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MASTER'S THESIS

IMPROVING CAPACITY UTILIZATION IN DENTAL CARE SERVICES USING BUSINESS ANALYTICS

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ABSTRACT

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Traditionally health care service providers have focused especially on the quality of service and waiting times while the third dimension costs have not got that much attention. For example, in several researches about capacity utilization in health care stated that capacity has not been utilized as well as it should. The aim of this study was to create a normative model, a so called slot machine, which output is the optimal number of customers that can be served during a particular day. The objective of the slot machine was to increase the provider's utilization rates without increasing customer waiting times.

This study was an empirical orientated case study where a large number of numerical data was utilized. Data was mostly treatment duration data and most of the analyzes in this master's thesis used history data from three years' time. Data was studied and the slot machine was programmed with the analytical program R. This study used both qualitative as well as quantitative research methods. Qualitative methods, such as literature research and narrative literary view, were used to gain understanding of the existing phenomenon. Quantitative methods were used to create and to verify a normative model, the slot machine. The purpose of the modelling was to increase understanding and prediction of the environment with several factors affecting to utilization rate. The functionality of the slot machine was tested daily in practice and in theory by using simulation. By simulating it was possible to test and to modify the slot machine before it was taken into use.

The utilization rates were increased and waiting time was decreased in the case company after the slot machine was utilized. Therefore, it can be stated that business analytics is an effective way to improve capacity utilization without jeopardizing customer waiting times.

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Perinteisesti terveydenhuollon palveluntarjoajat ovat keskittyneet erityisesti palvelun laatuun ja asiakkaiden odotusaikoihin, mutta kustannustietoisuus on jäänyt vähemmälle huomiolle. Esimerkiksi useissa kapasiteettitutkimuksissa terveydenhuollossa todetaan, että kapasiteettia ei ole käytetty niin tehokkaasti kuin olisi syytä. Tämän diplomityön tavoitteena oli rakentaa yksityiselle hammaslääkäriasemalle normatiivinen malli, niin sanottu slottikone, jonka avulla voidaan määritellä optimaalinen määrä asiakkaita, joita voidaan palvella kunkin päivän aikana. Slottikoneen päämääränä oli parantaa case-yrityksen resurssien käyttöasteita nostamatta asiakkaiden odotusaikaa.

Työ oli empiirispainoitteinen casetutkimus, jossa käytettiin hyväksi yrityksessä jo kerättyä dataa pääsääntöisesti tietoa hoitojen kestoista. Suurimmassa osassa tämän työn analyysejä käytettiin tietoa kolmen vuoden ajalta. Datan tutkiminen ja mallin rakentaminen tehtiin R-analytiikkaohjelmalla.

Tämä tutkimus oli luonteeltaan sekä laadullinen että määrällinen. Laadullisia menetelmiä olivat kirjallisuustutkimus ja kirjallisuuskatsaus. Määrällisiä menetelmiä käytettiin mallin rakentamiseen ja verifioimiseen. Mallinnuksen tavoitteena oli lisätä ymmärrystä sekä ennustettavuutta ympäristössä, jossa on paljon käyttöasteeseen vaikuttavia muuttujia. Slottikoneen toiminnallisuutta testattiin käytännössä päivittäin klinikalla sekä myös teoriassa simulaatiomallin avulla. Simuloinnin avulla slottikonetta voitiin testata ja muokata ennen käyttöönottoa.

Slottikoneen käyttöönoton jälkeen kapasiteetin käyttöasteet nousivat ja odotusajat laskivat case-yrityksessä. Näin ollen voidaan todeta, että liiketoiminta-analytiikka on tehokas tapa parantaa kapasiteetin käyttöastetta ja alentaa asiakkaiden odotusaikaa.

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19.09.2016
Tuukka Tirkkonen

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

This master's thesis is conducted for a Finnish company called Megaklinikka Oy providing private dental care services. This master's thesis was initiated by the company's objective to improve their utilization rate without jeopardizing customer waiting times by creating a model (slot machine) that optimizes the amount of customers they can intake in each slot, using data and business analytics.

This study focuses on capacity definition, measuring capacity utilization rate, effects of improving capacity utilization rate on customer waiting times, business analytics and appointment scheduling. This master's thesis concentrates more on verification and the results of using slot machine rather than focusing on slot machine's technical functionality.

According to Ward et al. (2014, p. 580), patient flow in healthcare facilities has depended on experienced managers with no training in operations to predict arrival surges and resource needs but in some cases expertise is no longer enough. Tools like closed-form mathematical modeling, discrete event simulation and empirical/statistical analysis have been employed to improve patient flow, reduce waiting, and potentially improve patient outcomes. Several clinics have begun to use these approaches to predict resource utilization and downstream consequences (Ward et al. 2014, p.580) – and that is what slot machine at Megaklinikka is all about.

1.1 Study's background

According to Hjelt et al. (2011, p. 55), there is a great need for developing services and new operational models in Finland. According to several researches, capacity utilization in health care could and should be utilized a lot better. Inappropriate utilization of hospital resources has been an issue of concern to medical staff, administrators and policy makers worldwide including for example the United States, Canada, France, Australia, The Netherlands, Switzerland, Norway and Turkey (Badran & Saad 2010, p. 134-135). According to a research, where Kaarna et al.

(2010, p. 3803) conducted a case study in three hospital units in a Finnish hospital, capacities were also poorly utilized. In a case study where the capacity utilization rates of 600 hospitals in the USA were studied, utilization rate ranged from 67.4 to 91.2 percent (Ferrier et al. 2008, p. 113) where utilization rate of 91.2 can be considered as very good. According to Andersen and Blegvad (2006 p. 149), most empirical analyses find that cost-efficiency is higher in the private sector than in the public sector. Higher cost-efficiency is usually resulted from higher utilization rate.

There may be a tradeoff between maximum capacity utilization and customer waiting time. When service sector companies try to achieve maximum capacity utilization it may lead to longer customer waiting times. Although it may be impossible to eliminate all waiting time, Kaarna et al. (2007, p. 1649) state that minimizing waiting time reduces costs for the society without sacrificing service level quality. Also scheduling is considered as one of the important criteria for the efficiency of the health care sector (Alrefaei et al. 2011, p. 100) where effective scheduling systems goal is also to match the demand with capacity so that resources are better utilized and customer waiting times are minimized (Cayirli & Veral 2003, p. 519).

In public dental care in Finland, the maximum customer waiting time is three months but it can be six months in total if treatment can be postponed without jeopardizing patient’s health. In September 2013 almost 90 percent of the patients were able to be treated in a six months’ time after asked to be treated. The number of customers who have waited for over six months has been reduced between the years 2011 and 2013. (Advisory Board on Municipal Finances and Administration 2014, p. 44-45)

Even though there are several studies about capacity utilization rate in health care services there were only few studies that focused on capacity utilization rate in dental care services. The concept of using capacity utilization rate is probably quite new in health care and in dental care services although it is used for a long time in the industry sector. Finland being on the edge of recession (Tilastokeskus 2015) and going through economically critical times drives also the public sector to find new ways to cut costs and use resources more effectively. Traditionally public sector service providers may have had different attitude towards cost-effectiveness compared to manufacturing companies. For example, Kaarna et al. (2007, p. 1649) state that hospitals have focused especially on quality of service and waiting times while the third dimension costs have not got that much attention. Now more and more service sector companies are looking for ways to improve cost effectiveness and workable models from the industry sector - or at least they should consider doing so. It is also noticeable that private sector health care service companies pursue to make profit as much as any other private sector industrial company.

One way to increase cost effectiveness could be using data analytics. Traditionally healthcare service providers have utilized business data in their operations far less regularly and comprehensively than most other industries and have underinvested in advanced managerial technologies like reporting systems and data visualization (Ward et al. 2014, p.574-575). With investments in healthcare IT implementation and a shift in focus from quantity of treatment to overall healthcare value, the stage is set for the application of advanced analytics. Even though the American healthcare system has suffered from constrained resources, increasing demand and questionable value, future looks more promising due to increasingly sophisticated and widespread uses of data and analytics. It can even be stated that analytics must play a pivotal role in the transformation of American healthcare into an efficient, value-driven system. (Ward et al. 2014, p. 571-572) According to Nastase & Stoica (2010, p. 604), current research reveals a clear link between business performance and the use of business analytics.

1.2 Aims and scope

The aim of this study is to create a slot machine, a workable model which output is the optimal number of customers that can be served during a particular day. The objective of the slot machine is to increase provider's utilization rates without increasing customer waiting times. In order to reach this aim, three research questions with sub-questions were created. Research questions are presented in table 1.

Table 1. Research questions

Main questions	Sub-questions
1. How to add customers with the use of business analytics, without increasing customer waiting time and without decreasing customer satisfaction?	1a. What is the relationship between customer satisfaction and waiting time? 1b. What is the relationship between capacity utilization rate and customer waiting time?
2. How to measure capacity utilization rate in dental care environment?	
3. How to test the functionality of the slot machine in theory and in practice?	

The main outcomes of this study are therefore to determine means to increase utilization rate without increasing waiting time and to conclude whether the slot machine improves case company's efficiency or not. Testing of the slot machine is conducted in practice by building measures and in theory by making a simulation model. This study will also give a framework for measuring capacity utilization rate in dental care services in general. Also the relationship between capacity utilization rate and customer waiting time in dental care environment is studied.

Since there are not enough studies focusing for example on capacity utilization rate in dental care services, this study will learn from capacity utilization rate in health care services - even though the nature of dental care service processes may be different from other health care processes.

1.3 Research methods and data

Research methods can be divided into two categories: quantitative and qualitative. However, it is difficult to see the difference between quantitative and qualitative research, and usually they are seen as complementary approaches instead of being rival approaches (Hirsjärvi et al. 2005, p. 127).

Quantitative research is originated from natural science and therefore emphasizes universal laws of cause and effect. It is common for quantitative research to make conclusions from earlier studies and earlier theories as well as to present hypotheses and collect data. In quantitative approach it is important that observed data is suitable for numeric measurement as well as to bring the material in a statistically processable form. (Hirsjärvi et al. 2005, p. 130-131)

Typical features for qualitative research are for example to favor people in data collection where the researcher trusts more on his own observations and discussions with examiners rather than measured data. It is also typical in qualitative research to use qualitative methods in order to collect data as well as to select the target group appropriately rather than using random sample. (Hirsjärvi et al. 2005, p. 155) Similarly, Corbin and Strauss (2015, p. 4), define qualitative research as a form of research in which a researcher collects and interprets data, making the researcher as much a part of the research process as participants and the data they provide.

According to Corbin and Strauss (2015, p. 5), most common reasons to choose qualitative rather than quantitative methods are:

- To explore the inner experiences of participants
- To explore how meanings are formed and transformed
- To explore areas not yet thoroughly researched
- To discover relevant variables that can later be tested through quantitative forms of research
- To take a holistic and comprehensive approach to the study of phenomena.

The purpose of the research can be categorized into three types of study: exploratory, descriptive and explanatory. An exploratory study is a mean to find out for example what is happening, to seek new insights or to ask questions and to asses phenomena in a new light (Saunders et al. 2009, p.138-139). Saunders et al. (2009,

p. 140) state that, there are three principal ways of conducting exploratory research: a search from literature, interviewing experts in the subject or conducting focus group interviews.

According to Saunders et al. (2009, p. 140), the object of descriptive research is to portray an accurate profile of persons, events or situations. This method is often seen as an extension or a piece of explanatory research since it is seen to be necessary to have a clear picture of the phenomena on which one wishes to explore before collecting data. Explanatory studies try to establish causal relationships between variables. Statistical tests, such as correlation, is a part of explanatory research. (Saunders et al. 2009, p. 140)

According to Cooper and Schindler (2014, p. 63), the term *model* is used in research to represent phenomena through the use of analogy. Models allow to characterize present or future conditions. In many cases the purpose of the model is to increase understanding, prediction, and control of the complexities of the environment. Models can be categorized as descriptive, predictive and normative. Descriptive models are used to visualize variables and relationships. Predictive models are used to forecast future events and normative models are used to inform about actions that should be taken. A model may originate from empirical observations about behavior based on researched facts and relationships among variables. (Cooper & Schindler 2014, p. 63-64)

Simulation is an appropriate research method for handling the dynamics and complexity of the real world, especially in operations research (Happach & Tilebein 2015, p. 240; Järvinen & Järvinen 2004, p. 53). Simulation is an imitation of the real situation and commonly the aim of the simulation is to test new organizational model, especially when new activity or process is intended to take into use (Järvinen & Järvinen 2004, p. 53). In order to cope with complexity and to provide a new foundation for theory development, scholars suggest using idealized models. Idealization creates simplification which enables empirical evaluation since empirical evaluation is difficult to conduct in constantly changing environments. (Happach & Tilebein 2015, p. 239-240)

Simulation using a computer is often performed with programming language and simulation program is based on a model of the phenomenon being simulated. Using programmed simulation models, it is easy to identify changes in the variables. Computer simulation is suitable for developing and for testing models. The better the underlying model corresponds to the reality, the more accurate the simulation is and therefore describes reality better. (Järvinen & Järvinen 2015, p. 54)

Case study is a strategy for doing research which involves empirical investigations of a particular phenomenon within its real life context using multiple sources of evidence. It can be divided into single case and to multiple case studies, where single case is often used to represent a critical case or a unique case. (Saunders et al. 2009, p. 146)

This study is an empirical orientated case study where a large number of numerical data is utilized. Data is mostly treatment duration data and most of the analyzes in this master's thesis, where data is utilized, use history data from three years' time. Data collection process in the case company is briefly discussed in chapter 4.4. The data is analyzed with statistical methods which are further discussed in chapter 2.4.

This study uses both qualitative as well as quantitative research methods. Qualitative methods, such as literature research and narrative literary view, are used to gain understanding of the existing phenomena. Also cases from other studies are utilized. Quantitative methods are used to create and to verify a normative model, the slot machine, which functionality is tested in practice and in theory by using simulation.

Data was studied and the slot machine was programmed with R-program. Queries from database were collected with PostgreSQL. Simulation models were created by using Python. There are plenty of statistical softwares available but in this case R was used since it has several advantages compared to other softwares. According to Wolfgang (2011, p. 167), there are two main advantages in R compared to other softwares: it is free and it grows on a daily basis. R is an open source project and researchers contribute to it every day. Also another advantage of R is that there are a lot of libraries. A library is an add-on package that adds extra functionality to the software. For example, there are packages to analyze geographical data, to create interactive graphs and to mine written text. Analyzing data in R is typically done by executing a variety of functions, for example there are functions to compute the average or standard deviation from a set of numbers. Python was selected for the same reasons.

Main references for this study are books and scientific articles about capacity, customer waiting time and appointment scheduling as well as business analytics and performance measurement.

1.4 Structure of the study

This study is divided into seven chapters. Theory used in this study is presented in chapters two and three. Chapter two focuses on definition and implementation objects of business analytics as well as business analytics methods used in this study. Chapter three focuses on capacity and waiting time and topics such as definition of capacity, capacity levels, capacity classifications, customer waiting time types, customer perceived value of time as well as measuring waiting time and utilization are discussed. This chapter also studies the relationship between waiting time and utilization rate.

Empirical part of this study is presented in chapters four and five. Chapter four focuses on case company Megaklinikka and the framework in which the slot machine is implemented to. Chapter five focuses on functionality of the slot machine and on the verification of the slot machine using simulation and measurements. Chapter six sums up the main results from this study and chapter seven wraps up study with conclusions. The structure of this thesis is presented in figure 1.

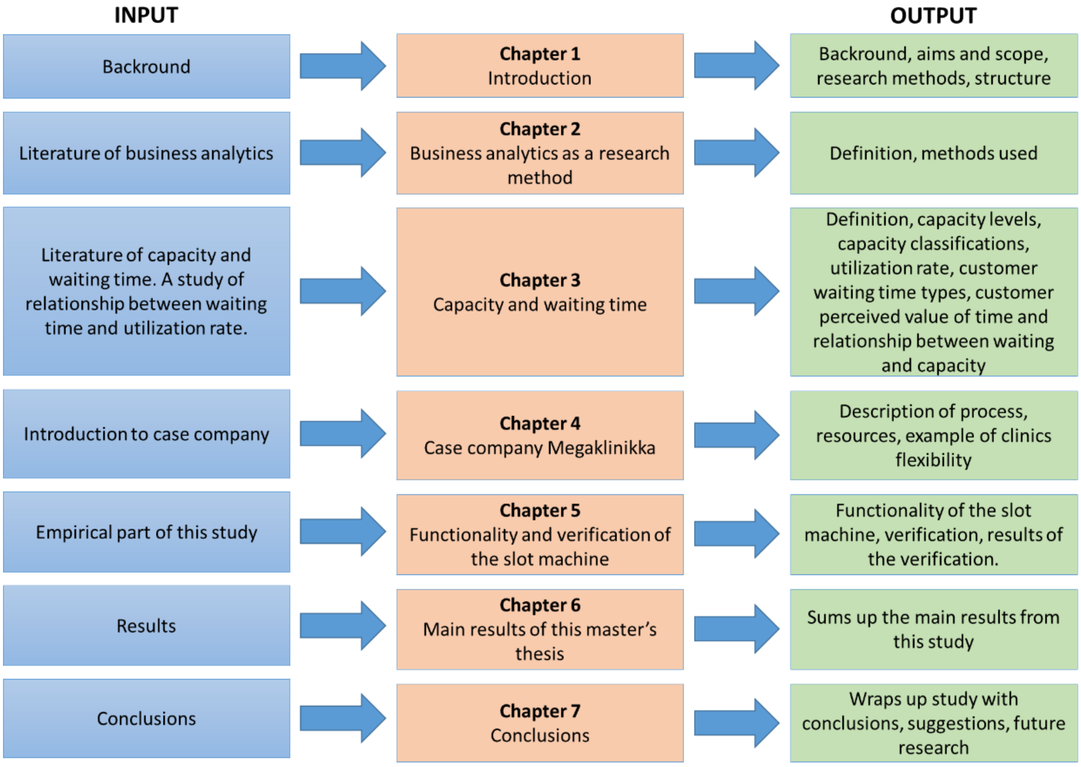

Figure 1. The structure of the research.

2 BUSINESS ANALYTICS AS A RESEARCH METHOD

2.1 Introduction to business analytics

Traditionally industry and business have mainly utilized data to record and to monitor transactions. In recent years a broader awareness of the analytical value of data has been gaining ground and is reflected by growing interest in business analytics. (Coleman et al. 2016, p. 1) According to Delen & Demirkan (2013, p. 361), business analytics is gaining popularity more rapidly than any other managerial paradigm - companies in every industry around the globe have started using analytics to analyze their data, combining information regarding past circumstances, present events and projected future actions (Bose 2009, p. 155).

Business analytics is an approach to data analysis that provides a deeper understanding of the business process, the market and the economic environment or the industry competitors. These techniques include methods such as ratio analysis, leading economic indicators, workforce optimization, purchasing analysis, risk analysis, demand forecasting and customer value calculations. (Nastase & Stoica 2010, p. 604-605; Schläfke et al. 2013, p. 113) The purpose of business analytics has always been to provide managers timely and reliable information which they can use to make right decisions more constantly. (Nastase & Stoica 2010, p. 604-605)

Analytics should be easily integrated into delivery component so that results can be shared with managers and decision makers. The implementation technologies should include a wide portfolio of algorithms, visualization techniques, flexible data exploration and data manipulation capabilities in order to produce accurate models. (Bose 2009, p. 159)

2.2 Definition of business analytics and business analytics categories

Analytics is used to understand business objectives easier through reporting of data to analyze trends, to create predictive models, to foresee future problems and opportunities as well as to analyze/optimize business processes to enhance company's performance (Delen & Demirkan 2013, p. 361). Nastase and Stoica (2010, p. 605) define business analytics as a group of approaches, organizational procedures and tools used in combination with one another to gain information, to analyze this information, and to predict outcomes for the problem. Coleman et al. (2016, p. 1) define the term business analytics, as it means the totality of data-based reasoning methodology used for the objective of analyzing, predicting and controlling processes in business and in industry.

There are three to four different categories under business analytics depending on definition but usually there are three main categories: descriptive, predictive and prescriptive analytics (Delen & Demirkan 2013, p. 361; Coleman et al. 2016, p. 1-2). These three categories are visualized in figure 2.

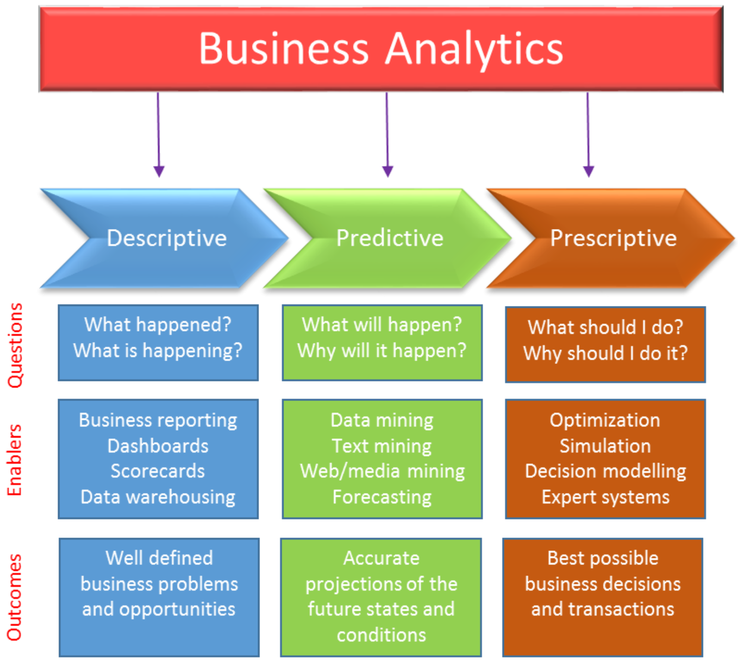

Figure 2. Business analytics categories (modified Delen & Demirka 2013, p. 361)

Descriptive analytics

Descriptive analytics uses the data to describe what happened and what is happening (Delen & Demirkan 2013, p. 361) but it does not tell anything about the future. Descriptive analytics summarizes, condenses and aggregates data in a way to make big and complex data sets more easily accessible and comprehensible, for example with the use of graphics and statistical metrics (Coleman et al. 2016, p. 1) including for example simple business reporting, ad-hoc reporting and interactive reporting. The main output is the identification of business opportunities and problems (Delen & Demirkan 2013, p. 361).

