BSC THESIS INDUSTRIAL ENGINEERING AND MANAGEMENT

FACULTY OF BEHAVIOURIAL, MANAGEMENT AND SOCIAL SCIENCES

ASSESSING THE EFFECT OF EXPANDING E-HEALTH CARE ON THE STAFF CAPACITY IN THE PULMONARY PAEDIATRICS DEPARTMENT

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AUGUST 2024

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Assessing the effect of expanding e-health care on the staff capacity in the pulmonary paediatrics department

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Publication date: August 2024

Number of pages without appendices: 39
Number of pages including appendices: 57

Preface

In front of you lies my thesis, which is written to complete the Bachelor programme in Industrial Engineering and Management at the University of Twente.

This thesis has been conducted externally at Medisch Spectrum Twente. My gratitude goes out to my external supervisor, Mattiènne, who provided valuable feedback and insights that improved the research quality. Moreover, I would like to thank the other employees in the paediatrics department. Your answers to my questions, enthusiasm and interest showed in my research helped in staying motivated and gave me a very pleasant working experience at the department.

My gratitude also goes out to my supervisors at the University of Twente. To Daniela, my first supervisor, who was always available for questions and provided valuable feedback during our regular meetings. These meetings helped me to maintain pace in the research process, for which I am grateful. To Sopany, my second supervisor, thank you for offering a different perspective to the thesis, and providing feedback that helped me improve the final versions of this work.

Lastly, I would like to thank my family and friends for their support and help in thinking along when I got stuck during the process.

Enjoy reading this thesis!

Lydia Mak
August 2024

Management summary

As a summary of this thesis, this section shortly mentions the research context, problem definition, research methodology, results, conclusions and recommendations.

Research context

This research is undertaken at the paediatrics department of Medisch Spectrum Twente, a top clinical hospital in Enschede. Since five years, they make use of an e-healthcare application for children with asthma. The application has a chat function, and by providing patients with home monitoring devices, patients can also send lung functions which can be monitored by healthcare professionals in the hospital.

Problem definition

In this thesis, we aim to solve the core problem "a lack of insight in the time spent on e-health care". The paediatrics department of Medisch Spectrum Twente perceives this as a problem because they are asked by health insurance companies to include more patients in the aforementioned e-health application, but they have little knowledge about what healthcare professional capacity they need to achieve this. To solve the problem, the following research question is formulated: *"What is the effect of expansion of the e-health care on the staff capacity in the pulmonary paediatrics department?"*.

Research methodology

To solve the core problem, a simulation study is conducted. After formulating the problem statement and the research approach, the problem and its context are analysed by providing insight into the e-health care pathway and the time spent by different types of healthcare professionals on asthma e-health care. Next, a solution to the problem is formulated by conducting a systematic literature review to research which type of stochastic simulation model is suitable for predicting the time spent on patients included in the e-health care pathway. Then, we create a conceptual model and specify the architecture and design of the simulation model. Lastly, with the simulation model, experiments are conducted to draw a conclusion about the main research question from the results.

Results

The e-health care pathway is modelled using the Business Process Modelling Notation by splitting it up in three processes. These are for lung functions, chat messages and monitoring. In the literature, we find that a Monte-Carlo simulation is the most suitable simulation method for this research. The stochastic input distributions in this simulation model consist of the number of lung functions received, number of chats received and number of chats sent according to the exponential distribution with parameters retrieved from historical data. Next to that, to be able to calculate the total time spent per week on asthma e-health care, a questionnaire is provided to the healthcare professionals involved with asthma e-health care. The outcome of the questionnaire together with the findings of the data analysis are combined in a formula which sums up the time spent on different activities concerned with e-health care. With the formula, we calculate both the time spent in the current situation with the available data, as well as the time spent with the simulation model. The simulation dashboard shows the output of the calculation, which is comparable with the results of using the dataset with the same number of patients.

Conclusions & recommendations

When increasing the number of patients, a linear increase is observed in time spent for all healthcare professionals, where the time spent for some types of healthcare professionals increases more heavily than for others. Additionally, a shift in task division is observed between the technical physician and asthma nurse, where the technical physician performs percentually more work than the asthma nurse in a situation with 40 included patients, but less work than the asthma nurse in a situation with 100 included patients. The simulation model can be used by Medisch Spectrum Twente to predict the time spent on e-health care when the number of patients is increased, keeping in mind the variability given with the confidence interval. To analyse the robustness of the results, a sensitivity analysis is performed with the variables used in the formula. We conclude that the effect of each variable on the total time spent differs for each healthcare professional, but that the time spent which is calculated by multiplying one variable by another shows higher sensitivity when the variable that is not changed has a high value.

Recommendations to Medisch Spectrum Twente are to evaluate the model's assumptions when the number of included patients increases and to calculate the costs of e-healthcare by using the time spent given as model output and adding any additional costs.

Contents

1 Introduction

This chapter gives an introduction to Medisch Spectrum Twente in Section 1.1 and to the e-health application used in the paediatrics department in Section 1.2. Next, the problem statement is written in Section 1.3 and the research methodology used to solve the problem is described in Section 1.4.

1.1 About Medisch Spectrum Twente

Medisch Spectrum Twente (MST) is located in the centre of Enschede. It is a top clinical hospital, which also offers academic care in a few areas of expertise. MST's four core values are: taking care of its employees; working together with regional healthcare institutions; using technology as a tool for the right treatment and appropriate care; and giving patients control over their own health (*Medisch Spectrum Twente - Topklinisch Ziekenhuis*, nd). This research is executed at the paediatrics department, and more specifically, for the asthma e-health care team within this department.

1.2 About the Puffer app

Asthma is a chronic lung disease, which includes symptoms such as coughing, wheezing, shortness of breath and chest tightness. The severity of symptoms differs from person to person. In some cases, patients may need emergency care in the hospital to treat an asthma attack. Asthma can not be cured, but it can be managed with the right treatment to prevent daily life limitations and improve long-term outcomes regarding asthma self-management from patients. Also, different external factors can increase asthma symptoms, such as having a cold, changes in the weather, dust, smoke, fumes, grass, tree pollen, animal fur and feathers, strong soaps, perfume and other conditions (*Astma*, 2023).

About five years ago, the Puffer app was introduced at the paediatrics department of MST for patients with asthma, with as main goal to prevent exacerbations and emergency care. With home monitoring devices such as a smart spirometer to measure lung functions or a smart inhaler to measure the quality of the medication inhalation, asthma is being monitored from a distance. Via the app, parents and children can communicate with healthcare professionals, which makes it easier to discuss treatment plans. They can also send multimedia or share lung function measurements. The app is being monitored by the asthma team in the paediatrics department (*eHealth astmazorg - Medisch Spectrum Twente*, nd).

The use of the Puffer app has resulted in 85% fewer hospital admissions, 81% fewer ED visits and 83% fewer outpatient visits (van der Kamp, 2023). E-health did cause a task redivision. An asthma e-health team has been started up, which monitors the app and reacts to messages in the chat next to the regular care they provide in the outpatient clinic. Currently, there are about 40 patients included in the app, but there are plans to upscale the usage of this type of care (*Een nachtje gemonitord erover slapen - Medisch Spectrum Twente*, nd). Over the past years, more than a hundred children have been treated by using the e-health app.

1.3 Problem statement

Health insurance companies have asked the paediatrics department to include more patients in the e-health care pathway. These patients can be patients with severe asthma elsewhere in the region, or patients that are already receiving care from MST with less severe asthma. From the paediatrics department, there is a clear indication that there is a lack of insight into the time and costs spent on e-health care, which is the core problem of this research. In Figure 1.1 it can be seen which action problems are a result of this core problem.

In the problem cluster, the lack of insight into what staff capacity is needed to expand e-health care without unbalanced workload is chosen as the most important action problem, as there is currently no temporary solution available for gaining more insight into this problem.

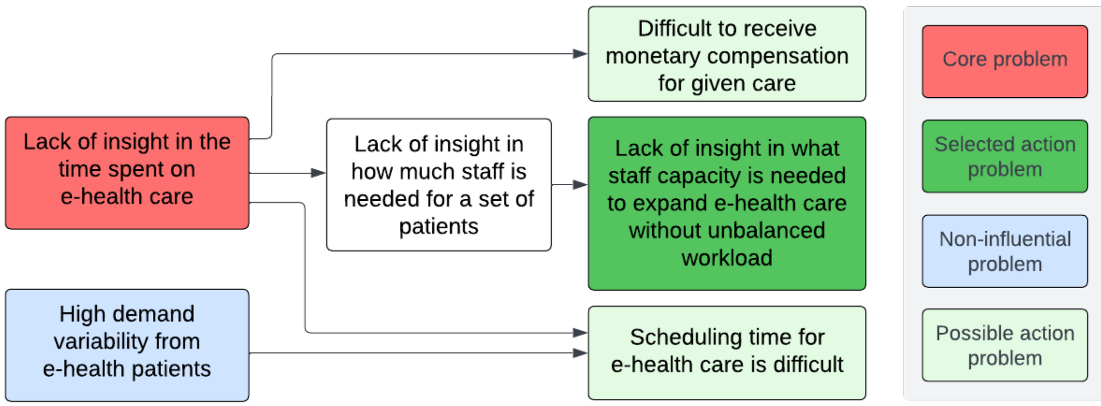


Figure 1.1: *Problem cluster*

According to Heerkens et al. (2017), the norm and reality of the defined action problem should be expressed as a concrete quantifiable variable. It is difficult to measure the core problem, because a lack of insight is not something that can be quantified in a number or percentage. However, the reality in the paediatrics department is that there is currently only an indication of the time spent through their practical experience, but that there is no clear calculation of the time spent on e-health care. Therefore, the norm is that there should be a justified calculation of how much time is spent on e-health care.

1.4 Research methodology

To be able to solve the core problem, a research methodology must be set up. This includes the problem solving approach in Section 1.4.1, the research design in Section 1.4.2 and the research scope in Section 1.4.3.

1.4.1 Problem solving approach

To be able to provide a suitable solution to the presented problem, the following deliverables will be provided to MST:

- A stochastic simulation model to calculate the needed capacity for a desired set of patients.
- A dashboard that summarizes the main findings of the model.

The Managerial Problem Solving Method (MPSM) is a framework commonly used for solving managerial problems for Industrial Engineering and Management research (Heerkens et al., 2017). However, most steps are broad and thus do not fit the creation of a stochastic simulation model specifically, which is one of the deliverables to MST. Therefore, the MPSM is combined with a research method for modelling and simulation. We follow the first three steps of the MPSM, defining the problem, formulating the approach and analysing the problem, after which we will continue with the simulation methodology.

As described by Montevechi et al. (2016), eight methods can be identified to guide the development of simulation projects. From these eight methods, two have a greater number of activities to be performed. This does not necessarily mean that the other methods do not include those activities, but they are not explicitly written down in the methodology. Therefore, it is preferred to use a methodology with a greater number of steps, as it gives useful guidance for the simulation project. Since the methodology from Balci (2011) is the most recent of the two, this is the methodology that will be applied for this bachelor thesis after the third step of the MPSM has been finished. The methodology can be seen in Figure 1.2.

The chosen research methodology follows 9 steps, where the arrows in the methodology show the interactions between the different steps. These interactions exist because the design of the simulation model sometimes requires a step back when insights from a next step are obtained. The use of the steps in the simulation research methodology will be explained further in the research design.

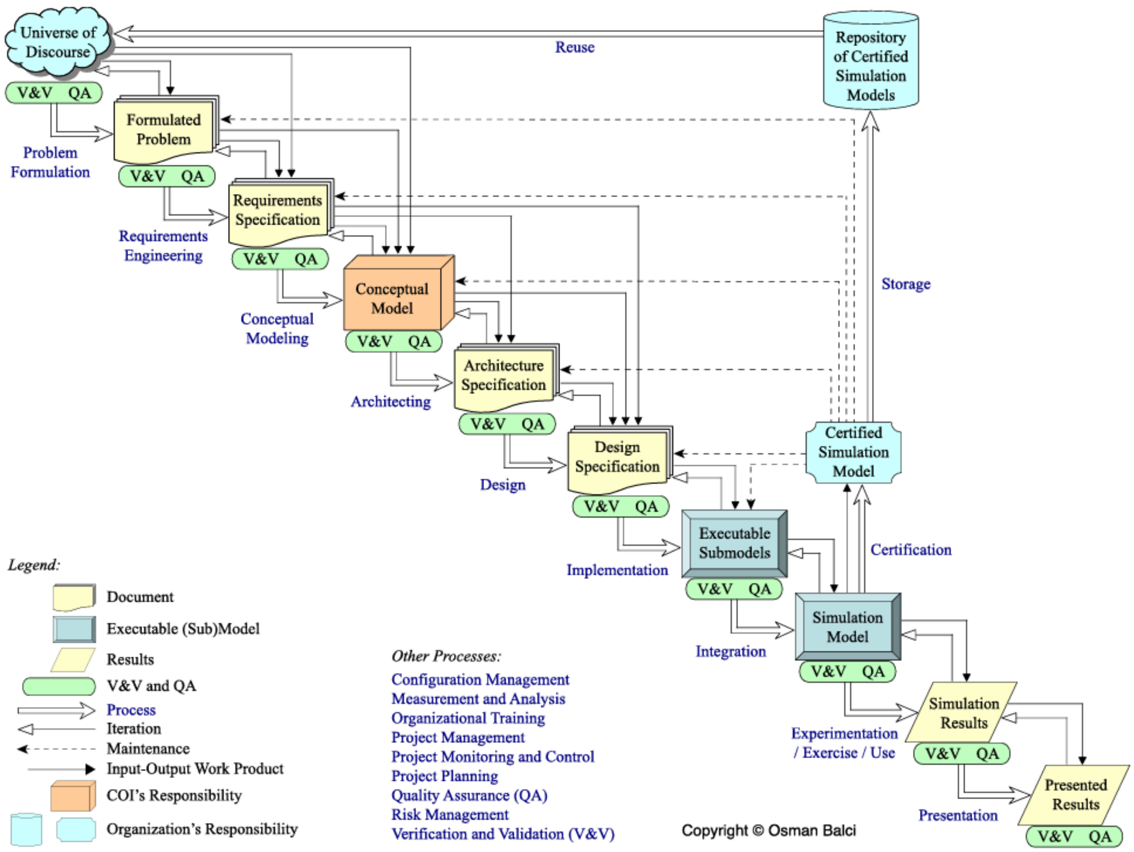


Figure 1.2: *Simulation project methodology (Balci, 2011)*

1.4.2 Research design

To solve the problem as described in Section 3, the main research question has been defined as:

"What is the effect of expansion of the e-health care on the staff capacity in the pulmonary paediatrics department?"

To answer this question and to provide a structured way of constructing the simulation model, a few sub-questions are defined. These sub-questions are based on the simulation project methodology as described by Balci (2011).

According to Heerkens et al. (2017), the first step of the MPSM is to formulate the problem statement, which has been done in chapter 1.3. Next, the approach should be formulated, which is the purpose of this chapter. The third step of the MPSM is about analysing the problem and its context. This will be investigated with the first two sub-questions.

