admissions (see sub step 1c).

1b. Group admissions based on chosen criterion

To all unique values of the chosen grouping criterion, a class is assigned (e.g. if the diagnosis is the grouping criterion, all present diagnoses get assigned a class). The model then matches each admission with its corresponding class.

1c. Typify classes based on chosen requirements for primary and unpredictable classes

This sub step typifies the formed classes to specify whether or not the model will be able to predict the LOS of the class. There are three types of classes: primary, secondary and unpredictable classes. The model only creates LOS formulas for primary classes considering the requirements for regression explained in section 4.1.3. Unpredictable classes never become predictable in the model. Secondary classes only become predictable if they are aggregated with a primary class. The user needs to choose the required number of admissions for primary and unpredictable classes, see Figure 7.

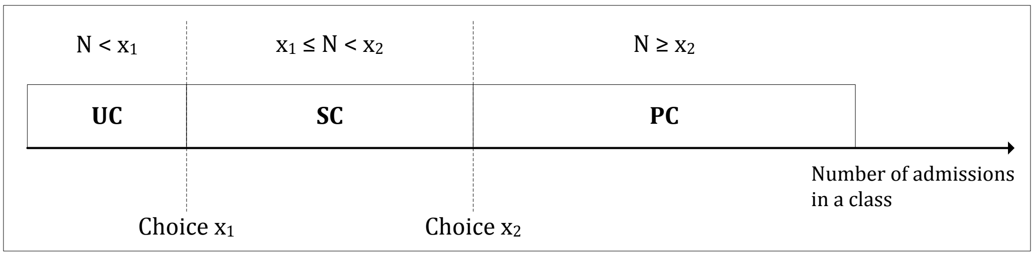

Figure 7: Representation of the user's choices regarding class types. N: number of admissions in a class, UC: unpredictable class, SC: secondary class, PC: primary class, x_1: requirement for unpredictable classes, x_2: requirement for primary classes.

Primary classes

The choice for primary classes must be based on the number of predictor variables included in regression analysis. A large number of predictors require a large number of admissions within a group. The rule of thumb for this choice states that 10 admissions are needed to test one predictor variable [51]. When the requirement is set too high, the model will only be able to create LOS formulas for few classes. On the contrary, when the requirement is set too low, the model can include few predictor variables. This decreases the accuracy of the LOS predictions. The requirement for primary classes is illustrated in Figure 7 as choice x_2.

Unpredictable classes

The LOS of a class that contains few admissions cannot be generalized due to the high level of coincidence. The user needs to choose the accepted influence of coincidence by setting the required number of admissions for a class to possibly become predictable. Classes containing fewer admissions than required are labeled as unpredictable and are excluded in the model. The requirement for unpredictable classes is illustrated in Figure 7 as choice x_1.

Secondary classes

Secondary classes contain a number of admissions equal to or greater than the requirement for unpredictable classes, and fewer admissions than the requirement for primary classes.

1d. Perform outlier analysis

Outliers within classes are detected and substituted in order to purify the data [21]. More classes will be suitable for aggregation after outlier analysis and therefore the LOS of more admissions will become predictable.

An outlier is defined as a value outside the outlier interval. The outlier interval is formed by a lower and upper bound, of which the formulas [21] are defined as:

$$OI_{LB} = \mu_{Ln(LOS)} - 2\ SD \tag{4.1}$$

$$OI_{UB} = \mu_{Ln(LOS)} + 2\ SD \tag{4.2}$$

with

OI_{LB}	lower bound of the outlier interval;
OI_{UB}	upper bound of the outlier interval;
$\mu_{Ln(LOS)}$	average log transformed LOS of the class;
SD	standard deviation of the log transformed LOS of the class.

An outlier is substituted by the existing value closest to the lower or upper boundary, see Figure 8.

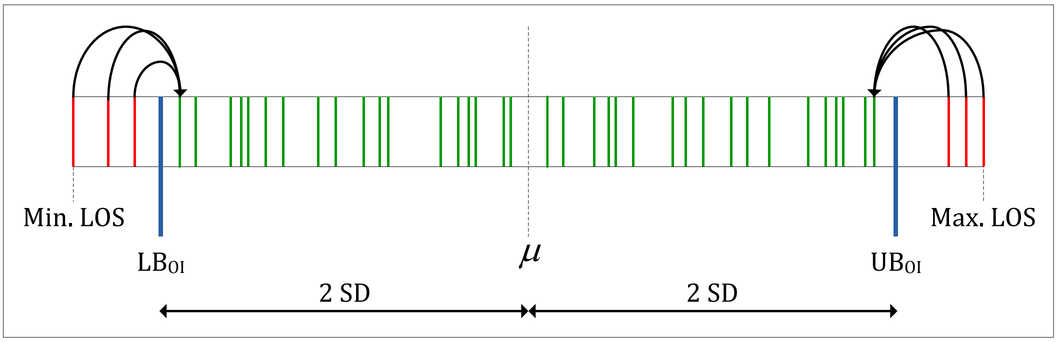

Figure 8: Visualization of outlier analysis. LB: lower bound, OI: outlier interval, UB: upper bound, μ: average value, SD: standard deviation.

4.1.2 Group admissions

The classes formed in section 4.1.1 are aggregated to satisfy minimal sample sizes required for regression analyses (see section 4.1.3). Also, data clustering is proven to be effective in literature [23, 36]. Grouping admissions into classes involves two sub steps, see Figure 9. The sequence of the steps ensures that the most homogenous groups possible are formed. This improves the accuracy of LOS predictions.

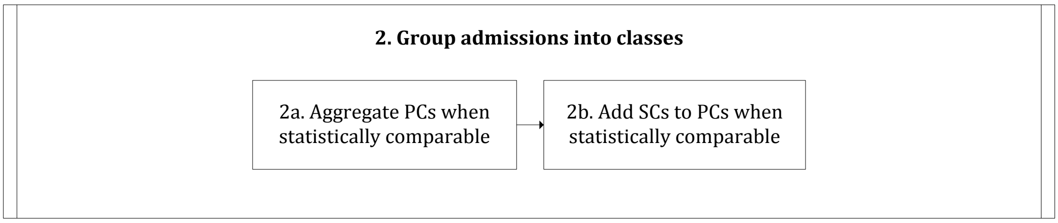

Figure 9: Flowchart step 2: group admissions into classes. See Appendix D for the corresponding legend. PC: primary class, SC: secondary class.

2a. Aggregate primary classes when statistically comparable

Primary classes are statistically comparable when the confidence interval[11] (CI) of one primary class falls into the confidence interval of another primary class [51]. We chose to set the level of confidence to 95% as it is the most often used confidence level in practice.

The confidence interval is formed by a lower and upper bound, defined as:

$$CI_{LB}^{PC} = \mu_{Ln(LOS)} - \left(z_{\frac{1-p}{2}} \frac{SD_{PC}}{\sqrt{N_{PC}}} \right) \tag{4.3}$$

$$CI_{UB}^{PC} = \mu_{Ln(LOS)} + \left(z_{\frac{1-p}{2}} \frac{SD_{PC}}{\sqrt{N_{PC}}} \right) \tag{4.4}$$

with

CI_{LB}^{PC} lower bound of the confidence interval for primary class PC;
CI_{UB}^{PC} upper bound of the confidence interval for primary class PC;

[11] Field, A.: "For a given statistic calculated for a sample of observations (e.g. the mean), the confidence interval is a range of values around that statistic that are believed to contain, with a certain probability (e.g. 95%), the true value of that statistic (i.e. the population value)." [51]

$\mu_{Ln(LOS)}$	average log transformed LOS of primary class PC;
$z_{\frac{1-p}{2}}$	z-score corresponding to the probability value p for the confidence interval;
SD	standard deviation of the log transformed LOS of primary class PC;
N_{PC}	number of admissions in primary class PC [51].

When two primary classes are comparable, the primary class with the narrowest CI is added to the other primary class. The CI of the aggregated primary class is then recalculated and this procedure is repeated until all possible primary classes are aggregated. If a primary class can be aggregated with multiple other primary classes, the choice for aggregation is based on the smallest difference between the boundaries of the CIs of the primary class in dispute and the CIs of the possibilities.

2b. Add secondary classes to primary classes when statistically comparable

Once all primary classes are aggregated where possible, the model checks whether the typified secondary classes can be added to one or multiple primary classes. Aggregation occurs based on the same principle used to aggregate primary classes, described in sub step 2a.

4.1.3 Regression analysis

Regression analysis is conducted for the primary classes created in step 1 and 2. Multiple linear regression was chosen based on its proven performance in research [5, 21, 22, 49] and its ease of use [50, 52]. A high ease of use corresponds with a high chance of acceptance and usability of the technology in practice [53].

Prior to regression, predictors must be transformed and selected. The computational model uses the standard Excel formula for linear regression. Five steps are involved in the process of regression analysis, see Figure 10.