Predictive analytics

Predictive analytics uses data and mathematical techniques to discover explanatory and predictive patterns, such as trends and associations, by representing the relationships between data inputs and outputs (Delen & Demirkan 2013, p. 361). Some authors use the term advanced analytics instead of the term predictive analytics. For example Bose (2009, p. 156) describes advanced analytics as a general term which means applying various predictive analytic techniques to data in order to answer questions or solve problems.

Predictive analytics describes what will happen and why will it happen. Predictive analytics include data mining, text mining, Web mining, statistical time-series forecasting based on historical data, statistical learning and machine learning as well as statistical analysis to see patterns in the data (Delen & Demirkan 2013, p. 361; Coleman et al. 2016, p. 1-2; Bose 2009, p. 155-156). The main outcome of predictive modelling is an accurate projection of the future events and the reasons that have led to these events (Delen & Demirkan 2013, p. 361) but it does not give suggestions on how to proceed.

Prescriptive analytics

Prescriptive analytics uses data and for example mathematical algorithms to determine a set of high-value alternative courses-of-actions or decisions given a complex set of objectives, requirements, and constraints with the goal of improving business performance. These algorithms may rely on data, on expert knowledge or a combination of both. Prescriptive analytics includes for example optimization modelling, simulation modelling and multi-criteria decision modelling. The main outcome is either the best course of action for a given situation or a set of information that could lead to the best possible course of action. (Delen & Demirkan 2013, p. 361) Also prescriptive analytics transforms the result of descriptive analytics and predictive analytics into business decisions (Coleman et al. 2016, p. 2).

Difference between business intelligence and business analytics

The difference between business analytics (BA) and business intelligence (BI) is that while BA uses descriptive, predictive and prescriptive analytics, BI uses descriptive analysis only. As mentioned above, descriptive analytics and BI provide historical, metric-driven information and answer to questions such as how many units did a company sell, what did the customer buy and for what prize. BI is characterized by the creation of rules and alerts and the distribution of known facts to people (Nastase & Stoica 2010, p. 605) by getting the right information to the right people at the right time so they can make decisions that improve performance (Bose 2009, p. 156).

According to Nastase and Stoica (2010, p. 605), decisions based on BI information have a low impact on the business. Many organizations have discovered that the effective use of information requires more than reports that show historical data and therefore in addition to BI, predictive analytics started gaining just as much attention as BI (Bose 2009, p. 157). However, Nastase and Stoica (2010, p. 605-606) also state, that BI is still a highly valuable part of an overall business analytics environment, offering an excellent general purpose for ad-hoc analysis and basic operational reporting. BI leans strongly on visualization and according to Ward et al. (2014 p. 575), growing amount of research has demonstrated that managers make better decisions and have more confidence to make a decision when data is provided to them in graphs or tables that are easy to interpret and understand.

2.3 Requirements and challenges in business analytics

In order to effectively use business analytics, certain requirements need to be fulfilled, for example data availability, IT infrastructure and competence such as analytics skills. Company using data analytics should already have necessary IT infrastructure such as enterprise resource planning (ERP) system, data warehouse or customer relationship management (Schläfke et al. 2013, p. 113) and business analytics system including analytic capabilities such as data collection, integration with multiple data sources, data mining and business intelligence capability (Nastase & Stoica 2010, p. 613-614). Business analytics systems also depend largely on the quality and quantity of the data as well as accuracy, integrity and timeliness of the data management system (Delen & Demirkan 2013, p. 361).

An enormous amount of data is created worldwide every day (Coleman et al. 2016, p. 1) because it is relatively easy and cost effective to collect and store large datasets nowadays (Delen & Demirkan 2013, p. 360). However, Ward et al. (2014, p. 573-574) state that data in health care systems is not necessarily designed with analytics in mind and that is why it is not always easy to extract data.

The volume of information has itself become a problem and managers worldwide complain that they do not trust the information they receive or cannot get the information from their system. Businesses struggle to gather information closely to real time in order to improve the present actions. (Nastase & Stoica 2010, p. 604) Business analytics also use past data, which can be misleading because past data is not always a good predictor of current and future performance (Schläfke et al. 2013, p. 113).

Also accessing to real-time data can be problematic if data is refreshed rarely. Instead of collecting as much data as possible, institutions should take the opposite approach and ensure that they collect the minimal set of data elements required – it is better to have smaller set of high-quality elements with a high completion percentage than a large set with spotty coverage. (Ward et al. 2014. p. 577)

Since starting to use analytics has high initial costs and it changes the organizational process significantly, sufficient care needs to be put in its introduction. Otherwise high expenses with low early benefits can lead to low morale (Bose 2009, p. 165). Also one has to be careful to protect privacy of personal information for example when analyzing personal medical information. In business analytics individual privacy disclosure occurs when the identity of an individual or the specific value of sensitive information of an individual is revealed during the analysis. Organizational privacy disclosure occurs when information about the business operations are disclosed to unauthorized parties. (Bose 2009, p. 166)

Analysis depends upon the context in which it is being performed: clinical care and performance improvement can require different data perspectives. Clinical analytics involves improving patient care which may include genetic data as well as clinical records. These are often narrative and may be more difficult to analyze on a large scale. Performance data may be subjected to for example availability and quality. (Ward et al. 2014. p. 574)

2.4 Business analytics methods

2.4.1 Data exploration and summaries

Data exploration is a key step in data analysis as it is important to first understand data and explore it for patterns, anomalies and outliers. Methods for data exploration are for example data summaries and visualizations. (Wolfgang 2011, p. 9) In order to visualize one can use for example histograms, boxplots and scatterplots.

In order to investigate the distribution of individual variables, one should investigate summary statistics such as the mean (or median) and the standard deviation (Wolfgang 2011, p. 11). Statistical dispersion denotes how stretched or squeezed values from sample are distributed (Holopainen & Pulkkinen, p. 88) and standard deviation is used to calculate how much values are fluctuating around the typical value – that is, the mean (Wolfgang 2011, p. 11).

While coefficient of variation (cv) is not typically a part of summary statistics, it provides information about the dispersion of a distribution and it is a ratio of standard deviation and mean. Coefficient of variation is calculated as in formula (1) (Holopainen & Pulkkinen 2013, p. 93):

$$cv = \frac{s}{\bar{x}} \tag{1}$$

where

$\bar{x}$ = mean

s = standard deviation

Even though summary statistic is seen as a beneficial way to summarize important aspects of a distribution by single number, it is limited because it only captures a single aspect of that distribution (Wolfgang 2011, p. 13).

2.4.2 Removing outliers

An outlier is an observation which deviates significantly from other observations. It may be caused by for example an error in measuring, writing or copying. However, outlier can also be real value even though it would be rare. Even one outlier might have significant impact on analysis. (Holopainen & Pulkkinen 2013. p. 287) For example if one have a small sample size of ten with values 10, 9, 10, 8, 10, 8, 9, 7, 9 and an outlier with value of 2, mean with the outlier would be approximately 8.2 and 8.9 without the outlier. Also standard deviation would drop approximately from 2.3 to 1.0 if the outlier is removed.

There are several ways to detect and remove outliers: for example Tukey's IQR test and Modified Thompson Tau test. In this master's thesis Tukey's IQR test is used. Tukey's test for outlier detection is designed on the basis of first quartile (Q_1), third quartile (Q_3) and inter quartile range (IQR). IQR is the difference between third and first quartile. The boundaries to label an observation to be an outlier is constructed by subtracting 1.5 times IQR from Q_1 for lower boundary while adding 1.5 times IQR in Q_3 for upper boundary. (Adil & Rehman 2015, p. 92) Mathematical equations are in formulas 2 and 3 (Adil & Rehman 2015, p. 92):

$$IQR = Q_3 - Q_1 \quad (2)$$

$$Outliers\ are\ removed\ if: x < Q_1 - 1.5\ IQR\ or\ x > Q_3 + IQR \quad (3)$$

Tukey's technique is used for detecting outliers in univariate distributions for symmetric as well as in slightly skewed datasets but its performance worsens as the symmetry of the distribution decreases. For example, if distribution is left skewed the upper boundary exceeds from the maximum of the data and may ignore outliers while lower boundary will identify a lot of observations as outlier which are not outliers. (Adil & Rehman 2015, p. 91)

2.4.3 Coefficient of correlation

A correlation measures the strength and direction of the linear relationship between two variables where a large positive value implies a strong positive correlation (Wolfgang 2011, p. 18). One has to take into account the scale of the variables: if variable is in interval scale or in ratio scale one can use for example Pearson's correlation coefficient and if the variable is in ordinal scale one can use for example Spearman's coefficient of rank correlation (Holopainen & Pulkkinen 2013, p. 233).

One has to notice that Pearson's correlation coefficient and Spearman's coefficient of rank correlation only measure a linear relationship between the variables. Correlation coefficient (*r*) is always between -1 to 1 where positive values mean positive correlation and negative values mean a negative correlation. If coefficient of correlation is zero or near zero, variables are not correlated. (Holopainen & Pulkkinen 2013, p. 233) However, correlation does not necessarily imply causation because, for example, one alternative hypothesis to X causing Y or Y causing X, is that there might be a different cause common to both X and Y (Stewart et al. 2001, p. 75).

After measuring coefficient of correlation one should also measure significance level (p-value) of correlation (Holopainen & Pulkkinen 2013, p. 242). Usually when p-value is less than 0.05 null hypothesis is rejected: correlation between variables is seen.

2.4.4 Normal distribution

Normal distribution is the most common distribution. It has been proved that when the values of random variables are affected by many small independent factors it converges to the normal distribution. For example, human mental and physical attributes, products attributes in industry and measurement errors are approximately distributed as normal. (Holopainen & Pulkkinen 2013, p. 144)

If X is continuous random variable which can get all real values between (-∞, ∞) and expected value of X is μ (mu) and standard deviation is σ (sigma) and probability density function is like in formula (4):

$$f(x) = \frac{1}{\sigma * \sqrt{2\pi}} * e^{-\frac{1}{2}*\left(\frac{x-\mu}{\sigma}\right)^2} \tag{4}$$

random variable X follows normal distribution with parameters mu and sigma. This is notated as in formula (5) (Holopainen & Pulkkinen 2013, p. 145):

$$X \sim N(\mu, \sigma) \tag{5}$$

Normal distribution has attributes which can use in statistical decisions. If
X~ N(μ, σ):

- 68 percent of values from random variable is between [$\mu - \sigma$, $\mu + \sigma$]
- 95 percent of values from random variable is between [$\mu - 1.96\sigma$, $\mu + 1.96\sigma$)
- 99 percent of values from random variable is between [$\mu - 2.58\sigma$, $\mu + 2.58\sigma$). (Holopainen & Pulkkinen 2013, p. 148)

One of the most remarkable theorem in statistics is central limit theorem. If it is assumed that random variables $X_1, X_2, \dots, X_n$ are independent variables and each follows the same distribution. In that case sum variable $X = X_1 + X_2 + \cdots + X_n$ follows approximately normal distribution when *n* is large enough. The bigger the *n*, the closer the distribution is to normal. (Holopainen & Pulkkinen 2013, p. 152)

2.4.5 Gamma and Weibull distributions

Gamma distribution is widely used for modelling lifetime distributions in reliability theory (Kulkarni & Powar 2010, p. 431). Along with Weibull, it is also the most popular distribution for analyzing lifetime data. Both gamma and Weibull distributions uses two parameters, scale and shape, and due to these parameters, it is quite flexible to analyze any positive real data. (Gupta & Kundu 2001, p. 117-118). Both distributions allow increasing and decreasing hazard rate, depending on the shape parameter, that gives an extra edge over the exponential distribution which has only constant hazard rate (Gupta & Kundu 1999, p. 173). This master's thesis uses the following notations (formula 6) of the probability gamma distribution (modified Råde & Westergren, p. 435):

$$f(x) = \frac{\beta^{\alpha}}{G(\alpha)} x^{\alpha-1} e^{-\beta x} \tag{6}$$

where

α = shape parameter

β = scale parameter

G = Gamma function

α, β > 0

Shape and scale parameters can be calculated from distributions mean and variance (or standard deviation) as in formulas 7 and 8 (Bouraoui al. 1999, p. 154):

$$\alpha = \left(\frac{\mu}{\sigma}\right)^2 \tag{7}$$

$$\beta = \frac{\sigma^2}{\mu} \tag{8}$$

According to Wen et al. (2009, p. 2486-2487) shape and scale parameters for Weibull distribution can be calculated as in formulas 9 and 10:

$$k = \left(\frac{\sigma}{\mu}\right)^{-1.086} \tag{9}$$

$$c = \frac{\mu}{G(\frac{1+1}{k})} \tag{10}$$

where

k = shape parameter

c = scale parameter

G = Gamma function

2.4.6 Fitting distributions

Fitting distributions to data is a very common task in statistics and consists choosing a probability distribution for the random variable (Delignette-Muller & Dutang 2015, p. 1). Before fitting distributions to a data set, it is necessary to choose good candidates among a set of distributions, where descriptive statistics can be used for advantage as Delignette-Muller and Dutang (2015, p. 3) state. Especially the skewness and kurtosis are useful, where a non-zero skewness reveals a lack of symmetry and the kurtosis value quantifies the weight of tails in comparison to the normal distribution where kurtosis equals 3 (Delignette-Muller & Dutang 2015, p. 4).

One can use four goodness-of-fit plots to analyze and to select the right distribution: Histogram and theoretical densities, Q-Q plot, Empirical and theoretical CDFs as well as P-P plot. The Q-Q plot emphasizes the lack-of-fit at the tails of the distribution while the P-P plot emphasizes the lack-of-fit at the center of the distribution. (Delignette-Muller & Dutang 2015, p. 7-8)

Goodness-of-fit statistics aims at measuring the distance between the fitted parametric distribution and the empirical distribution. There are usually used three goodness-of-fit statistics: Cramer-von Mises, Kolmogorov-Smirnov and Anderson-Darling. These three statistics emphasizes different aspects of distribution for example, Anderson-Darling statistics gives more weight to distribution tails. (Delignette-Muller & Dutang 2015, p. 10)

2.4.7 Forecasting

There are several techniques to forecast, for example qualitative Delphi method, time series analysis such as Moving average or Trend projections as well as causal method Regression model. In this study time series model Exponential smoothing was selected. Traditionally Simple exponential smoothing is used for demand forecasting, however in this study it is used to weight treatment durations. It is also suitable for large data sets.

Simple exponential smoothing (SES) provides an exponentially weighted moving average of previously observed values: it uses only past values of a time series to forecast future values of the same series. SES model is often valid if data contains no predictable trends or seasonality. Where moving average gives equal weights to the past values, exponential smoothing gives more weight in the recent observations and less to the older observations. (Lee & Lee 2015, p. 2450)

The weight of the most recent observation is assigned by multiplying the observed value by alpha ($\propto$), and the number chosen for alpha is called smoothing constant which must be between 0 and 1. Alpha value closer to 1 means that values are weighted heavily in relation to those in the past. Alpha value closer to 0 weights more values in the past compared to recent values. The weights will eventually sum up to 1, regardless of the chosen smoothing constant alpha. (Lee & Lee 2015, p. 2450-2451) Exponentially smoothing equation is as in formula 11 (Lee & Lee 2015, p. 2450):

$$\hat{Y}_{t+1} = \propto * Y_t (1 - \propto) * \hat{Y}_t \tag{11}$$

where

$\hat{Y}_{t+1}$ = *new smoothed value for the next period*

$\propto$ = *smoothing constant (0 < $\propto$ < 1)*

Y_t = *actual value of the series in period t*

$\hat{Y}_t$, = *old smoothed value of the forecast in period t.*

2.4.8 Probability

Probabilities in this study is used to calculate the probability that one of the resource's time is exceeded during a particular day while using simulation in order to test the slot machine. This is further discussed in chapter 5.2. Probability that A or B or C occurs, whether variables are independent or not, is calculated as in formula 12 (Råde & Westergren 2004, p. 425):

$$\mathrm{P}(\mathrm{A} \cup \mathrm{B} \cup \mathrm{C}) = P(A) + P(B) + P(C) + P(A \cap B \cap C) - P(A \cap B) - P(A \cap C) - P(B \cap C) \qquad (12)$$

where

$$P(A \cap B) = P(A) * P(B)$$

3 CAPACITY AND WAITING TIME

3.1 Capacity

One of the most difficult decisions managers have to make is to determine the optimal level of capacity. Having too much capacity is costly but also when having too little capacity, because some customer's demands may be unfilled which can lead to lost customers (Horngren et al. 2005, p. 309). Also when service sector companies try to achieve maximum capacity it may lead to too long customer waiting times which may also mean lost customers. One problem about capacity is that different people mean different things when talking about capacity. McNair and Vangermeersch (1998, p. 22) state that the first step in capacity cost management in a company is to reach consensus on the definition of the term capacity.

3.1.1 Definitions of capacity and capacity levels

Capacity is an ability which uses a wide variety of resources to create value to an organization. If resources are not fully used, organization generates waste. (McNair & Vangermeersch 1998, p. 1) Resources can be for example machines, tools, work force or buildings. In dental care for example, dentists, hygienists, nurses and materials are regarded as resources (Oscarson et al. 1998, p. 161). Vehmanen & Koskinen (1997, p. 223) state that the main point of the capacity examination is to focus on unused capacity which allows for example to calculate the cost of waste.

Horngren et al. (2005, p. 309) state that there are four kinds of capacity levels: theoretical capacity, practical capacity, utilized normal capacity (also known as normal capacity) and utilized master-budget capacity (also known as budgeted capacity). However, McNair and Vangermeersch (1998, p. 27) state that there are five levels of capacity: utilized actual capacity on top of these four. Vehmanen and Koskinen (1997, p. 224) state that there is also target capacity: according to them, there are six capacity levels. Theoretical, target and practical capacities are capabilities of the company's resources while utilized normal capacity, utilized budgeted capacity and utilized actual capacity are driven by current company performance (Koskinen &

Vehmanen 1997, p. 224; McNair & Vangermeersch 1998, p. 28). In other words, theoretical, target and practical capacities are the maximum amount of production or services that company can achieve and utilized normal capacity, utilized budgeted capacity and utilized actual capacity indicates how good company is to utilize its capacity.

Theoretical capacity is the level of capacity when producing at full efficiency at all time (Horngren et al. 2005, p. 309). It is the amount of work that process can complete using a 24/7 operation with zero waste. It does not allow adjustments for example to preventive maintenance, unplanned downtime or shutdowns. When theoretical capacity is used, the capacity reporting system provides the actual deployment of the capability of resources, process and system. Practitioners and academics usually rejects theoretical capacity because it is seeing impractical and unattainable which can be demotivating. However, it is the only capacity level that gives a stable cost estimate regardless of how resources are used. (McNair & Vangermeersch 1998, p. 28-29)

Target capacity is the maximum throughput that unit can produce in ideal circumstances in a given time period when some time of the time period is allowed to be waste time (Koskinen & Vehmanen 1997, p. 224). For example, when a company is working only in one shift, the target capacity is the amount of work that could be done in one shift instead of the amount of work that could have done in all shifts. Vehmanen and Koskinen (1997, p. 226) state that according to studies, most of the companies in USA does not use target capacity because it represents standards that cannot be achieved just like in theoretical capacity. McNair and Vangermeersch doesn't even mention target capacity.

Practical capacity is the maximum throughput that unit can produce in a given time period when some of the target capacity is wasted (Koskinen & Vehmanen 1997, p. 224). Horngren et al. (2005, p. 310) define practical capacity, as it reduces theoretical capacity by considering unavoidable nonproductive time for example scheduled maintenance and shutdowns for holidays. McNair and Vangermeersch (1998,

p. 28) refer practical capacity and they even state that it is inferior compared to theoretical capacity because it builds waste into the cost standards. But they also remind that one has to be careful using practical capacity because one might start trying to hide waste or accept it.

Utilized normal capacity is the average and expected capacity utilization of machine, process or plant over a defined period of time (McNair & Vangermeersch 1998, p. 28). In utilized normal capacity waste and downtime is part of "normal" activity and are not considered separately (Koskinen & Vehmanen 1997, p. 224).

Utilized budgeted capacity is the planned utilization of the affected resources over the coming time period. *Utilized actual capacity* is the amount of capacity used by the company for period production: it tells what happened during the period. (McNair & Vangermeersch 1998, p. 28) Koskinen and Vehmanen (1997, p. 226) state that according to studies, companies in USA often uses budgeted or actual capacity because it allocates all capacity costs to products. However, one might end up to "death spiral" when using budgeted capacity. Death spiral happens when demand is lower than practical capacity and company decides to raise price of the product. (Vehmanen & Koskinen 1997, p. 227) Raising the price of the product can lead to lower demand and when demand is lower, company may have to raise the price of the product again and so forth. In no time the company is in death spiral. Practical capacity is a better way of estimating costs in a long run compared to budgeted capacity utilization and it also avoid death spiral (Koskinen & Vehmanen 1997, p. 227). In figure 3 is an example of different capacity levels.