1. *"How can the e-health care pathway for asthma patients in the paediatrics department be defined?"*

2. *"How much time is currently spent by different types of healthcare professionals on asthma e-health care?"*

2.1 *"How much time is spent on the different healthcare activities by each type of healthcare professional?"*

2.2 *"How can the total time spent by each type of healthcare professional be calculated?"*

After analysing the problem context, the next step of the MPSM is to formulate (alternative) solutions. Here, the simulation project methodology as proposed by Balci (2011) will be introduced. The methodology starts with problem formulation, which has been addressed in chapter 1.4.1. Next, the requirements need to be specified. Requirements of the stochastic simulation model are that the characteristics of e-health care need to be incorporated in the model, so the requirements follow from the previous sub-question. The next step is to create a conceptual model, for which it is necessary to know the type of stochastic simulation that needs to be used. To find the appropriate type of simulation model, sub-question three is formulated.

3. *"Which type of stochastic simulation is suitable for predicting the time spent on patients included in the e-health care pathway?"*

The third step of the simulation methodology is creating a conceptual model. Next, the architecture needs to be specified, which means that a suitable simulation software should be chosen. Then, according to the chosen architecture, the design has to be specified. To finish these steps, sub-question four has been formulated.

4. *"How should the e-health care pathway be modelled into a stochastic simulation model?"*

The findings of sub-question four can be used to implement the design into executable submodels and to integrate those into a simulation model. For this, no separate sub-questions are needed, because this step corresponds to the programming of the findings in the previous sub-questions. The next steps in the simulation methodology are to experiment with the model to obtain simulation results and to present the results. These steps are performed in sub-question five.

5. *"What is the relationship between the number of patients included in e-health care and the health care professional capacity?"*

After completing all the research questions, recommendations will be given to Medisch Spectrum Twente regarding the outcomes of the research.

1.4.3 Research scope

Due to time constraints, there are some boundaries on what this thesis can include. First of all, the paediatrics department has a lack of insight in the time spent on e-health care, which also results in lack of insight into the costs of e-health care. This is something that would be very useful to include in the research, but which will not be included in the simulation model. Because the costs spent on e-health care are almost directly related to the time spent on e-health care, the outcomes of the model can still be used by the paediatrics department to estimate costs.

Furthermore, it could be interesting to integrate the planning of the regular appointments in the paediatrics department as well when investigating the time spent on e-health care, as the appointment schedule also has influence on the moments of time that medical professionals spend time on the Puffer app. However, this would significantly increase the modelling problem, and take the focus away from gaining insight into the time spent on e-health care specifically. Therefore, it has been decided to only look at the time spent on the e-health care pathway in the paediatrics department.

2 The e-health care pathway

To be able to get insight in the time spent on the e-health care pathway, it is important to understand how the e-health care pathway for asthma patients is defined. This chapter answers the following research question: *"How can the e-health care pathway for asthma patients in the paediatrics department be defined?"*. First, an explanation on business process models is provided in Section 2.1, after which the visualisation of the e-health care pathway in a business process model is shown in Section 2.2. The presented information is gathered by observations and interviewing the healthcare professionals from the asthma team at Medisch Spectrum Twente.

2.1 Business process model

For visualising the e-health care pathway the Business Process Model and Notation (BPMN) has been used. BPMN provides "a notation that is readily understandable by all business users, from the business analysts that create the initial drafts of the processes, to the technical developers responsible for implementing the technology that will perform those processes, and finally, to the business people who will manage and monitor those processes" (Weske, 2012).

In the e-health care pathway, there are three events that trigger the healthcare professionals to put time into the e-health care pathway. Those are a lung function or a chat being sent by patients and staff members monitoring the patients included in the Puffer app. Therefore, the business process model has been divided in three activities, where the activities modelled are all from the perspective of the asthma team in the paediatrics department. In these processes, the symbols as presented in Figure 2.1 are used. Additionally, e-health patients also sometimes visit the outpatient clinic for an appointment. Because we do not consider this as a part of e-health care in this thesis, a more elaborate description of this process is given in Appendix C.

Figure 2.1: *Symbols used in the business process model (Bizagi, One Platform; Every Process. User Guide Modeler, nd)*

The green circles represent the starting events. A process can be started by the healthcare professionals *(Figure 3.1)*, because a message from a patient is received *(Figure 3.2)* or because a certain condition is satisfied *(Figure 3.3)*. The red circles represent the end events. Processes can end normally because no further action is needed *(Figure 3.4)*, they can be terminated because a patient is excluded from e-health *(Figure 3.5)* or ended with a message because a concluding chat message is sent by the healthcare professionals *(Figure 3.6)*. Also, a message intermediate event can occur if an (additional) message is being received in the middle of a process *(Figure 3.7)*. Each task being performed by the healthcare professionals is modelled as an activity *(Figure 3.8)* and if a certain situation requires another process to start, a subprocess is included in the model *(Figure 3.9)*. In the model, exclusive gateways are used such that a path is taken based on a condition being satisfied

(Figure 3.10). Also, parallel gateways are used to separate paths without checking for any conditions in case a patient needs to go through both paths *(Figure 3.11)*. Lastly, data objects are used to indicate where the healthcare professionals need to document any specific information *(Figure 3.12)*.

2.2 Visualisation of the e-health care pathway

By using the BPMN, the e-health care pathway and all the steps involved can be modelled. This visualisation gives a good overview of the daily activities of the healthcare professionals and can be used in the next chapters to indicate which data is needed as input variables for the stochastic simulation model.

2.2.1 Lung function

When patients regularly send lung function measurements, the asthma team can monitor the lung functions that are being performed in a home environment and anticipate any decrease in lung function timely. In Figure 2.2 it can be seen which steps are performed by healthcare professionals when a lung function is received.

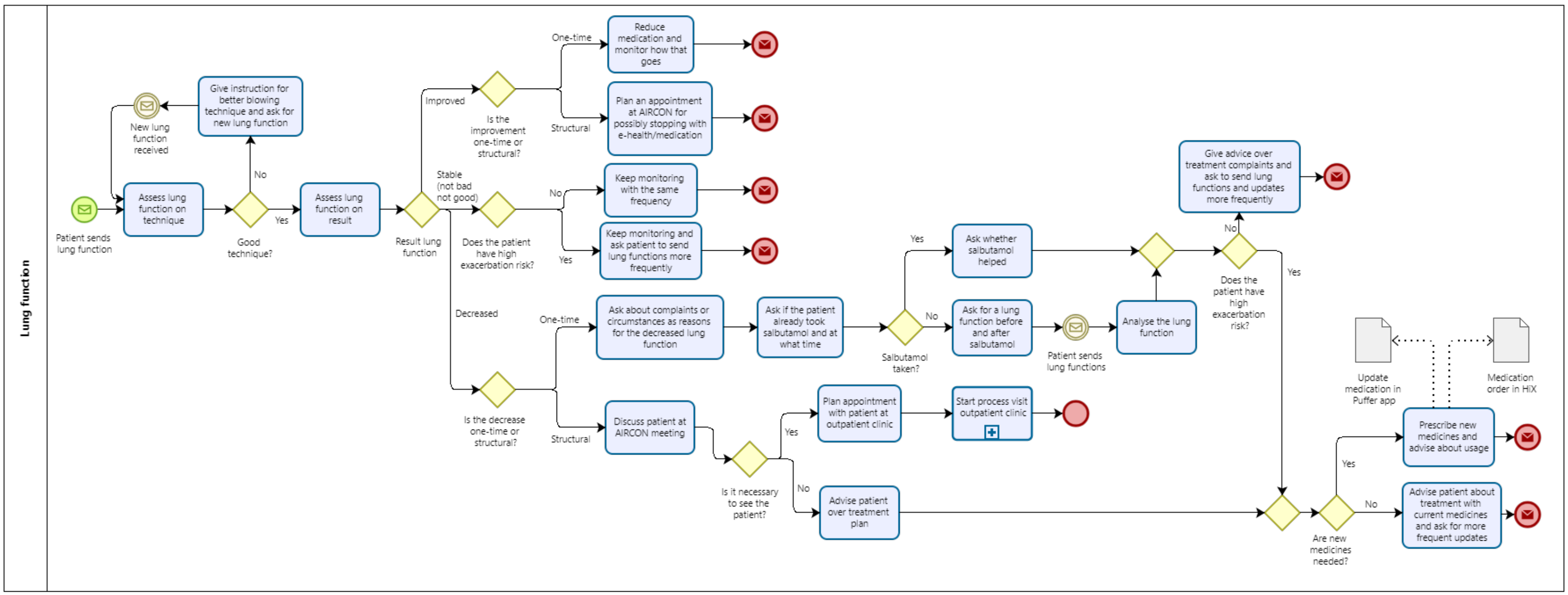


Figure 2.2: Lung function process

When blowing a lung function with a spirometer, it is important that the right technique is used. This is difficult to assess from a distance, but the curve of the spriometry graph can give indications on whether the air is blown out correctly, and video's can be sent in the chat to show the blowing technique. Because the blowing technique can be incorrect, but also because there can be other circumstances that can result in a decreased lung function, it is important for the healthcare professionals to ask about the patients' circumstances.

Also, a lung function before and after salbutamol can be requested by the healthcare professionals. The results of this indicates whether the medicine helps enough or whether additional medicines are needed. For children with high exacerbation risk, more often additional medicines and closer monitoring is needed. An exacerbation is a severe asthma attack, which is for the hospital considered as an exacerbation when the patient has to be admitted to the hospital or when the medicine prednison has to be used. High exacerbation risk can occur because a patient has had many exacerbations before, because of allergen exposure, or other factors, which will be further elaborated in chapter 3.1.2.

2.2.2 Chat message

Patients can send a chat message at any time. Reactions to the chat follow within one working day usually. The app also includes an emergency button for urgent asthma complaints, to which a response is given by the asthma team as soon as possible. This is in practice within about 10 minutes during working hours and outside of that usually within one hour. It should be noted that sometimes questions that are not asthma related are asked in the e-health app, but for modelling the e-health care pathway we will assume that the received chats are about asthma. In Figure 2.3 it can be seen which steps are being performed by healthcare professionals when a chat message is being received.

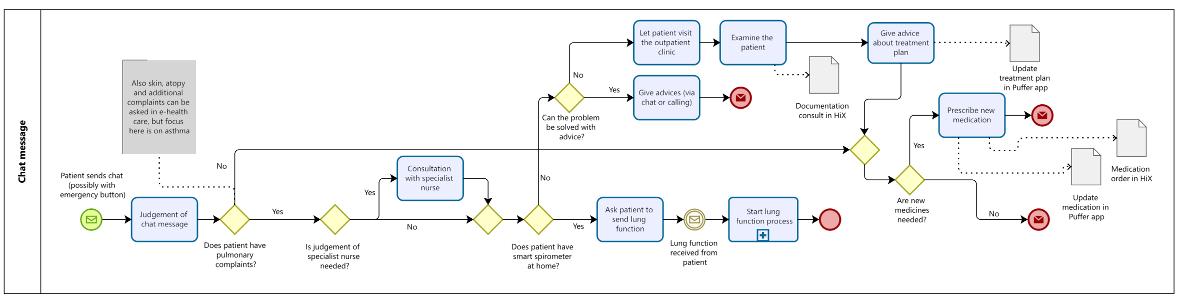


Figure 2.3: *Chat message process*

The chats are being monitored and answered by the asthma nurse and the technical physicians. If needed, consultation with the specialist nurse is done or in severe cases with the paediatricians. If the asthma nurse or technical physicians notice that different medication is needed, this needs to be prescribed by the specialist nurse or paediatrician. When advice is given, this can be a single text with explanation on what to do, but it could also be a longer chat interaction in case the patient has questions about the advice given.

2.2.3 Monitoring

Monitoring is mentioned by the healthcare professionals as the most time consuming process of the e-health app. Many patients do not regularly send chat messages or lung functions, which means that they need to be reached out to by the hospital. This process starts with a conditional event, because there must be inactive patients for the process to start. When it is started, first chats are sent to those patients, and when reactions do not follow for a long time they will also be called. If after that still no reaction is given, then the process will start again when a new monitoring moment takes place.

Also, approximately every month every patient is being screened and a status update is written in their electronic patient file. In this status update, developments in lung functions, medication adherence, complaints communicated via the chat and other important updates are summarised. In Figure 2.4 both monitoring processes can be seen.

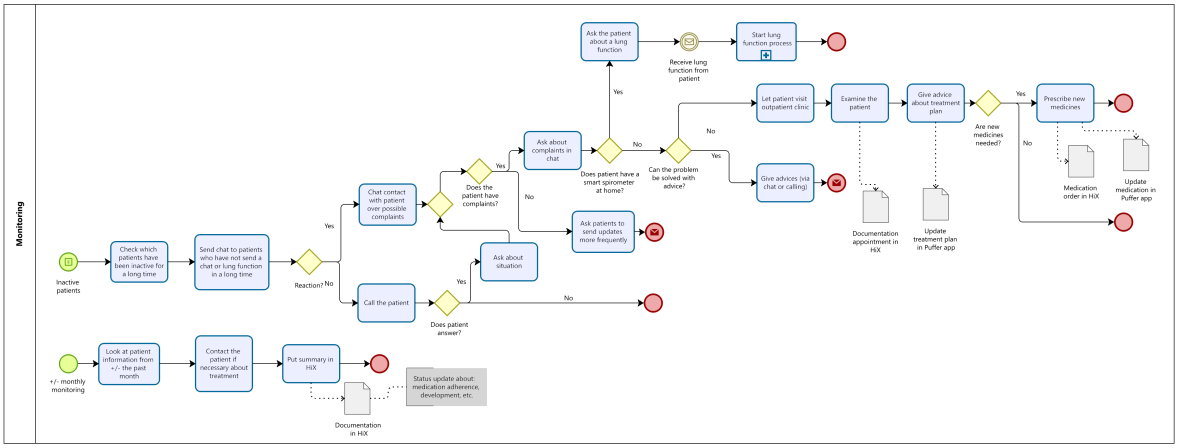


Figure 2.4: *Monitoring process*

2.3 Difference with conventional pathway

In the conventional pathway for asthma patients, patients come to the hospital when they experience asthma symptoms. Then a lung function test is performed in the outpatient clinic after which conclusions are taken about treatment plans. However, taking this test at the hospital might not always represent the situation with severe complaints or with the allergic exposures that a child has within its home environment. The main difference with the e-health care pathway is that these lung function tests are performed and monitored more often and in the home environment. This allows for quicker and more tailored changes in treatment plans and therefore usually prevents symptoms from worsening. As described in Section 1.2, using e-health care prevents most emergency visits. Additionally, the aim of the e-health care pathway is to replace the regular outpatient clinic visits. These emergency and outpatient clinic visits require much time from the medical staff, so reducing those by using e-health care is beneficial from a staffing perspective if e-health care proves to take less time.

2.4 Conclusion

To conclude, this chapter answers the sub-question: *"How can the e-health care pathway for asthma patients in the paediatrics department be defined?"*. The e-health care pathway can be split up in three processes, which are the lung functions, chat messages and monitoring. The processes are modelled in a business process model, and have complex patient journeys with interactions between the different processes. These three processes partially replace the emergency care and regular outpatient clinic visits at the paediatrics department.

3 Theoretical framework

In this chapter, first a theoretical perspective to the research is given in Section 3.1. Next, sub-research question 3 is answered by a systematic literature review, of which the main findings are discussed in Section 3.2. Lastly, additional literature is reviewed in Section 3.3 to gain more insight into how to apply the stochastic simulation method found in Section 3.2.