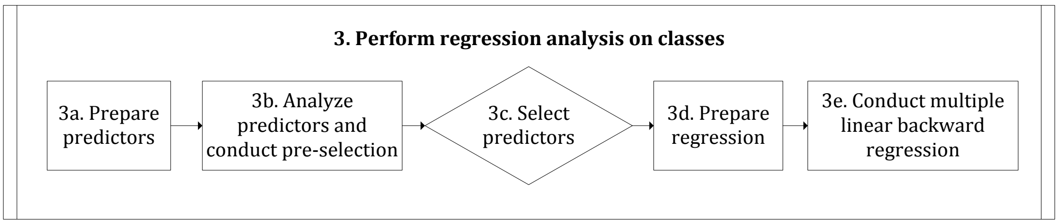

Figure 10: Flowchart step 3: Perform regression analysis on classes. See Appendix D for the corresponding legend.

3a. Predictors preparation

To serve as predictors in regression, variables need to be continuous or dichotomous. Therefore, all categorical predictors defined in step 1a are translated into dummy variables (see Appendix C).

3b. Predictors analysis and pre-selection

A prerequisite for multiple regression includes the non-existence of multicollinearity[12]. Multicollinearity exists if the absolute correlation between

[12] Multicollinearity exists when predictors (approximately) measure the same effect. [54]

two predictors is equal to or larger than 0.9 [51, 54]. A correlation matrix is therefore made. In the existence of multicollinearity, one of the predictors is chosen based on the largest individual influence on the outcome variable. This influence is determined by performing univariate regression analysis[13].

3c. Predictors selection

The number of predictors that can be included in multiple regression depends on the number of cases in the class. Ten cases per predictor are needed to prove a predictor's influence on the outcome variable with statistical significance [51]. If the number of predictors left exceeds the number of allowed predictors, the model selects predictors based on the univariate analysis conducted in step 3b. The predictors with the smallest significant influence on the outcome variable are eliminated.

3d. Regression preparation

The model creates a regression table as input for the standard Excel formula for linear regression. The regression table starts with the (aggregated) class numbers, the admission year and number, and the outcome variable. Subsequently, the selected predictors are included in the table.

3e. Multiple linear backward regression

The model starts by including all selected predictors in the regression procedure. The standard Excel formula for linear regression results in a matrix built up as follows:

$$\begin{bmatrix} a_n, a_{n-1}, \dots, a_1 & b \\ SE_n, SE_{n-1}, \dots, SE_1 & SE_b \\ R^2 & SE_y \\ F & d_f \\ SS_{reg} & SS_{resid} \end{bmatrix} \tag{4.5}$$

with

a_n	regression coefficient for the independent variable x_n;
n	number of independent variables in analysis;
b	intercept of the line;
SE_n	standard error for the coefficients $a_n, a_{n-1}, \dots, a_1$;
SE_b	standard error for the constant b;
R^2	explained variance of the model;
SE_y	standard error for the estimated outcome variable Y;
F	F-statistic to determine the level of coincidence;
d_f	number of degrees of freedom;
SS_{reg}	explained Sum of Squares;
SS_{resid}	residual Sum of Squares (retrieved from help file Microsoft Excel 2010).

The model eliminates independent variables step by step based on their significance value (p-value). Each significance value is compared against the

[13] Linear regression with one predictor variable. [51]

removal criterion of $p < 0.1$ [50]. From all non-significant variables, the variable that makes the smallest contribution to the dependent variable is eliminated. This elimination process is repeated with the remaining variables until all independent variables in the model make a significant contribution to the dependent variable.

4.1.4 Resulting LOS formulas

The model creates an LOS formula for each primary class based on the results of multiple regression performed in section 4.1.3. The results include the regression coefficients of the predictor variables ($a_n, a_{n-1}, \dots, a_1$) and the intercept (b). With these values, LOS formulas such as equation 3.1 are created. A table containing these results is made to serve as input for the user model, see Table 4.

Class	b	a_1	a_2	a_{n-1}	a_n
1	0.4	2	0	-4	1
2					
n-1					
n					

Table 4: Setup of LOS formulas table serving as input for user model containing an example

Each index number of a regression coefficient corresponds to a specific predictor variable (e.g. a_1 could be the regression coefficient corresponding to the predictor variable 'gender').

The LOS formula of the example presented in Table 4 would equal:

$$LOS = 2\, a_1 - 4\, a_{n-1} + a_n + 0.4$$

4.2 User interface

The user interface is a spreadsheet in Microsoft Excel that predicts the expected LOS corresponding to an inserted admission with associated predictor values. The user interface presents the influencing predictor variables for the admission in dispute and the expected LOS, expressed in (semi-)days. Possible users of the interface concern the attending physician, admission planner or head nurse. The interface consists of five steps; see the flowchart in Figure 11.

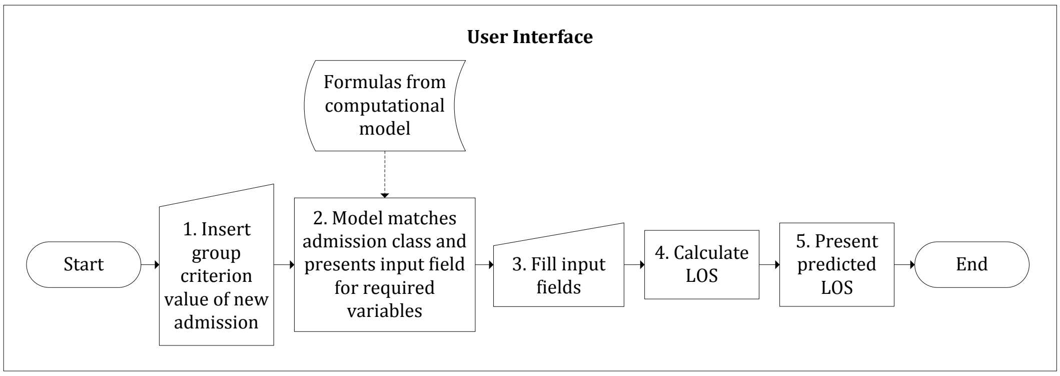

Figure 11: Flowchart of the user interface. See Appendix D for the corresponding legend.

4.2.1 Select group criterion value of new admission

Input for the user model includes the group criterion value of the new admission. Every group criterion value belongs to a class formed in the computational model. The user can choose from a proposed list with all existing values.

4.2.2 Match admission with LOS formula

The model matches the selected group criterion value with its corresponding class. The LOS formula of that class is then derived.

4.2.3 Fill input fields

Each LOS formula contains specific predictor variables. The user is asked to insert the required predictor values to calculate LOS.

4.2.4 Calculate LOS

With the required predictor values, the predicted LOS for the admission is calculated.

4.2.5 Present predicted LOS

The calculated expected LOS in (semi-)days is presented to the user. The user can copy the predicted LOS to the patient's admission form and adjust it when necessary (at user's discretion).

5 Results

This chapter presents the results of the model applied to the ECH. A description of the data and the user's choices is presented in section 5.1. Section 5.2 discusses the results of the computational model while section 5.3 presents the results of the user interface.

5.1 Emma Children's Hospital data

The ECH data were retrieved from the databases LOCATI and DBC_DS[14]. These databases were combined in Microsoft Access to retrieve as many explanatory variables as possible. Missing explanatory variables from literature included:

- Arisen complications;
- Head circumference (in neonates);
- Involvement of multiple (pediatric) disciplines;
- Logistical problems in arranging a patient's transport to home or to another institution after discharge;
- Need for home care after discharge;
- Number of other disciplines involved;
- Number of previous hospital admissions;
- Presence of a secondary diagnosis;
- Risk of malnutrition;
- Weight/BMI.

These variables could not be retrieved due to difficulties in combining various databases present in the AMC.

Data between 01/01/2012 and 10/06/2013 were available. Earlier admissions could not be included due to differences in diagnosis registration. Data were divided into a training set containing 80% of the data and a test set containing the other 20%, as suggested in [51]. The training set formed the input for the computational model. The test set was used to test the accuracy of the application to prospective data.

Using Microsoft Access, two filters were applied to the data, see Table 5.

Variable	Filter 1	Filter 2
Age	≤ 18	≤ 10
Admission date	01/01/2012 – 10/06/2013	01/01/2012 – 10/06/2013
Admission code	Clinical admission	Clinical admission
Admission ward	Pediatric wards	Women's wards
Diagnosis description	$\neq Empty$ $\neq 0$ $\neq Traject$	$\neq Empty$ $\neq 0$ $\neq Traject$
Discharge ward	Pediatric wards	Women's wards
LOS in hours	$\geq 2\ hours$	$\geq 2\ hours$

Table 5: Applied filters to ECH data.

[14] These databases are part of the current electronic patient file ZIS. The database DBC_DS contains diagnosis treatment combinations (in Dutch: DBC) corresponding to hospital diagnoses.