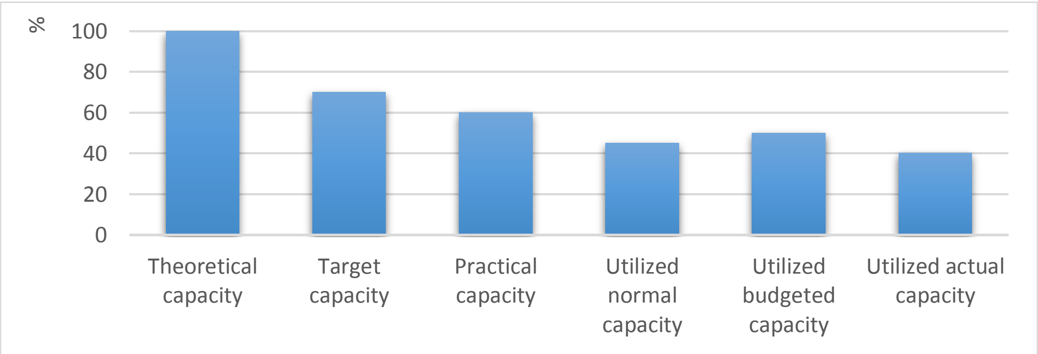

Figure 3. Different capacity levels (modified Koskinen & Vehmanen 1997, p. 225)

As the figure 3 example shows, utilized actual capacity is most likely much lower than theoretical capacity. Target capacity is always lower than theoretical capacity and practical capacity is always lower than target capacity.

3.1.2 Capacity classifications

When the capacity level of process has been established, the focus shifts to measuring the classification of the capacity deemed to be available for use (McNair & Vangermeersch 1998, p. 30). Koskinen and Vehmanen (1997, p. 231) state that there are four different major capacity classification categories: productive capacity, unplanned nonproductive capacity, excess capacity and (planned) nonproductive capacity. McNair and Vangermeersch (1998, p. 30) state that there is also fifth category: planned idle capacity.

Productive capacity provides value to the customer and is used to actually produce a product or provide a service (McNair & Vangermeersch 1998, p. 30) and in this case product or service should be the kind of product or service that meets the requirements, for example customer expectations or competitive product, which are set (Koskinen & Vehmanen 1997, p. 231). Productive capacity should be based on the theoretical maximum value-creating ability of the firm (McNair & Vangermeersch 1998, p. 31). In ideal circumstances all of the theoretical capacity would be productive capacity. Company's goal should always be to improve productive capacity. (Koskinen & Vehmanen 1997, p. 231-232)

Planned idle capacity is nonproductive capacity that is not scheduled for use due for example to temporary lack of demand, preventive maintenance or planned shutdowns. *Unplanned nonproductive* capacity is capacity planned for use that is temporarily out of action due to process variability (McNair & Vangermeersch 1998, p. 31). It contains setup time (for example machine preparation when exchanging product), maintenance (planned and unplanned), waste (scrap, rework and yield loss) and standby capacity (sick leave or material availability problems) (Koskinen & Vehmanen 1997, p. 233-235).

Excess capacity is permanently idle capacity that is not usable under existing operating, marketing or policy conditions (McNair & Vangermeersch 1998, p. 31). Excess capacity is usually divided into three classes: marketable-, non-marketable- and off limits -excess capacity (Koskinen & Vehmanen 1997, p. 236; McNair & Vangermeersch 1998, p. 83). Excess capacity is marketable when company has excess capacity even though there is market for it. Excess capacity is non-marketable when company has excess capacity even though there is no market for it. Companies should get rid of non-marketable excess capacity. Off-limits capacity is excess capacity that is not available in use, for example law which prohibits working on specific holidays. (Koskinen & Vehmanen 1997, p. 236)

Planned nonproductive capacity is capacity that is neither in a productive state nor in one of the defined idle states. It includes setups, unplanned maintenance, scrap making or correcting errors also rework. (McNair & Vangermeersch 1998, p. 31) Vehmanen and Koskinen (1997, p. 232) state that planned nonproductive capacity is a waste caused by unwillingness of using the maximum amount of capacity. For example, working in only one shift instead of working in three shifts is a waste of capacity caused by unwillingness.

Capacity levels and classifications are visualized in figure 4. It is similar to CAM-I Capacity Model that helps industry to understand better current and potential impacts of capacity on throughput and profitability. CAM-I Capacity Model is introduced in chapter 3.1.5.

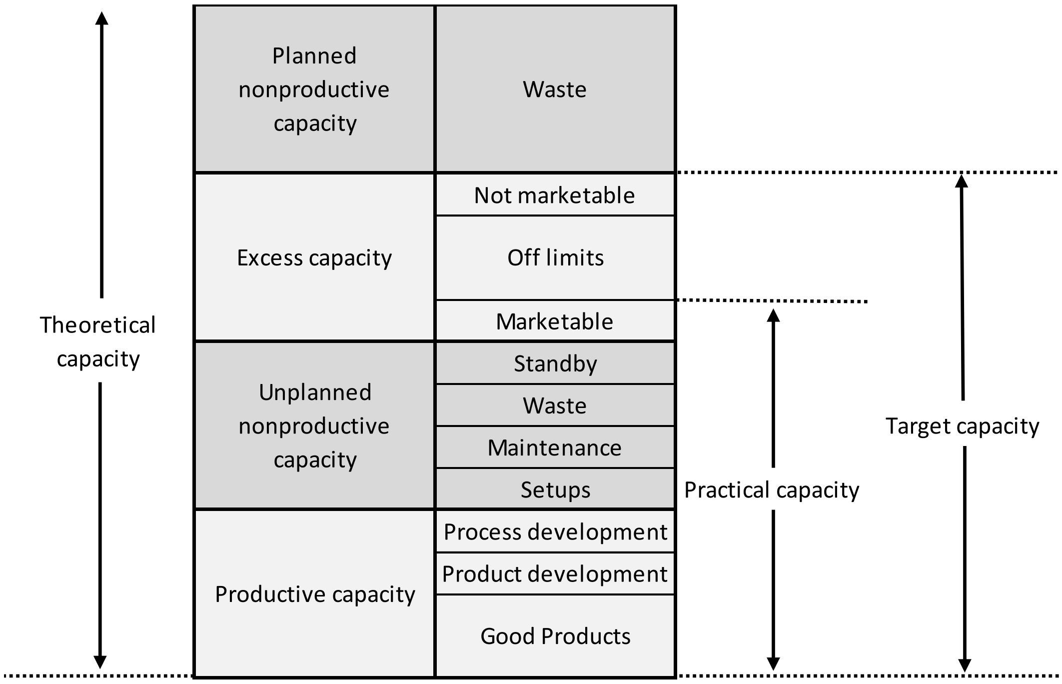

Figure 4. Capacity levels and classification (modified Koskinen & Vehmanen 1998, p. 232)

As the above figure shows, target capacity does not include waste which is planned nonproductive capacity for example working in one shift instead of working in three shifts. Practical capacity compared to target capacity doesn't include not marketable and off limits excess capacity but includes marketable excess capacity.

3.1.3 Capacity utilization rate

Utilized capacity is the amount of production or services are performed in a given time period and capacity utilization rate is the rate of utilized capacity compared to capacity. Capacity utilization rate can be calculated as in formula 13 (Neilimo & Uusi-Rauva 2005, p. 50):

$$Capacity\ utilization\ rate = \frac{Utilized\ capacity}{Capacity} x\ 100\ [\%] \qquad (13)$$

Capacity utilization rate is a measure of how resources are being used. The theoretically best capacity utilization rate is 100 percent and in order to achieve that the machine must never be out of service because of breakdowns or lack of parts. Since breakdowns and lack of work do occur occasionally, it is unrealistic to have utilization rate of 100 percent. (McNair & Vangermeersch 1998, p. 45)

Utilization rate target in hospitals has historically been commonly 85 percent (Green 2004, p. 17) but most of the hospital planners advocates a utilization rate of 75-80 percent (Ennis et al. 2000, p. 1204). According to the Badran's and Saad's (2010, p. 136) questionnaire to Saudi hospitals in Riyadh City, appropriate utilization rate ranged from 35 to 60 percent depending on ownership (MOH, Private, Military). In a case study where studied capacity utilization rates of 600 hospitals in USA the utilization rate ranged from 67.4 to 91.2 percent (Ferrier et al. 2008, p. 113).

If capacity utilization rate is in a long run lower than planned, company will make significant losses. Capacity must vary according to peaks of demand if products or services cannot be stored or demand postponed. (Kaarna et al. 2010, p. 3797) The amount of excess capacity is depending on what level of capacity is used. According to Koskinen and Vehmanen (1997, p. 240), practical capacity should be used when demand is steady. When demand is volatile companies should use normal capacity utilization, that costs of the expected value of excess capacity is zero in a circumstances, where capacity equals to demand (Koskinen & Vehmanen 1997, p. 245).

3.1.4 Bottlenecks decreasing capacity utilization

Low capacity utilization rate may also indicate that there is a bottleneck in the company's process. A bottleneck occurs when the work to be performed exceeds the capacity available to do it (Horngren et al. 2005, p. 671). For example, when in a dental clinic have treatment rooms and nurses available in order to serve a customer but there are not enough dentists that the customer can't be served. In that case resource pool dentists would be a bottleneck because dentists were the constraining factor. Theory of bottlenecks is based on an idea that there is one resource which doesn't allow additional production. In order to add production, the bottleneck resource should be first increased. The idea is to focus on one bottleneck at a time, eliminate that bottleneck, and then focus on to the next bottleneck. It is a continuous process of evaluating the impacts on bottleneck resources and continuously eliminate one bottleneck after another to increase production. (Kaplan & Atkinson 1998, p. 38)

Ahmed & Amagoh (2014, p. 352) studied bottlenecks in a dental clinic in Kazakhstan and conclude that activities “consultation between customer and dentist”, “X-ray and other analysis”, “dentist’s diagnosis” and “dentist’s treatments” were bottlenecks. One has to take to account that above study only studied bottlenecks in customer perspective while there may be other bottlenecks to be consider in a process which measures overall dental care process.

3.1.5 CAM-I Capacity Model

According to McNair & Vangermeersch (1998, p. 82), there are two capacity reporting models which have been developed to help industry to understand better current and potential impacts of capacity on throughput and profitability: CAM-I- and CUBES -models. While CAM-I model focuses on time-based measurements, CUBES (Capacity Utilization Bottleneck Efficiency System) model is more activity-based and analytical. CAM-I model seeks understanding and control over the process, CUBES focuses on supporting continuous improvements with the use of dynamic simulations. (McNair & Vangermeersch 1998, p. 82-84) This study focuses on CAM-I Capacity Model because it is more suitable for this study. CAM-I Capacity Model is shown in figure 5.

<table>
<tr><th>Rated Capacity</th><th>Summary model</th><th>Industry Specific Model</th><th>Strategy Specific Model</th><th>Traditional Model</th></tr>
<tr><td rowspan="13">Rated Capacity</td><td rowspan="5">Idle</td><td>Not marketable</td><td>Excess no usable</td><td rowspan="4">Theoretical</td></tr>
<tr><td rowspan="3">Off limits</td><td>Management policy</td></tr>
<tr><td>Contractual</td></tr>
<tr><td>Legal</td></tr>
<tr><td>Marketable</td><td>Idle but usable</td><td>Practical</td></tr>
<tr><td rowspan="5">Nonproductive</td><td rowspan="2">Standby</td><td>Process balance</td><td rowspan="8">Scheduled</td></tr>
<tr><td>Variability</td></tr>
<tr><td>Waste</td><td>Scrap
Rework
Yield loss</td></tr>
<tr><td>Maintenance</td><td>Scheduled
Unscheduled</td></tr>
<tr><td>Setups</td><td>Time
Volume
Changeover</td></tr>
<tr><td rowspan="3">Productive</td><td>Process development</td><td></td></tr>
<tr><td>Product development</td><td></td></tr>
<tr><td>Good Products</td><td></td></tr>
</table>

Figure 5. CAM-I Model (McNair & Vangermeersch 1998, p. 83)

As shown in figure 5, rated capacity is idle capacity + nonproductive capacity + productive capacity. Idle capacity is capacity that is not currently scheduled for use, for example due to lack of demand, unavailability, or marketable but idle conditions. Nonproductive capacity is not idle nor productive capacity and it includes standby, waste, maintenance as well as setups. Productive capacity includes process and product development as well as good products. In next chapter is introduced this study's capacity model for dental care services.

3.1.6 Traditional dental care capacity defining model

In a research where Kaarna et al. (2010, p. 3803) case studied capacity utilization rate in three hospital units in a Finnish hospital, they used modified CAM-I Capacity model which was modified to define capacity in hospital. In order to make same kind of model which defines capacity in dental care, one must first know the dental care service process. This capacity defining model is based on traditional dental care processes while there are also "single visit" dental care clinics, where processes differ from traditional processes, for example due to enterprise resource planning system (ERP). Also another thing to consider is that the traditional dental care process in this study is the basic situation when customer arrive to dental clinic – it does not include services such as tooth implants or laser teeth whitening where processes may be different.

Ahmed and Amagoh (2014, p. 350-351) identified the following stages that in dental care visiting patient go through:

1. customer at the reception
   - customer is greeted and personal details are collected
   - customer makes request about the type of treatment needed
   - receptionist gives customer a price list
   - customer is registered into system
   - receptionists check staffs schedule to determine availability for customer treatment
   - receptionists assign customer to a dentist
   - customer selects required services and returns price list to receptionists
   - dentist is informed of waiting customer
2. customer at the dentist
   - consultation between customer and dentist
3. customer is transferred to X-ray
   - X-ray and other tests are collected and stored
4. customer at the dentist
   - dentist makes diagnosis based on results of X-ray and other tests
   - dentist implements treatment
5. customer is transferred to receptionist
   - receptionist prepares invoice and customer pays

There are three major events that customers go through: customer at the reception (twice), customer is transferred to different places from different places (four times) and treatment. But there are also other events that enables customers dental care service. After every customer, rooms and machines have to clean up (Oscarson et al. 1998, p. 161). Naturally there is from time to time some cancelled (by customer) and unused appointments (no-shows). Also law requires in Finland that dentists must take a 30 minutes long break from work if days working hours are more or equal to four hours (Työehtosopimus 2013). Nature of dental care services is that clinics are not usually open 24/7.

Based on information above, in figure 6 is modified capacity defining model for dental care service which is similar to one used in above Kaarna et al. research. It is based on CAM-I model and it has influences from levels and classifications figure.

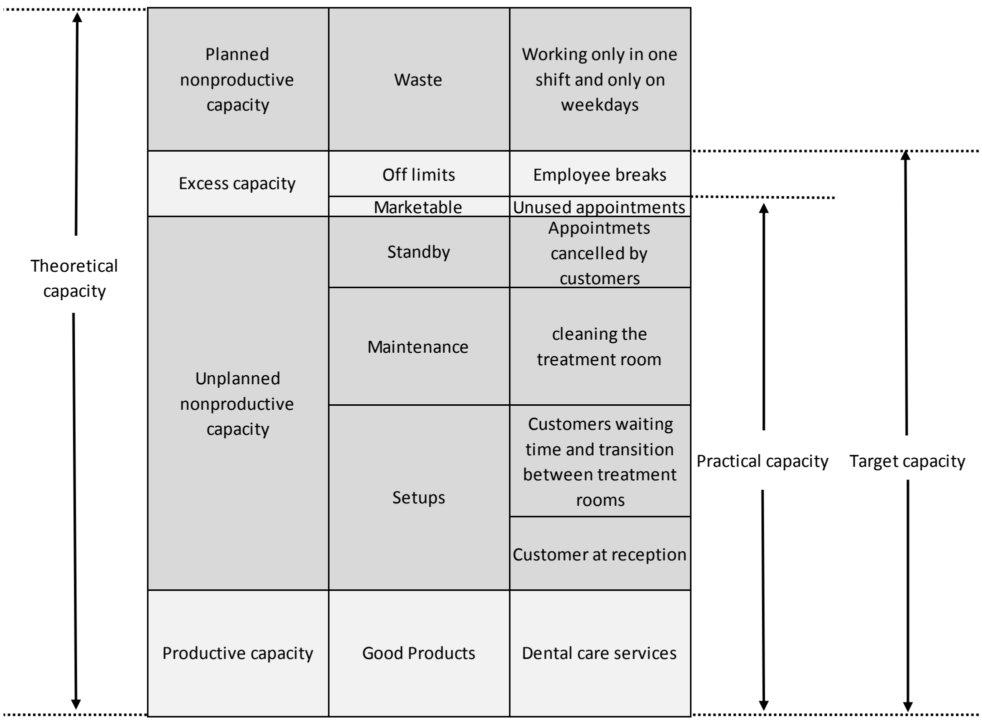

Figure 6. Defining capacity in traditional dental care services (Author)

As figure 6 shows that in this model target capacity is theoretical capacity without planned nonproductive capacity waste which in this case is working in one shift and only in weekdays. In this study, definition of practical capacity is target capacity without off limits excess capacity such as employee breaks.

3.2 Customer waiting time

According to Grigoroudis and Siskos (2010, p. 4), the most popular definitions of customer satisfaction are based on fulfillment of customer expectations where satisfaction is a standard of how offered “total” product or service fulfils customer expectations. Similarly, Davis and Vollmann (1990, p. 6) state that customer satisfaction is based upon expectations, performance, and the difference between these two. Cayirli & Veral (2003, p. 519) point out that surveys indicate that excessive waiting is often major reason for patient’s dissatisfaction and reasonable waiting times are expected in addition to clinical competence.

3.2.1 Waiting time types

Customer may spend time waiting before (pre-process waiting), during (in-process waiting) or after (post-process waiting) a transaction. Pre-process waiting is considered the most important since it has the greatest influence on perceptions of service quality. (Lin et al. 2015, p. 29-30) For example, at a dental clinic pre-process waiting occurs when customer is waiting to be signed up at the reception, in-process waiting is when customer waits dentists to operate in treatment room and post-process waiting is when customer waits at the reception to pay for the services.

Pre-process waiting can be categorized to scheduled, which can be pre-scheduled or post-scheduled, and to queued waiting (Lin et al. 2015, p. 30). Pre-scheduled waiting occurs for example when a customer arrives earlier than scheduled to wait in a dental clinic and post-scheduled occurs when a customer arrives to dental clinic on time but does not get served due to service delays. Queue waits refer to first-serve scenarios such as banks and post offices where customers must line up to receive the service (Lin et al. 2015, p. 30).

3.2.2 Customer perceived value of time

A customer with a tight schedule may be less tolerant towards long waiting times when compared to a customer with no schedule at all. For example, a business man waiting ten minutes may be more frustrated compared to a pensioner or a student.

In a case study where Davis and Vollmann (1990, p. 65-66) studied the relationship between waiting time and customer satisfaction in a fast food company, they found out that customer activities before and after visiting the fast food company significantly affected the relationship between waiting time and customer satisfaction. These activities were shopping, at work/school, at home, out for a walk/drive, doing errands and visiting friend/relatives. Customers who had at work/school activity before or after being served tended to be more impatient than the other customers.

Also according to Lucas and Heady (2002, pp. 569), people with more flexible time schedule had lower stress while driving and time urgency compared to people who were in a hurry. Lin et al. (2015, p. 30) state that the effects of time pressure and personality (impatience) should be controlled to reflect the different time value functions of individual customers.

One might think that customer satisfaction expectations towards waiting time may differ relation to time of the week. For example, customer may not mind waiting longer on weekends compared to weekdays (Davis and Vollmann 1990, p. 62). Davis and Vollmann (1990, p. 65) noticed that there was no significant relationship between weekday and weekend in customer satisfaction due to waiting time. However, one has to take to account that a fast food restaurant customer’s expectations towards waiting time may be different from a customer who is using dental care services.

One noticeable remark is that Davis and Vollmann presented graphs where the customer satisfaction/waiting time trend line was linear instead of being exponential as might be anticipated. According to Lin et al. (2015, p. 32), customer perceived value of time increases as impatience increases. This is visualized in figure 7.

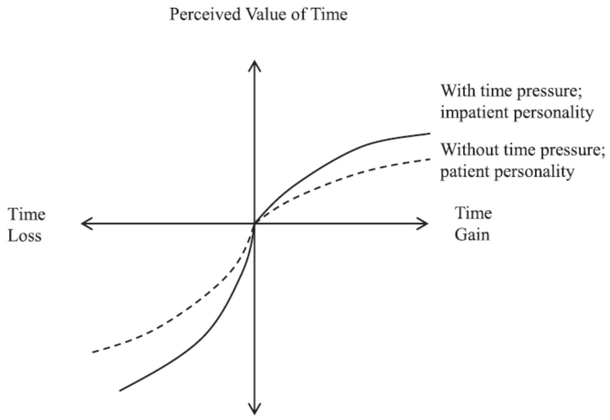

Figure 7. Customer perceived value of time with and without time pressure (Lin et al. 2015, p. 32)

As in figure 7 is shown, perceived value of time curve is not as linear as it is exponential and customers with time pressure experience time loss more significantly than customers without time pressure.

3.3 Performance measurement of capacity and waiting time

Performance is associated with two key processes: performance management and performance measurement. These two processes cannot be separated because performance management both proceeds and follows performance measurement as Brudan (2010, p. 111) states.

This master's thesis' theory on performance management focuses on performance measurement because there was no intention to measure company's performance in a holistic way nor build a measurement framework such as Balanced Scorecard (BSC) – it would be a subject for another master's thesis. Performance management system BSC incorporates four main measurement perspectives: Financial, Customers, Internal-business-processes as well as Innovation and learning (Tonchia & Quagini 2010, p. 48).