3.1 Theoretical perspective

The theoretical perspective first describes the impact of implementing e-health care in a hospital in Section 3.1.1. Thereafter, factors contributing to severe asthma complaints are studied in Section 3.1.2.

3.1.1 Impact of e-health care

The outcome of this thesis will be contributing to planning and control decisions made by Medisch Spectrum Twente. According to Hulshof et al. (2012) there are four hierarchical levels in decision-making, which are strategic, tactical and operational, where operational is subdivided in offline and online decision making. This thesis will eventually impact the strategic planning, as it will be predicting the needed resource capacities, in this case, staffing, over a relatively long planning horizon. Additionally, it impacts the tactical planning, which for MST involves decision-making about whether to include more patients in e-health care.

In their research, Hulshof et al. (2012) also identify six care services as offered by care facilities accommodated with examples. E-health care as provided with the Puffer app can be seen as home care services, as the patient receives care at the patient's home by being monitored from the hospital. In practice, this replaces partly the ambulatory care services, emergency care services and inpatient care services, as it reduces the number of hospital visits.

For predicting the needed resource capacities in the future, a stochastic simulation model needs to be made that considers the variability in time spent on e-health care on different days. This is suitable for the system that we are going to model, because a stochastic simulation has "at least some random input components" (Law, 2015). These random input components have to represent the high variability in patient demand at the paediatrics department. In the stochastic simulation model, we need to consider the increased staff capacity needed for including more patients in the Puffer app, but also keep in mind that this decreases the ambulatory, emergency and inpatient care services.

3.1.2 Factors contributing to asthma complaints

From conversations with healthcare professionals involved with asthma care, it became clear that most time is spent on patients when they experience an asthma exacerbation, which is a severe asthma attack. This is also the case for e-health care. In case e-health patients experience the first symptoms of an asthma exacerbation, they reach out to the hospital via the chat. The goal of e-health is to prevent an exacerbation by providing the needed care before the exacerbation takes place. Since there can be multiple reasons why asthma symptoms are triggered, and thus more time is spent by healthcare professionals on e-health care, a literature review has been performed to identify factors that contribute to asthma complaints or a severe asthma attack, of which the search log can be seen in Appendix D.

From the literature review, we concluded that many different factors contribute to asthma complaints, and thus to more time spent by healthcare professionals on e-health care. Seasonality is an important factor, which could be explained by the presence of viral respiratory infections and allergies. Also, a previous exacerbation has often been mentioned as a strong predictor. Since there are many factors contributing to the time spent on e-health care, a stochastic simulation model is a suitable method that allows for variation in the time spent per day by healthcare professionals.

Seasonality was first mentioned by Covar et al. (2008), who observed that exacerbations have the greatest chance of occurrence in the fall, and the least chance of occurrence in summer. Teach et al.

(2015) support this by mentioning that some factors influence exacerbation risk all year around, such as pulmonary functions and previous exacerbations, but factors such as allergies vary by season. Leung et al. (2023) quantified this more, by writing that "up to 80% of childhood asthma attacks are associated with viral upper respiratory infections", in which peak seasons can be defined from March to June and September to December.

The occurrence of previous exacerbations has often been mentioned as an important factor. Covar et al. (2008) even concluded that a history of previous exacerbations is the most important risk factor for exacerbations.

Since many factors contribute to asthma exacerbations, Oland et al. (2017) have grouped several factors contributing to a higher exacerbation rate. They mention "environmental risk factors", "adherence with asthma medication", "psychological functioning" and "wellness and lifestyle", which all have complex interactions between each other. Engelkes et al. (2016) did not group factors, but mentioned eczema, respiratory infections, high blood eosinophilia, specialist visits for asthma, previous exacerbations and ICS prescriptions as significant predictors for an asthma exacerbation.

Thao et al. (2023) and Sotir et al. (2003) did not mention previous exacerbations or seasonality but they both saw a relationship between allergies and asthma exacerbations. Since Medisch Spectrum Twente gathers data on allergies of e-health patients, this is a factor that could be taken into account in the stochastic simulation model as well.

3.2 Type of stochastic simulation used

When considering stochastic simulation models, there are different types of models to apply. Therefore, the following sub-question has been formulated: *"Which type of stochastic simulation is suitable for predicting the time spent on patients included in the e-health care pathway?"*.

To answer this sub-question, a systematic literature review has been performed, of which a more elaborate explanation and theoretical framework can be seen in Appendix E. After performing the search, no literature could be identified that applies a stochastic simulation model to predict the time spent on an e-health app. However, there is existing literature on stochastic simulation models applied in healthcare settings to address capacity issues such as bed allocation, nurse staffing etc. The characteristics of the models used in other healthcare settings are studied to understand whether the model could be used for modelling the e-health care pathway.

Four studies have been analysed and the types of stochastic simulations mentioned are summarised in Table E.4 in the Appendix. From the literature review, it could be concluded that five stochastic simulation models have been applied in healthcare settings, which are discrete-event simulation, discrete-time simulation, agent-based simulation, simulation optimization and Monte-Carlo simulation.

Discrete-event simulation has been applied the most in the reviewed literature. Discrete-event simulation was found to be most useful because of its ability to model complex discrete, dynamic and stochastic systems in healthcare (Wang, 2023), because it can incorporate fluctuating arrival rates (Laan et al., 2018) and because it has been applied for evaluating the time and costs spent on a care process (Anderson et al., 2017). This seems like a suitable simulation method. However, to correctly model discrete event simulation, it is necessary to have available data on inter arrival times, to be able to model the occurrence of events. In this research, we only have access to data on a daily basis, so another suitable simulation method should be found.

Discrete-time simulation models in fixed time increments and can be used if only daily numbers of arrivals and discharges are known instead of inter arrival times (Kakad et al., 2023), which already seems more applicable than discrete-event simulation with the available data. Laan et al. (2018) implemented discrete-time simulation to make a discrete time queuing model, which updates the state of the model for a fixed time step and is able to model stochasticity in patient arrivals. This is suitable for the available data for modelling patient arrivals, but updating the model for every time instance is not necessary, because we want to determine the patient arrivals based on sampling from a distribution, instead of based on the previous state of the model.

Simulation optimization is about the optimization of a given objective function satisfying some constraints (Wang, 2023). As the aim of the simulation model is to find out how much time is spent on e-health, instead of optimizing the time spent on e-health, this method is also not relevant.

Agent-based simulation is useful for "modelling systems where the decisions of, and interactions between, individual agents and their actions are likely to affect those aspects of overall system behaviour under study" (Kakad et al., 2023). This type of simulation could be suitable for this thesis. However, the available data is not detailed enough to model interactions between different agents, which is why it would be difficult to implement this simulation without making too many assumptions.

Monte-Carlo is the second most popular method to model healthcare operations, and is used to estimate an unknown function by generating independent sample paths by applying random numbers (Wang, 2023). Since we are interested in the average time spent per week based on probability distributions generated from historical data, the Monte-Carlo simulation would be a suitable simulation method for this research.

3.3 Application of Monte-Carlo simulation

To gain more insight in the way that Monte-Carlo simulation is applied in hospital capacity modelling, additional literature has been reviewed. By using the search string '("Monte-carlo") AND (hospital OR healthcare OR "e-health") AND ("time spent")', seventeen articles were found on PubMed, of which four remained after exclusion. A table containing the findings of these articles can be seen in Table F.1 in Appendix F.

From the literature, we can see that all articles describe the usage of probability distributions as model input. Job et al. (2023) have drawn input parameters from a distribution based on 12-month retrospective patient data for their Monte-Carlo simulation. They use either Beta, Gamma or Normal distribution. Antonanzas et al. (2006) use probability distributions for most input parameters, of which either beta distribution, Dirichlet distribution or log-normal distribution. Lingervelder et al. (2022) mention that "all input parameters were represented by a distribution to acquire probabilistic values and 95% confidence intervals". However, no specific distribution type is mentioned. Maniadakis et al. (2006) have assigned distributions to transitions between states, asthma exacerbation occurrence probabilities and resources utilisation rates. They also iterated the Monte Carlo simulation model 5000 times, while the other three articles mention 10000 repetitions.

Furthermore, all four articles mention that they perform a sensitivity analysis. As a reason for performing a sensitivity analysis, Lingervelder et al. (2022) mention that they perform it "to determine the effect of individual parameters on the cost outcome". Maniadakis et al. (2006) state that "to assess the robustness of the model and the validity of the results multiple one-way sensitivity analyses were performed in most important underlying input data". Especially the newly gathered data in this research is likely to have uncertainties. Therefore, performing a sensitivity analysis can give insight into which assumptions influence the output of the stochastic simulation model the most.

3.4 Conclusion

To conclude, the theoretical perspective shows that this research will impact the hospital's strategic and tactical planning and that e-health results in a decrease of the needed ambulatory, emergency and inpatient care services. Next to that, several factors contributing to asthma exacerbations have been found in the literature, which underline the need for a stochastic simulation model.

With a systematic literature review, we answer sub-question 3: *"Which type of stochastic simulation is suitable for predicting the time spent on patients included in the e-health care pathway?"*, where we find that a Monte-Carlo simulation is the most suitable simulation method.

Lastly, we conclude from the literature research on how to apply the Monte-Carlo simulation that the designed Monte-Carlo simulation model should exist of input parameters that are sampled from a distribution which is fitting to the available data. Next to that, the model must be iterated about 5000-10000 times. Lastly, the most important input parameters must be identified, and we must perform sensitivity analyses to test the effect of these parameters on the simulation outcomes.

4 Current situation

To construct the simulation model, we first need to understand the current situation. We do this by answering the sub-question *"How much time is currently spent by different types of healthcare professionals on asthma e-health care?"*. First, we perform a retrospective data analysis in Section 4.1 to find out how often the different healthcare activities take place. Furthermore, we hand out a questionnaire to the healthcare professionals of the asthma e-health team, of which the findings are presented in Section 4.2. This gives more insight into the time spent on different healthcare activities by each type of healthcare professional. With those outcomes, the calculation of the total time spent is described in Section 4.3. Finally, we discuss the limitations of this calculation in Section 4.4 and provide a conclusion on the sub-question in Section 4.5.

4.1 Data Analysis

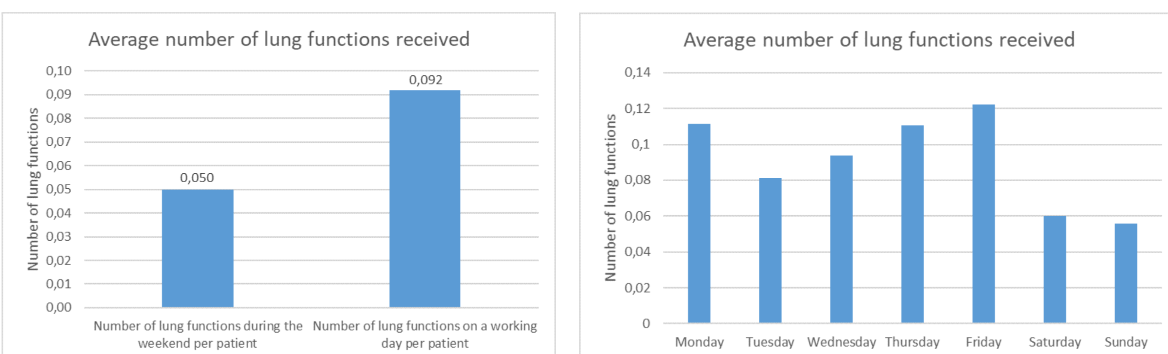
The data analysis contains three different parts. Section 4.1.1 presents the results of analysing the lung functions sent, Section 4.1.2 those of the received chats, and Section 4.1.3 those of the sent chats.

4.1.1 Lung functions

To analyse the number of lung functions sent, an export data file of the Puffer app has been used, which contains information about the date of the sent lung function, patient information and technical values of the performed lung function test.

Since the dates of the lung functions are known, the frequencies of sent lung functions could be determined for each day in the dataset. Because multiple inclusions and exclusions of patients in e-health care have taken place throughout the dataset period, the frequencies could not directly be used. Instead, weighted frequencies are used throughout this research, which are the frequency of lung functions sent on a certain day, divided by the number of included patients on that day.

Contact via the Puffer app mainly takes place during the week. Therefore, the data has been divided into working days or weekends. In Figure 4.1a, it can be seen that on working days about twice as many lung functions are being received as during the weekend. Figure 4.1b shows the average number of weighted lung functions on each day of the week. During the week, there is some variation in the number of lung functions received. The peak on Friday can be explained by the fact that the asthma nurse usually contacts many inactive patients on Fridays, with which she could also ask for a lung function. Next to that, many patients send lung functions before or after they play sports, to check whether their medication works well to prevent asthma complaints. However, there is no data available on the days that children have sports practice, so this can not be matched with the observed peaks.

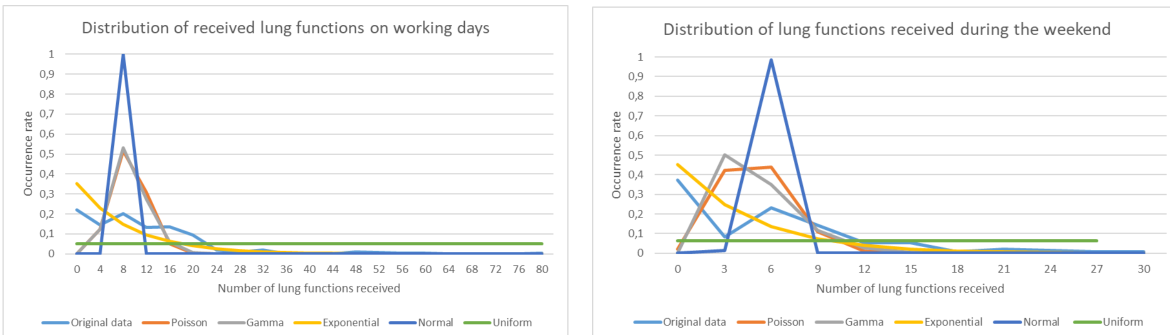


(a) *Average number of lung functions received per patient during the weekend or on a working day*

(b) *Average number of lung functions received per patient per day of week*

Figure 4.1: *Lung function data (n=1051, January 2023 to May 2024)*

To model the lung functions in the simulation model, a fitting distribution for the number of lung functions received needs to be determined. This distribution is per patient per day, such that we can multiply it with the number of patients given as input to the simulation model for each modelled day. Since there is a big difference between lung functions received during the weekend and during weekdays, a distinction will be made between these. The different days of the week will not be taken into account, because from observations it became clear that lung functions are often sent because a healthcare professional asks for it after a chat message has been received, as can be seen in Figure 2.3 in the chat message care pathway. Since there is no data available on how many lung functions are sent after a received chat message, it would not correctly represent the situation at Medisch Spectrum Twente if a different distribution is found for each day of the week. The gamma, poisson and exponential distribution have been fitted with the data, as can be seen in Figure 4.2. The average number of lung functions received per patient per day has been multiplied with a factor 100 so the Poisson distribution could be tested, which needs integer numbers as input. From the analysis, the results of the exponential distribution are the most comparable with the original data.