The difference between filter 1 and filter 2 concerns the restrictions set for the age of the patient and the admission and discharge ward. Filter 1 was applied to ensure that only pediatric admissions were included in the dataset. Filter 2 ensured that admissions of newborns were included[15] and admissions of teenage mothers were excluded. Teenage mother admissions were excluded since the required care is assumed to be adult care. General wards were excluded to avoid possible difference in LOS with organizational cause. To ensure that admissions with missing diagnosis were excluded, the diagnosis description was set not to equal zero or to be empty. Additionally, the diagnosis description 'Traject' (Dutch) was excluded for its unclear content. LOS was set to a minimum of two hours in both filters as diagnosis-treatment combinations and corresponding diagnosis description are only assigned to admissions that minimally endure two hours.

5.2 Results computational model

This section presents the results of the computational model applied to the training set. The setup of this section follows the steps of the computational model, see Figure 12. Section 5.2.1 starts with the results of the data preparation.

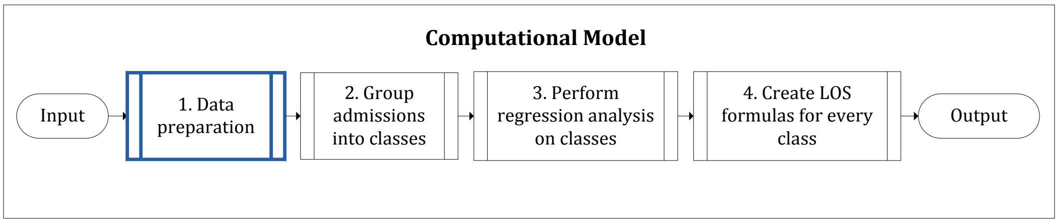

Figure 12: Flowchart of the computational model. See Appendix D for the corresponding legend.

5.2.1 Results data preparation

The input table included 23 variables; see Table 6 for an overview of the variables in the training set and corresponding type. The diagnosis description was selected as grouping criterion. This choice was based on an analysis of various aggregation options, see Figure 13.

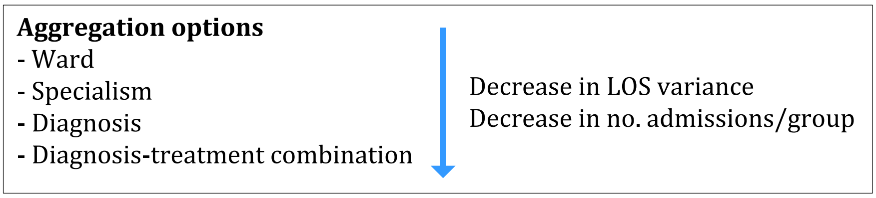

Figure 13: Choosing the optimal grouping criterion.

The analyzed aggregation options included the admission ward, specialism, diagnosis and diagnosis-treatment combination. The analysis showed that the diagnosis description was the highest level for which variation in LOS was still acceptable (based on the researcher's assessment).

[15] Newborns can be admitted to obstetrics or the maternity ward.

Variable	Abbreviation	Type
Patient number		Negligible variable
Gender - Man (1) - Woman (0)		Predictor: dichotomous
Date of Birth		Negligible variable
Age		Predictor: continuous
Admission year	adm_year	Basic variable
Admission number	adm_nr	Basic variable
Admission day - Weekend day (1) - Weekday (0)	adm_day	Predictor: dichotomous
Start date		Negligible variable
Admission source - Delivery room AMC - Emergency Room - General Practitioner - Home - Hospital birth AMC - List - Other - Other hospital - Outpatient Clinic	adm_source DR ER GP HOME HB LIST OTHER OH OC	Predictor: categorical
Admission type - Acute (1) - Elective (0)	adm_type	Predictor: dichotomous
Admission ward - Gynecology - Infants & Pediatric Surgery - Maternity ward - Neonatal Intensive Care - Obstetrics - Older Children - Pediatric Oncology - Pediatric Intensive Care - Teenagers	adm_ward GYN I&PS MW NIC OBS OLCH PO PIC TEEN	Predictor: categorical
Admission specialism - General pediatrics - General surgery - Neonatology - Pediatric cardiology - Pediatric endocrinology - Pediatric gastroenterology - Pediatric hematology/ immunology - Pediatric nephrology - Pediatric neurology - Pediatric oncology - Pediatric otolaryngology - Pediatric plastic surgery - Pediatric pulmonology - Pediatric surgery - Traumatology	adm_spec GPED GSUR NEO PC PEC PGE PHI PNEP PNEU POC POT PPS PPUL PS TRA	Predictor: categorical
Discharge ward		Negligible variable
LOS (hr)		Negligible variable
LOS (day)		Negligible variable
Ln(LOS(day))		Outcome variable
AGB specialism		Negligible variable
Diagnosis code		Negligible variable
Diagnosis description		Grouping criterion
Health product code		Negligible variable
Health product description		Negligible variable
Diagnosis description hospital		Negligible variable
1st treatment description hospital		Negligible variable

Table 6: Variables present in the training set and assigned types.

A primary class was defined as a class containing 40 or more admissions in order to ensure that minimally half of the existing predictor variables could be included in regression analysis. This choice was made at the researcher's discretion by balancing the importance of the number of predictable diagnoses and the expectable accuracy of the predictions. Classes were typified as unpredictable when they attained less than 10 admissions. This choice was based on the statement that at least 10 admissions are needed to prove a predictor's significance. The choices imply that classes with a number of admissions between 10 and 40 were defined as secondary classes.

Summary of the variables	
Number of present variables	23
Outcome variable	1
Basic variables	2
Grouping criterion	1
Predictors *(cont.* 1, dich.† 3, cat‡. 2)*	6
Number of negligible variables	13

Table 7: Summary of the training set variables
* Continuous predictor
† Dichotomous predictor
‡ Categorical predictor

Initial grouping of the admissions based on present diagnoses resulted in 472 classes. These included 23 primary classes, 61 secondary classes and 388 unpredictable classes, see Table 8. Outlier analysis resulted in 92 classes containing outliers (19.5%).

Summary of initial classes	N_{class}	$\%_{class}$	$N_{admissions}$	$\%_{admissions}$
Number of classes	472	100 %	4849	100%
Primary classes	23	4.9 %	2513	51.8 %
Secondary classes	61	12.9 %	1269	26.2 %
Unpredictable classes	388	82.2 %	1067	22.0 %

Table 8: Summary of the initial classes formed

Primary classes formed 4.9% of the dataset. These classes contained 51.8% of all admissions. This implies that the model was able to predict 51.8% of the admissions.

5.2.2 Results admissions grouping

Initial classes were formed after the data preparation. In the second step of the model, possibilities for aggregation of the initial classes were explored (see Figure 14).

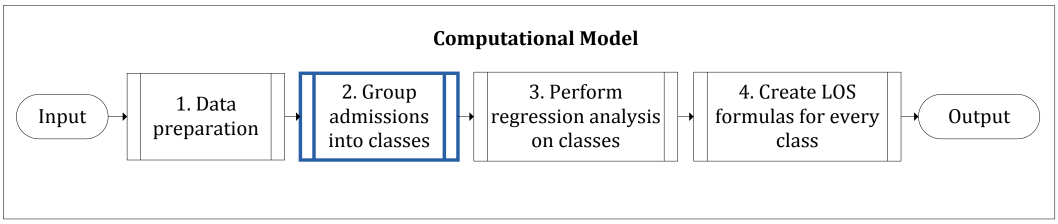

Figure 14: Flowchart of the computational model. See Appendix D for the corresponding legend.

The primary groups were compared to check for statistical comparability. In total, six aggregations occurred within the primary classes. Results showed that aggregation resulted in smaller standard deviations and narrower confidence intervals for all aggregated classes. Hence, more homogeneous groups were formed.

Subsequently, the secondary classes were compared with the primary classes to check for statistical comparability. One aggregation occurred. Table 9 presents the properties of the primary classes after aggregation.

Class	N	Mu_Ln(LOS)*	sd_Ln(LOS)†	CI_Ln(LOS)‡
273	581	1.264	0.788	0.064
471	70	0.615	0.294	0.069
162	80	0.447	0.328	0.072
67	74	0.650	0.352	0.080
220	507	1.493	0.959	0.083
404	66	-0.065	0.479	0.116
73	67	-0.178	0.513	0.123
88	186	1.002	0.918	0.132
164	149	1.220	0.825	0.133
39	96	1.157	0.703	0.141
399	72	0.760	0.631	0.146
193	127	0.816	0.839	0.146
285	114	1.079	0.963	0.177
332	77	1.426	0.823	0.184
329	98	1.383	0.944	0.187
24	91	1.100	0.927	0.190
309	70	2.182	1.497	0.351

Table 9: Primary class properties after aggregation, sorted by confidence interval. Diagnosis description in Dutch.
* Average log transformed LOS
† Standard deviation of log transformed LOS
‡ Confidence interval of log transformed LOS

With the aggregation completed, totals for the various classes were calculated, see Table 10. The 17 (aggregated) primary classes contained 24 diagnoses. This corresponded with 52.1% of all admissions being predictable.

	No. classes	Admissions	Percentage
Total	**472**	**4849**	**100 %**
Predictable	**24**	**2525**	**52.1 %**
Primary classes	23	2513	51.8 %
Aggregated secondary classes	1	12	0.3 %
Unpredictable	**448**	**2324**	**47.9 %**
Typified unpredictable classes	388	1067	22.0 %
Non-aggregated secondary classes	60	1257	25.9 %

Table 10: Totals of the aggregation of admissions.