This study focuses only on Internal-business-processes perspective. In internal-business-process perspective managers identify the critical processes in which the organization must excel and these processes enable the business unit to deliver the value propositions that will attract and retain customers. Internal-business-process measures the internal processes that will have the greatest impacts on customer satisfaction and achieving organization's financial objectives. (Kaplan & Norton 1996, p. 26)

Operational performance is traditionally evaluated in terms of efficiency and effectiveness and the easiest way to do that is by using financial indicators. However, over time, internal and external operating environments became more complex and people began to recognize that pure financial reporting is an inadequate basis for managing modern business. Most managers want to predict what will happen next and that is why organizations started to look at non-financial indicators of performance. (Brudan 2010, p. 113; Bourne & Neely 2000, p. 3; Schläfke et al. 2013, p. 110; Neely 1999, p. 206) In the late 1980s measures such as shareholder value, economic profit, customer satisfaction, employee satisfaction, internal operations performance, intellectual capital and intangible assets were introduced (Bourne & Neely 2000, p. 3).

Behm (2013, p. 592) describes performance measurement as a black box: measures can reveal what is going in and coming out of the black box but they don't necessarily reveal what is happening inside the black box. He also states that one can create measures of the process going inside the black box but it is not certain that the measures actually determine whether the inputs are converted into high-quality or low-quality inputs: significant contributors could be correlated with other factors that are the real causes. An example of this is visualized in figure 8.

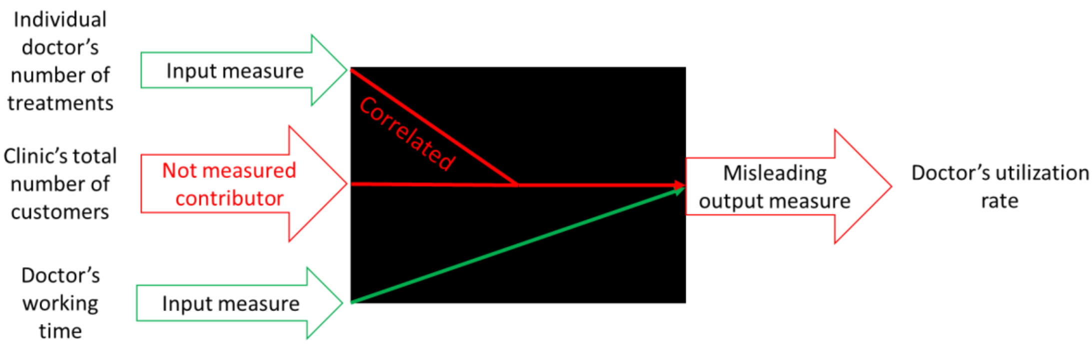

Figure 8. Measurement's black box in the context of dental care (author)

As one can see from the figure 8, if clinic's total number of customers or similar input measure is not in use, doctor's utilization rate is likely misleading. That is why comparing actual performance against the performance criterion requires a variety of outcome measures combined with input measures because factors such as economic conditions affect to measures (Behm 2003, p. 593-594). As in the example above, if dental clinic is measuring utilization rate of employees they must obtain data from reservation rate: low reservation rate compared to high reservation rate is likely to lower the utilization rate.

Evaluation is a usual reason for measuring performance (Behm 2003, p. 588) and to evaluate the performance, managers have to compare that performance with standards such as past performance, performance of a similar company, professional or industrial standard or company's expectations – without comparison it is impossible to determine whether company is performing well or poorly.

Also one aspect to consider concerning the results of the measures is that different people may have different perceptions of the results and without any standards, it may be difficult to interpret the results. One way to apply standards is to use a grading system that people can understand, especially if the results are presented to all employees, as there may be employees who do not see the difference between good and bad value. There are various techniques available such as Likert scales, rank ordering (with ordinal values: 1st, 2nd, 3rd, etc.), scaling (for example from 0 to 10), allocating and mappings (Tonchia & Quagini 2010, p. 40-41).

Measures can reveal whether organization is performing well or poorly but do not answer the question why. If managers have too many performance measurements they may not have time to consider every measures' outcome (Behm 2003, p. 592). Although Behm (2003, p. 596) states that in order to learn, managers need a large number and wide variety of measures. If "many" measures is too much and "few" measures is not enough, how many measures should there be?

According to Kaplan & Norton (1996, p. 162), each of the four perspectives in BSC can require between four and seven separate measures. They state that businesses often have up to 25 measures which is too much - it will be too complicated and time consuming for an organization to absorb. They even state that ten independent measures might be too many in some cases. However, companies could have hundreds of measures that they can monitor to ensure that they are functioning as expected but these are not the drivers of competitive success and these measures should be measured diagnostically: BSC is not a replacement for an organization's day-to-day measurements. (Kaplan & Norton 1996, p. 163-164)

Measuring capacity and waiting time in service operations

According to Jääskeläinen et al. (2012, p. 43), measurement of the service operations has proven to be significant challenge where biggest challenges in performance measurement are associated with intangibility, heterogeneity, inseparability and perishability characteristics of services compared to manufacturing. In customized services every single output may be regarded as tailored and as a result of non-repetitive service process which makes measuring more complicated (Jääskeläinen et al. 2012, p. 47).

The level and nature of customer participation in service operations sets a profound starting point for measurement. As customers have a central role in service operations, the level of customer participation affects the choice and definition of measurement objects. In practice this may mean that customer expectations and the fulfillment of their desires should be measured. (Jääskeläinen et al. 2012, p. 46-47)

According to Kaplan & Norton (1996, p. 120), service organizations should identify the defects in their internal processes that could adversely affect costs, responsiveness or customer satisfaction. Companies can for example create an index to indicate the defects in their internal processes that lead to customer dissatisfaction. Reasons for customer dissatisfaction can be for example long waiting times, inaccurate information, access denied or delayed, request or transaction not fulfilled, customer not treated as valued or ineffective communication. (Kaplan & Norton 1996, p. 120)

The role of demand also brings another aspect to the measurement of service performance because the perishability and simultaneous production and consumption of services complicate capacity management in service organizations. Problem can be for example how to compare organizations' performance during high and low demand. In some services the capability to meet demand is crucial and measurements should then be addressed to the ability to meet the demand with certain quality or time-related criteria. In some other services the capability to meet demand is less important than the efficiency of resource utilization. (Jääskeläinen et al. 2012, p. 47)

3.4 Increasing utilization and reducing waiting using appointment scheduling

Health care service providers struggle to balance between supply and demand. To achieve this balance is often difficult because of the uncertainty in the patient arrival and service times, patients' and providers' preferences, cancelations and no-shows. (Gupta & Denton 2008, p. 805) The objective of appointment scheduling is a tradeoff between the service provider and the customers: the customer prefers to have short waiting time and the service provider prefers to have as little idle time and overtime as possible and also to finish treatment on time (Kaandorp & Koole 2007, p. 217; Qu et al. 2013, p. 197).

According to Tsai and Teng (2014, p. 428), the design of an appointment system has three components: an appointment rule, patient classification or preference and an adjustment policy for walk-ins and no-shows. The appointment rule has also other three components: appointment block sizes, appointment intervals and the initial block design. The appointment interval can be fixed or variable and the initial block design can be present or absent.

3.4.1 Appointment rules

The single-block rule assigns all patients to arrive as a block at the beginning of the clinic session and, on the other side of the spectrum, the individual-block rule gives patients unique appointment times distributed evenly over the clinic session. (Tsai & Teng 2014, p. 428; Fries & Marathe 1981, p. 324). Most of the appointment systems have modifications and combinations of these two systems. (Fries & Marathe 1981, p. 324)

Single-block system creates long waiting times for customers but shortens idle time for employees (Alrefaei et al. 2011, p. 100) which increases capacity utilization rate. In this system, when treatment times are random or when customer arrive late, the customer waiting time can be low but the provider's idle time can be high (Fries & Marathe 1981, p. 324) and high idle time causes capacity utilization rate to decrease.

A sequencing rule in scheduling based on the consultation time variance, where customer was considered as low variance or high variance, empirical research showed that setting customers with low variance at the beginning of the session and customers with high variance at the end of the session would minimize patient waiting time and doctor idle time in most instances (Alrefaei et al. 2011, p. 101). However, since the schedule has to be ready in advance and the arriving requests are handled dynamically, the use of patient classification is somewhat limited. A realistic application would require that patients are assigned to pre-marked slots when they make an appointment (Cayirli & Veral 2003, p. 529). But if slots are limited to certain patient classes only, there is a risk that a number of patients from alternative classes getting treatment is also limited.

3.4.2 Patient classification and service durations

According to Cayirli & Veral (2003, p. 529), when scheduling patient classification can be used for two purposes: to sequence patients at the time of booking and/or to adjust the appointment intervals based on the distinct service time characteristics of different patient classes. Service time requirements can be either known or random. In some cases, for example in routine follow-up appointments, it may be reasonable to assume that service times are approximately known. However, in some procedures, service times can vary significantly from one patient to another. (Gupta & Denton 2008, p. 807)

Work load can also affect to service duration – medical staff may work faster on days when their calendar is heavily booked as compared to lightly booked days. Also patient attributes such as age and cultural background may affect to service durations. (Gupta & Denton 2008, p. 807) For example in a study, where chest examination times on X-ray machine were measured, was found that patient’s age had a significant impact on the average examination length and the variances of the times for patients age 60 or older and those under 20 were both significantly higher (Tsai & Teng 2014, p. 428). Also the presence of student doctors may increase all service durations (Gupta & Denton 2008, p. 807).

3.4.3 Adjustment policies

According to Gupta and Denton (2008, p. 805), late cancellations and no-shows are important in environments where capacity is tight or where no-shows and cancellations consists a significant proportion of all appointments. LaGanga & Lawrence (2007, p. 251) state that no-shows reduce provider productivity and clinic efficiency and limit the ability of a clinic to serve its client population by reducing its effective capacity. They propose appointment overbooking as a mean to reduce the negative impact of no-show.

LaGanga & Lawrence (2007, p. 262) used simulation to several different sized clinics and found out, as quite expected, that overbooking increased patient waiting time and clinic overtime and improved provider productivity. However, it is worth noting, that waiting time and overtime were smaller in big clinics than in small clinics. LaGanga & Lawrence (2007, p. 270) state that appropriate appointment overbooking can provide an effective and important means to improve capacity utilization. Their results indicate that overbooking can especially improve clinic utility when service time variability is large.

3.4.4 Open access scheduling

In order to improve healthcare accessibility and reduce patient no-show, open access scheduling was introduced. The key difference in open access scheduling compared to traditional model is that customers can go to their own provider on a short notice where as in traditional model customer's next visit is scheduled months in advance at the end of his current visit. (Qu & Shi 2009, p. 99) In traditional dental care, appointments are arranged and booked in advance and same-day urgent care is piled on top of an already full schedule (Tsai & Teng 2014, p. 428) - resources, customer and treatment duration are "tied up" in advance. Because this system is unable to offer appointments soon, it can lead to high no-show rates.

The advanced-access system tries to eliminate appointment delay entirely, with the clinic having to offer an appointment to patients on the same day as they reserve treatment, whether reason for treatment is urgent or not. Even though there are substantial benefits in this system, it is more vulnerable to the variations in arrival demand and is sensitive to the imbalance between demands and capacities. (Tsai & Teng 2014, p. 428)

3.4.5 Benefits of using appropriate appointment schedule

Qu et al. (2013, p. 200-201) developed a two-phase approach for designing a weekly scheduling template in order to address the multi-category appointment problem. In phase one, given the categorization of service types, they assigned exactly one service category for each clinic session during one week and determined the optimal number of appointments that should be reserved for each service type in the clinic session. After that they formulated a model to balance provider's workload during a clinic session, by a given demand forecast, the average service time and the anticipated no-show rate of each service type.

In phase two, they allocated the appointments, whose number and service types were specified in phase one, to time slots in each clinic session. Each clinic session was divided into equal-length time slots. The model was developed to minimize the weighted sum of patient's waiting time, provider's idle time and provider's overtime in each clinic session by given the number of appointments reserved for each service type in the session, the no-show rate and the service time distribution of each service type.

Qu et al. found out that scheduling template at best reduced customer waiting time 40 percent, while provider's idle time was decreased 3 percent. However, depending on case, waiting time decreased in a range from 40 to 78 percent, while providers idle time increased in a range from -3 to 38 percent. (Qu et al. 2013, p. 210-211).

While the main focus in this master's thesis is not to create weekly scheduling template, there are still some interesting aspects in study conducted by Qu et al. that can be used for advantage in this master's thesis. For example, categorizing service types and calculating provider's workload by demand forecasting, average service time and the anticipated no-show rate must be taken into consideration while planning the slot machine. A list of factors and decisions that need to be taken into account while creating an appointment system can be found in appendix 2.

3.4.6 Performance measurements to evaluate appointment system

According to Cayirli and Veral (2003, p. 524), there are several performance criteria to evaluate appointment systems but often studies list results in terms of the mean waiting time of the patients and the mean idle time of the doctor, and/or the mean overtime of the doctor. There is a list of usually used criterions to evaluate appointment system in appendix 1.

As can be seen from the list in appendix 1, there are several ways to measure customer waiting time and doctor idle time other than mean, for example by time, by variance and by frequency distribution. Measures used in this master's thesis are discussed in chapter 5.3.

3.5 Relationship between customer waiting time and capacity utilization

According to Rhea & Germain (1979, p. 637), having the customer to wait allows greater utilization of resources but the savings achieved by increasing utilization must be balanced against the effect on waiting time. In order to examine this relationship in dental care services, a simulation modelling example was conducted to find out the relationship between utilization rate and customer waiting time.

In this example, there were one hour slots and 16 customers. Every customer's treatment duration followed the same distribution and was considered as "average customer". In this example, average customer's treatment duration follows approximately gamma distribution with parameters mu = 60.0 and standard deviation = 26.6. Every two customers had a scheduled starting time in the beginning of the slot. This example clinic used fixed appointment interval with initial block (block size is two). There was only one doctor in scenario 1, two doctors in scenario 2, three doctors in scenario 3 and four doctors in scenario 4. Customers in slots in scenarios one to four are visualized in figure 9.

Scenario 1	
Slot	**Doctor 1**
Slot 1	Customer 1A
	Customer 1B
Slot 2	Customer 2A
	Customer 2B
Slot 3	Customer 3A
	Customer 3B
Slot 4	Customer 4A
	Customer 4B
Slot 5	Customer 5A
	Customer 5B
Slot 6	Customer 6A
	Customer 6B
Slot 7	Customer 7A
	Customer 7B
Slot 8	Customer 8A
	Customer 8B

Scenario 2		
Slot	**Doctor 1**	**Doctor 2**
Slot 1	Customer 1A	Customer 1B
Slot 2	Customer 2A	Customer 2B
Slot 3	Customer 3A	Customer 3B
Slot 4	Customer 4A	Customer 4B
Slot 5	Customer 5A	Customer 5B
Slot 6	Customer 6A	Customer 6B
Slot 7	Customer 7A	Customer 7B
Slot 8	Customer 8A	Customer 8B

Scenario 3			
Slot	**Doctor 1**	**Doctor 2**	**Doctor 3**
Slot 1	Customer 1A	Customer 1B	
Slot 2		Customer 2A	Customer 2B
Slot 3	Customer 3A		Customer 3B
Slot 4	Customer 4B	Customer 4A	
Slot 5		Customer 5B	Customer 5A
Slot 6	Customer 6A		Customer 6B
Slot 7	Customer 7B	Customer 7A	
Slot 8		Customer 8B	Customer 8A

Scenario 4				
Slot	**Doctor 1**	**Doctor 2**	**Doctor 3**	Doctor 4
Slot 1	Customer 1A	Customer 1B		
Slot 2			Customer 2A	Customer 2B
Slot 3	Customer 3A	Customer 3B		
Slot 4			Customer 4A	Customer 4B
Slot 5	Customer 5A	Customer 5B		
Slot 6			Customer 6A	Customer 6B
Slot 7	Customer 7A	Customer 7B		
Slot 8			Customer 8A	Customer 8B

Figure 9. Customers in slots in simulation modelling example (author)

As one can see from the above figure, scenario 1 is heavily overbooked and scenario 4 has a lot of excess capacity. Treatment durations for every customer were randomized using random gamma function which used average customer's mu and standard deviation which were converted to gamma functions alpha and beta. Each scenario used the same treatment time for specific customer but treatment time was randomized again after each iteration. After each iteration, doctor(s) utilization rate and customers waiting time was collected. There were 2000 iterations and after that the average doctor utilization rate and the sum of customer waiting time was calculated. This set of 2000 iterations were made 5 times. Results are visualized in figure 10.

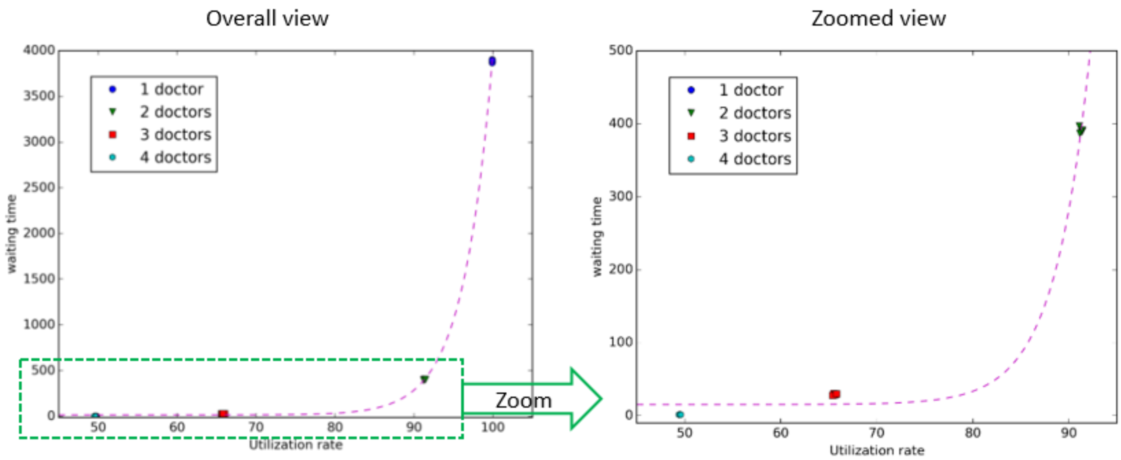

Figure 10. Simulation result of relationship between utilization rate and waiting time (author)

In the figure above, on the left hand side is the overall view where data points from all scenarios are shown, and on the right hand side is the zoomed view from the area from overall view that is marked with the green dashed line. Since the number of iterations was 2000, every individual scenario's data points are very close to each other (as seen on the right hand side). One can also see from the figure that waiting time increases in a nonlinear way as utilization rate increases. The red dashed line describes fitted exponential curve and it follows data points quite closely: waiting time seems to increase nearly exponential as utilization rate increases.

In addition, the same simulation was conducted with different expected treatment durations (i.e. different reasons for treatment), where mu was set to 30, 45 and 60 minutes while keeping the same standard deviation. Simulation results with different mu-values is in figure 11.

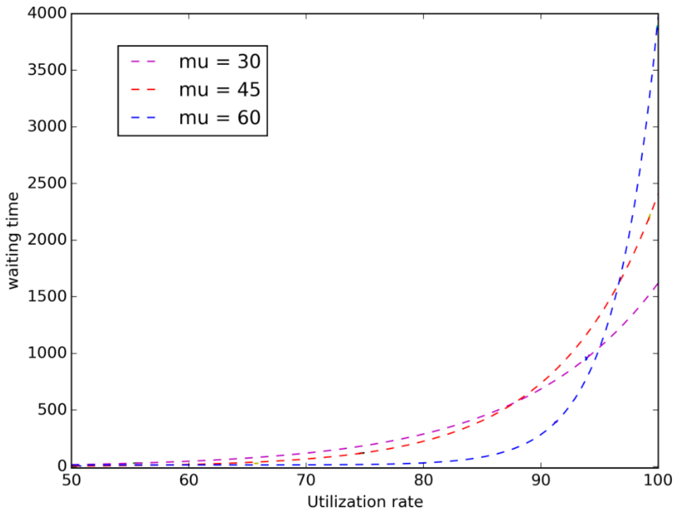

Figure 11. Simulation results of relationship and waiting time with different mu-values (author)

As one can see from the above figure, changing mu-value influences to the curve. Curve still increases in a nonlinear way with different mu-values instead of being linear. With longer expected treatment duration, curve seems to rise more suddenly compared to shorter expected treatment duration. However, this simulation case was modelled only in a small clinic where block size was only two. As LaGanga & Lawrence state (see. chapter 3.4.3), waiting times are smaller in bigger clinics compared to smaller clinics: relationship between waiting time and utilization rate might be slightly different in bigger clinics. This simulation example was theoretical, and other factors such as customer age as well as employee satisfaction and work ethics are likely to influence the relationship between utilization rate and waiting time.

Howell et al. (2001, p. 4) studied the relationship between waiting time and capacity utilization in industrial environment and state that, to match capacity to workload causes the time required to install any specific fixture to increase in a highly nonlinear fashion. This is visualized in figure 12.

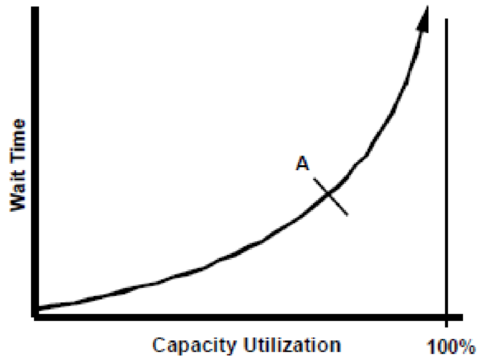

Figure 12. Relationship between waiting time and capacity utilization (Howell et al. 2001, p. 4)

As in figure 12 is shown, increasing capacity utilization lengthens customer waiting time similarly compared to figure 11.