(a) Distribution of lung functions received on working days per patient per day (Lambda = 0,1090, n=854, January 2023 to May 2024)

(b) Distribution of lung functions received during the weekend per patient per day (Lambda = 0,2002, n=197, January 2023 to May 2024)

Figure 4.2: *Lung function input distributions*

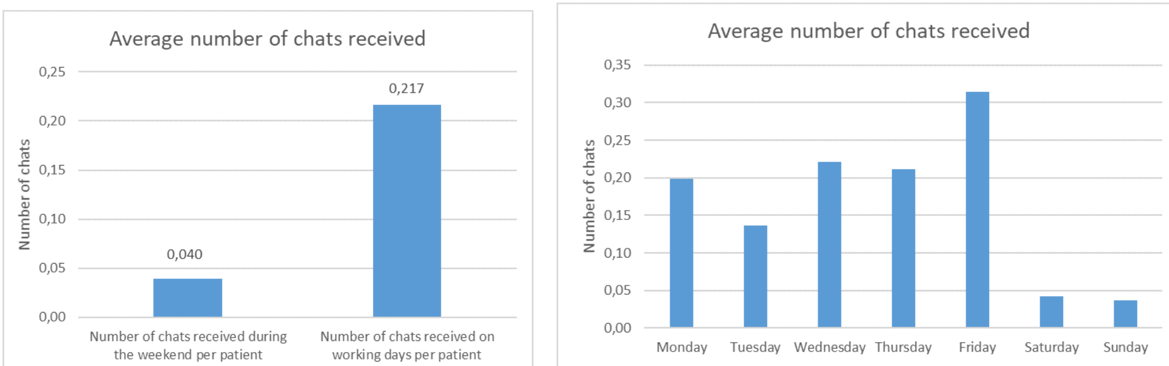
Appendix H also describes how a parameter for the exponential distribution has been found that is optimised by using the Sum of Squares Error (SSE). These found parameters have not been used because the simulation results of the original parameters fit better with the calculations performed on the dataset.

4.1.2 Chat messages received

The analysis of the chat messages is split up in received and sent chat messages, so that we can include them both as separate arrival rates in the simulation model.

Figure 4.3 shows that there is a significant difference between received chats during the weekend and on working days, which is because healthcare professionals typically do not respond to chats during the weekend, unless there is an acute situation. Of course, patients can send chats during the weekend, which will then have to be answered the Monday after the weekend. However, because the patients know that the chat will not be monitored, the number of chats received during the weekend is limited.

The data about received chats also shows a big difference between the days of the week. This could be useful to create different arrival rates in the simulation model for each day of the week. However, the number of messages received also depends on the time that healthcare professionals allocate to e-health care on a certain day to contact inactive patients for example. Therefore, there will only be separate arrival rates for a working day or a day during the weekend.

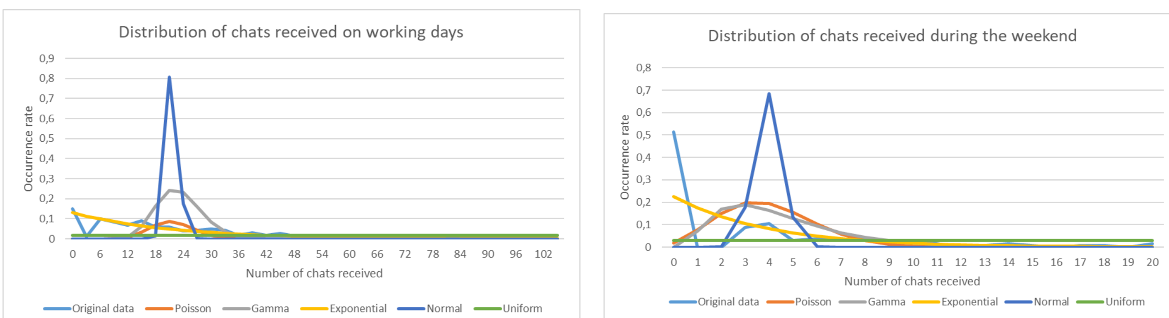


(a) Average number of chats received per patient during the weekend or on a working day

(b) Average number of chats received per patient per day of week

Figure 4.3: *Received chat data (n=2385, January 2023 to May 2024)*

The data of received chats has also been fitted with the gamma, poisson and exponential distribution. Again, the exponential distribution was found to be the most fitting, as can be seen in Figure 4.4. The exponential distribution for the chats received during the weekend in Figure 4.4b seems to be less fitting, but this dataset is also relatively small, and the exponential distribution approximates the distribution best compared to the poisson and gamma distribution.



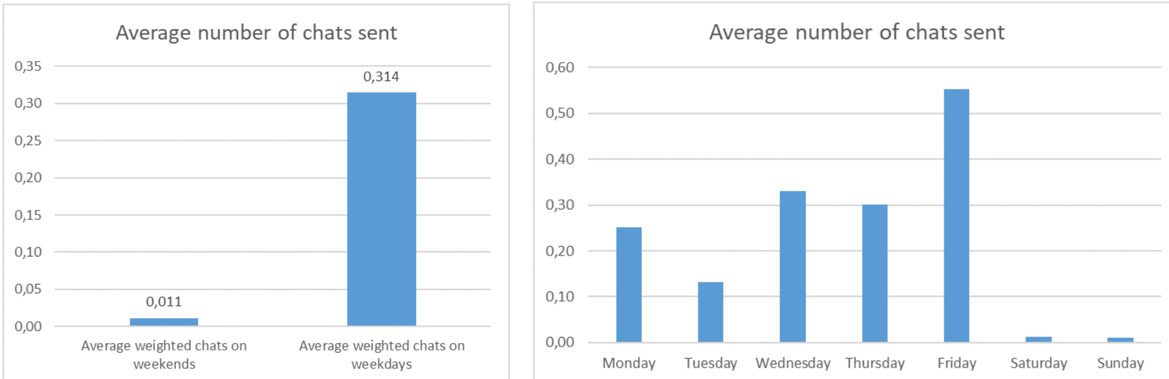
(a) Distribution of chats received on working days for 100 patients (Lambda = 0,0462, n=2219, January 2023 to May 2024)

(b) Distribution of chats received during the weekend for 100 patients (Lambda = 0,2531, n=166, January 2023 to May 2024)

Figure 4.4: *Received chat distributions*

4.1.3 Chat messages sent

The data of sent chat messages has also been analysed per day of the week. Figure 4.5a shows that the number of chat messages sent in the weekend is very small. This makes sense, because the Puffer app is not monitored during the weekend by the healthcare professionals, except in severe cases when an agreement is made with the patient to contact them. As can be seen in Figure 4.5b, there is also a difference between each day of the week, which is partially corresponding to the data of received chats in Figure 4.3b. However, we can see that the peaks on Friday are higher for the sent chats, which is because on Friday usually more time is taken by the asthma nurse to contact inactive patients.



(a) Average number of chats sent per patient during the weekend or on a working day

(b) Average number of chats sent per patient per day of week

Figure 4.5: *Sent chat data (n=3174, January 2023 to May 2024)*

Because of the low number of chats received during the weekend, no distribution can be found that accurately represents the chats sent during the weekend. Therefore, we will assume in the simulation model that all chats sent by the healthcare professionals are sent on a working day. For the distribution of chats sent on working days, the exponential distribution fits best, as can be seen in Figure 4.6.

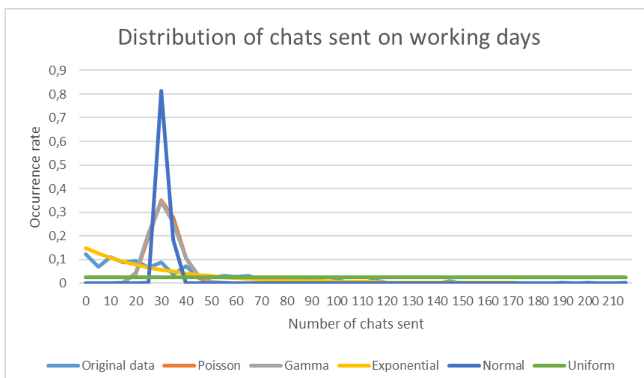


Figure 4.6: *Distribution of chats sent during working days for 100 patients (Lambda = 0,0318, n = 3127, January 2023 to May 2024)*

The available data also shows by which type of healthcare professional a message is sent. Figure 4.7 shows that the asthma nurse sends the majority of the messages. The two technical physicians also send a big part of the messages. The pediatricians almost never send messages, and the specialist nurse only sends a message in the exceptional and more complex cases.

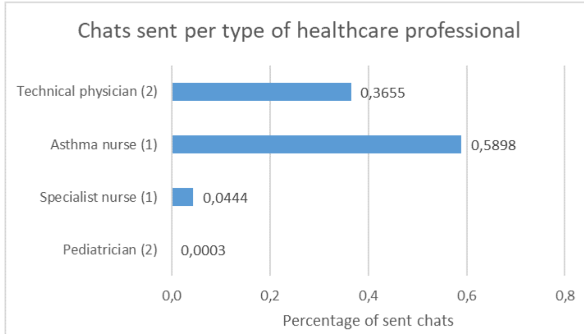


Figure 4.7: *Proportion of sent chats per type of healthcare professional (n=3174, January 2023 to May 2024)*

4.2 Time spent by different healthcare professionals

From the data analysis, more insight is created into the number of lung functions and chats received by the asthma e-health team. However, this does not yet result in a conclusion of the time spent on asthma e-health care. Therefore, a questionnaire is given to the healthcare professionals about the time they spend on asthma e-health care. The specific questions asked can be found in appendix G. Together with the company supervisor, the outcomes of the questionnaire were evaluated and changed where necessary. This was especially needed for the number of patients to discuss, because the responses from the different specialists were not well aligned, and for the time estimations from the asthma nurse, because responses were not always quantified. An additional reason to evaluate the outcomes thoroughly is the small questionnaire sample size, which consisted of answers from two pediatricians and technical physicians and one asthma nurse and specialist nurse. This means that the questionnaire is sensitive to interpretation mistakes for both answering the questions and summarising the results. However, the sample size covers all healthcare professionals working on e-health care, which means that the answers are representative for the situation at Medisch Spectrum Twente. The results of the questionnaire combined with follow-up questions and alterations can be seen in Table 4.1.

In the available data, we can not easily make a distinction on which messages are sent for monitoring purposes and which are sent as an answer to a question received from a patient. Since these two types of messages follow a different e-health care pathway, as described in Section 2.2, an assumption has to be made on the time spent to send a chat.

Other remarks in the questionnaire were that it takes time to log into the computers at MST, the workspace environment when working from home and the Puffer app. These environments have to be logged into about twice a day with two-factor authentication, so that needs to be taken into account for the total time spent on e-health. Logging into the environment at MST takes about 1.5 minutes and from home about 5 minutes. Additionally, some healthcare professionals mentioned that the discussions about patients are sometimes quickly done during the lunch or in between different appointments, which makes it difficult to keep track of. Lastly, some of the healthcare professionals spend time on the app by working on research to improve the app itself, or by updating information pages or other activities around the Puffer app. This is also time that can be taken into account as “extra time”.

4.3 Calculating the total time spent

To calculate the total time spent on e-health care, a formula can be set up for the Pediatrician (P), Specialist Nurse (SN), Technical Physician (TP) and Asthma Nurse (AN). This formula can use the results of the data analysis in Section 4.1 and the questionnaire results of Section 4.2 as input. Not every healthcare professional performs all tasks, therefore, a zero value will be used when calculating with this formula if the task is not performed by a type of healthcare professional.

Table 4.1: *Results of questionnaire and follow-up questions about the time spent on asthma e-health care (n=6)*

	Pediatrician	**Specialist nurse**	**Technical Physician**	**Asthma nurse**
Percentage of lung functions assessed	-	25%, in consultation with TP	100%	-
Time needed to assess lung function	-	1-2 minutes	0,5 minutes	-
Time spent on reading a chat	-	1-2 minutes	0,5-1 minutes	2 minutes
Number of patients to discuss about per week	2	5, with AN 60%, with TP 40%	4-5	2, with TP and SN
Time needed to discuss per patient	5-10 minutes	10 minutes	2 minutes	5 minutes (when discussing with paediatrician 15 minutes extra)
Time needed to send a chat after a question or lung function received	-	5-10 minutes	1-3 minutes	2 minutes
Number of inactive patients contacted via chat per week	-	3-4	3-5	20
Time needed to send a chat to an inactive patient	-	1-2 minutes	1 minute	1 minute
Number of inactive patients to call with per week	-	0-2 per week	-	1
Time needed to call an inactive patient	-	10 minutes	-	5-15 minutes
Number of e-health updates written per week	-	1 per week	3 per week	1 per week
Time needed to write an e-health update	-	15 minutes	12.5 minutes	10 minutes

Using Equation 4.1, we find the time spent on asthma e-health care in the current situation as presented in Table 4.2. The table also shows the average number of FTE needed, which is calculated based on the average time spent in hours per week, where 1 FTE equals 36 hours. These findings are used to validate the simulation model for the current situation at MST. For this, we used the dataset from January 2023 to May 2024 again, with the number of lung function or chat arrivals divided by the number of included patients, and multiplied by 40 patients, because this corresponds to the current situation.

Figure 4.8 also shows a visualisation of the total time spent in minutes per working day for the asthma nurse. The grey line in the graph indicates the average time spent per day, such that peaks in time spent can be more easily identified. The columns consist of a fixed part of time, which includes the time spent on discussing patients, calling patients, e-health updates and extra time, and a variable part of time spent on lung functions, reading chats and sending chats. In reality, the fixed part of time is also variable, but since we do not have daily data available on these variables they are considered as a fixed number per day in this research. The graph for the asthma nurse is shown, since this graph shows the most variability in time. The graphs for the pediatrician, specialist nurse and technical physician are added in Appendix I, which show approximately the same variability, but in different proportions. The graph shows that in the winter months, relatively wider peaks in time spent on asthma e-health care are observed than in the summer months, where peaks become smaller more easily. This supports the findings in literature as described in Section 3.1.2, from which we concluded that severe asthma symptoms show seasonality.

$$
\begin{aligned}
\text{Total time}_{\text{P/SN/TP/AN}} = {} & \text{Percentage of lung functions assessed} \times \text{Number of lung functions received} \times \\
& \text{Time for lung function assessment} \\
& + \text{Percentage of chats read} \times \text{Number of chats received} \times \text{Time spent reading} \\
& + \text{Number of patients to discuss} \times \text{Time needed to discuss one patient} \\
& + \text{Percentage of chats sent} \times \text{Number of chats sent} \times \text{Time needed to send a chat} \\
& + \text{Number of inactive patients to call with} \times \text{Time needed to call one patient} \\
& + \text{Number of e-health updates per week} \times \text{Time needed to write e-health update} \\
& + \text{Extra time}
\end{aligned}
$$

Equation 4.1: *Calculation of the total time spent for each healthcare professional*

Table 4.2: *Time spent on asthma e-health care in the current situation of 40 included patients in hours per week (n = 1894, Janauari 2023 to March 2024)*

Type of healthcare professional	Average time spent (hours/week)	Average number of FTE needed
Pediatricians	0,280	0,008
Specialist nurse	1,717	0,048
Technical physicians	3,121	0,087
Asthma nurse	2,500	0,069

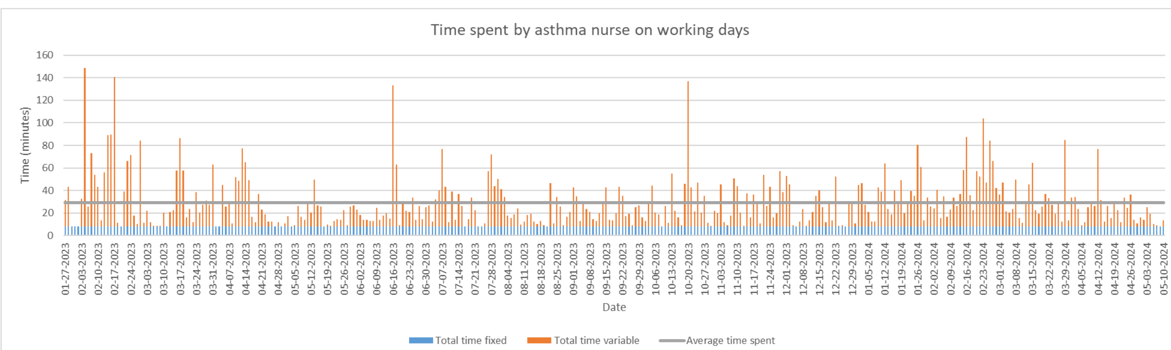


Figure 4.8: *Time spent divided in fixed time and variable time per working day for the asthma nurse*

4.4 Limitations

The calculations in the previous section provide a way of putting a number to the time spent on e-health care. However, there are multiple reasons why this number can only be seen as an estimation of the total time spent on asthma e-health care.