5.2.3 Results regression analysis

In the third step of the model, regression analysis was performed on the remaining primary classes (see Figure 15).

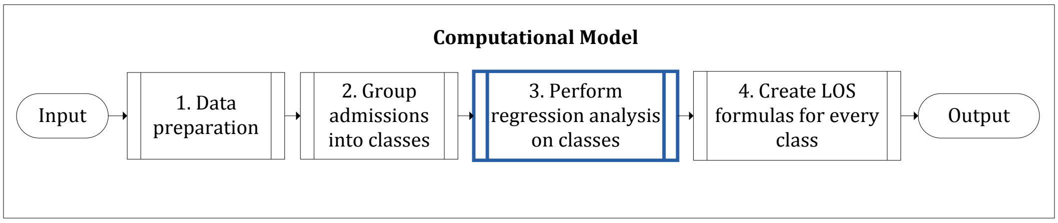

Figure 15: Flowchart of the computational model. See Appendix D for the corresponding legend.

Regression analysis started with preparing the predictors. If needed, predictors were selected based on multicollinearity and univariate analysis. In the ECH data, multicollinearity occurred in eight of the 17 primary classes, see Table 11.

Class	Selected predictor	Eliminated predictor
88	Admission specialism: Neonatology	Admission source: Hospital birth AMC
88	Admission specialism: Neonatology	Admission ward: Obstetrics
162	Age	Admission ward: Teenagers
164	Admission specialism: General pediatrics	Admission ward: Pediatric Intensive Care
309	Admission source: Hospital birth AMC	Admission ward: Obstetrics
309	Admission source: Hospital birth AMC	Admission specialism: Neonatology
329	Admission specialism: Neonatology	Admission source: Hospital birth AMC
329	Admission specialism: Neonatology	Admission ward: Obstetrics
332	Admission specialism: Pediatric nephrology	Admission source: Outpatient Clinic
404	Admission specialism: Pediatric pulmonology	Admission source: Outpatient Clinic
471	Age	Admission ward: Teenagers

Table 11: Occurred multicollinearity in primary classes.

Multicollinearity was detected six times between the variables ‘Neonatology’, ‘Hospital birth AMC’ and ‘Obstetrics’. In class 88 and 329, the correlation between these three variables was one. Therefore, selection of one of the variables was arbitrary and occurred based on the sequence of appearance in the data. The variables ‘Age’ and ‘Teenagers’ were strongly correlated twice, resulting in multicollinearity. Multicollinearity also occurred between ‘General Pediatrics’ and ‘Pediatric Intensive Care’. Finally, ‘Outpatient Clinic’ showed multicollinearity once with ‘Pediatric nephrology’ and once with ‘Pediatric pulmonology’.

Seven variables in the dataset were typified as predictors (user’s choice, see Table 6). This implies that selection of predictors was required when classes contained less than 70 admissions. (As stated in section 5.2.1, at least 10 admissions are needed to prove a predictor’s significance.) Selection occurred twice. The predictors ‘Admission type’ and ‘Age’ were eliminated.

The remaining predictors were included in regression analysis. In the backward stepwise selection procedure, predictors were eliminated based on their p-value. The selection procedure was repeated until all predictors left had a significant influence on LOS. The eliminated predictors are presented in Table 12. A maximum of six iterations were needed to eliminate all non-significant predictors. On average, four of the seven predictors were eliminated in the backward stepwise selection procedure.

Class	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5	Iteration 6
24	Gender	Adm_day	-	-	-	-
39	Age	Adm_type	Adm_day	-	-	-
67	Adm_ward	Age	Adm_type	Gender	Adm_day	-
73	Adm_ward	Adm_day	Adm_spec	-	-	-
88	Adm_source	Adm_ward	Adm_type	Adm_day	Gender	Age
162	Adm_day	Adm_type	Gender	-	-	-
164	Adm_type	Gender	Adm_spec	Adm_source	Adm_day	-
193	Adm_ward	Adm_day	Adm_spec	Gender	Age	Adm_type
220	Age	Gender	Adm_type	Adm_day	-	-
273	Adm_spec	Age	Adm_day	Adm_type	-	-
285	Adm_spec	Gender	Adm_ward	Adm_day	-	-
309	Adm_spec	Age	Adm_day	Adm_ward	Gender	-
329	Gender	Adm_ward	Adm_source	Adm_day	Adm_type	-
332	Age	Adm_source	Gender	Adm_type	Adm_day	-
399	Adm_ward	Gender	Age	Adm_type	-	-
404	Adm_ward	Adm_day	Gender	-	-	-
471	Adm_ward	Adm_source	Gender	Age	Adm_type	Adm_day

Table 12: Eliminated predictors in multiple regression analysis.

5.2.4 Resulting LOS formulas

The fourth and final step of the computational model involved creation of the resulting LOS formulas (see Figure 16).

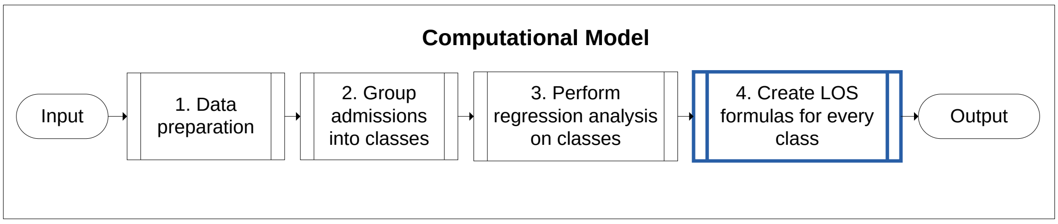

Figure 16: Flowchart of the computational model. See Appendix D for the corresponding legend.

The LOS formulas were created with the remaining predictor variables as explained in section 4.1.4. In one of the classes, all predictors were eliminated (As stated in section 5.2.3). No LOS formula was created for this class and the admissions in this class could not be predicted. The end totals (Table 13) therefore differ from the totals presented in Table 10.

	No. classes	Admissions	Percentage
Total	**472**	**4849**	**100 %**
Predictable	**23**	**2455**	**50.6 %**
Primary classes	22	2443	50.4 %
Aggregated secondary classes	1	12	0.2 %
Unpredictable	**449**	**2394**	**49.4 %**
Typified unpredictable classes	388	1067	22.0 %
Non-aggregated secondary classes	60	1257	25.9 %
Non-predictable primary classes	1	70	1.5 %

Table 13: End totals of the classes in the dataset.

Table 14 presents the remaining LOS formulas. The accuracy of the LOS formulas was expressed in the percentage of variance in LOS that can be explained by the predictor values (R^2). R^2 was one of the output variables of the standard Excel formula for regression (section 4.1.3). Average R^2 of all primary classes was 25.4%.

Class	R2	b	man	age	adm_day	adm_type	x1adm_source_HOME	x2adm_source_OC	x3adm_source_LIST	x4adm_source_OH	x5adm_source_GP	x6adm_source_HB	x7adm_source_DR	x1adm_ward_OLCH	x2adm_ward_TEEN	x3adm_ward_I&PS	x4adm_ward_PIC	x5adm_ward_PS	x6adm_ward_OBS	x7adm_ward_NIC	x8adm_ward_MW	x1adm_spec_GPED	x2adm_spec_PPUL	x3adm_spec_POT	x4adm_spec_PNEU	x5adm_spec_PC	x6adm_spec_NEO	x7adm_spec_PGE	x8adm_spec_PS	x9adm_spec_TRA	x10adm_spec_PE	x11adm_spec_PHI
404	0.53	0.98				0.43	-0.66		-1.18	-0.90																						
67	0.52	1.42					-0.55	0.07	-0.86	0.16																						
309	0.52	1.29				-0.88	2.12	1.92	-0.62	1.41		1.99																				
24	0.40	-0.72		0.08		0.62	1.27	0.98	1.12	2.16	1.90			0.68	1.58																	
39	0.39	1.55	-0.28				0.08	0.26	-0.36	0.75				0.44	0.98	0.83	-0.14					-1.06	-0.72									
73	0.30	-0.27	-0.26	0.04				0.84		0.90																						
285	0.23	0.03		0.04		0.89	-1.58	-0.17	0.14	0.91																						
332	0.22	2.30												-0.24	0.45	0.85	1.83	0.49											-1.44			
193	0.22	0.95					0.59	0.57	-0.36	0.89																						
162	0.22	2.86		-0.17				0.74	0.32	0.18				-2.27		-2.65		-2.55														
399	0.14	-1.32					1.50	1.05	0.97																				1.15			
220	0.12	-0.58					-0.17	0.33	-0.26	0.66		0.11	-0.39	1.70	1.16	1.89	1.19		-0.65		-0.84						2.55	0.40				
329	0.08	3.03		-0.04																		-2.11							-1.56			
164	0.06	1.41		-0.04										-0.55	0.65	0.41																
273	0.06	1.10	0.19				0.09	-0.20	0.05	0.73				0.03	-0.05	-0.02	1.57	0.61														
88	0.05	1.85																				-0.68				-1.12			-0.83	-1.17		

Table 14: LOS formulas. See Table 6 for abbreviations.