4 CASE COMPANY MEGAKLINIKKA OY

4.1 Megaklinikka company's business model

Megaklinikka is a Finnish company that belongs to Panostaja corporation. Megaklinikka company's concept is a single visit model where all treatments that a customer requires are conducted during one visit as long as it is medically feasible and the customer accepts all treatments. Megaklinikka has a clinic in Helsinki and it is expanding also to Stockholm where new clinic is expected to start operating in the beginning of September 2016. Megaklinikka also provides company's concept to public dental care service providers.

Megaklinikka company's quite unique operational model is enabled by their own Enterprise Resource Planning system called "Clinic Information System" (CIS). For example, CIS sends automatically a text message to next customer to come to the clinic 30 minutes in advance.

4.2 Description of traditional dental care process and Megaklinikka's process

The difference between traditional dental care process and Megaklinikka single visit model is illustrated in figure 13.

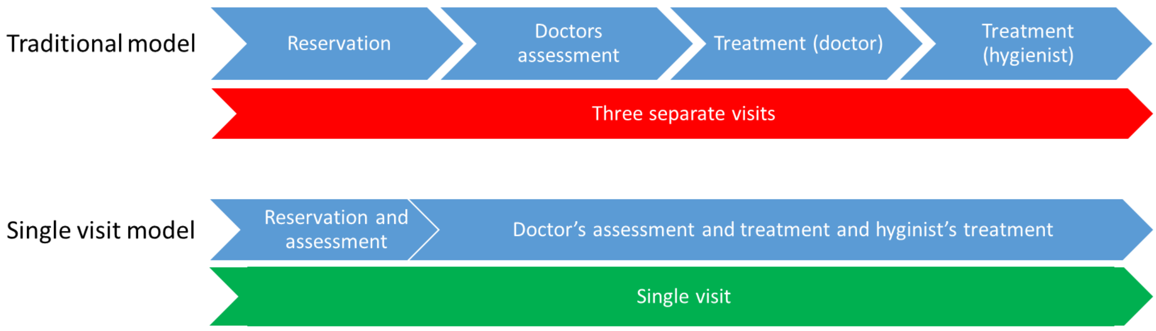

Figure 13. Differences between traditional model and single visit model (author)

As can be seen from the figure 13, customer visits the clinic three times in the traditional dental care model. When customer arrives to the clinic in traditional dental care process, doctor makes an assessment on which treatments need to be conducted and customer makes another appointment based on the assessment. When customer arrives to the clinic for the second time, doctor makes necessary treatments. If the customer needs a hygienist treatment, he/she must schedule third appointment. When customer arrives to the clinic for the third time, hygienist makes necessary treatments. After every customer, rooms and instruments must be cleaned which takes approximately 10-15 minutes.

Single visit model in Megaklinikka

Figure 14 illustrates the reservation process in Megaklinikka.

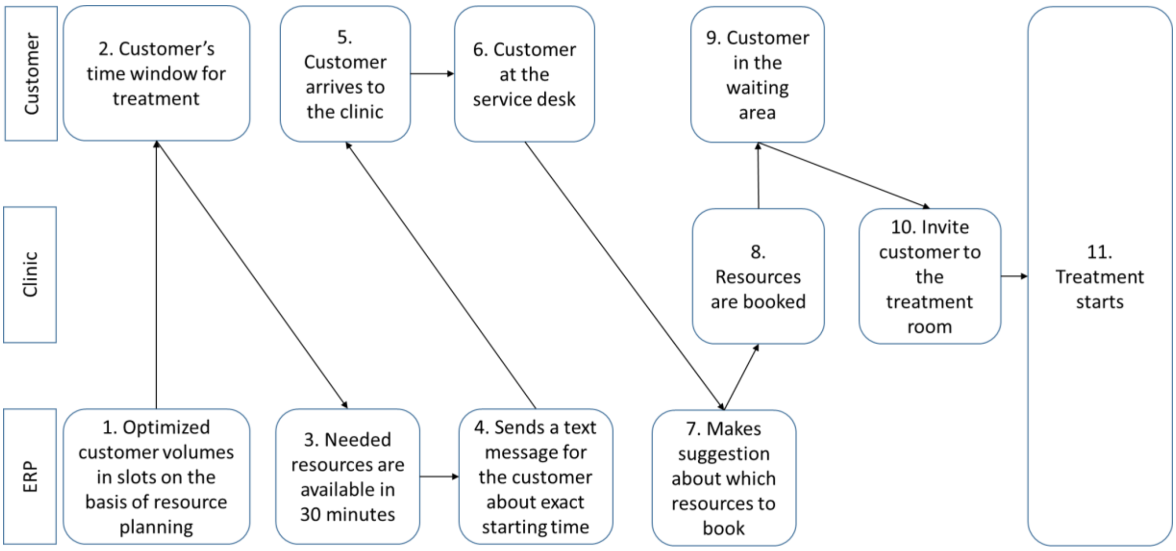

Figure 14. Reservation process in Megaklinikka (author)

As can be seen from the above figure, Megaklinikka's enterprise resource planning system enables single visit model system. Customer can make an appointment from appointment schedule which can be found from Megaklinikka Company's home page. Calendar view with pricing of Megaklinikka's dental care services is shown in figure 15.

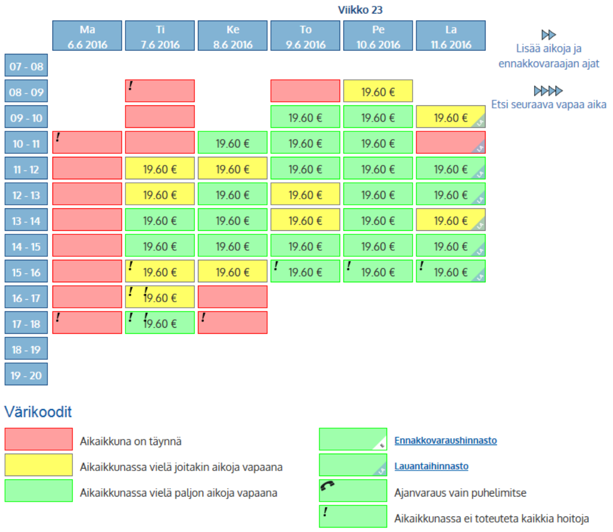

Figure 15. Appointment schedule (Ajanvaraus 2016)

If there are no available times in the slot, slot is filled with red and if there are times available in the slot, slot is filled either yellow or green depending on how many available times are left in the slot. Prices in the slots are reservation fees. After customer has selected a slot, he or she fills an information form. In the information form customer selects reasons for treatment. Basic dental care form with list of reasons is shown in figure 16.

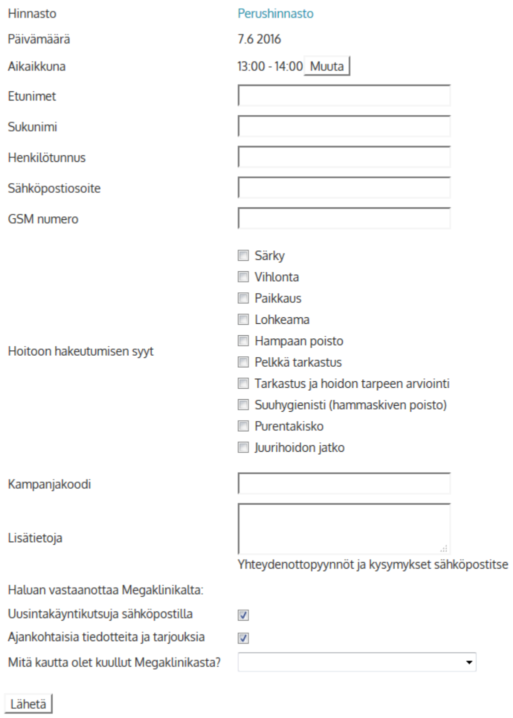

Figure 16. Basic dental care form with list of reasons (Uusi varaus 2016)

As can be seen from the figure 16, there are several reasons to choose from the list of reason for treatment and one can choose one reason or as many reasons as he wants. There are ten different reasons to choose from: ache, sensitivity, crack, check up, check up and assessment, hygienist, restoration, removal, occlusal splint and root treatment continuation. These ten different reasons make 1023 possible combinations of individual set of reasons why customer makes an appointment. There are also 19 reasons to choose from in specialized dental care calendars where reasons for making an appointment can be for example surgical consultation, surgical operation, whitening and ceramic consultation.

When a customer has selected a slot and filled the form, he or she receives a text message 30 minutes before he/she should come to the clinic. For example, if customer has selected a slot 11-12 he/she receives a text message between 10:30 to 11:30 so that appointment would start between 11:00 to 12:00. After entering to the clinic the customer waits for an employee to pick him up to the treatment room. After resources needed are available in the room, treatment can start. If the customer needs a different resource type, an employee sends a request to have another kind of resource. For example, if the customer needs a hygienist, the nurse sends a request that specific room needs a hygienist, and when a hygienist is available, hygienist comes to the same room where the customer is – the customer does not leave the room. After the treatment is finished, the customer goes to the reception and pays for the treatment.

4.3 Appointment system in Megaklinikka

Megaklinikka has a Variable-block with Fixed-interval rule which allows different block sizes during the clinic session, while keeping appointment intervals constant or at least nearly constant: majority of the treatments start at the beginning of slot while some treatments may start later. The slot machine can take several factors into account when calculating optimal slot sizes, such as patient classifications and adjustments for no-shows and for walk-ins. These decisions are discussed in chapter 5.1**.** Variable-block with Fixed-interval rule is visualized in figure 17.

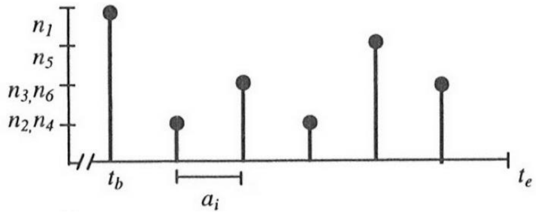

Figure 17. Variable-block with Fixed-interval rule (Cayirli & Veral 2003, p. 527)

In the figure above, a_i is appointment interval, t_b is time when session begins, t_e is time when session ends and n_i is block size for the ith block.

4.4 Resources and data in Megaklinikka

There are several different resource types in the Megaklinikka clinic: doctors, nurses, hygienists, rooms, receptionists, equipment maintenance and replenishers. In most cases where customers come to the clinic, treatment is conducted by a doctor and an assistant. The assistant can be either a nurse or a hygienist. There are also some cases when the treatment is conducted only by a doctor or only by a hygienist, for example if the reason for treatment is tooth scaling.

There are usually two or three employees in the reception and one of them is a shift manager who takes care that the day goes smoothly – shift manager's role is like being a transport coordinator in a transport company. Shift manager takes care for example that every customer has correct resources in the room, makes sure that employees keep track of their estimated treatment end time and employees do not have too long breaks.

Employees in the equipment maintenance clean and sharpen treatment instruments. Replenishers clean the room after each customer and replenish the room's instruments. There are only a few replenishers working during the day which is why usually also nurses or hygienists replenish the rooms. There are also other tasks which are not directly clinical treatment, for example preparing ceramic prosthetics, pharmacy orderings and inventory. Usually hygienists do these tasks, and when they do, they are away from the clinical operations.

Megaklinikka can be seen as a data driven company. Since the company started operating a decent amount of data has been collected into a relational database. There are data in multiple tables and most of the data is saved in a way that enables smooth data analyzing. Data is also refreshed often.

Managers at Megaklinikka developed their own Clinical Information System that collects data automatically from multiple sources. Treatment data is collected semi-automatically by employees. If employees collect data correctly data is currant, however, this is not always the case.

4.5 An example of a clinic’s flexibility

In order to explain the flexibility of the clinic and the functionality of the slot machine, a hypothetic example of appointment scheduling was created. In this example, the clinic is open from 8 am to 12 am and there are three doctors, three treating rooms and 13 customers who have reserved a time for treatment. Customer information can be found in table 2.

Table 2. Clinics flexibility example: reserved customers (author)

Customer	Treatment duration	Slot		Customer	Treatment duration	Slot
1	0:45	8		8	0:15	10
2	0:45	8		9	0:30	10
3	1:00	8		10	1:00	10
4	0:15	9		11	0:30	11
5	0:35	9		12	0:30	11
6	0:30	9		13	1:00	11
7	0:30	10		average	0:45	x

Treatment durations are expected treatment durations where each duration length is randomized from 15 minutes to 60 minutes in 15 minutes’ intervals. Customers have been divided to slots quite evenly: slot 10 has four customers and other slots have three. If there were more customers than these, who have already scheduled an appointment, their treatment duration is expected to be 45 minutes, which is a time that an average customer spends in a treatment room in this example. If one would not add any extra customers (i.e. open slots), doctors would idle a lot. This is visualized in figure 18.

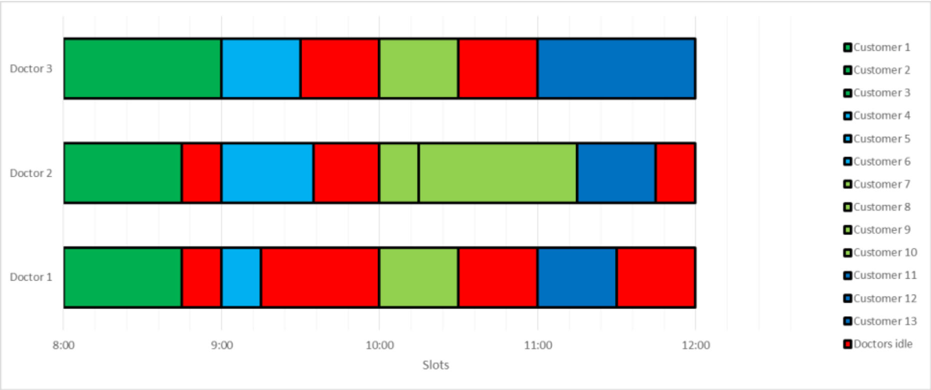

Figure 18. Example of clinics flexibility: no added customers (author)

In the above figure, the customers who have reserved time to slot 8 are marked with dark green, slot 9 customers are marked with light blue, customers in slot 10 are marked with light green and customers in slot 11 are marked with dark blue. Doctors' idle time is marked with red. One has to remember that if a customer reserves a treatment to slot 10, treatment cannot start before ten a clock. As one can see, there is only one gap (doctor 1, slot 9) where doctor idles as much or more than 45 minutes: at least one customer could be added. This is visualized in figure 19.

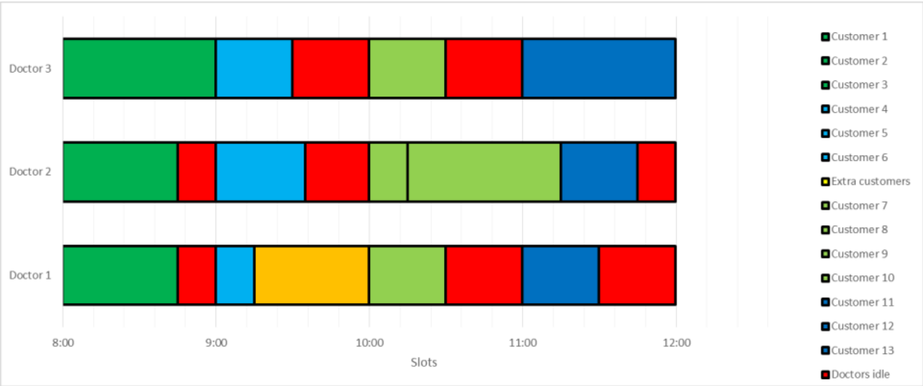

Figure 19. Example of clinics flexibility: one added customer (author)

In the above figure, same colors are used, but extra customer is marked with yellow. Even though there are still plenty of idle time, the gaps are too small for adding customers. However, since the treatment does not have to start exactly at the beginning of the slot, and customers are informed for the right starting time for 30 minutes before the treatment, there are room to add four more customers. This is visualized in figure 20.

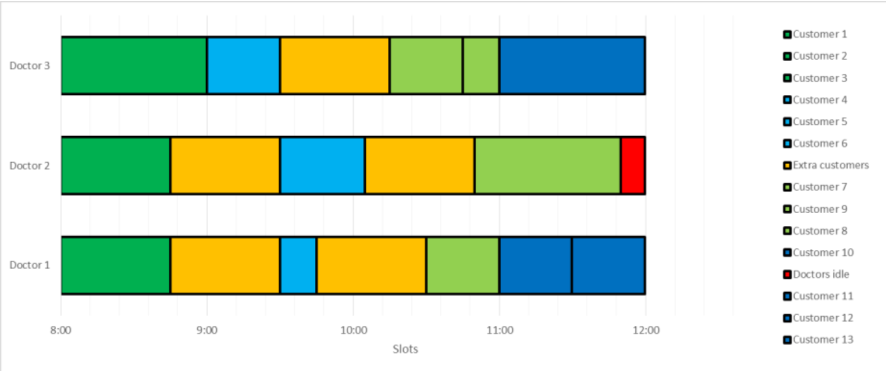

Figure 20. Example of clinics flexibility: five added customers (author)

As one can see from the above figure, all treatments start on time (i.e. in the correct slot) and there is no overtime for the doctors. Idle time for doctors has reduced to minimal. Summary of this example's idle time is in table 3.

Table 3. Summary of the clinics flexibility example (author)

	Scenario 1	Scenario 2	Scenario 3
Customers	13	13	13
Added customers	0	1	5
Doctors idle time	235	190	10

In the first scenario, there were 13 customers and idle time was 235 minutes. In the second scenario, where one customer was added, total number of customers were 14 and idle time was 190 minutes. In the third scenario, where five customers were added, total number of customers were 18 and doctors' idle time was reduced to 10 minutes.

In this example, where there is only three doctors and three treatment rooms, even one longer than expected customer visit results to a relatively high risk that customers have to wait and treatments do not start in the right slot. However, Megaklinikka has 18 treatment rooms and approximately ten doctors working at the same time: clinic is not as sensitive to the variation in the treatment duration. This means that the overall treatment durations for each day should be approximately as forecasted. This is discussed further in chapter 5.2.

4.6 Coefficient of correlation between customer waiting time and customer satisfaction

Megaklinikka collects data of the customer satisfaction. Customer can choose whether or not he/she wants to answer to customer satisfaction questionnaire. Results of the questionnaire are linked to customer's other information such as treatment duration information. There are a few questions in the questionnaire and one of them is "Would you recommend Megaklinikka to your friend?". This question is a strong indicator to examine whether customer liked the overall service or not. There are three possible choices to choose from: passable, satisfactory and excellent, where passable is seen as the worst and excellent as the best option.

In order to calculate coefficient of correlation, satisfaction and waiting time data from six months' time was examined. There were 413 answers where waiting time ranged from 0 to 80 minutes. Waiting times and answers are plotted in figure 21.

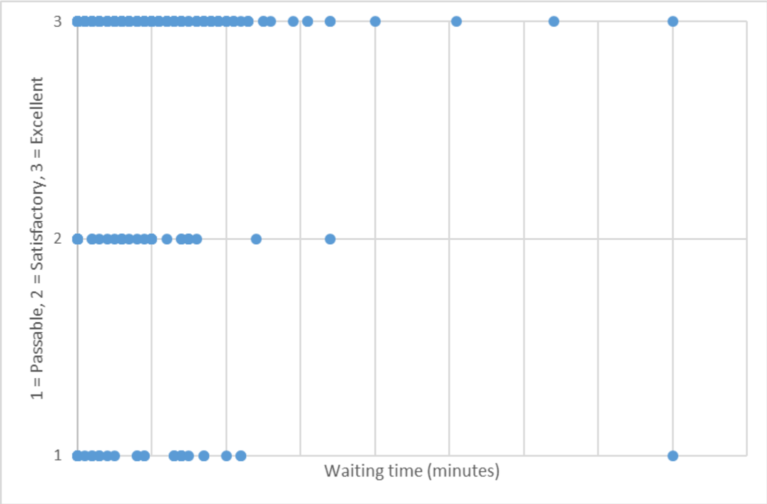

Figure 21. Waiting time and customer satisfaction (author)

As can be seen from the figure 21, customers have answered “excellent” even though they have waited for relatively long and only one customer, who had waited relatively long, answered “passable”. This indicates that there is no correlation between waiting time and satisfaction. In order to be sure, coefficient of correlation was calculated.

Even though opinion scale is usually considered as ordinal scale, in some cases opinion scale can be converted into interval scale as in this study in order to calculate Pearson’s coefficient of correlation. Coefficient of correlation between waiting time and satisfaction was -0.0701 (almost zero) which indicates that there is no (linear) correlation between those two variables. In order to determine that low coefficient of correlation is not a sampling error, p-value was also calculated. Hypothesis were as followed:

$$H_0: \rho = 0 \ (no\ linear\ relationship)$$
$$H_1: \rho \neq 0 \ (linear\ relationship)$$
$$Null\ hyptheisis\ is\ rejected\ if\ P < 0.05$$

P-value was 0.155 (two-tailed test), which is more than 0.05. This means that null hypothesis (H_o) is not rejected: there is no statistically significant linear relationship.

5 FUNCTIONALITY AND VERIFICATION OF THE SLOT MACHINE

Two versions of the slot machine were created. In the first version it was assumed that every resource type is in the room as long as the customer. However, this is not true in most cases in practice. For example, if the average time that the customer spends in treatment room with specific reason, that requires both hygienist and doctor to be present, was 35 minutes, the slot machine subtracted 35 minutes from both resource classes. The second version of the slot machine calculated how long each resource type was expected to be present in the treatment room. For example, in the above example, where an average customer spent 35 minutes in the treatment room, new version of the slot machine calculated that resource type 'doctor' was in fact 20 minutes in the treatment room, hygienist was there for an average of 15 minutes and nurse was there for an average of 35 minutes. Also some other adjustments were made during the development process. In the next chapter is explained how the current version (version 2) of the slot machine works.