First of all, the healthcare professionals indicated that the questions asked in the questionnaire are difficult to answer, because the time spent differs for each patient and text, and also differs per time of the year. Performing a time-motion study, in which the time spent on the different healthcare activities are timed, could be a valuable addition to the questionnaire data, but this would have to be done over a long period to be able to find accurate averages, which does not fit the time limit of this research.

Next to that, every separate message sent to a patient counts as a message in the data analysis. So if a healthcare professional prefers to split an advice into multiple texts, when another healthcare professional puts that all in one text, the data can give an incorrect representation of the reality. It could be that the effect of this is limited, because a healthcare professional who regularly splits up texts in more smaller texts could also indicate that less time is spent on sending one chat. This problem could be solved by finding the average number of characters sent in a text for each healthcare professional. The time that healthcare professionals indicated they need to send a text can then be divided by the average number of characters in a text, such that we find the average time spent per text character.

Lastly, when a healthcare professional has a longer conversation with a patient on the same day, sending and reading texts also costs less time, because no additional time is needed to read into the patients case. This could be solved by analysing the number of chats sent per day per patient number in the data, and retrieving additional information about the time spent on sending a chat to a patient when chats have already been sent to that patient on the same day.

4.5 Conclusion

This chapter answers the research question *"How much time is currently spent by different types of healthcare professionals on asthma e-health care?"*. We find that the number of lung functions, as well as the number of chats received and sent all have an exponential distribution. For the lung functions and chats received, a distinction is made for an exponential parameter of a working day or during the weekend. Additionally, a questionnaire is given to healthcare professionals about the time spent on healthcare activities, and a calculation for the total time spent on e-health has been provided. With this calculation, we find that in the current situation, the pediatricians spend the least time in hours per week, followed by the specialist nurse, who spends significantly more time. The asthma nurse spends the most time per week on e-health care, slightly more than the technical physicians. Lastly, the time spent per week seems to be more during the winter months. This seasonality aspect should be explored in further research to be able to make justified seasonality assumptions for the simulation model.

5 Simulated situation

In this chapter, first the research question, *"How should the e-health care pathway be modelled into a stochastic simulation?"*, is answered. This is done by describing the conceptual model in Section 5.1 and the architecture and design specifications in Section 5.2. These findings are combined in a simulation model, of which the model description and findings are presented in Section 5.3. They answer research question five: *"What is the relationship between the number of patients included in e-health care and the health care professional capacity?"*. Lastly, a sensitivity analysis is performed about the model results in Section 5.5 and a conclusion is given.

5.1 Conceptual model

As is described in the problem solving approach in Section 1.4.1, a conceptual model of the simulation model needs to be created. A conceptual model is "a non-software specific description of the computer simulation model (that will be, is or has been developed), describing the objectives, inputs, outputs, content, assumptions and simplifications of the model" (Robinson and Macmillan, 2014).

The objective of the model follows from the main research question. We define it as: "the model should provide the required number of hours per week for each type of healthcare professional based on a given expansion of the e-health care".

As input variables, we need to define the expansion of e-health care. One of the input variables is thus the number of patients included in e-health. Additionally, a Monte-Carlo simulation runs for many repetitions. These repetitions can be modelled as the number of years for which we run the simulation, which only has to be decreased to decrease runtime or increased to increase accuracy of the results. Other input variables are the time it takes to perform certain tasks, which follow from Table 4.1 and the results from the data analysis. In principle, these don't have to be changed. However, they should be included and being able to change them adds flexibility to the model in case the task division in the paediatrics department changes. The output variables must include the average time in hours spent per week.

Content-wise, some assumptions and simplifications of the model have already been made in previous chapters. In Chapter 2 about the e-health care pathway, the pathways are modelled with a great level of detail, which is not easily modelled in a Monte-Carlo simulation. Therefore, we first decide to consider outpatient clinic visits as a part of regular care, also if it concerns an e-health patient. In further research, it could be useful to compare the amount of regular care an e-health patient uses in comparison with the amount of care a patient not included in e-health uses and add that to the simulation model.

Arrivals that can be modelled stochastically are the received lung functions and chats, and the sent chats. In the sent chats, no distinction can be made between chats regarding complaints or to inactive patients. Additionally, we assume that time spent on activities and the number of inactive patients called, e-health updates written and number of patients discussed are constant per patient per week, while this is in the real situation not the case. Figure 5.1 shows a visualisation of the conceptual model for the Monte-Carlo simulation.

5.2 Architecture and design specification

To build the Monte-Carlo simulation, we can use any program that can run many repetitions by using probability distributions. Excel/VBA is chosen as the simulation architecture, because Excel is intuitive to use for the healthcare professionals and the provided file can be safely stored in the MST working environment. Next to that, any code built in VBA can be easily linked to a dashboard in an Excel worksheet.

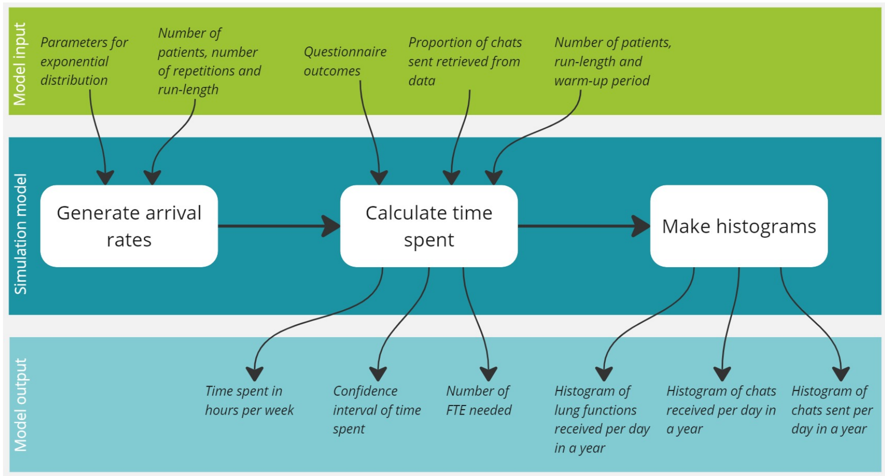


Figure 5.1: *Conceptual model*

5.3 Simulation implementation

Combining the conceptual model and the architecture and design specification, a simulation model has been created, of which the VBA code can be seen in Appendix J. We describe the input values used in Section 5.3.1, and discuss the typical simulation characteristics warm-up period, run-length and number of repetitions in Sections 5.3.2, 5.3.3 and 5.3.4 respectively.

5.3.1 Simulation model description

The created simulation model in Excel/VBA prints its results on the dashboard shown in Figure 5.2. The output in the green table shows the average time spent in hours per week together with a 95% confidence interval, which means that 95% of the values of the time spent over all days deviate with a maximum of the specified output in the table. The average time spent is also translated to the number of FTE needed for e-health care in the paediatrics department, where 1 FTE equals 36 hours. On the dashboard, the values in the "simulation settings" table and the "observed variables" table can be changed. The maximum value of "Run-length (Years)" is 89, and the maximum value of "repetitions" is about 2200. After that the values become too large for VBA arrays. The warm-up period must be at least one year lower than the run-length. In case the wrong values are given as input in the dashboard, a message box is displayed explaining the issue, and the simulation will not be run. The graphs on the dashboard show the stochasticity in the arrivals of lung functions received, chats received and chats sent for one year.

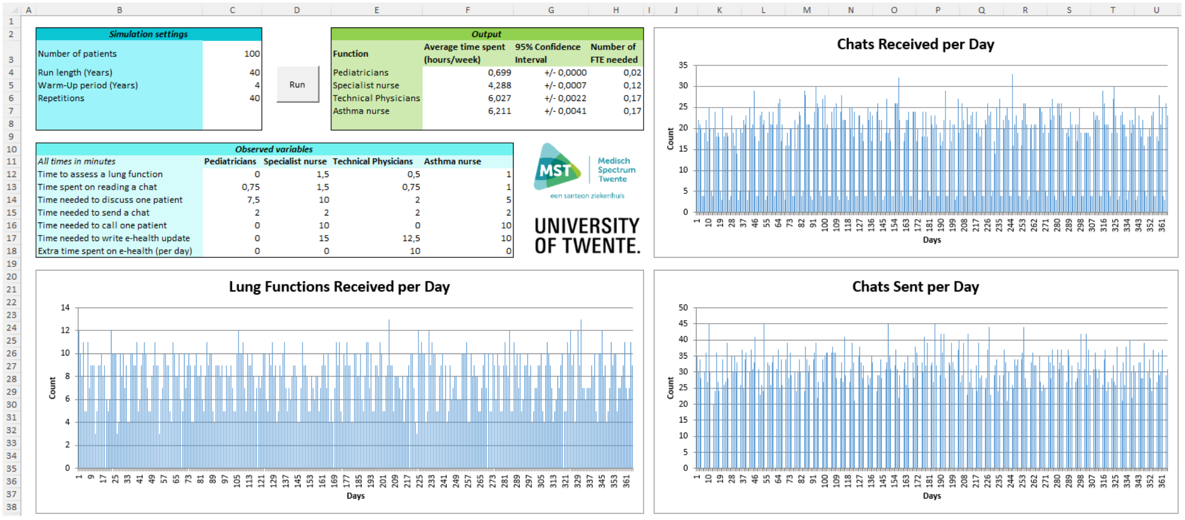


Figure 5.2: *Simulation dashboard*

To MST, the most important part of the dashboard is the output in the green table and the ability to change variables on the dashboard such as the number of patients and the observed variables. The displayed graphs are not useful at the moment, except for acknowledging the stochasticity of the output. It could be more useful to display graphs similar to Figure 4.8 about the time spent on each day in the datset on the dashboard. However, since we do currently not have any seasonality included in the model, plotting a similar figure would show a level of detail of which there is too much uncertainty.

Together with the values as presented in the dashboard, the numbers as stated in Table 5.1 were used as simulation input. Both follow from the questionnaire results of 4.2. Additionally, the lambda values as presented in Table 5.2 are used to draw random numbers from the exponential distribution. With the lambda values the arrivals of lung functions, received chats and sent chats are calculated. The random numbers drawn are always divided by 100 and multiplied with the number of patients given in the dashboard, because the lambdas are retrieved from a dataset transformed to 100 included e-health patients.

Table 5.1: *Assumptions in VBA code*

	Pediatricians	**Specialist nurse**	**Technical Physicians**	**Asthma nurse**
Percentage of lung functions assessed	0%	25%	100%	10%
Number of patients to discuss per week	2	5	4	4
Percentage of chats sent	0,03%	4,44%	36,55%	58,98%
Percentage of chats read	5%	20%	40%	70%
Number of inactive patients called	0	1	0	1
Number of e-health updates written per week	0	1	3	1

Table 5.3 shows the results of the simulation. It is compared with the total time calculated by using the dataset of January 2023 to May 2024, which is the same dataset as used in Chapter 4. We can see that the results are very comparable, and therefore we conclude that the calculation in the simulation model runs correctly.

Table 5.2: Parameters used for the exponential distribution

Parameter	Value
Lambda lung functions received on working days	0,1090
Lambda lung functions received in the weekend	0,2002
Lambda chats received on working days	0,0462
Lambda chats received in the weekend	0,2531
Lambda chats sent on working days	0,0318

Table 5.3: Simulation results compared with data for 40 patients

Time spent by healthcare professional	Data results (hours per week)	Simulation results (hours per week)
Total time Pediatricians	0,2797	0,2800
Total time Specialist nurse	1,7165	1,7169
Total time Technical physicians	3,1206	3,1154
Total time Asthma nurse	2,5001	2,4936

5.3.2 Warm-up period

The warm-up period ensures that there is no initialisation bias by running the model until it reaches a steady-state condition, and collecting only the results from after this point (Robinson and Macmillan, 2014). In Figure 5.3 it can be seen that the simulation output stabilises after about 290 days, and becomes nearly a flat line after about 1200 days. To obtain accurate results, we round 1200 days up to a warm-up period of 4 years.

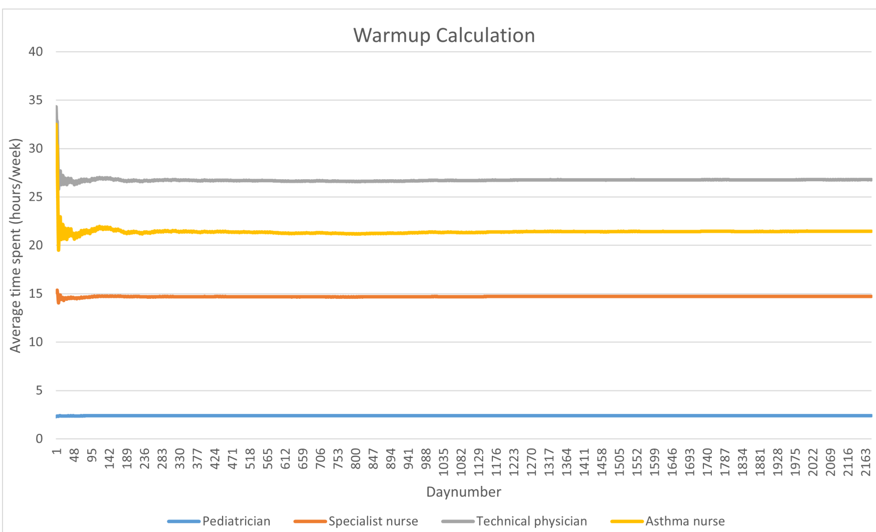


Figure 5.3: Warm-up period time series analysis

5.3.3 Run-length

Since we determined a warm-up period of 4 years, the run-length must at least be higher than 4 years, as otherwise no results will be collected by the simulation model. Robinson and Macmillan (2014) mention that a run-length of at least ten times the length of the warm-up period can be used as a rule of thumb. Because of the warm-up period of 4 years, we set the run-length at 40 years.

5.3.4 Number of repetitions

Typically, a Monte-Carlo simulation runs many repetitions, and takes the average value of those repetitions as output value. To find out how for many repetitions the model needs to run to generate reliable results, we run the simulation model several times, in which we change the number of repetitions.