5.3 Results user interface

The 20% most recent admissions available in the ECH dataset were used to test the user interface. The test set contained 1212 admissions. The LOS of these admissions is predicted by matching the diagnosis with existing diagnoses in the training set. LOS predictions were only made for those admissions that had a diagnosis that was assigned to a predictable class. Table 15 summarizes the results of the test set.

Test set characteristics	N	%
Admissions in test set	1212	100%
Predictable admissions in test set	468	38.6%
Average absolute deviation of predictions	2.6 days	91.7%

Table 15: Summary of the test set results.

Table 15 shows that the LOS of 38.6% of the admissions in the dataset was predicted. The other 61.4% were admissions with diagnoses that could not be predicted by the tool. The average absolute deviation between observed and predicted LOS was 2.6 days. Average absolute deviation in percentage was calculated to correct for the relative length of LOS. The absolute average deviation between observed and predicted LOS in percentages was 91.7%.

The results specified per class are presented in Table 16. The percentage explained variance (R^2) retrieved from the computational model, is presented for each class to compare the explanatory power with the predictive power of the model. High average absolute deviations correspond with inaccurate LOS predictions and vice versa.

Class	no. adm*	R2†	av_abs_dev_day‡	av_abs_dev_%ˣ
404	33	0.53	0.6	76%
67	18	0.52	0.3	31%
309	16	0.52	11.6	491%
24	2	0.40	4.0	103%
39	84	0.39	1.8	47%
73	20	0.30	1.1	65%
285	22	0.23	2.6	54%
332	16	0.22	2.2	113%
193	28	0.22	0.9	72%
162	18	0.22	0.9	43%
399	13	0.14	0.8	103%
220	135	0.12	3.6	87%
329	25	0.08	2.2	151%
164	1	0.06	1.5	150%
273	13	0.06	2.5	66%
88	24	0.05	4.0	122%

Table 16: Average absolute deviation between predicted and observed LOS, expressed in days and in percentage. The table is sorted on explained variance, R^2.

*: number of predicted admissions in the class

†: percentage of variance in LOS that can be explained by the model

‡: average absolute deviation expressed in days

ˣ: average absolute deviation expressed in percentage

A histogram was made to check the distribution of occurring average deviations in percentage considering that extreme values strongly influence average deviation (see Figure 17). Negative average deviations correspond with overestimation of LOS by the model. LOS was overestimated by the model for 64% of the admissions in the test set.

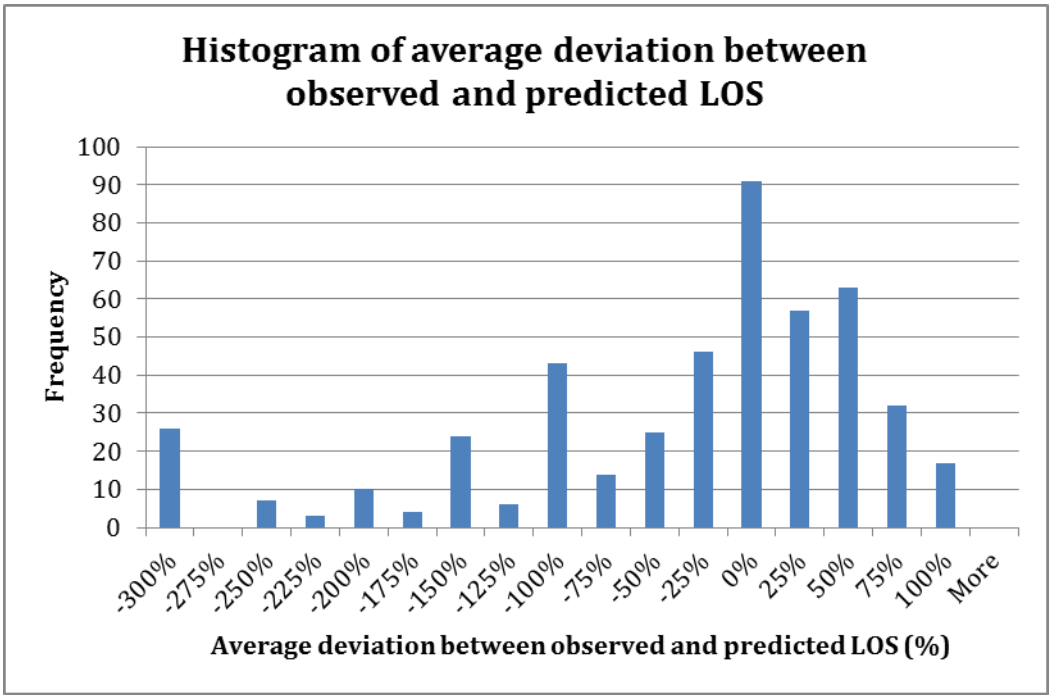

Figure 17: Histogram of occurring deviations between predicted and observed LOS.

6 Interpretation of the results

This chapter addresses the interpretation of the results presented in Chapter 5. Corresponding recommendations to improve the results are included in the sections. The chapter is divided in the interpretation and recommendations regarding the computational model (section 6.1) and the interpretation and recommendations regarding the user interface (section 6.2).

6.1 Interpretation results computational model

In this section, the results of the computational model are interpreted. Section 6.1.1 discusses the data preparation, section 6.1.2 discusses the grouping of admissions and section 6.1.3 discusses the regression analysis.

6.1.1 Interpretation results data preparation

The accuracy of LOS predictions is expected to improve when as many independent variables as possible can be included in the dataset. Inclusion in the dataset does not directly mean inclusion in the LOS formulas; the model will determine whether these variables indeed significantly influence LOS. Not all variables suggested in literature were available in the ECH dataset. The IT infrastructure of the ECH therefore needs to be adjusted. The weight of the patient, possible secondary diagnoses and the need for homecare after discharge are expected to have the most added value as they are most often proved in literature as LOS predictors (see section 3.3).

R6.1	**Include as many independent variables as possible in the dataset to improve the accuracy of the predictions (priority: weight of the patient, secondary diagnoses and need for homecare)**

The requirements for primary and unpredictable classes related to the number of admissions per group criterion value. The chosen requirements in this case study resulted in 51.8% of the admissions belonging to a primary class for which the model created LOS formulas. A sensitivity analysis was conducted to determine the influence of the primary class requirement on the percentage of admissions predictable and the accuracy of the admissions, see Figure 18.

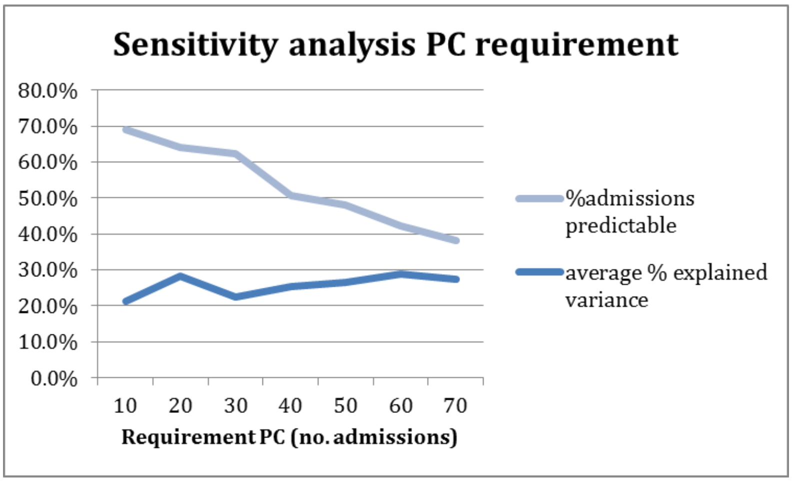

Figure 18: Sensitivity analysis of the requirement for primary classes. PC: primary class.

The number of predictable diagnoses was expected to increase while the accuracy was expected to decrease when the required number for primary classes was lowered. Figure 18 confirms this expectation.

It is recommended to expand the requirements with a maximum allowable confidence interval (CI) once more data are gathered. Narrow confidence intervals yield homogeneous classes which improves the accuracy of LOS prediction. This expansion was not applied to the ECH dataset due to its small size.

R6.2	**Expand the requirement for primary classes with a maximum allowable CI to improve the accuracy of the predictions**

The variety in the ECH dataset and its limited size are expected to cause the limited percentage of predictable admissions. The number of predictable diagnoses, and therefore admissions, is expected to increase when more admissions per class are included in the dataset. The effect of dataset size on the outcomes of the model was analyzed by running the model for two different datasets, see Table 17.

Values	Dataset 1 (Jan. – Dec. 2012)	Dataset 2 (Jan. 2012 – June 2013)
Number of classes	438	515
Average R^2 *	22.4 %	17.6 %
% predictable admissions	51.5 %	60.9 %

Table 17: Comparison of datasets with different sizes to analyze the influence of dataset size on LOS predictions.