In order to define whether or not the slot machine operated properly, two approaches were used: in theory using simulation and mathematics as well as in practice by measuring each days' success.

5.1 Functionality of the slot machine

Introduction to slot machine

There are a few assumptions related to the slot machine: that there are not no-shows and that the service times of customers are independent. Customers who need to be scheduled during a block are not homogenous – they may have different medical reasons, require different types of equipment and staff resources and vary considerably in the required service time. Even though appointment interval (block width) is one hour, treatment can continue to the next slot: treatment duration can be longer than one hour. However, if all customers assigned to a block are served before the block ends, the staff idles.

The slot machine can be used for days in the future as well as for days in the past but the main reason to use slot machine is to use it for predicting the future. The slot machine optimizes how many customers there can be during the day and which slots they should be in. The slot machine uses history data from three years' time.

Calculating available time for resources

Even though every resource type is important, critical resources in order to finish a treatment are doctors, nurses, hygienists and rooms. First slot machine calculates how many resources of every resource type there will be available for every slot. The number of resources per slot is multiplied by 60 minutes in order to find out how much resource time there is in a slot. After that the slot machine calculates doctors' quickness. If a specific doctor is quicker than an average doctor, resource time is added to doctors' resource pool with certain formula. The slot machine calculates break time for each resource type and subtracts break time from resource pool. It uses history data to determine when employees usually take breaks.

Available resource time for room (room capacity) is calculated as number of rooms multiplied by 60 minutes. There are 18 rooms in the clinic. If none of the rooms is out of order, there are 1080 minutes of available room time in each slot.

Expected duration for employee resources

Expected treatment time is calculated differently depending on situation: is expected treatment time calculated for employees (doctors, nurses and hygienists) or for rooms. When calculating expected duration for employee resources it is important to know how long each *resource* is in the room. When calculating expected duration for rooms it is important to know how long each *customer* is in the room.

First the slot machine gets all different combinations of reasons for treatment that have been used in the last three years. After that the slot machine calculates expected duration for every single reason for treatment for every employee resource from three years' time. If there are more than 20 occurrences of history durations for specific reason, expected duration is calculated with simple exponential smoothing, otherwise it is the mean of durations.

When calculating expected durations for employee resources for different reasons for treatment, outliers are not removed. This is because, in some cases the customer needs a doctor and in some cases the customer does not need a doctor, and when the customer does not need a doctor, that situation cannot be removed since it is not likely an outlier.

If there is no history data from specific reason for treatment, expected duration is the average duration of all treatments. The average treatment duration is mean from durations of three years' time for all possible combinations of reason for treatments for every employee resource.

Since there is a time gap between two customers, which is not shown in treatment durations, for example employees need to change the room and make notes, an average waste time is added for employees' expected treatment duration. Also the rooms need to be cleaned and replenished after every treatment, which is why after every treatment certain amount of time is added for nurses.

Expected duration for rooms

Expected duration for single reason for treatment is the mean of the durations that customers have been in the room for that reason. One main difference when calculating expected duration for rooms in comparison to employees is that outliers are removed. For example, it is not likely that the customer spends only one minute in the room. Outliers are removed using the Tukey IQR rule (see chapter 2.4.2).

Calculating how many customers to add and optimizing slot sizes

After available resource time and expected treatment times for specific day are calculated, the slot machine subtracts expected durations from available treatment time for each resource type in every slot. After that, the slot machine calculates slot capacities with current customers. Slot capacity is calculated as in formula (14):

$$\mathit{Slot\ capacity} = \mathit{Number\ of\ current\ customers\ in\ slot} + \frac{\mathit{Remaining\ slot\ time\ (for\ certain\ resource\ types)}}{\mathit{Average\ treatment\ time\ (for\ certain\ resource\ types)}} \tag{14}$$

If the remaining slot time is minus, slot capacity is less than number of current customers in a slot and vice versa. Certain resource types are doctors, assistants and rooms – nurses or hygienists are not calculated because it does not matter whether there are only nurses or only hygienists available. However, the slot machine warns if there are too little time left with hygienists by adding text "no more hygienist treatments". If there is no hygienist time left but plenty of time left with nurses and doctors, why should not more customers be let in with reasons other than hygienist treatments? The number of customers to add in a slot is the number of current customers + slot capacity and it is the minimum customers to add from each resource type. For example, if in a certain slot doctors could do treatment for two average customers, assistants could do treatment for three average customers and there is room time for five average customers, the number of added customers in that slot is two because doctors are a constraining resource.

However, the optimal slot size may be bigger or smaller than the slot capacity. The slot machine calculates optimal slot sizes in a way that the first slots of the day are bigger and at the end of the day smaller than the slot capacity. Overall slot capacity per day remains the same – it only is divided to slots differently. This is because if optimal slot size would be the same size as slot capacity and in case where treatment durations are not as long as expected, employees would idle and wait for next slots' customers. The clinic has some flexibility due to the fact that customer can be called to the clinic during one-hour window (see. Chapter 4.5). An algorithm that determines, how customers should be spread out in slots throughout the day was therefore created to the slot machine.

Reports

There is an example of a slot size proposal pdf –file in appendix 3. There are three tables in the slot size proposal. The first table from the top contains information about available resources for a specific date. It shows the number of resources in slots and available resource time (in minutes) in slots.

The second table contains information about resources with current customers. In the first four columns is shown how much resource time is left in slots. The fifth column informs which resource is a constraining resource – a constraining resource can be doctor, assistant or room. The fifth column warns if there is less than 45 minutes hygienist time left.

The third table contains information about slot sizes. The first column shows the number of current customers, the second column shows slot capacity, the third column shows optimal slot sizes, the fourth column shows 80 % of the optimal slot sizes and the fifth column shows 90 % of the optimal slot sizes.

One should not set the number of available slots to optimal slot sizes too much in advance since, if employees get sick during the night and the slots are full, there are not enough resources to serve customers on time.

5.2 Verification of the slot machine using simulation approach

Introduction to simulation approach

A simulation model was created by using Python. The simulation model calculates how much resource time there is left with the current customers and after adding extra customers - how much resource time is left if all slots are as full as the slot machine proposes. However, this simulation model does not include rooms. After the slot machine has run a specific day, it saves certain information about the day to an Excel file with three separate sheets. Sheet1 has information about current reservations, such as reason and slot (reservation time) as well as distribution information: expected (mean) duration and variance for each resource type. Assistant's mean and variance are the sum of mean and variance of nurse and hygienist.

Sheet2 contains information about available resource time at the beginning of the day for each resource type in each slot. Sheet3 contains the same information as Sheet1, except there are average customer information (distribution statistics) in the slots that the slot machine proposes to have more customers. Before conducting simulation, one has to know the distributions of treatment durations.

Treatment duration distributions

Two examples of doctor and assistant treatment duration distributions are visualized in figure 22.

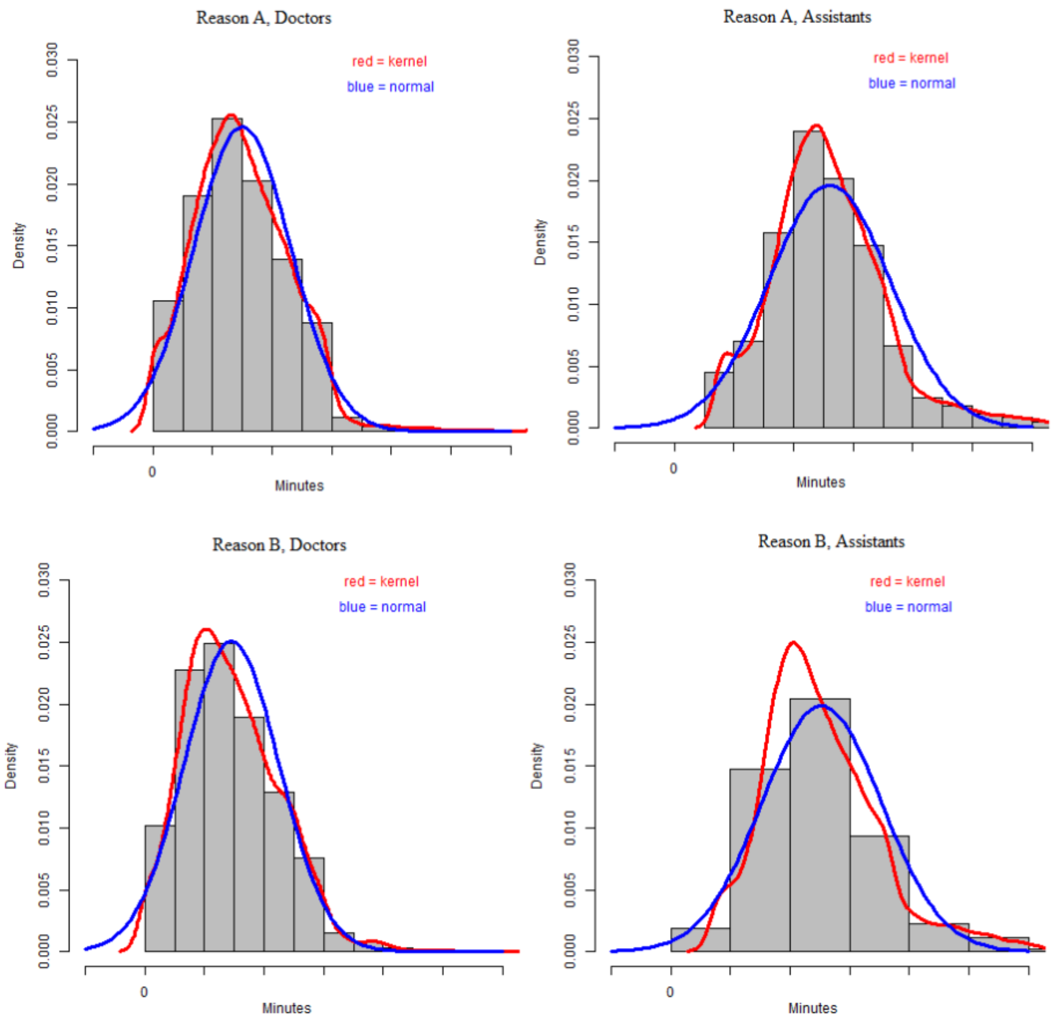

Figure 22. Examples of treatment duration distributions (author)

As can be seen from the graphs, histograms are right-skewed. The red line illustrates Kernel density estimator which is used to smooth and to estimate the density function. It removes the influence of selected bin widths from the histogram. Blue line illustrates the normal distribution using data sets mu and variance. Blue line appears to trace Kernel line quite well (at least with doctors) which indicate that distribution could be normal. However, duration data is always non-negative, while it appears to be possible to have negative values by using normal distribution, according to the above figure. In the table 4 are probabilities that duration values are less than zero.

Table 4. Probability that duration value is less than zero (author)

Treatment	P (Duration < 0)
Reason A, Doctor	3.2 %
Reason B, Doctor	3.4 %
Reason A, Assistant	0.5 %
Reason B, Assistant	0.6 %

As can be seen from the above table, distribution cannot be normal, since there is a chance that randomized duration is less than zero while using normal distribution. In order to narrow down the possibilities for the right distribution, skewness and kurtosis is calculated as in table 5.

Table 5. Skeweness and kurtosis (author)

Reason and resource	Skewness	Kurtosis
Reason A, doctor	0.705	4.874
Reason B, doctor	1.100	6.000
Reason A, assistant	0.671	3.772
Reason B, assistant	1.176	5.880

As can be seen from the above table, there is a positive skewness in all cases and kurtosis is not too far from 3. That is why three common right-skewed distributions are considered: Weibull, gamma and lognormal. In the appendix 4 is goodness-of-fit plots of doctor duration for reason A and in the appendix 5 for assistant.

From the density histogram plot (top left) in appendix 4 can be seen, that Weibull or gamma distribution is the best fit for doctors. From the Q-Q plot can be seen that gamma and Weibull distributions describes tails of the distribution the best. However, Weibull distribution describes the center of the distribution the best as seen from the P-P plot. Weibull distribution appears to be the best fit according to these plots.

From the density histogram plot in appendix 5 can be seen, that lognormal or gamma distribution is the best fit for assistants. From the Q-Q plot can be seen that lognormal distribution describes the tails of the distribution the best while it appears that gamma distribution describes the center of the distribution the best as seen from the P-P plot. Either lognormal or gamma distribution appears to be the best fit. Goodness-of-fit statistic for doctors and for assistants with specific reason for treatment are presented in table 6.

Table 6. Goodness-of-fit statistics (author)

	Resource	Weibull	gamma	lognormal
Kolmogorov-Smirnov statistic	Doctor	0.08	0.13	0.22
	Assistant	0.06	0.05	0.07
Cramer-von Mises statistic	Doctor	14.9	43.7	137.7
	Assistant	12.1	4.3	9.6
Anderson-Darling statistic	Doctor	109.2	261.7	789.2
	Assistant	78.5	30.3	63.1

According to these goodness-of-fit statistics, all statistics favor Weibull distribution for doctors and gamma distribution for assistants. The reason why doctors' distribution is different compared to assistants is probably the fact that while assistants are most of the times needed, doctors are not always needed in order to do the treatment.

Similar study was conducted for all resource types with different reasons for treatment. Even though there are 1023 combinations for different reasons for treatment, and in the above is only two examples, most of the remaining distributions for different reasons are quite similar to these two, at least when there are a lot of occurrences in the history for each particular reason. Even though distributions for assistants are not all exactly gamma distributed, simulation model assumed they were.

Functionality of the simulation model

The simulation model calculates duration for each reason separately based on a reason's distribution statistics (mean and variance) which are converted to alpha and beta values in order to use random gamma and random Weibull functions. Random function returns random treatment duration. After the duration for each reason is calculated in a slot, slot treatment duration is subtracted from available resource time in that slot. If available resource time after subtracting treatment duration is less than zero, it is added to the next slot otherwise (resource idles) it is not.

If cumulative resource time in a slot is less than cumulative treatment time in the previous slot, there are customer(s) who have to wait. If cumulative resource time at the end of the day is less than cumulative treatment time, resource has overtime.

2500 iterations were needed in order to have sufficient confidence level. Number of iterations was determined from a distribution where the mean is 27.8 and the standard deviation is 12.5 as well as from the simulation model's result (mean expected treatment time left). This is visualized in figure 23.

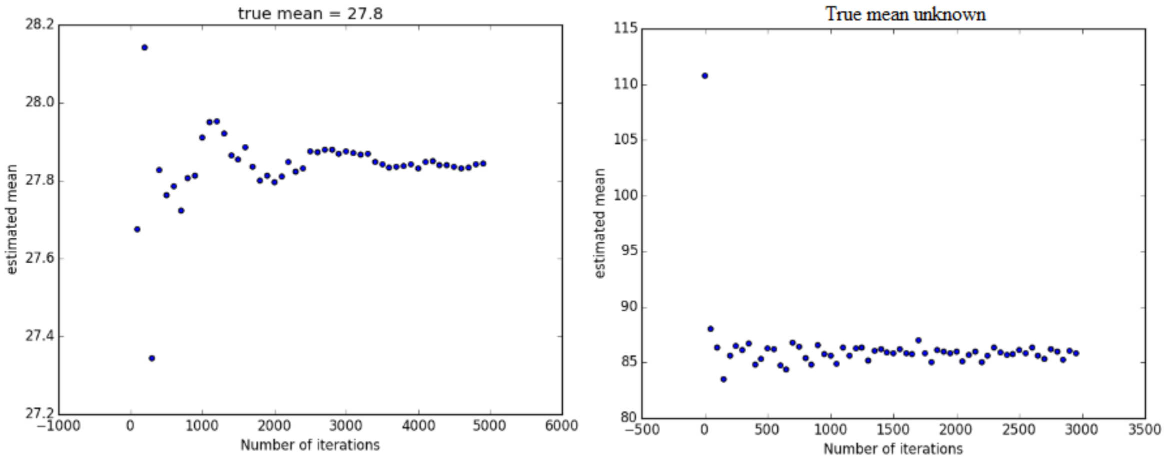

Figure 23. Determining the correct number of iterations (author)

In the figure 23 above, on the left hand side is iterations and estimated mean from single distribution and on the right hand side from simulation model's result. As can be seen from both of the graphs, estimated mean does not fluctuate much after 2500 iterations and therefore any additional iterations do not result in a significant change to the estimated mean.

Results of the simulation

Result of the simulation is a histogram distribution and distribution statistics of available resource time with current customers and with extra customers, as well as percentage of times that expected treatment time exceeded zero at the end of the day. Simulation also calculates the percentage of times that *every* customer in a slot had to wait during the day. This means that this simulation does not take into account that there may be individual customers waiting in slots. Two relevant example results are shown in figures 24 (doctors) and 25 (assistants).

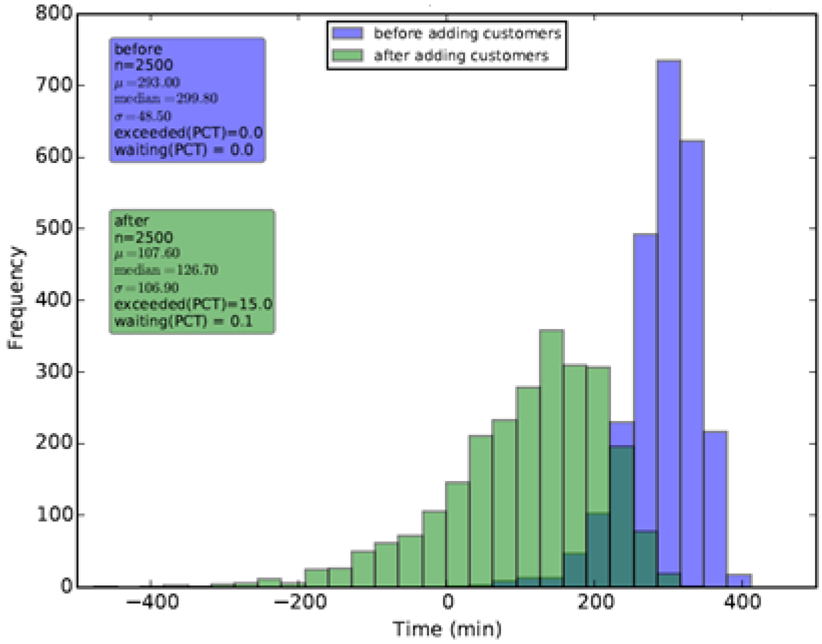

Figure 24. Distribution of expected resource time left (doctors) at the end of the day (author)

In the above figure, blue histogram marks the expected treatment time left with current customers and green histogram marks expected treatment time left with extra customers (if there were as many customers as slot machine proposes). Bars in dark green mean that both cases fall into that area.

Mean doctor time left in that day is approximately 290 minutes before adding extra customers and approximately 110 minutes if slots are full. According to this simulation, the probability that the doctor time is exceeded is zero percent with current customers and 15.0 percent if the slots are full. If the slots are full, there is a 0.1 percentage chance that every customer in some slot are not getting treatment during that slot.

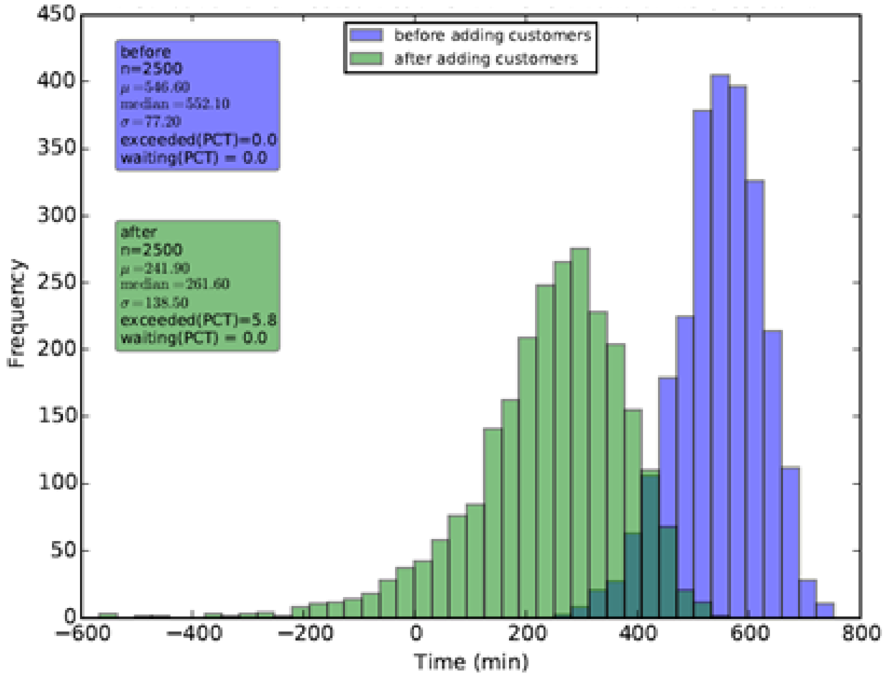

Figure 25. Distribution of expected resource time left (assistant) at the end of the day (author)

In the figure 25 above, mean assistant time left in that particular day is approximately 550 minutes before adding extra customers and approximately 242 minutes if the slots are full. According to this simulation, the probability that assistant time is exceeded is zero percent with current customers and 5.8 percent if the slots are full.

This simulation was run for nine days from July 11th to July 21st 2016. Overtime percentages for doctors, hygienists and assistants were collected with current customers. After that, probability that some resource class is going to have overtime was calculated as in formula (15):

$$P(All\ resources) = P(Doctor) + P(Hygienist) + P(Assistant) + P(Doctor \cap Hygienist \cap Assistant) - P(Doctor \cap Hygienist) - P(Doctor \cap Assistant) - P(Hygienist \cap Assistant) \quad (15)$$

Results are in table 7, where days real overtime grade is in the last column.