Figure 5.4 shows the value of the confidence interval for an increasing number of repetitions. It can be seen that the confidence interval converges and becomes a flat line for all types of healthcare professionals from 40 repetitions. Therefore, we recommend to set a minimum number of repetitions of 40. As can be seen in Table 5.4, the simulation runtime does not increase much between 1 and 100 repetitions, so choosing a higher number of repetitions is also possible. Since the simulation model takes the average time spent in hours per week over all simulated years with independent arrivals, this means that we collect 40 repetitions of 36 years, which results in an average value over 74.880 weeks. Since the literature study in Section 3.3 suggested to run the simulation for a range of 5000-10000 repetitions, 40 repetitions combined with the established runtime is enough for accurate simulation results.

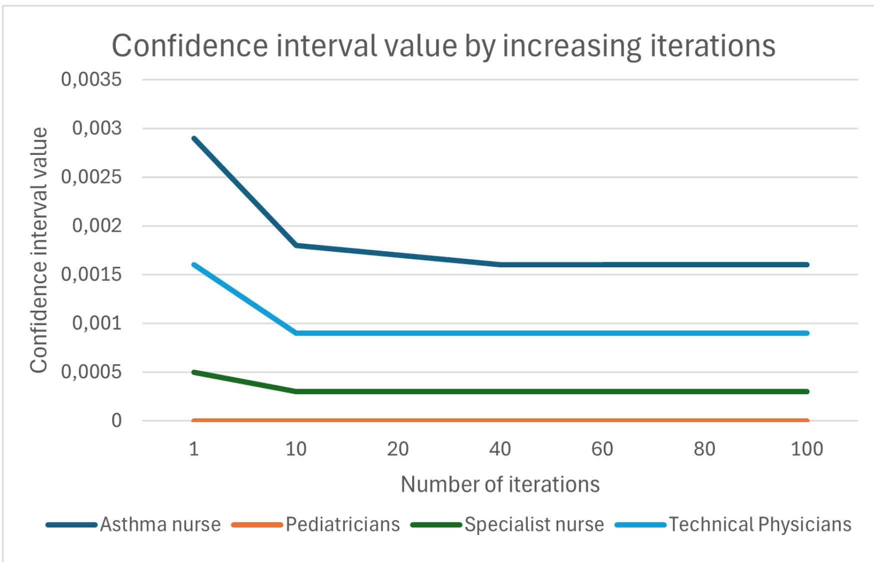


Figure 5.4: *Confidence interval values for an increasing number of repetitions*

Table 5.4: *Simulation runtime for increasing number of repetitions*

repetitions	**Runtime**
1	<1 second
10	<1 second
20	∼1 second
40	∼1 second
60	1-2 seconds
80	1-2 seconds
100	∼2 seconds

5.4 Simulation results

In this section, we describe the findings of the model about the required time of healthcare professionals for an increased number of e-health patients. This corresponds to the last step of the simulation methodology provided by Balci (2011), which is presenting the results.

As described in 1.3, the paediatrics department is asked to include more patients in e-health care. According to healthcare professionals at the paediatrics department, it is realistic to include a maximum of about 100 patients in the Puffer app. Since there are about 40 patients included in the current situation, we investigate the effect of increasing the number of patients stepwise from 40 to 100. In Figure 5.5 the time spent in hours per week for each type of healthcare professional can be seen.

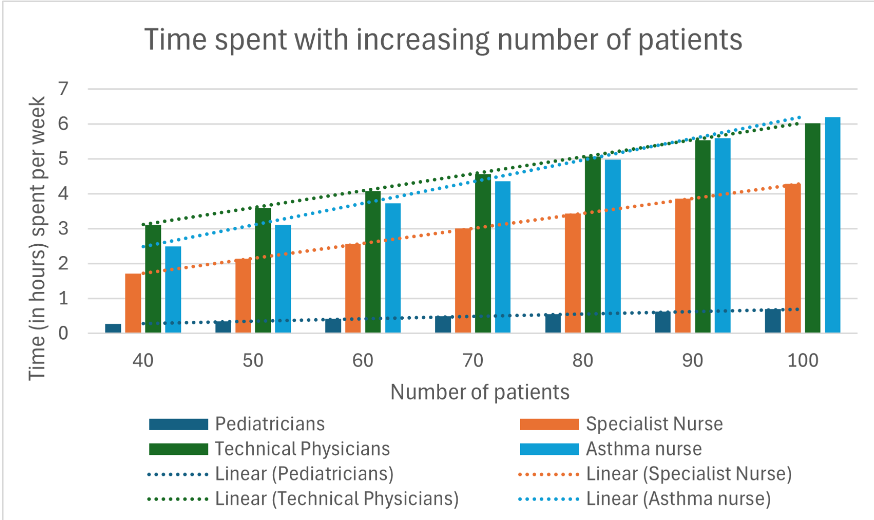


Figure 5.5: *Time spent by each type of healthcare professional with increasing number of patients*

The graph shows that the time spent increases linearly with the number of patients for each type of healthcare professional. This is logical, because all variables that contribute to the total time spent are dependent on the number of patients, for which more patients means more time spent. The graph also shows that the total time spent increases more with the number of patients for the asthma nurse than for the technical physicians. Where in the situation with 40 patients the technical physicians spend the most time on e-health care, the asthma nurse spends the most time in the situation with 100 patients. The time spent by the pediatrician increases the least with the number of patients, which is desired by the paediatrics department, as the pediatrician is the most expensive healthcare professional.

Table 5.5 illustrates the differences in time expenditure for an increased number of patients even better. The time spent by the pediatricians increases the least, followed by the specialist nurse. The asthma nurse shows the highest increase in time, about one hour per week more than the technical physicians. Next to the increase in average time spent, we also observe an increase in the confidence interval of the time spent per week, which means that the average time spent has a larger variety when the number of patients increases.

Table 5.5: *Increase in time expenditure when expanding e-healthcare from 40 to 100 patients*

Number of patients	**Pediatricians**	**Specialist nurse**	**Technical Physicians**	**Asthma nurse**
Increase in time expenditure (hours/week)	0,42	2,58	2,92	3,73
Increase in confidence interval	0,0000	0,0004	0,0013	0,0024
Increase in FTE needed	0,01	0,07	0,08	0,10

Since we observe differences in the increase in time spent, it is also interesting to research whether the task division shifts when the number of patients is increased. This effect is displayed in Figure 5.6. The figure shows that the percentage of tasks performed for a larger number of patients shows an almost stable percentage of time spent on e-health care for the pediatricians, a slight increase in the percentage of time spent on e-health care for the asthma nurse and specialist nurse, and a decrease of more than 5% for the technical physicians. This change in task division is because the parameter "extra time" only has a value for the technical physicians, and the extra time is in this case not dependent on the number of patients.

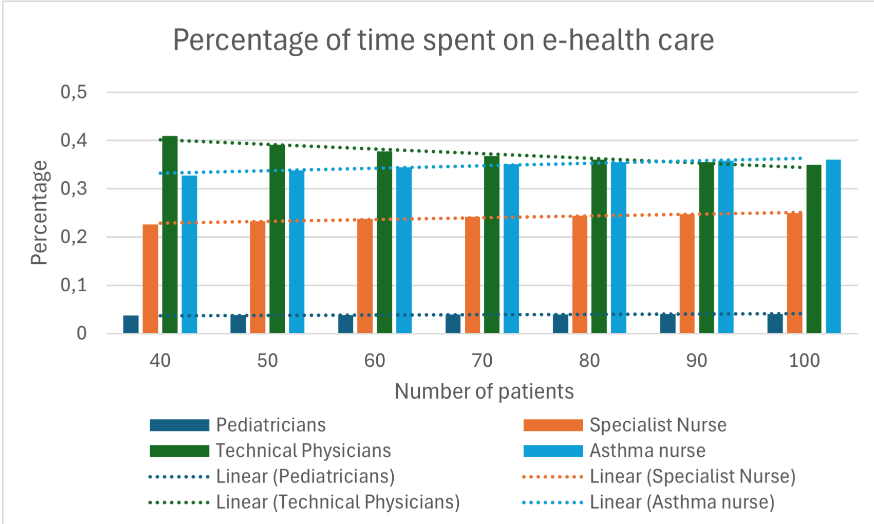


Figure 5.6: *Percentage of time spent by each healthcare professional compared to the total time by all healthcare professionals with an increasing number of e-health patients*

Figure 5.7 shows the time spent per patient when the number of patients is increased. This graph supports our findings that the "extra time" is the reason for the change in task division in the paediatrics department. The graph shows a constant time spent per patient for the pediatricians, specialist nurse and asthma nurse, and a non-linear decrease in time spent per patient for the technical physicians. The decrease for the technical physicians is non-linear, because the "extra time" value remains constant when the number of patients increases, so the value becomes a smaller percentage of the total time spent on e-health care.

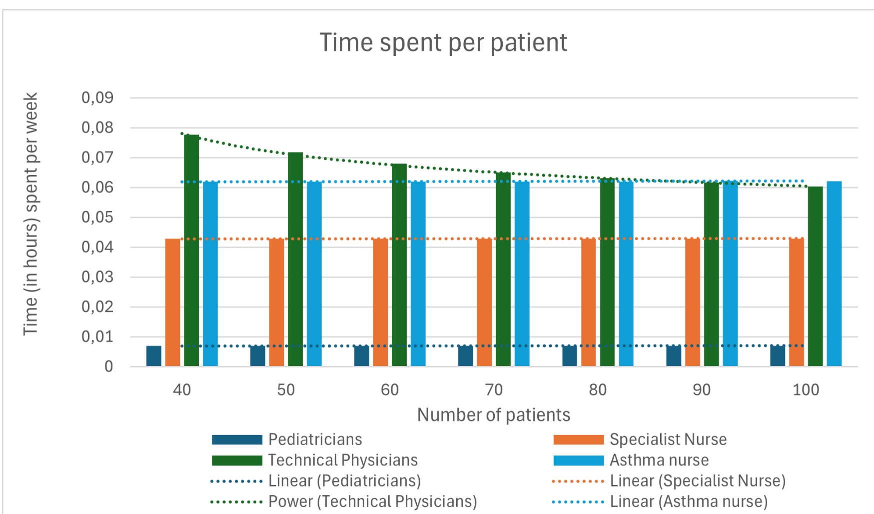


Figure 5.7: *Time spent per patient by each healthcare professional with an increasing number of patients*

It is important to note that these estimations of the time spent by each healthcare professional are based on the retrospective data of the e-health patients currently included in the Puffer app. There is no guarantee that the number of chats and lung functions will be similar when more patients are included, as the patients currently included are typically the most unstable patients. When it becomes clear that there is a possibility to include about 60 patients more, it could be that more stable asthma patients will be included, who require less contact with the hospital.

Lastly, the output of the simulation displays the average number of hours spent per week. In reality, the time spent can differ a lot per week, as different external factors have an effect on the complaints that children with asthma experience, as described in 3.1.2. This can be included in further research and implemented in the simulation model.

5.5 Sensitivity analysis

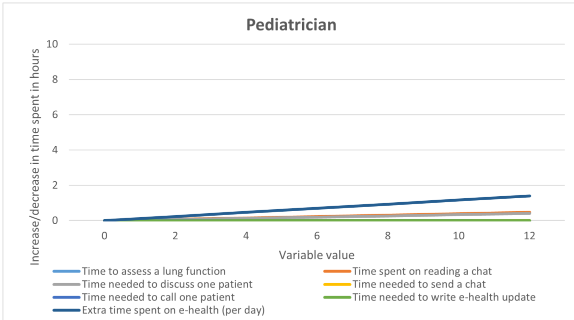
The simulation model runs on several input factors, which partly follow from gathered data and are otherwise based on assumptions. The observed variables as presented in the dashboard about the time spent on certain activities follow from the questionnaires given to healthcare professionals. However, there is uncertainty about the correctness of these values, because they also had to be estimated by healthcare professionals. Next to that, assumptions are made in the code about the percentage of lung functions assessed, the percentage of chats read by healthcare professionals, the number of patients to discuss, the number of inactive patients to call and the number of e-health updates written per week, which also follow from the questionnaire and additional interviews. These values can not be checked by comparing the simulation model with historical data, as the values have been used to calculate the total time spent for both the historical data and the simulation model. Therefore, we should investigate the effect that these input values have on the simulation outcomes.

According to Robinson and Macmillan (2014), a sensitivity analysis is useful for "assessing the effect of uncertainties in the model particularly the assumptions and category C data (which is not available and not collectable data)", "understanding how changes to the experimental factors affect the responses", and "assessing the robustness of the solution".

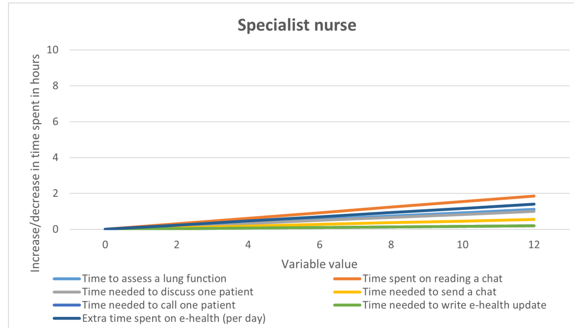
First, we change the estimated times which are taken as input values from the table with observed variables in the dashboard presented in Figure 5.2. The values for each type of healthcare professional are changed at the same time, because the time spent by one healthcare professional does not influence the time spent by another type of healthcare professional. Values between zero and twelve minutes per activity performed with a step size of two are used to perform the sensitivity analysis.

Figure 5.8a shows that most of the parameters do not impact the total time spent by the pediatrician at all or only to a small amount, which is logical since the pediatrician does not perform many tasks related to e-health care. The extra time spent on e-health influences the total time spent by the pediatricians the most. For the specialist nurse, we can see in Figure 5.8b that the time spent on reading a chat and the extra time spent on e-healthcare per day impact the total time spent the most. The influence of all variables on the total time is in general limited as well, which is because the specialist nurse is involved with a variety of tasks related to e-health, but only for the more complex cases, which are usually a small part of patient demand. Figure 5.8c shows a strong influence of the variables "time to assess a lung function", "time needed to send a chat" and "time spent on reading a chat" on the total time spent by the technical physicians. This is because the technical physicians are mostly involved with the chats and the lung functions, which makes the total time increase much more than for the pediatricians and specialist nurse. The other variables have a limited influence on the total time spent because the technical physicians do not often perform those tasks. The total time spent by the asthma nurse is most influenced by the variables "time spent on reading a chat" and "time needed to send a chat", as can be seen in Figure 5.8d. This is as expected, since the asthma nurse handles the majority of the chat messages.