* Percentage explained variance

The average explained variance was lower in Dataset 2. This is due to the fact that the variance in LOS can increase when more data per class is available. This is certainly expectable when the enlargement of the dataset is proportionally large. The percentage of admissions predictable by the model is higher for Dataset 2. This is in line with the expectations.

The tradeoff between the accuracy of the predictions and the number of predictable admissions is a challenge. When the predictions are used for planning purposes, accuracy is essential. The percentage of admissions predictable is most important when the goal is to focus on discharge since focus on discharge is also achieved by less correct LOS predictions at admission. It is recommended to use the model for planning purposes when the dataset is enlarged since predictions are more valuable when they are based on large datasets (low level of coincidence). In the ECH dataset, more historical admissions could not be included due to difficulties with different diagnosis registration types.

R6.3	**Enlarge the ECH dataset by translating the different diagnosis registration types or waiting for future admissions to predict a higher percentage of admissions and to improve the accuracy of the predictions**

6.1.2 Interpretation results admission grouping

Admissions were grouped before multiple regression in order to increase the number of predictable classes. Admissions were aggregated when statistically comparable. In the ECH dataset, only one secondary class was aggregated with a primary class (with the chosen requirements for class types). Other aggregation policies should therefore be explored. For example, clinical relevance could be incorporated by fixed aggregation of diagnoses based on an expert's opinion (e.g. physician). The impact of various aggregation criteria was not determined in this study due to time deficiency.

R6.4	**Explore other aggregation policies in order to increase the number of predictable classes**

A consistent relation between a class' explained variance (R^2) and whether or not the class was aggregated was not detected. Therefore, it is not clear whether aggregation of classes was desired in the ECH dataset.

6.1.3 Interpretation results regression analysis

Independent variables were eliminated during regression analysis when they had no significant influence on LOS. The number of eliminations per variable shows the predictive power of each variable, see Table 18. The variable 'Admission day' was eliminated in all but one of the classes, implying that 'Admission day' was a poor predictor of LOS for the ECH dataset. The influence of the admission day was expected to be low since 58% of the admissions were elective. In planning elective admissions, the weekend is taken into account to prevent unnecessary prolonged stays. The variable 'Gender' predicted LOS poorly as well. This was not expected since Tump et al.[20] concluded that the baseline LOS increased by 22% for males. The difference in explanatory power of gender is assumed to be caused by the difference in the size of the dataset used (Tump: n=142, this study: n=4849). The variables 'Admission source' and 'Admission specialism' had the highest predictive power on LOS. Various studies confirm their relationship with LOS [20, 55, 56].

Variable	No. times eliminated
Adm_day	16
Adm_source	5
Adm_spec	6
Adm_type	12
Adm_ward	10
Age	10
Gender	14

Table 18: Summary of the number of times variables got eliminated during regression analysis.

The selection of predictors influenced the accurateness of LOS predictions. In eight of the 17 primary classes, multicollinearity was detected. Multicollinearity was expected to occur between 'Neonatology', 'Hospital birth AMC' and 'Obstetrics' due to the logical combination of values. Additionally, multicollinearity was expected between 'Admission type' and 'Admission source: ER', and 'Admission type' and 'Admission day'. Patients admitted from the ER are acute patients and elective admissions generally do not occur in the weekend. The reason for absence of multicollinearity is expected to be caused by unjustified value registration. If an admission is registered and the type of admission is not specifically selected by the health professional, the default value of the variable is included (elective). Unjustified value registration can be prevented by removing default values in registration databases and by obligating the health professional to select the correct value.

R6.5	**Remove default values in registration systems to prevent unjustified values**

The selection of predictors during multiple regression (Table 12) showed that few existing predictors significantly influenced LOS. This endorses the need for more independent predictor variables, as recommended in R6.1.

6.1.4 Interpretation results LOS formulas

The accurateness of the LOS formulas is expressed in the percentage explained variance, R^2. Six of the 16 LOS formulas for the predictable primary classes had an R^2 under 20%. The low predictive power in these classes is expected to be due to the broadly defined diagnoses pertaining to these classes. It is therefore recommended to choose a more detailed grouping criterion (e.g. a more specified diagnosis) when dataset size allows. This matches the instruction regarding the grouping criterion in section 4.1.1.

R6.6	**Choose a more detailed grouping criterion when dataset size allows to improve the accuracy of the predictions**

The average R^2 of this study (25.4%) was compared with results from models in literature to get an indication of relative performance, see Table 19. Important to note is that the number of available independent variables was restricted in this study since only ex-ante available variables were taken into account (see chapter 3). Therefore, the average R^2 of this study was expected to be lower than the average R^2 of the explanatory models from literature.

Research	Average R^2
Van Houdenhoven et al. [22]	34.0%
De Lourdes Guzman Castillo [21]	17.5%
Tump et al. [20]	47.6%

Table 19: Average explained variance of LOS explanatory models in literature.

The model developed in this study performed better than the model developed in [21]. This is expected to be caused by the specificity of the dataset; the dataset used in this study was limited to pediatric admissions, while in [21] a complete hospital's dataset was used.

6.2 Interpretation results user interface

Predictions were made using a test set to determine the predictive ability of the LOS prediction tool. The ability was assessed by the percentage of admissions predictable and the deviation between predicted and observed LOS.

In the training set, 51.8% of all admissions belonged to a primary class for which an LOS formula was created. These formulas were used to predict the admissions in the test set. For 40.7% of the admissions in the test set, LOS was predicted by the tool. This decrease is expected to be partly due to the relative small training set: 43 of the 259 diagnoses in the test set did not occur in the training set. This corresponded with 4.7% of the admissions. The remaining difference (6.4%) is expected to be due to the characteristics of the test set.

Regarding the accuracy of the predictions, it was expected that admissions matching with classes with a high R^2, would be predicted more accurately than classes with a low R^2. The results (Table 16) showed that this expectation was not met. Class 309 (corresponding to the diagnosis 'other cardiac diseases') had the largest average absolute deviation (491%), while having an R^2 of 51.6% in the computational model. This large average absolute deviation was analyzed by running the computational model for the complete dataset (training set + test set). Results showed that the R^2 for the same diagnosis in this new dataset was 43.6%, implying a decrease of 8%. Therefore, it can be concluded that the admissions in the test set were not a representative sample of the training set.

The average absolute deviation between observed LOS and LOS predicted by the tool was 91.7%. In comparison, the average absolute deviation between observed LOS and LOS predicted by physicians was 147.6%. This implies that the tool's predictions are more accurate than the physician's predictions. However, both predictions still deviate strongly from the observed LOS.

7 Conclusion

The objective of this research was to develop a generic prediction tool prototype which accurately predicts the individual hospital LOS, based on patient characteristics and organizational factors known at admission.

This research demonstrates that the developed LOS prediction tool can predict the LOS of patients admitted to the ECH with higher accuracy than physicians can based on their medical experience. Average absolute deviation between the tool's predictions and observed LOS was 91.7%. This is an improvement in comparison to the average absolute deviation between the physician's predictions and observed LOS, which was 147.6%.

The prediction tool consists of an LOS explanatory model and an application to prospective data. In that way, LOS predictions of new admissions are based on the LOS of comparable historical admissions. The accuracy of the predictions is therefore dependent on the accuracy of the explanatory model (expressed in R^2). Average R^2 of the model was 25.4%.

Two limitations of the ECH training dataset restricted the performance of the tool. First, due to the training set size, the model could only predict the LOS of 40.7% of the admissions in the test set. The rest of the admissions were not predictable since too few admissions per diagnosis were available. Second, the number of present influencing LOS variables in the ECH training set was restricted. Seven proposed variables in literature were not available in the training set (e.g. the weight of the patient and the presence of a secondary diagnosis). This was due to difficulties in combining various databases in the ECH. The location from where the patient was admitted (e.g. home, other hospital, ER) and the admission specialism had the highest predictive power on LOS. Gender and admission day (weekday or weekend day) were the poorest predictors of LOS.

Due to the large average absolute deviation between the tool's predictions and observed LOS, it is not yet recommended to base the admission planning of the ECH on LOS predictions made by the tool. The dataset first needs to be enlarged and more influencing LOS variables need to be included in order to increase the accuracy of the predictions. Due to the generic character of the prediction tool, new or enlarged datasets are easily analyzed.

7.1 General discussion

In the development of the LOS prediction tool, multiple choices were made. These choices are discussed in this section and recommendations are presented where applicable.

The choice to base the LOS prediction tool on multiple regression was made for its proven performance in literature, expected suitability for automation, its ease of use and its applicability to the ECH data. The expected suitability for automation turned out to be unjustified. Regression analysis is generally performed manually and the researcher's knowledge influences the results. For example, the researcher manually includes predictors when clinically relevant, independent of the outcomes of the univariate analysis (see section 4.1.3). Automating these choices is time consuming and sometimes not even possible. Multiple assumptions had to be made to be able to complete the model and the influence of these assumptions is unclear. It is therefore interesting to analyze the difference in outcome between manually conducted statistical analyses and automated analyses in order to possibly correct the assumptions and improve the accuracy of the predictions.