Table 7. Probability for resource overtime with current customers

Day	P(Doctor)	P(Hygienist)	P(Assistant)	P(All)	Overtime grade
1	0.016	0.002	0.000	0.018	8.1
2	0.086	0.446	1.000	1.000	5.3
3	0.000	0.002	0.000	0.002	8.4
4	0.000	0.002	0.000	0.002	8.0
5	0.001	0.002	0.000	0.002	7.4
6	0.000	0.000	0.000	0.000	7.7
7	0.022	0.165	0.274	0.407	7.6
8	0.001	0.001	0.000	0.001	7.3
9	0.000	0.000	0.000	0.000	9

During these days the average overtime grade was 7.6 and as can be seen from the above table, there is one day were probability for overtime was 100 percent: July 12th. During that day the overtime grade was only 5.3 which is 2.3 below average. Coefficient of correlation between overtime probability and real overtime grade was 0.84 which indicates that this simulation model works. However, sample size is really small and this simulation model is theoretical and it does not take into account all possible waste time: it is assumed that everything goes as smoothly as possible. If there had been as many customers as proposed by the slot machine, probabilities of overtime would be as presented in table 8.

Table 8. Probability for resource overtime with added customers (i.e. slot proposal)

Day	P(Doctor)	P(Hygienist)	P(Assistant)	P(All)
1	0.025	0.002	0.00	0.027
2	0.085	0.439	1.00	1.00
3	0.150	0.002	0.058	0.201
4	0.00	0.003	0.029	0.032
5	0.048	0.001	0.066	0.112
6	0.002	0.002	0.003	0.007
7	0.180	0.984	0.931	0.999
8	0.001	0.001	0.002	0.004
9	0.133	0.001	0.089	0.211

These results indicate that the slot machine proposes somewhat realistic slot sizes although it proposed too optimistic slot sizes for the days July 12th and July 19th. On July 12th there were approximately 37 percent more hygienist treatments compared to average day which decreases assistant time significantly. Reasons why the slot machine occasionally proposes too optimistic slot sizes is further discussed in chapter 7.1.

5.3 Verification of the slot machine using measures

Usually, when determining whether or not scheduling is beneficial, these measures are used: customer waiting time, provider’s staff idle time and overtime. In this master’s thesis provider’s staff idle time was replaced with provider’s staff capacity utilization rate. It is not meaningful to measure both staff idle time and capacity utilization rate since they correlate to each other: if staff members idle, it decreases capacity utilization rate. Measures used in this master’s thesis are: utilization rates for resources, employee break time, employee overtime and customer waiting time as well as customer satisfaction. Every grade is between 4 and 10. It is also important to measure the rate of reservation in order to minimize the effect of low reservation rates to these measures.

Measures are divided into three categories: resource effectiveness, customer promise and working time realization. Resource effectiveness consists of utilization rate measures, customer promise contains customer waiting time as well as customer satisfaction and working time realization consists of employee overtime and break time. Every category gets a grade as a weighted average and an overall grade for each day is formed as a weighted average of every category's grade. An example of forming each category's grade and overall grade is in table 9.

Table 9. The formation of overall grade (author)

Resource effectiveness		
Resource	*Grade*	*Weight*
Room	4,1	20 %
Doctor	9,4	30 %
Nurse	5,9	25 %
Hygienist	4,7	25 %
Categorys grade		**6,3**
categorys weight		**60 %**

Customer promise		
Customer	*Grade*	*Weight*
Waiting time	7,1	50 %
Satisfaction	9,1	50 %
Categorys grade		**8,1**
categorys weight		**30 %**

Working time realization		
Employee	*Grade*	*Weight*
Overtime	7,1	65 %
Break time	9,1	35 %
Categorys grade		**7,8**
categorys weight		**10 %**

Overall grade	**7,0**
Rate of reservation	94,8 %

As one can see from the above table, since resource effectiveness category's weight is much bigger than in other categories, overall grade is closer to that category's grade than to others. Mean without weighting would be 7.4 instead of being 7.0.

Modified CAM-I capacity model in Megaklinikka

Capacity utilization is calculated using Megaklinikka modified CAM-I capacity model which is presented in figure 26.

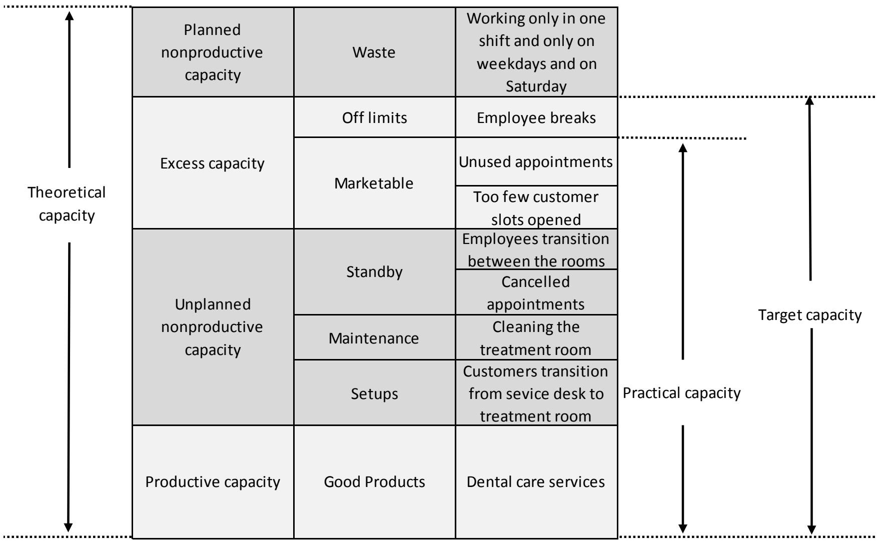

Figure 26. Modified CAM-I capacity model in Megaklinikka (author)

As one can see from the above figure, there are some differences in this model compared to traditional dental care model. For example, in this model there are employees' transition between the rooms instead of customer's transition between the rooms and too few customer slots open which is not the case in the traditional model.

The main difference between this model and traditional dental care model is the block sizes. For example, cleaning the treatment room block size is bigger in traditional dental care model because treatment rooms are cleaned after every procedure, whereas in Megaklinikka all treatments are done at once, and only after that rooms are cleaned.

Traditional model also has a higher no-show. In traditional model unused appointments are rare while in Megaklinikka's case it is rare to have full reservation rate. It would be too inaccurate to adjust all block sizes into right sizes without conducting a case study from both traditional and single visit models: in Megaklinikka CAM-I capacity model and in traditional CAM-I capacity model block sizes are directional.

Calculating utilization rate for employees

Employee capacity utilization rate is calculated for doctors, hygienists and nurses. It is calculated from practical capacity and employee breaks are subtracted from overall working hours: employee capacity = working hours – breaks. Employee utilization is the time that an employee treats customers. Utilization rate is calculated as in formula (16):

$$Utilization\ rate = \frac{Employee\ utilization}{Employee\ capacity} * 100\ [\%] \qquad (16)$$

For example, if doctor's working hours are from 8am to 4pm and he/she is on a break for 30 minutes, capacity for that doctor is 7.5 hours. If that doctor treats customers for 6 hours, his capacity utilization rate is: (6 / 7.5) x 100 = 80 percent. Since there are several doctors per day, capacity for all doctors is the sum of all doctors' capacity and utilization is the sum of all doctors' utilization. Grades for employee utilization are defined as in formula (17):

$$Utilization\ grade = ((Utilization\ rate - 50) * \frac{1}{7}) + 5 \qquad (17)$$

This function is visualized in figure 27.

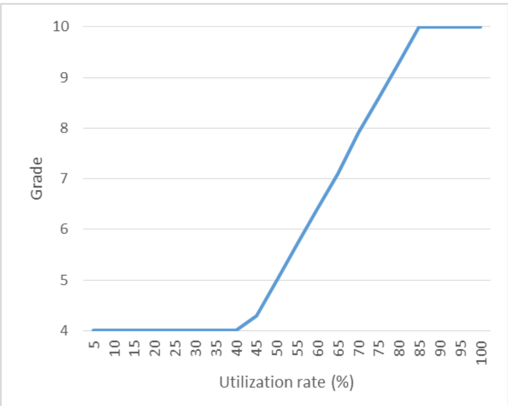

Figure 27. Employee utilization rate grade function (author)

As one can see from the above figure, if the utilization rate is lower than 40, grade is four and if the utilization rate is higher than 85, grade is ten. Values between 40 to 85 increase linearly as utilization rate increases.

Calculating utilization rate for rooms

Room capacity utilization rate is calculated slightly different compared to employees. It is calculated from target capacity instead of practical capacity, since it is impossible to calculate the effects of employee breaks to room capacity. Since there are 18 treatment rooms in the clinic, capacity for the rooms is calculated as follows: opening hours x 18 x 60 minutes. Room utilization is the time when customer is being treated so it does not include for example cleaning of the treatment room. For example, if the clinic is open from 8 am to 4 pm, the capacity of the rooms is: 8 hours x 18 rooms x 60 minutes = 8640 minutes. When the treatment time for the day is 6200 minutes, capacity utilization rate is: (6200 / 8640) x 100 ≈ 72 percent. Grade for room utilization is defined as in formula (18):

$$Room\ utilization\ grade = \left((Room\ utilization\ rate - 40) * \frac{1}{6}\right) + 5 \qquad (18)$$

Function for room utilization rate grade is visualized in figure 28.

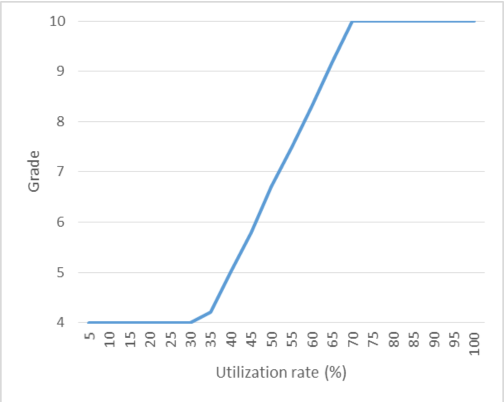

Figure 28. Grading function for room utilization (author)

As one can see from the above figure, utilization rate less than 30 gets a grade of 4 and utilization rate more than 70 gets a grade of 10. The same grade for room utilization is achieved with lower utilization rate compared to employee utilization rate because room utilization was not seen as important as employee utilization and it is more difficult to achieve high room utilization. Grade for room utilization, where utilization rate is between 30 to 70, is increasing also linearly as utilization rate increases.

Calculating employee overtime and break time

Employee overtime is an average overtime of every employee and break time is an average break time of employees. The grade for overtime is calculated as in formula (19):

$$Overtime\ grade = 10 + (mean\ overtime * (-0.5)) \tag{19}$$

This means that every (average) overtime minute decreases grade by 0.5 from the maximum 10. Grade for break time is calculated as in formula (20):

$$Break\ time\ grade = ((Break\ time - 15) * \frac{1}{3}) + 5 \tag{20}$$

Grade function for break is visualized in figure 29.

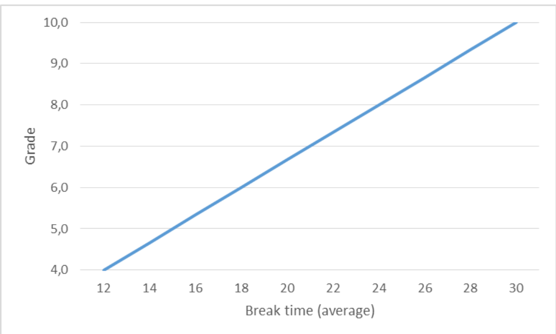

Figure 29. Function for break time (author)

Grade for break time increases as break time increases. One notable aspect is that if break time is more than 30 minutes, break time grade is still 10, instead of decreasing closer to grade 4. This is because employee utilization rate already takes too long breaks into account: if break time is more than 30, employee idles which is shown in decreased utilization rate.

Calculating customer waiting time

Customer's waiting time is the difference between the time when customer enters the room and the time that customer was informed, timestamp in the text message, to come to the clinic (pre-process waiting). Waiting time for all customers is calculated as frequencies instead of average waiting time because average waiting time may be misleading.

For example, if there are two waiting scenarios as followed: in scenario A there are two customers and both of them waits for five minutes. In scenario B there are two customers but one of them do not wait at all and the other customer waits for ten minutes. In both scenarios customers average waiting time is five minutes. Are customers in scenario A as dissatisfied as customers in scenario B? Probably the customer in case B, who waited for ten minutes, is more dissatisfied to waiting compared to both customers in case A. Using average waiting time, customer's perceived value of time is treated as linear instead of treating it as nonlinear. However, one advantage in using average waiting time compared to waiting time frequencies, is that average waiting time is easier to interpret.

Even though, there was not seen correlation between waiting time and overall customer satisfaction (see chapter 4.6), waiting times were treated non-linearly since it is Megaklinikka company's competitive edge not to allow customers to wait. Waiting time frequencies has seven classes and each frequency is multiplied with its class's error points. This is illustrated as an example in table 10.

Table 10. Waiting time error points (author)

Waiting time (minutes)	Error points	Frequency	Class error points
< 0	0	20	0
0-5	1	10	10
5-10	2	9	18
10-15	3	10	30
15-20	5	0	0
20-30	8	1	8
> 30	12	0	0
	Total	**50**	**66**

As one can see from the table above, error points increases as waiting time increases. Error points increasing function is visualized in figure 30.

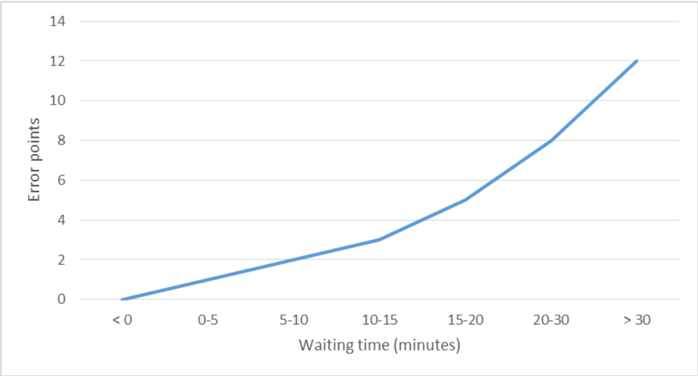

Figure 30. Error points -function (author)

As one can see from the above figure, error points increases in a nonlinear way as waiting time increases. After total error points and number of customers is calculated, waiting time index is calculated as error points divided by number of customers. Waiting time index would be in the above example: 66/50 = 1.32. Since this number does not tell much to a reader, it is converted to grade using as in formula (21):

$$Waiting\ time\ grade = 10 - (Waiting\ time\ index * 1.5) \qquad (21)$$

In above example grade for waiting time would be: 10 - (1.32 x 1.5) = 8. As error points increase, grade decreases linearly but because error points increases nonlinearly, high waiting time frequencies decreases waiting time grade nonlinearly.

Results of the measures

Measurement data was collected from January 1st to August 8th 2016. April 20th the slot machine was taken into use. Data contains grades as well as utilization rates for resources. Since utilization rate and customer waiting time have a strong relationship, one can assume that the slot machine works if either utilization rate increases and customer waiting time remains approximately the same or customer waiting time increases and utilization rate remains the same. Also rate of booking influences the utilization measures, which is why only days where rate of booking is more than 90 percent are taken into account. Results of the day's success grades are presented in appendix 6.

As one can see from the appendix 6, *before column* contains information of specific grade before using the slot machine and *after column* contains information after the slot machine was taken into use. Overall grade has slightly improved after the slot machine was taken into use. Three measures that have improved the most are room utilization (+0.99), customer waiting time (+0.88) and overtime (+0.36) whereas only measure with decreased value is customer satisfaction (-0.08). All categories, resource effectiveness, customer promise and working time realization, have improved. Since in the measures, grade values are similar and the most important aspects were utilization and waiting time, a closer look at utilization rate percentages and waiting time grades is in order (table 11).

Table 11. Utilization rate of resources and waiting time (author)

	change
Room utilization rate (%)	+6.5
Doctor utilization rate (%)	+1.1
Nurse utilization rate (%)	+1.6
Hygienist utilization rate (%)	+1.3
Customer waiting time (grade)	+0.9

As one can be seen from the table 11, utilization rates of all resource classes has increased. Room utilization rate has increased the most, approximately by 6.5 percentage points after the slot machine was utilized, while customer waiting time grade has increased by 0.9. Utilization rates of doctors, nurses and hygienists has increased by over one percentage points.

Increasing customer waiting time by one grade can mean for example:

- 2 customer’s waiting more than 30 minutes, 1 customer waiting 20-30 minutes and 1 customer waiting 10-15 minutes less per day than before
- 4 customer’s waiting 20-30 minutes and 5 customer’s waiting 10-15 minutes less per day than before.

However, it is uncertain if these utilization rates have increased due to the slot machine or due to some other improvements such as improved employee capabilities or improved ability to match capacity to demand. Although it is unlikely that these improvements would have happened at the same time as slot machine was utilized.

6 MAIN RESULTS OF THIS MASTER'S THESIS

The aim of this study was to create the slot machine, a model which output is the optimal number of customers that can be served during a particular day. The objective of the slot machine was to increase provider's utilization rate without increasing customer waiting time. In order to reach this aim research questions RQ1, RQ2 and RQ3 with sub-questions RQ1a and RQ1b were created.

RQ1a: *What is the relationship between customer satisfaction and waiting time?*
Based on the literature review conducted, customer may spend time waiting before, during or after a transaction where waiting time before transaction (pre-process waiting) is considered as the most important aspect of waiting time since it has the greatest influence on perceptions of service quality. The relationship between customer satisfaction and waiting time was strong as customer dissatisfaction increases as waiting time increases. Studies showed that customer dissatisfaction can increase both in a linear and non-linear fashion as waiting time increases. Also customer's activities before and after service were seen as having an effect to the relationship between waiting time and customer satisfaction.

However, empirical study in the case company Megaklinikka showed that there is not a clear relationship between customer waiting time and customer satisfaction as coefficient of correlation was approximately zero ($r = -0.07$) where P-value was approximately 0.16 (two-tailed test).

RQ1b: *What is the relationship between capacity utilization rate and customer waiting time?*
Based on the literature review, having customer to wait can allow greater utilization of the resources. In industry sector waiting time was increasing in a highly nonlinear fashion as capacity utilization rate increases. Similarly, based on this study, utilization rate and waiting time in a dental care environment have a significant relationship: waiting time increases in a nonlinear way as utilization rate increases.

RQ1: *How to add customers with the use of business analytics, without increasing customer waiting time and without decreasing customer satisfaction?*
Business analytics can be used to describe what is happening, to predict what will happen using mathematical techniques to discover predictive patterns and to give the best course of action using for example mathematical algorithms.

Since utilization and customer waiting time have a strong relationship, one can increase utilization at the expense of customer waiting time. In order to increase utilization without jeopardizing customer waiting time, literature review showed that it is possible to minimize customer waiting times and maximize utilization rate using correct customer appointment system. One can for example create sequencing rule based on the consultation time variance: setting customers with low variance at the beginning and customers with high variance at the end of the session improves both utilization rate and customer waiting time. Also knowing and using the service time of the customers can reduce customer waiting time and provider's idle time.

RQ2: *How to measure capacity utilization rate in dental care environment?*
Literature review showed that while measuring performance significant contributors can be correlated with other factors that are the real causes. That is why it is essential to have a variety of outcome measures combined with input measures. In the utilization rate perspective this means one should obtain reservation rate as well since high reservation rate likely increases utilization rate.

Literature review showed also that companies should first reach to consensus of what capacity is. This can be done by for example using CAM-I Capacity Model. In order to measure capacity utilization rate in traditional dental care a capacity defining model was defined on the base of the literature, where practical capacity was seen as dental care services (good products), customer at the reception and customer waiting time (setups), cleaning the treatment room (maintenance), appointments cancelled by customer (standby) and unused appointments (marketable excess capacity). Target capacity was seen as practical capacity in addition with employee breaks (off-limits excess capacity). Theoretical capacity was seen as target capacity in addition to working in only one shift and only on weekdays (planned waste). In the empirical part of this study, a capacity defining model for Megaklinikka was also created.

RQ3: *How to test the functionality of the slot machine in theory and in practice?* Literature review showed that model testing can be conducted in theory by using simulation and in practice by using performance measures. There are several performance criteria to evaluate appointment systems in practice as well as in theory. Often studies list results in terms of the mean waiting time of the customers and the mean idle time as well as mean overtime of the provider. Simulation model in this study used only the mean overtime of the provider and the probability of overtime.

Since customer's perceived value increases as waiting time increases, this study's performance measures in practice used frequency distribution of patients' waiting time: two customers both waiting for five minutes is not the same as two customers waiting zero and ten minutes. Also provider's idle time was changed to provider's utilization rate. Also other factors such as employee break time and reservation rate were taken into account while measuring performance in practice.

Conclusion

Since the overall grade has improved and utilization rates have increased while customer waiting time have decreased after slot machine was utilized, one can conclude that slot machine has improved Megaklinikka company's internal process. It is worth noting that waiting time grade increased almost by 1 grade and even though utilization rates increased only by a small margin, during that time rate of reservation was almost 2 percentage points lower on average. Therefore, it can be stated that business analytics is an effective way to improve capacity utilization while decreasing customer waiting times.

7 CONCLUSIONS

7.1 Discussion about some of the results

Too optimistic slot sizes

Occasionally the slot machine proposed too optimistic slot sizes. One reason for too optimistic slot proposals can be the use of the average customer's expected treatment time which does not necessarily describe arriving customers well enough. That is why slot proposals should be updated constantly. Most of the time when the slot machine receives customer's reservation information, estimated durations were more accurate which lead to more accurate slot proposals.