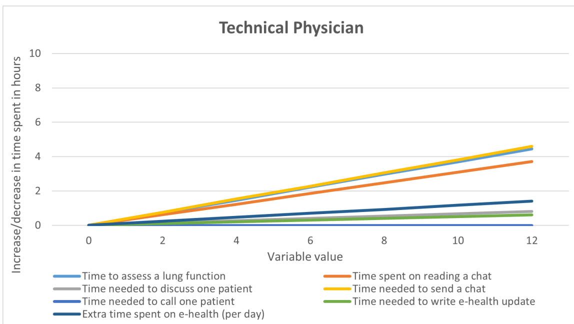
With the sensitivity analysis, we also investigate the influence of the assumptions made in the VBA code of the percentage of lung functions assessed in Figure 5.9a and of the percentage of chats sent in Figure 5.9b. Here, it can be seen that the effect on the total time spent of the percentage of lung functions assessed is different for each healthcare professional, while the effect of the percentage of chats sent is the same for each healthcare professional. This is because the estimated time spent on sending chats is the same for all types of healthcare professional, while for assessing a lung function, there are differences in the time spent. The number of chats sent has more effect on the calculation outcome that the percentage of lung functions assessed, but since we derive the percentage of chats sent



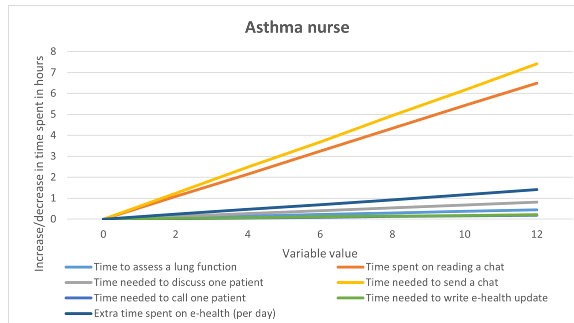
(a) Pediatricians



(b) Specialist nurse



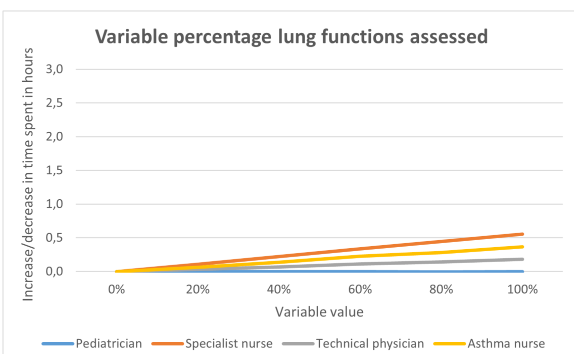
(c) Technical physicians



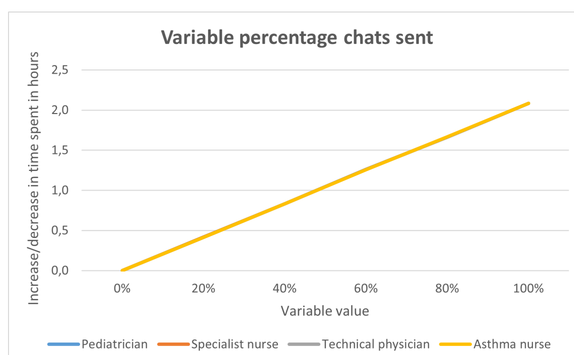
(d) Asthma nurse

Figure 5.8: *Sensitivity analysis performed with observed variables used in simulation model*

from historical data, it is likely that the current percentages correctly represent the current situation.



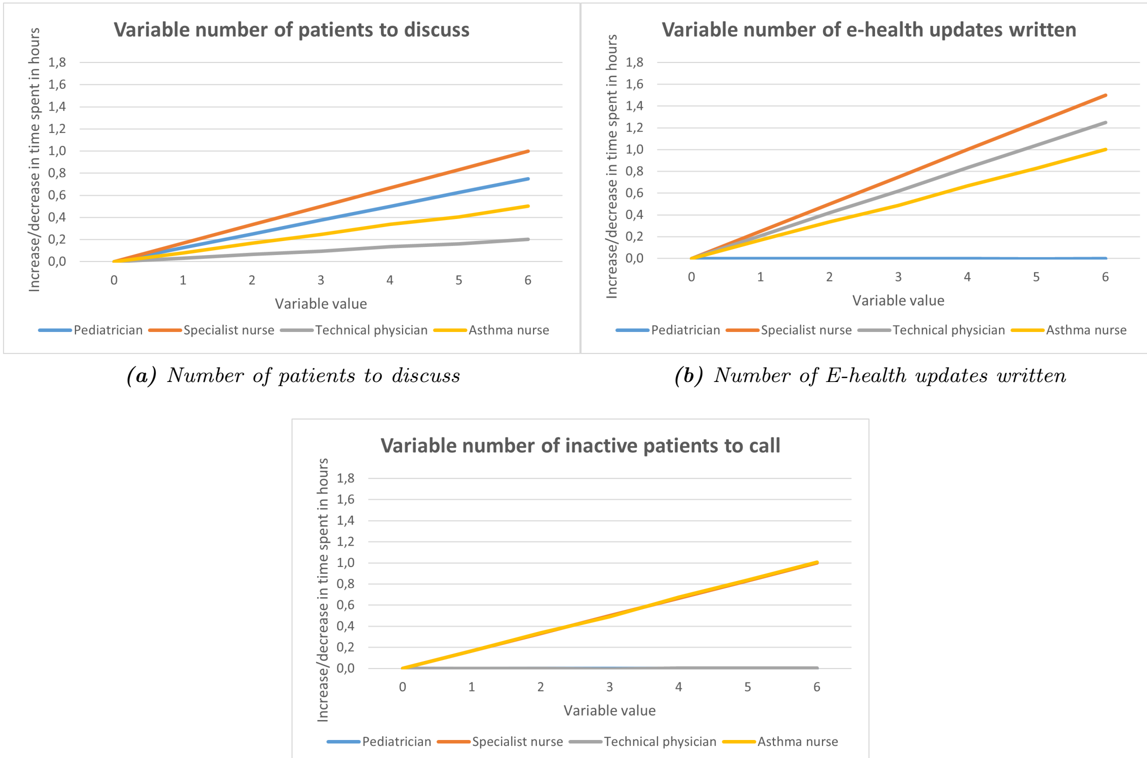
(a) Percentage lung functions assessed



(b) Percentage chats sent

Figure 5.9: *Sensitivity analysis performed with observed percentages used in VBA*

Lastly, we test several values in the VBA code for the number of patients to discuss (Figure 5.10a), the number of e-health updates written (Figure 5.10b) and the number of inactive patients to call (Figure 5.10c). Since the specialist nurse spends the most time per patient on those three tasks, we observe in the three figures that the time spent by the specialist nurse also increases the most when increasing the variable value. In these figures, we see that the effect of e-health updates written is zero for the pediatricians, because it is not part of their tasks, and that the effect of inactive patients to call is zero for both the pediatrician and the technical physician, because they also do not perform this task.



(a) Number of patients to discuss

(b) Number of E-health updates written

(c) Number of inactive patients to call

Figure 5.10: *Sensitivity analysis performed with observed numbers used in VBA*

For the effect of the variables presented in Figures 5.9 and 5.10 it is difficult to state what the exact cause is of the change in total time spent. This is because the total time spent on a certain activity is sometimes dependent on two estimated variables. Therefore, changing one variable, without changing the other one can impact the results of the simulation. For the previous sensitivity analyses, one variable was kept at its estimated value, while the other one was systematically changed. To investigate what the effect of changing both values is, we perform a multi-way sensitivity analysis.

For each set of variables that we test, the absolute increase in total time spent per week is the same for all healthcare professionals, because the total time spent is calculated with the same formula for each type of healthcare professional. In Table 5.6 the multi-way sensitivity analysis for the assessed lung functions is shown and the multi-way sensitivity analysis for the chats read is shown in Table 5.7. It is not necessary to perform the multi-way sensitivity analysis for the chats sent to assess the effect of uncertainties, since we know the exact division of chats sent by each healthcare professional from the data analysis. However, it is still interesting to analyse the results in case the task division in the paediatrics department changes in the future. Therefore, the results of this variable can be seen in Table 5.8. Lastly, Table 5.9 shows the multi-way sensitivity analysis for the pediatricians for the patients discussed. Because this table shows the same results as the multi-way sensitivity analyses for the patients called and e-health updates given, these tables are not shown here.

Comparing the tables, we see that the total time spent is mostly affected by the chats sent, followed by the chats read and lung functions assessed, and the least affected by the non-stochastic variables. This is in line with the arrival rate of the lung functions, chats read and chats sent, of which the lung function arrivals are the lowest, and the sent chats the highest. The effect of the non-stochastic variables is relatively small, which could also be concluded from Figure 4.8 about the time spent for each day in the dataset. The heat maps all show the same gradual change in colour, in which the colour change corresponds to the relative change within that table. This means that all sets of variables measured with the multi-way sensitivity analysis show a linear relationship.

Table 5.6: *Heat map of the multi-way sensitivity analysis for the pediatricians of lung functions assessed*

Time to assess a lung function / Percentage of lung functions assessed	0%	20%	40%	60%	80%	100%	Increase
0	0,280	0,280	0,280	0,280	0,280	0,280	0,000
2	0,280	0,428	0,576	0,724	0,871	1,024	0,744
4	0,280	0,575	0,873	1,170	1,470	1,754	1,474
6	0,279	0,726	1,173	1,615	2,054	2,510	2,230
8	0,280	0,874	1,462	2,051	2,670	3,241	2,961
10	0,280	1,029	1,766	2,510	3,235	4,005	3,726
Increase	0,000	0,749	1,486	2,230	2,955	3,726	

Table 5.7: *Heat map of the multi-way sensitivity analysis for the pediatricians of chats read*

Time to read a chat / Percentage of chats read	0%	20%	40%	60%	80%	100%	Increase
0	0,251	0,251	0,251	0,251	0,251	0,251	0,000
2	0,251	0,560	0,863	1,180	1,493	1,786	1,535
4	0,251	0,872	1,480	2,092	2,740	3,343	3,093
6	0,251	1,175	2,106	3,038	3,992	4,873	4,622
8	0,251	1,482	2,733	3,945	5,171	6,493	6,242
10	0,251	1,801	3,353	4,912	6,459	7,993	7,742
Increase	0,000	1,550	3,103	4,662	6,208	7,742	

Table 5.8: *Heat map of the multi-way sensitivity analysis for the pediatricians of chats sent*

Time to send a chat / Percentage of chats read	0%	20%	40%	60%	80%	100%	Increase
0	0,279	0,279	0,279	0,279	0,279	0,279	0,000
2	0,279	0,703	1,118	1,539	1,960	2,379	2,100
4	0,279	1,123	1,966	2,792	3,634	4,461	4,182
6	0,279	1,527	2,793	4,049	5,330	6,550	6,271
8	0,279	1,951	3,642	5,286	6,957	8,710	8,431
10	0,279	2,369	4,463	6,545	8,661	10,762	10,483
Increase	0,000	2,091	4,183	6,266	8,382	10,483	

Table 5.9: *Heat map of the multi-way sensitivity analysis for the pediatricians of non-stochastic variables*

Time to discuss one patient / Number of patients discussed	0	2	4	6	8	10	Increase
0	0,030	0,030	0,030	0,029	0,029	0,030	0,000
2	0,030	0,096	0,163	0,230	0,296	0,363	0,334
4	0,030	0,163	0,296	0,430	0,563	0,696	0,667
6	0,030	0,230	0,430	0,630	0,830	1,030	1,000
8	0,030	0,296	0,563	0,830	1,096	1,363	1,333
10	0,030	0,363	0,696	1,030	1,363	1,696	1,667
Increase	0,000	0,333	0,666	1,000	1,334	1,667	

5.6 Conclusion

This chapter answers the research question *"How should the e-health care pathway be modelled into a stochastic simulation?"*. The simulation model is constructed in VBA and linked to a dashboard in Excel. Random numbers for the arrival of lung functions, chats received and chats sent are drawn from an exponential distribution and assumptions on the time spent on several e-health care activities are given as input to the model. As output, we generate the average time spent per week for each healthcare professional, and we output a 95% confidence interval that any time spent on e-health on a day is within the confidence interval range.

Additionally, this chapter answers the research question *"What is the relationship between the number of patients in the different care pathways and the asthma care capacity?"*. We observe a linear increase of the time spent on e-health care with the number of patients for all healthcare professionals with a shift in the ratio of time spent for each type of healthcare professional.

Finally, to test the influence of several variables on the model outcomes, a sensitivity analysis is performed. This analysis shows that variables which have a long duration or are performed often per week have the biggest effect on the total time spent per week. Next to that, the multi-way sensitivity analysis shows that the total time spent is affected most by the stochastic variables with the highest arrival rates, and least by the non-stochastic variables and that all variable sets behave linearly. Therefore, it differs per type of healthcare professional which variables have the biggest effect on the total time spent. It is recommended to the paediatrics department to take these more sensitive variables into account and try to obtain more historical data to improve the variable values, as they are currently estimated by the healthcare professionals. These numbers can then be used to fine-tune the model.

6 Discussion

To be able to correctly interpret the findings of this thesis, we discuss several limitations in this section. First of all, the assumptions on time spent by healthcare professionals were based on questionnaire answers, of which sometimes interpretations had to be made. Some healthcare professionals mentioned a time that was much higher than for their colleagues for the same activity, or they did not quantify the time specifically. They also mentioned that they perceived it as difficult to estimate the average time spent on certain healthcare activities. As the time spent in the current situation and for a theoretical situation modelled with the simulation model uses the same assumptions based on the questionnaire answers, we were not able to validate these assumptions with existing data. In case Medisch Spectrum Twente wants to further validate the results, performing a time-motion study would be a possible addition. This could be achieved by asking healthcare professionals to track the time they spent on e-health care over a certain time period, or by asking an independent researcher to track the time spent.

In the e-healthcare pathways in Section 2.2, a distinction was made between chats sent by healthcare professional as a reaction to a chat from a patient, or for monitoring purposes. From the questionnaire it also followed that the time spent on these two types of chat messages differs. In case data on this is prepared in such a way that the difference can be analysed, this could improve the estimations on the time spent on sending chats, as there is a difference in time spent between the two different types of chats.

In the data analysis, we found that exponential distributions were most fitting for the available data, but the line of the original data did not match the curve of the exponential distribution perfectly. For the graphs with the highest number of data points, the exponential distribution matched best with the available data, which suggests that there are too little data points to be able to accurately match the exponential distribution for the graphs in which the exponential distribution deviated a lot from the original data. Next to that, the input parameters for the exponential distribution were optimised by minimising the Sum of Squares Error, as described in Appendix H, which did not result in simulation outcomes comparable with calculations made with the available data. In case the model is used in the future, it is advisable to recheck the input parameters with an updated dataset, and change these in the simulation model accordingly. It is expected that the exponential distribution will then match the distribution of the dataset better, as the dataset will be larger. This will also be helpful in determining whether there is a seasonality effect on the total time spent. Currently, we observed higher peaks in time spent during the winter months, but the dataset only consists of 15 months of data, of which the winter occurs twice. Therefore, there is too little data to state that during any specific month the total time spent is always lower or higher than the average amount of time spent.

Next to that, no difference in the size of the text is being made to model the time spent on sent chats. For further research, it could be interesting to make an assumption on the time spent on sending a chat based on the number of characters the chat contains, and include a stochastic input factor about the size of the text in the simulation model as well. Also, when several chats are sent shortly after each other to the same patient, the model currently keeps the time spent on each chat the same, while in practice the time spent on such chats decreases because the healthcare professionals are already more aware of the background of the patients' complaints.

Additionally, the number of lung functions, chats received and chats sent are modelled as independent arrivals. In fact, these are partially related, as can also be seen in the care pathways in Section 2. For the average time spent per week, it is not likely that there will be much difference when these variables would be modelled as dependent variables, but it is expected that the confidence interval of the time spent will become bigger. Therefore, especially for scheduling e-health care it is necessary to assume a higher variability than the model gives as output.