R7.1	**Analyze the difference in outcome between manually conducted statistical analyses and automated analyses to possibly improve the accuracy of the predictions**

An example of one of these assumptions concerns the selection of predictor variables when the number of typified predictors exceeds the number of allowed predictors in regression analysis (section 4.1.3). This selection is based on univariate analysis. In manually performed univariate analysis, clinical relevant variables are included independent of their significance. Reason for this includes the fact that it is possible that the model excludes variables that do not have individual significant influence but do have significant value in combination with other variables. In this study, the choice was made to select predictors purely based on their statistical relevance in order to create an automatic tool and to prevent subjectivity.

The choice to aggregate classes was enforced by the choice for multiple regression and the characteristics of the ECH dataset. Ultimately, the aggregation of classes resulted in one extra diagnosis becoming predictable by the model. It is therefore recommended to analyze the effect of class aggregation in other datasets. With the results, the choice to whether or not keep class aggregation in the model can be made. When class aggregation does not result in extra admissions becoming predictable by the model, aggregation should be eliminated as it increases the standard deviation of one of the classes involved in aggregation.

R7.2	**Analyze the effect of class aggregation in other datasets to get more validated results on whether or not class aggregation is suitable to enlarge the number of predictable admissions**

7.2 Recommendations for future research

The prediction tool is only tested on the dataset of the ECH. To assure the effectiveness of the tool, LOS predictions based on other datasets should be made. It is suggested to apply the tool to other departments of the AMC and to other Dutch hospitals. The tool is expected to perform best in regional hospitals since more standard care is provided. This results in fewer occurring diagnoses and more admissions per diagnosis. However, the added value of the prediction tool is expected to be biggest in academic hospitals predictions are more difficult to make.

R7.3	**Run the model on different datasets to assure the tool's effectiveness**

The model could be expanded with a functionality to predict discharge during the patient's stay. That way, the LOS could for example be predicted every day based on the patient's health status. To incorporate such a function, variables that influence the LOS during a stay must be determined. Diagnostic values such as blood levels and the oxygen saturation level are expected to be good predictors of LOS during a patient's stay (derived from the conducted interviews).

R7.4	**Include diagnostic variables in the model to predict discharge during a patient's stay**

The tool could be used as an aid to evenly spread the workload of personnel during a patient's stay. To achieve this, required actions per diagnosis need to be mapped and incorporated. Per day, the tool could then suggest required actions to achieve the predicted discharge date. We think this is only possible for standard actions since almost every admission proceeds differently.

R7.5	**Incorporate suggestions for required actions during a patient's stay in the tool to evenly spread workload during a patient's stay**

Additional to the previous recommendation, the tool could be used as an aid to evenly spread the workload between personnel on a ward. Currently, personnel get a number of patients assigned. With an estimation of the intensity of care of patients, patients could be assigned more evenly amongst personnel. Research regarding the estimation of the intensity of care is currently conducted at the AMC.

R7.6	**Incorporate the intensity of care of patients in the tool (when possible) to evenly spread workload between personnel**

7.3 Implementation advice

This section discusses recommendations to achieve implementation of the tool in the ECH.

Interviews with the management of the ECH wards showed that LOS prediction does not occur consequently. To achieve focus on discharge, starting at admission, LOS predictions for all admissions are required. It is therefore recommended to make LOS prediction mandatory. Consequent LOS prediction is only feasible if the digital databases that register LOS actively ask for LOS prediction when LOS is not predicted. Continuation then only becomes possible once LOS is predicted. The user can use the prediction tool to get support in predicting LOS.

R7.7	**Make digital databases actively ask for an LOS prediction if LOS prediction is not registered to achieve consequent LOS prediction**

In the ECH, expected LOS is currently registered in multiple digital locations. These include the digital planning board, the electronic patient file and the database OKplus. Confusion and unclear responsibilities occur due to these possibilities. One digital location should therefore be designated for registering LOS predictions.

In the short-term, it is recommended to declare the digital planning board as the designated location for LOS registration. All personnel involved have access to this program and it is easy to use. Due to the absence of connections between some of the AMC's databases, manual copying of LOS predictions is required to register LOS in all databases. Recommendations include identifying the databases to which LOS predictions must be copied and making individuals explicitly responsible.

In the long-term, it is recommended to register LOS in the AMC's new electronic patient file. This system, called Epic (implemented by the project 'EPD VUmc AMC' (EVA)), is expected to be implemented mid-2015. By using Epic, LOS registration will occur consistently AMC-wide. Possibilities to connect the LOS prediction tool with EVA are currently explored. With a digital connection, LOS prediction could be automated based on inserted admission characteristics. It should be noted that the predicted LOS is a suggestion and that the user can adjust the prediction at his or her discretion.

R7.8	**Assign one designated digital location to register LOS in order to achieve consistent LOS prediction**

The goal of the project is to achieve an optimal admission planning. Therefore, predictions of expected LOS are needed at admission. It is important that the people who implement the tool, clearly communicate this goal. Communication plays an important role in the implementation of technology [57]. Creating a support base amongst the users of the tool is a prerequisite for successful implementation. Additional to the goal, the method and usage of the tool should be communicated to the users. The short description of the method of the prediction tool and training instructions are presented in Appendix E.

R7.9	**Discuss the goal, method and instruction of the prediction tool with the users to increase the chance of successful implementation**

The LOS formulas form the basis of the LOS predictions. Since there is no "live" connection between the computational model and the electronic patient file, new historical admissions are not automatically included in the creation of the LOS formulas. Therefore, predictions are not always based on the largest dataset possible. The computational model should be executed every two months. It is estimated that, based on historical data, at least one admission per diagnosis occurs in two months. Extracting the new dataset and running the model is expected to take around 30 minutes.

R7.10	**Update the tool every two months to keep the predictions up to date**

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Appendix A

List of interviewees

Appendix B

Power analysis		Value
Input	Test type	2-sided
	Type confidence interval	1 group
	Expected intra-class correlation	0.7
	Distance from correlation to limit	0.15
	Number of measurements/raters	3
Output	Required number of cases	31

Table 20: Input and output values of the conducted power analysis performed in nQuery.

Appendix C

Multiple linear regression

In [21, 22], multiple regression is used to create formulas to calculate LOS predictions. Regression is the most widely used method for prediction models [21] and is therefore described in this section. The description is based on [50, 51].

Multiple regression analyses are used to build association and prediction models. Association models estimate the relation between an outcome variable and one central determinant. Prediction models focus on accurately predicting an outcome variable based on a set of possible independent variables. In the formulation of prediction models, the goal is to find the best prediction using the simplest model possible. By not including all possible independent variables, the standard error of the prediction becomes smaller.

Two types of regression exist; linear and logistic regression. Linear regression is used when the outcome variable is a continuous variable, while logistic regression is used when dealing with a categorical or dichotomous[16] outcome variable. In this study, linear regression is used since LOS is a continuous outcome variable.

In linear regression, a linear equation is fit to the data in the way that the squared differences between the line and the actual data points are minimized: minimizing the Total Sum of Squares, SS_T. The linear equation has the form of

$$Y = \sum_{1}^{n} a_n x_n + b, \tag{3.1}$$

where Y represents the outcome (dependent) variable, a_n represents the regression coefficient for the independent variable x_n, n represents the number of independent variables and b represents the intercept of the line.

Inaccuracy of the line always exists and is expressed by the sum of differences between each observed data point and the predicted value, the Residual Sum of Squares, SS_R.

To assess the goodness of fit of the line, the explained variance, R^2, is used:

$$R^2 = \frac{SS_M}{SS_T}, \tag{3.2}$$

where the Model Sum of Squares, SS_M, represents the reduction in the accuracy of the model resulting from fitting the regression model to the data,

$$SS_M = SS_T - SS_R \tag{3.3}$$

and SS_T equals the Total Sum of Squares.

[16] Variables that equal 0 or 1

There are three methods of regression, each including another way of selecting the independent variables. This research uses the backward stepwise method since the selection is based on a purely mathematical criterion – and therefore suitable for programming – and suppressor effects[17] are taken into account.

Backward stepwise method

The backward stepwise selection method places all independent variables in the model and eliminates variables based on their significance value (p-value). Each significance value is compared against a removal criterion. The variable that makes the smallest non-significant contribution to the dependent variable is eliminated. This procedure is repeated until all independent variables in the model make a significant contribution to the dependent variable.

After conducting multiple linear backward regression, all regression coefficients of the independent variables that significantly contribute to the outcome variable, are clear. With the coefficients and intercept value, the formula to predict the outcome variable can be composed.