Also for example doctors expected treatment time's coefficient of variation with average customer was quite high: 0.76. If there was only one customer to add, duration of that treatment could be anything between zero and 61 minutes with 95 percent confidence level. The more the slot machine proposes there to be average customers the more accurate *average (mean)* of average customer's treatment duration is, as seen from the table 12 below.

Table 12. Average customers' treatment duration depending on number of customers to add (author)

Customer's to add	Treatment duration per customer (confidence level = 95 %)
1	61.0
5	39.5
10	34.9
50	29.0
100	27.6
True mean < 27.6	

Relationship between waiting time and customer satisfaction

Customer waiting time and customer satisfaction was not seen having a relationship which indicates that waiting time is not the most important factor in customer's service expectations at Megaklinikka: waiting time is seen only one sector in the whole service process. Other aspects such as price of the service, experiences in other private dental care clinics as well as in public dental care clinics modify the expectations towards Megaklinikka. Customers may also have different perceptions on reasonable waiting time.

Another thing that can influence to low coefficient of correlation is that, customers who answered may have not represented the whole population. Since answering to the questionnaire is voluntary while deciding not to answer to the questionnaire is not necessarily random, should conduct an analysis of non-response. Analysis of non-response examines whether respondents are biased or not: if they are, questionnaire does not represent the whole population. For example, customers who experienced the whole treatment process positively may have had more positive attitude towards answering to the questionnaire compared to customers who experienced treatment process negatively.

Independency of service times assumption

There were some assumptions when using simulation in order to test the slot machine: the service times of customers are independent and all service times for hygienists are gamma distributed. This is not exactly true in practice, since for example in an overbooked day, doctors' likely treats customers quicker than normally and therefore service times are not independent. Also all service times for hygienists were not gamma distributed.

7.2 Suggestions for Megaklinikka

Future developing of the slot machine

Author had next no experience of R-programming and the whole time passed off making the slot machine's basic frame. Current version of the slot machine is a good frame from which to build from. Slot machine should take more factors into account, such as customer age, residence, visiting history and treatment contract type, if these factors correlate with treatment durations. This could be done using linear modelling.

One interesting add-on to make in to slot machine would be to calculate the cost of customer waiting time and the cost of doctor’s idle time and optimize whether there should be one more customer or not depending on which is less expensive: customer waiting time or doctor’s idle time. Or is it actually more profitable to have less customers. However, it might be difficult task to calculate the cost of customer waiting time.

No-show should have taken into account while constructing slot machine. If no-show is relatively big, slot machine should propose bigger slot sizes. However, it is not reasonable to just propose bigger slot sizes at random rather for example calculate the probability that certain customer belonging to certain customer group have higher probability not to show up. If there are two customers belonging to that “high no-show” -group in the same slot, slot proposal could be one bigger in that slot.

Slot machine should also be able to send information about constraining resources to human resources. For example, if adding one assistant could increase number of patients while doctors idle time would reduce, slot machine should send a message to human resources to try to find a nurse or hygienist. But only if, adding assistant would be profitable and likelihood that slots would be full is high.

Improving utilization rate by demand forecasting

It seems reservation rate could be bigger and is maybe a bigger concern than slot proposals at the moment. It is likely more difficult to obtain customers nowadays since compensation to the customer from Kela has reduced approximately by one fourth which makes private dental care less attractive option. One option could be to forecast demand in order to match capacity to demand. However, demand forecasting may be difficult using time series models in Megaklinikka since the slot sizes are restricted depending on available resources – it is difficult to know if there could have been more customers in slots, that were already full.

Another challenge in demand forecasting is that forecasts should be done two weeks ahead, since shifts need to plan two weeks in advance. This makes demand forecasting difficulty. Most customers schedule reservation 2-3 days before, and therefore there are not a lot of information about expected treatment durations two weeks earlier. Should therefore reasons for treatments also be forecasted? Reasons for treatment could be grouped with duration's mean and variance which would make forecasting easier: similar treatment distributions belong to group A and other similar treatments to group B. And therefore a number of group A and group B customers would be forecasted. Or maybe one option would be to just use average customers expected treatment duration.

Choosing reasons for treatment

In the slot machine perspective, customers should not be able to choose as many reasons for treatment as they can at the moment: list of reasons should be minimized in order to get more accurate expected treatment durations. Typically, in Megaklinikka coefficient of variation is between 0.2 and 1.8 where *cv* greater than 0.5 can be considered as high. High *cv* means that standard deviation is high compared to mean – values fluctuates around the mean quite much.

Customers probably don't know the difference between ache and sensitivity, the difference between check up and check up and assessment or whether to do teeth removal or not. Choosing similar reasons for treatment should be blocked, for example, if customer selects ache he/she cannot select sensitivity. One way to help customers to select correct reasons for treatment would be to make a "wizard" which asks few questions from customer and selects the right reason(s) for treatment. An example of wizard is in figure 31.

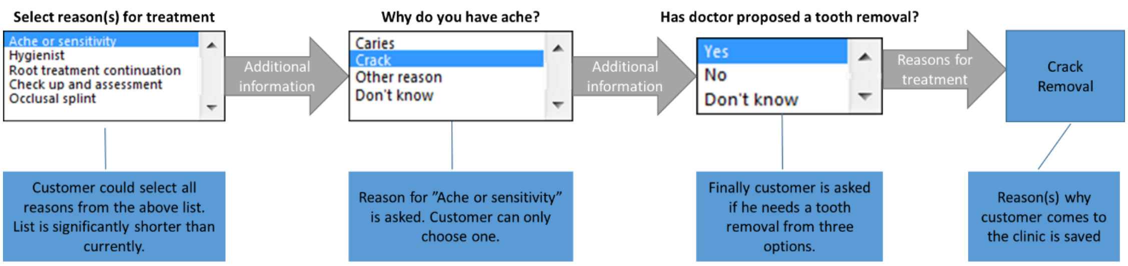

Figure 31. An example of choosing reason for treatment using wizard (author)

As one can see from the above figure, there are five different reasons in this example to choose from: ache or sensitivity, removal, hygienist, root treatment continuation, check up and assessment as well as occlusal splint. Ache or sensitivity is divided to caries and crack with or without tooth removal as well as other reason ache and ache (don't know). Since some of the reasons blocks other reasons, there are a lot less combinations of reasons. Number of different reasons to select for treatment would drop from 1023 to 74 combinations. For example, customer cannot choose caries and crack, rather caries or crack. There should also be a short coverage from all different reasons when selecting reasons for treatment in order to guide customer to select right reasons.

Another thing to consider is that, customer first selects reason for treatment and based on the reason(s) he/she gets to choose available service times from certain slots. If customer selects reason with low variance, he can only select slots in the beginning of the session and customers with high variance could select only slots at the end of the session. However, this can mean lost customers and would work only, if reservation rate doesn't reduce due to these changes: this arrangement assumes that customer does not care what time of the day treatment would be.

Relationship between customer waiting time and customer satisfaction

One interesting aspect to study in the future in Megaklinikka would be to study relationship between customer waiting time and customer satisfaction in the aspect of customer's time pressure. Does customers with time pressure value short waiting times more than customer's without time pressure and if so, how much they value short waiting times as well as what is the acceptable waiting time. Another thing to study considering waiting times is that, how many customers choose Megaklinikka because of the short pre-process waiting times – is short pre-process waiting time an important competitive edge.

Calculating cost of waste

Next thing to consider concerning utilization rates of resources, would be to calculate, what is the cost of unused capacity and what are the reasons for it. Is the reason for unused capacity unused appointments and too few opened customer slots, or is there other factors, such as high no-show rate or cancelled appointments? If it is costly, that customer's reserves appointment but does not show up or at the last moment cancels appointment, maybe reservation fee should be higher. One solution to decrease no-shows and cancelled appointments could be to collect conditional reservation fee: if customer comes to the clinic, reservation fee is compensated back to the customer by giving discount and if customer does not come to the clinic, customer does not get the reservation fee back.

Measuring performance in a holistic way

Since Megaklinikka is data driven company and measures a lot of day-to-day measures, they ought to consider a measurement system, such as Balanced Scorecard, that measures performance in a holistic way. Megaklinikka also renewed its strategies and measurement system would help company to keep track of their strategic goals and to communicate strategy "downstream".

7.3 Validation of the references and future research areas

Since there was between none to a few researches in the field of dental care services concerning topics such as utilization rate, waiting time and appointment systems, this master's thesis references are mostly from the field of health care services. In health care services processes might be slightly different from dental care processes and therefore some of the outcomes could be different in dental care.

Also some of the waiting time references were from fast food services where customers perceived value of time is most likely different compared to dental care services. Analyze in this master's thesis, where the relationship between customer waiting time and customer satisfaction were studied, showed that there is no relationship between customer waiting time and customer satisfaction while according to references, there are strong relationship. On the other hand, for example waiting time was seen increasing in a non-linear fashion as capacity utilization rate increases in industry as in dental care services.

There is a great need to study topics discussed above in a dental care environment since there is a lack of research data in these areas. One thing to research could be to study whether health care service processes differ significantly from dental care processes or not. This could be done for example by defining whether models created to health care services are valid also in dental care services. Even though these topics are researched more extensively in the field of health care compared to dental care, field of health care is still probably lacking research data concerning topics such as capacity and cost effectiveness compared to industry.

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APPENDICES

APPENDIX 1. List of factors and decisions when creating an appointment system (Cayirli & Veral 2003, p. 531).

1. Appointment Rule
   1.1. Block size (number of customers in a block)
      1.1.1. Individual
      1.1.2. Multiple
      1.1.3. Variable
   1.2. Appointment interval (interval between two appointment times)
      1.2.1. Fixed
      1.2.2. Variable
   1.3. Initial block (number of customers given an identical appointment time at the start of the session)
      1.3.1. With
      1.3.2. Without
   1.4. Any combination of the above
2. Patient classification
   2.1. None (all patients assumed homogeneous)
   2.2. Use patient classification for:
      2.2.1. Sequencing patients at the time of booking
      2.2.2. Adjusting appointment intervals to match service time characteristics of patient classes
      2.2.3. Any combination of the above
3. Adjustments
   3.1. For no-shows
      3.1.1. None
      3.1.2. Overbooking extra patients to predetermined slots
      3.1.3. Decreasing appointment intervals proportionally
   3.2. For walk-ins, second consultations, urgent patients, and/or emergencies
      3.2.1. None
      3.2.2. Leaving predetermined slots open
      3.2.3. Increasing appointment intervals proportionally
   3.3. Any combination of the above

APPENDIX 2. List of usually used criteria to evaluate appointment system (Cayirli and Veral 2003, p. 524)

1. Cost-Based Measures (mean total cost calculated using relevant combinations)
    1.1. Waiting time of patients
    1.2. Flow time of patients
    1.3. Idle time of doctor(s)
    1.4. Overtime of doctor(s)
2. Time-Based Measures
    2.1. Mean, maximum, and frequency distribution of patients' waiting time
    2.2. Mean, variance, and frequency distribution of doctor's idle time
    2.3. Mean, maximum and standard deviation of doctor's overtime
    2.4. Mean and frequency distribution of patients' flow time
    2.5. Percentage of patients seen within 30-minutes of their appointment time
3. Congestion Measures
    3.1. Mean and frequency distribution of number of patients in the queue
    3.2. Mean and frequency distribution of number of patients in the system
4. Fairness Measures
    4.1. Mean waiting time of patients according to their place in the clinic
    4.2. Variance of waiting times
    4.3. Variance of queue sizes
5. Other
    5.1. Doctor's productivity
    5.2. Mean doctor utilization
    5.3. Delays between requests and appointments
    5.4. Percentage of urgent patients served
    5.5. Likelihood of patients receiving the slots they requested
    5.6. Clinic effectiveness

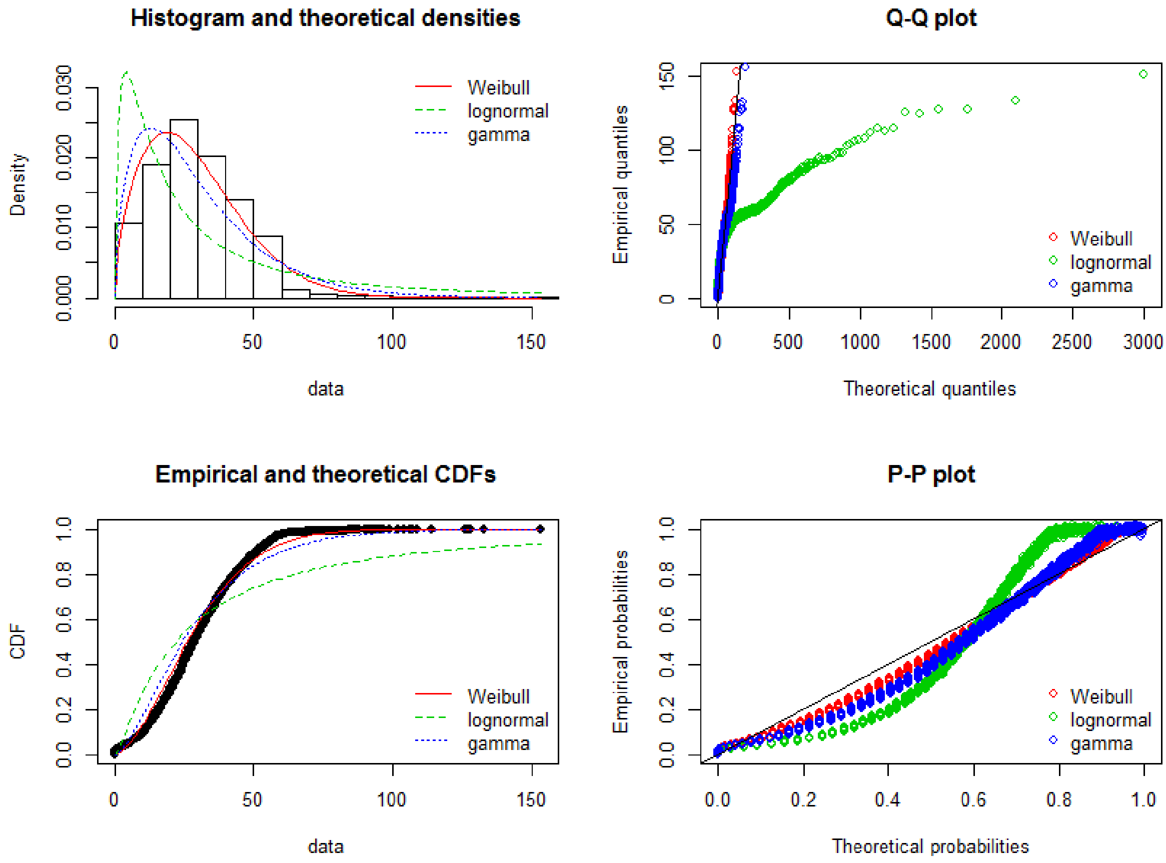
APPENDIX 3. An example of slot proposal pdf-file (author).

	Available resources (break time substracted)							
	Doctors (pcs)	Doctors (min)	Nurses (pcs)	Nurses (min)	Hygienists (pcs)	Hygienists (min)	Assistants (pcs)	Assistants (min)
Slot8	9	480	7.2	440	9	540	16.2	980
Slot9	10	510	8	480	10	600	18	1080
Slot10	10	510	9	540	9	540	18	1080
Slot11	10	420	9	470	9	420	18	890
Slot12	9.5	430	9	460	9	420	18	880
Slot13	9	420	9	480	9	450	18	930
Slot14	9	470	7.6	420	10	530	17.6	950
Slot15	8	420	7	400	8.6	470	15.6	870
Slot16	0	0	0	0	0	0	0	0
Slot17	0	0	0	0	0	0	0	0

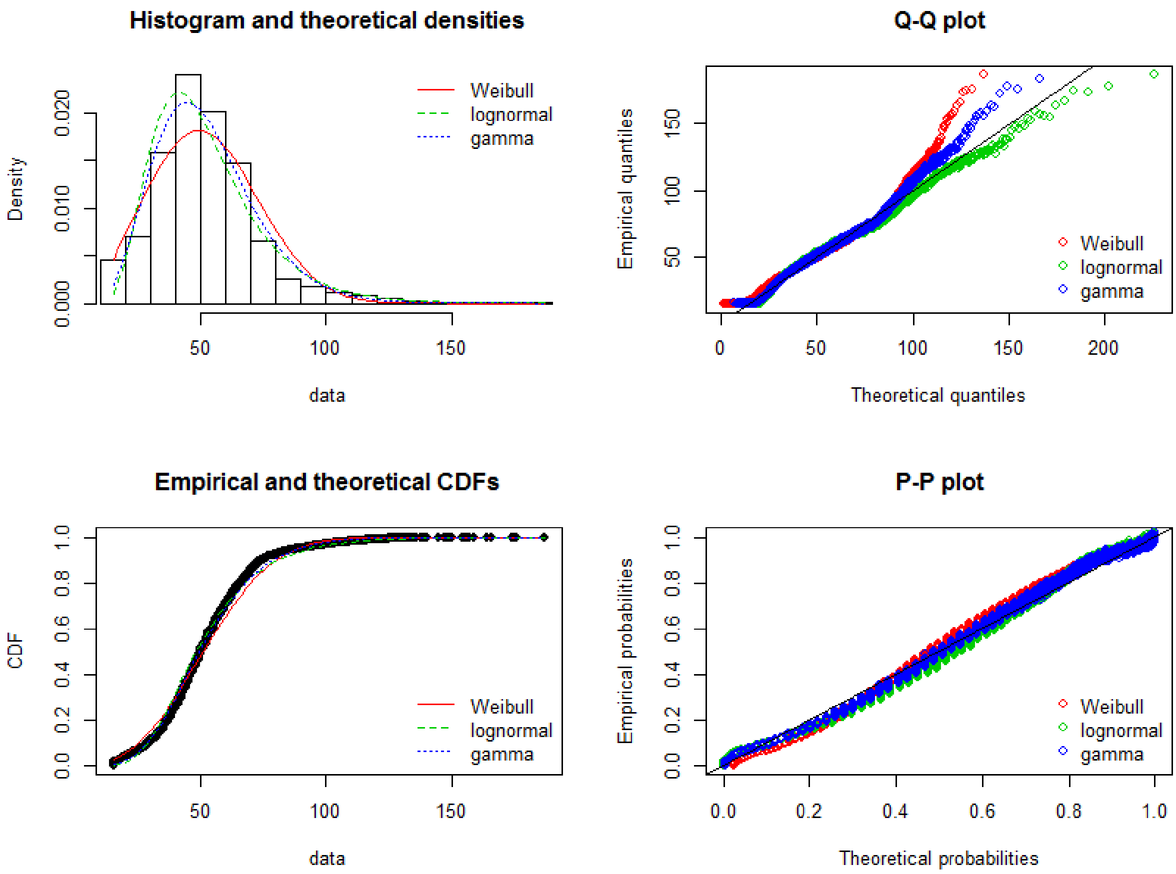
	Available resources (with current customers)					
	Doctor	Assistant	Room	Hygienist	Constraining resource	Alerts
Slot8	100	-80	50	-70	Assistants	No more hygienist treatments!
Slot9	320	280	430	230	Assistants	
Slot10	280	440	440	280	Assistants	
Slot11	290	420	730	220	Assistants	
Slot12	320	650	900	360	Assistants	
Slot13	180	770	890	420	Doctor	
Slot14	200	390	530	390	Assistants	
Slot15	300	550	820	360	Assistants	
Slot16	0	0	0	0		
Slot17	0	0	0	0		

	Slot sizes				
	Customers	Slot capacity	Optimal slot sizes	Slot size 80 %	Slot size 90 %
Slot8	15	13	17	14	15
Slot9	11	15	16	13	14
Slot10	11	18	18	14	16
Slot11	5	11	10	8	9
Slot12	3	13	12	10	11
Slot13	4	10	10	8	9
Slot14	9	15	16	13	14
Slot15	5	13	9	7	8
Slot16	0	0	0	0	0
Slot17	0	0	0	0	0
total	63	108	108	87	96

APPENDIX 4. Reason A, Doctor (author)



APPENDIX 5. Reason A, Assistant (author)



APPENDIX 6. Day's success grading results (author)

	Before (n = 36)			After (n = 34)			
	Min	mean	Max	Min	mean	Max	Change in average
Rate of booking	x	x	x	+0.2	-1.9	-1.9	-1.90
Room utilization grade	4.00	4.93	6.70	4.00	5.92	8.80	0.99
Doctor utilization grade	6.50	8.80	10.00	7.10	8.95	10.00	0.15
Nurse utilization grade	5.40	7.10	8.40	5.00	7.30	10.00	0.20
Hygienist utilization grade	4.40	7.83	9.50	5.10	8.02	10.00	0.19
Resource effectiveness category's grade	**5.70**	**7.36**	**8.50**	**5.80**	**7.69**	**9.70**	**0.33**
Customer waiting time grade	4.00	5.79	7.80	4.00	6.68	8.10	0.88
Customer satisfaction grade	9.00	10.00	10.00	9.00	9.92	10.00	-0.08
Customer promise category's grade	**4.40**	**7.59**	**8.90**	**5.50**	**7.93**	**9.10**	**0.34**
Overtime grade	4.00	7.10	9.80	5.00	7.46	10.00	0.36
Break time grade	7.20	9.01	10.00	6.70	9.13	10.00	0.12
Working time realization category's grade	**6.60**	**8.25**	**9.20**	**7.60**	**8.46**	**9.30**	**0.21**
Overall grade	**6.40**	**7.63**	**8.20**	**6.70**	**7.95**	**9.20**	**0.32**