Dummy variables for categorical predictors

Variables that serve as independent prediction variables in regression need to be continuous or dichotomous. Categorical variables cannot be included in their original form as regression analysis treats all independent prediction variables as numerical[18]. To overcome this restriction, dummy variables that equal 0 or 1 are created to represent the absence or presence of some categorical effect. The regression coefficients of dummy variables represent the increase or decrease in the outcome variable in proportion to a reference criterion. One of the options of the categorical variable therefore presents the '0' in all dummy variables. The choice of reference criterion is arbitrary. To illustrate the principle of dummies, an example is given:

Suppose we have variable X that influences outcome variable Y. Variable X is a categorical variable that can take on the values A, B or C. Variable X needs to be translated into two dummy variables:

Options	Cat_X_x1_B	Cat_X_x2_C
A	0	0
B	1	0
C	0	1

All dummy variables for a specific categorical predictor need to be kept together in analysis since they do not have intrinsic meaning of their own. When one of the dummy variables is eliminated in the backward stepwise method, all dummy variables representing the same categorical predictor need to be eliminated.

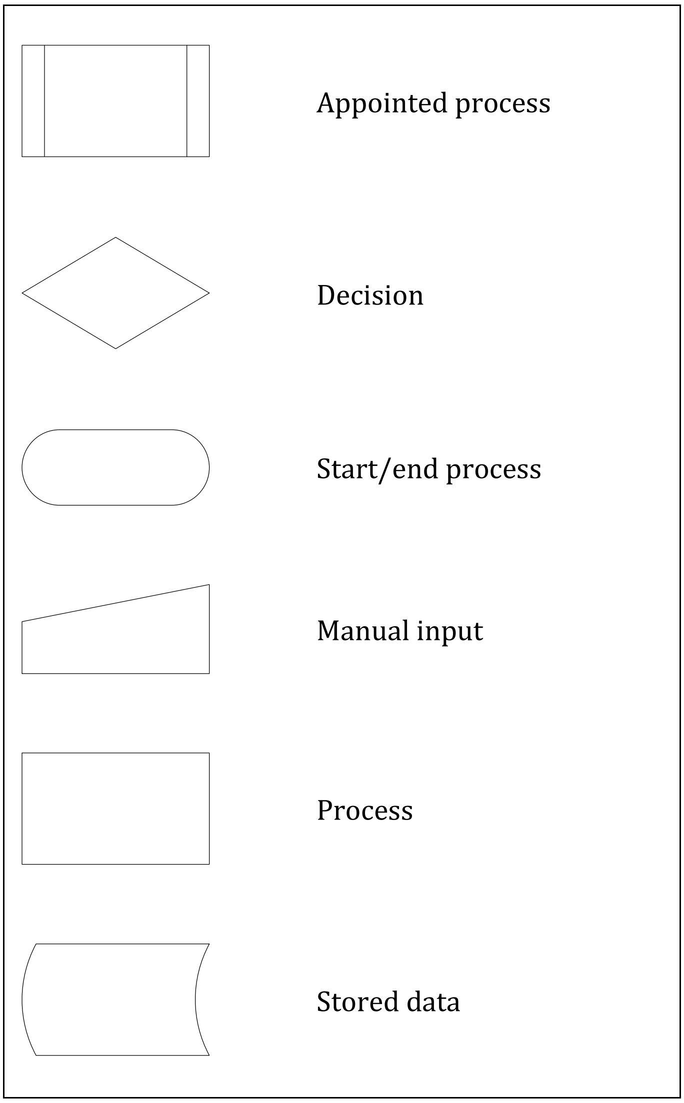
---

[17] "Suppressor effects occur when an independent variable has a significant effect but only when another variable is held constant. The forward stepwise method is more likely to exclude independent variables involved in suppressor effects."[51]

[18] Interval or ratio scale variables whose values present an order.

Appendix D

Flowchart legend



Appendix E

Implementation instructions

This section presents instructions to implement the prediction tool in practice. The instructions form part of the implementation advice presented in Chapter 0.

Short tool description

The tool creates LOS formulas for classes of admissions. These classes are based on diagnosis. For each class, the influence of admission characteristics (e.g. age, gender) is evaluated. The characteristics that significantly influence LOS are incorporated in the LOS formula.

Training instructions

The user instructions depend on the way LOS is registered. We present instructions for both the short-term and long-term scenario.

Short-term scenario

If the short-term scenario is applied, the user needs to insert the patient's diagnosis in the user model. The tool then matches the diagnosis with its corresponding class and the LOS formula is retrieved. The tool displays the admission characteristics influencing LOS and the user is asked to insert values of these characteristics. With all values known, the tool calculates the predicted LOS and presents it to the user. The user can then copy this prediction to the designated database (optionally after adjustment).

Long-term scenario

If the long-term scenario is applied and a digital connection between the prediction tool and EVA exists, the user instructions slightly differ. When the user inserts the patient's diagnosis in EVA, the corresponding class and LOS formula are automatically retrieved. Since all admission characteristics are inserted in EVA, the tool will automatically retrieve the required characteristics, calculate LOS and present the prediction in the designated place in EVA. The user can still adjust the prediction at his or her discretion.

Appendix F

Instruction manual computational model

This manual provides instructions to use the computational model. The user needs to make multiple choices during the model execution. These choices are based on the user's assessment. Input and background regarding the choices is given in the following sections.

1. Supply input table

Variables that the user expects to influence LOS need to be included in the input table. Suggestions for predictor variables are given in Table 3, section 3.4. Discontinuous variables need to be redefined in dichotomous or categorical variables with the smallest amount of option values when possible, to improve the accuracy of the model.

2. Apply lognormal transformation to LOS

Lognormal transformation of LOS needs to be applied to predict LOS using multiple regression. The log transformed LOS needs to be included in the input table.

3. Run model

The model is started by clicking the 'START' button. The model directly asks the user to make choices regarding variable types and class requirements. These choices are explained in the following steps.

4. Choose variable types

The possible variable types include the outcome variable, a basic variable, a predictor, a negligible variable or the grouping criterion.

The outcome variable of the LOS prediction tool is the log transformed LOS.

The basic variables are formed by the admission year and number. Combination of these values corresponds to unique admissions to ensure that each admission is traceable.

Predictor variables are the variables expected to influence the outcome variable. Different subtypes for predictor variables exist: dichotomous, categorical or continuous.

All variables typified as negligible variables are neglected in the model.

The grouping criterion forms the basis of the admission aggregation. The variance in LOS and the number of admissions within a group need to be balanced to make this choice. The ideal group criterion yields minimal variance within a group, maximal variance between groups and as many admissions per group as possible. With a minimal variance and many admissions within a group, the model can accurately predict LOS for new patients having the same group criterion value (e.g. diagnosis). With a maximal variance in LOS between groups, distinct classes are generated. This benefits the accuracy of the predictions. The group criterion must be a categorical variable. This to ensure that the model creates a limited amount of classes and aggregation of classes can possibly occur.

5. Choose requirements for class types

There are three types of classes possible in the model: primary, unpredictable and secondary classes. The model only creates LOS formulas for primary classes considering the requirements for regression explained in section 4.1.3. Unpredictable classes never become predictable in the model. Secondary classes only become predictable if they are aggregated with a primary class. The user needs to choose the required number of admissions for primary and unpredictable classes.

Primary classes

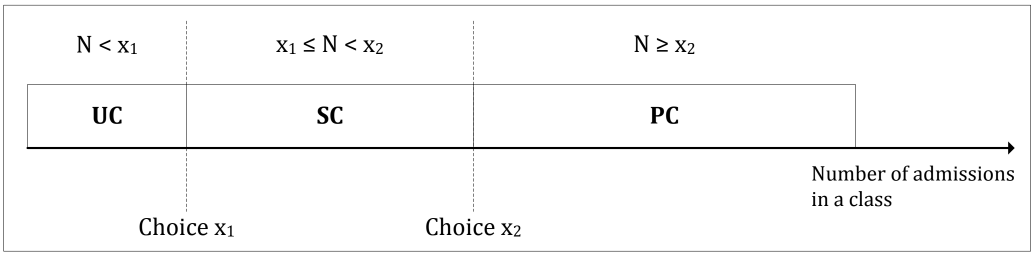
The choice for primary classes must be based on the number of predictor variables included in regression analysis. A large number of predictors requires a large number of admissions within a group. The rule of thumb for this choice states that 10 admissions are needed to test one predictor variable [51]. When the required number of admissions for a class to be a primary class is set too high, the model will only be able to create LOS formulas for few classes. On the contrary, when the required number of admissions is set too low, the model can include few predictor variables. This decreases the accuracy of the LOS predictions. The requirement for primary classes is illustrated in Figure 14 as choice x_2.

Unpredictable classes

The LOS of a class that contains few admissions cannot be generalized due to the high level of coincidence. The user needs to choose the accepted influence of coincidence by setting the required number of admissions for a class to possibly become predictable. Classes containing fewer admissions than required are labeled as unpredictable and are excluded in the model. The requirement for unpredictable classes is illustrated in Figure 14 as choice x_1.

Secondary classes

Secondary classes contain a number of admissions equal to or greater than the requirement for unpredictable classes, and fewer admissions than the requirement for primary classes.



6. Resume model

Resume the model by clicking the 'CONTINUE' button. The model runs the rest of the steps and results in a table containing the LOS formulas for the primary classes.