Another point of discussion is that in the current dataset, there is diversity in the characteristics that the patients have, such as their age, the number and type of allergies they have, and how severe their asthma is. There is no guarantee that the characteristics in a future set of included patients will have the same diversity as in the current situation. Therefore, to improve the forecast on the total time spent, the patient characteristics can be matched with input parameters as well. With this, patient characteristics can either be randomly drawn or given as input to the model, and the estimations on the total time spent per week can be based on the patient characteristics of the included set of patients.

There is also a steady increase in the number of patients over the dataset period. In the beginning, only 10 patients were included in e-health care, while at the end of the dataset period, about 40 patients were included. Throughout the research, the data has always been transformed for a constant number of patients, such that the data could be compared. However, this means that the influence from individual patients on the data is bigger in the beginning of the dataset period. Because of that, it is also difficult to draw conclusions on specific periods of time or patient characteristics that result in a higher workload from e-health care.

7 Conclusion and recommendations

In this chapter, we state the conclusion to the main research question in Section 7.1, after which we give recommendations to Medisch Spectrum Twente and discuss possible future research in Section 7.2.

7.1 Conclusion

This study was conducted to find the answer to the main research question: *"What is the effect of expansion of the e-health care on the staff capacity in the pulmonary paediatrics department?"*. The incentive for this research was that the paediatrics department at Medisch Spectrum Twente has a lack of insight into the time spent in e-health care, which resulted in too little insight into what staff capacity is needed for an expansion of the e-health care they provide to patients with asthma.

By creating a Monte-Carlo simulation with exponential input distributions, we found that when expanding e-health care to a set of 100 patients, the time spent by all healthcare professionals increases linearly. The time spent by the asthma nurse increases the most, followed by the technical physicians, specialist nurse and lastly the pediatricians. By increasing the included number of patients in e-healthcare, a shift in task division is also observed, where the most important results are that the technical physicians perform less work and the specialist nurse and asthma nurse perform more work in terms of percentage of time spent on e-health care.

In our literature search, we did not find any articles that use a stochastic simulation model to predict the time spent on an e-health app. Therefore, this research shows a scientific contribution to the field of healthcare operations modelling in an e-health context. More specifically, the way we quantify the total time spent on e-health is an interesting scientific contribution, because healthcare organisations often want to know this to make a cost-benefit analysis of e-health care interventions. In practice, this means that a better understanding in the time spent on e-health care is useful for determining the necessary healthcare professional capacity for e-health care at the paediatrics department of Medisch Spectrum Twente.

Even though the research contributes to science, it is not likely that the research is easily generalisable to other e-health applications. This is because the built simulation model runs on many assumptions, made from both the data and the observations made in the paediatrics department. Also, it is specifically applied to the e-health care pathway at the paediatrics department at Medisch Spectrum Twente. This is not a standard care pathway that is used in many hospitals because the e-health application is developed specifically by healthcare professionals from the paediatrics department for their patients.

7.2 Recommendations and further research

Based on the information gathered during this research, we make recommendations to the paediatrics department of Medisch Spectrum Twente. First of all, by evaluating the simulation model, we found that variables that have a long duration or are performed often per week have the largest effect on the total time spent per week. When the number of included patients is increased, these variables should be evaluated and updated in the simulation model to gain insight in the time spent in a future situation. This could be done by handing out a questionnaire to the healthcare professionals again or by timing the time spent on each task.

Additionally, from the problem cluster in Section 1.3 it became clear that there are two action problems that we did not focus on in this research. The first being "difficult to receive monetary compensation for given care". Multiplying the average time spent per week with the hourly pay rate of healthcare professionals and adding any other e-healthcare expenses can provide more information about the costs of e-health to the healthcare insurance companies, which is helpful in conversations about reimbursements. The other action problem is "scheduling time for e-health care is difficult". Further research can be done into reasons for higher peaks on different days of the week. This can be used for creating an e-health care demand forecast that can be used for reserving time to spend on e-health care throughout each week.

In Section 1.2, we saw that the use of the Puffer app has decreased the amount of care provided to asthma patients in the hospital itself. Including the decrease in care provided in the hospital is interesting further research to investigate whether including more patients results in a net decrease in time spent on e-health care by all types of healthcare professionals. In case the average time spent on in-hospital care for the pediatrician and specialist nurse decreases more than it increases for a higher number of included e-health patients, it is advisable to include more patients in e-health, as these healthcare professionals are most expensive to the hospital. In case the time spent by the technical physicians and asthma nurse increases more than it decreases, it could be useful to include another asthma nurse or technical physician who partially takes up these tasks. Another option would be to allocate some of the tasks that the technical physicians and asthma nurse currently do to other healthcare professionals, such that the workload within the paediatrics department stays in balance.

As described in Section 3.1.2, there are several factors that cause severe asthma symptoms, leading to a need for hospital care. Matching several factors with available data on the existing set of e-health patients could result in more predictable e-healthcare demand throughout the different weeks, which can improve the scheduling of e-healthcare. To match factors causing severe asthma symptoms with the average time spent per week on e-health care, it is also useful to change the fixed variables such as the “time spent on dicussing patients” to stochastic variables. This could be done by gathering data on the number of patients discussed, the number of patients to call with, the number of e-health updates written and extra time spent per week. This data can then be used to calculate the total time spent per week for each week of the dataset, such that it can be compared with the occurrence of possible factors that cause severe asthma symptoms. Additionally, this data can then be fitted to distributions such that it can be included in the simulation model for more accurate predictions of the time spent per week.

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Appendix A Statement on use of AI

"During the preparation of this work the author used ChatGPT in order to establish related search terms for the systematic literature review and to assist in the VBA code writing for the simulation model. Also, Mendeley has been used for collection and storage of the literature used in the project plan. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the work."

Appendix B Approval ethics committee BMS

As can be seen in Figure B.1, the ethics committee BMS has approved the request for carrying out this research.

Req...	Title	Researcher	Application	Appr.superv.	Status
240420	Assessing the effect of expanding e-health care on the capacity in the paediatrics department	Mak, L.	21-03-2024	22-03-2024	Approved by commission

Figure B.1: *Research approval of the ethics committee BMS*

Appendix C Visit to outpatient clinic

Most patients visit the outpatient clinic about once a year for a regular check-up, but the aim of e-health care is to reduce this as much as possible. When a patient experiences complaints for a long period, this could also be more often. When everything is going well with a patient, a checkup can also occur less often. In Figure C.1 it can be seen which activities are being performed when a patient visits the outpatient clinic.

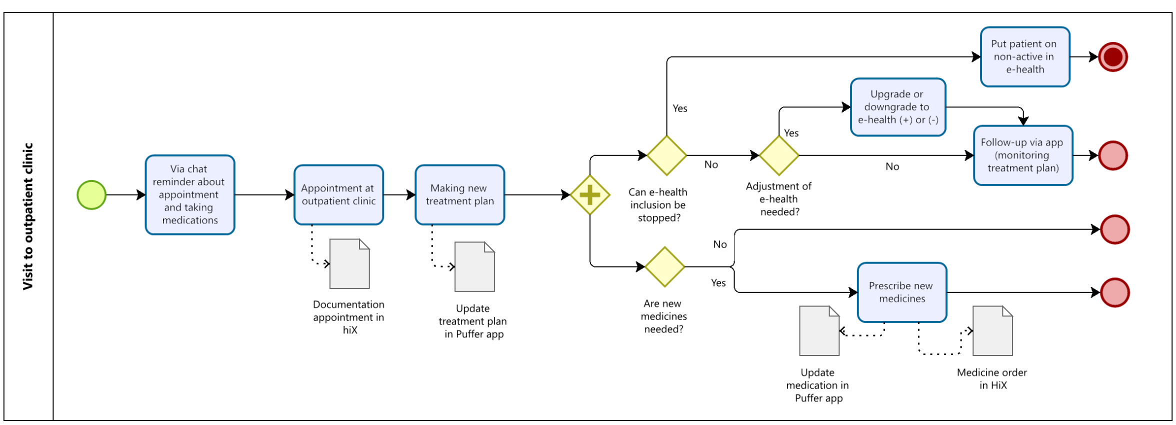


Figure C.1: *Outpatient clinic visit process*

The outpatient clinic visits are being done by the technical physicians in combination with the asthma nurse. These staff members are under supervision of the pediatrician, which means that treatment plans and medication subscriptions need to be checked by them. It can be questioned whether the outpatient clinic visit is officially part of e-health, because there is usually no contact via the Puffer app about it except for a reminder to bring the medication as a patient. Typically, e-healthcare also contributes to a decrease in outpatient clinic visits, because patients have better control over their asthma and complaints are treated sooner.

When the patient visits the outpatient clinic, there can be several different types of appointments. This could be an exercise test, consult or call with the pediatrician in case of complex treatment changes, consult or call with the specialist nurse in case of difficulties with contact via e-health, or because of persisting complaints from the patient. Also, a consult with the asthma nurse can be scheduled to explain asthma management issues, or a lung function can be performed, which is usually in combination with one of the previously mentioned types of consults and performed with a technical physician.

The patient can either have e-health(-), which contains only the chat function, or e-health(+), which has the chat function and a smart spirometer at home to measure lung functions. Reasons for an upgrade or inclusion in e-health could be that the patient had an asthma exacerbation, has difficult-to-treat asthma, a bad perception of symptoms, difficulties with asthma self-management, or that doctors suspect that the patient has bad therapy compliance or inhalation technique and uncontrolled asthma. A reason for a downgrade or exclusion from e-health could be that the patient has good enough asthma self-management to proceed without e-health or without sending lung functions. Another reason could be that the patient prefers the regular type of healthcare over e-healthcare treatment.

Appendix D Literature review on factors contributing to asthma complaints

In Table D.1 the search log for the literature review on factors contributing to severe asthma complaints can be seen.

Table D.1: *Search log of the literature review on factors contributing to asthma complaints*

Date	Source	Search string (databases) or search method (other sources)	Total hits	Remarks
24-05-2024	PubMed	((factor*[Title/Abstract]) AND (asthma[Title/Abstract])) AND (complain*[Title/Abstract]) Filtered on free full-text, full text available, and article language: English	120	Only a few relevant articles, search string too broad, asthma should be used in combination with complaints.
24-05-2024	PubMed	((cause*[Title/Abstract] OR reason*[Title/Abstract])) AND ((asthma[Title/Abstract] OR (asthma exacerbation[Title/Abstract]) OR (asthma complaint*[Title/Abstract]))) AND children Filtered on free full-text, full text available, and article language: English	2101	Many results, but many seem quite relevant.
27-05-2024	PubMed	((trigger*[Title] OR factor*[Title] OR cause*[Title] OR reason*[Title]) AND (asthma[Title] OR asthma exacerbation*[Title] OR asthma complaint*[Title])) AND (child*[Title]) Filtered on free full-text, full text available, and article language: English	351	Lot of articles mention factors that cause childhood asthma, so will eliminate childhood as search term.
27-05-2024	PubMed	((trigger*[Title] OR factor*[Title] OR cause*[Title] OR reason*[Title]) AND (asthma[Title] OR asthma exacerbation*[Title] OR asthma complaint*[Title])) AND (child*[Title]) NOT (childhood [Title]) Filtered on free full-text, full text available, and article language: English	250	Many articles still refer to the development of asthma, so will focus only on asthma exacerbations in keywords.
27-05-2024	PubMed	((trigger*[Title] OR factor*[Title] OR cause*[Title] OR reason*[Title]) AND (asthma[Title] OR asthma exacerbation*[Title] OR asthma complaint*[Title])) AND (child*[Title]) NOT (childhood [Title]) Filtered on free full-text, full text available, and article language: English	250	Many articles still refer to the development of asthma, so will focus only on asthma exacerbations in keywords.
27-05-2024	PubMed	(trigger*[Title] OR factor*[Title] OR cause*[Title] OR reason*[Title]) AND ("asthma exacerbation*"[Title/Abstract]) AND (child*[Title]) NOT (childhood [Title]) Filtered on free full-text, full text available, and article language: English	21	Good results, so final search term.

Appendix E Systematic literature review on stochastic simulation models

To be able to justify which articles resulting from the systematic literature review are relevant, inclusion and exclusion criteria are defined. If all inclusion criteria are met, and none of the exclusion criteria are met, an article is deemed relevant. The inclusion and exclusion criteria are mentioned in Table E.1 and E.2.

Table E.1: *Inclusion criteria*

Inclusion criteria	
Criterion	**Explanation**
Article is written in English or Dutch	If not in English or Dutch, I can not understand the text, and thus not correctly interpret the research.
Article is written after 2000.	Mobile health applications started to exist in the early 2000s (Park et al., 2014).
Source describes a model with some sort of demand variability.	The e-health app used in the paediatrics department also has demand variability, so to be able to use the model presented in the literature it needs to contain variability.
The model described is applied in a healthcare setting.	If the model is not applied in a healthcare setting, it is much more difficult to check whether the reasoning for a specific type of model aligns with the type of situation for the e-health care app studied in this thesis.

Table E.2: *Exclusion criteria*

Exclusion criteria	
Criterion	**Explanation**
Too much focus on the medical benefits of e-health.	This thesis focuses on the time capacity of hospital staff, so examining medical effects of using e-health (e.g. better quality of life) is out of the scope.
Too much focus on the technological aspects of designing an e-health app.	This thesis focuses on the implementation of an existing e-health app, so anything technological about the app itself is out of the scope.
Too much focus on creating an optimal schedule based on fixed resources.	The aim of this thesis is to find out what capacity is needed for a given number of patients, so in this case, the resources are the variable. Creating an optimal schedule would be the next step and thus out of the scope of this thesis.

In Table E.3, the number of search results from the systematic literature review on selecting a suitable type of stochastic simulation can be seen.

Table E.3: *Number of search results found*

Records identified through database searching (Scopus & PubMed)	**299**
Additional records identified through article citations	1
Total records identified	**300**
Duplicates	212
Records after duplicates removed	**88**
Records included after screening on title and abstract	**14**
Full-text articles excluded based on exclusion criteria	9
Articles included in project plan	**5**

After performing the search, four articles were found to be relevant according to the inclusion and exclusion criteria. An explanation on the models described in these articles can be seen in Table E.4.

In Table E.5, an overview of the models mentioned in each article can be seen. From this conceptual matrix, it can easily be seen that discrete-event simulation is the most applied stochastic simulation model. In Table E.4, it can also be seen that three of the sources provide argumentation why the discrete-event simulation is a suitable model to use.

Table E.4: *Explanation of concepts described in the literature*

Concept / Source	(Kakad et al., 2023)	(Laan et al., 2018)	(Wang, 2023)	(Anderson et al., 2017)
Discrete-event simulation	Modelling from event to event	Evaluate schedules while taking into account fluctuating arrival rates and patients with personal preferences for a specific physician.	"... by far the most popular method to model healthcare operations. ... enables the study of discrete, dynamic and stochastic systems with various levels of detail and complexity in the healthcare environment."	It is "often used for comparison of alternative scenarios". "DES is time-based and takes into account resources, constraints and how the process and activities interact with each other as time passes."
Discrete-time simulation	Modelling in fixed increments. "Requires aggregation of multiple events during a fixed time period, which results in loss of some interactions between events."	Used to model stochasticity in patient arrivals in the SMIP model.	Not mentioned	Not mentioned
Agent-based simulation	Useful for "modelling systems where the decisions of, and interactions between, individual agents and their actions are likely to affect those aspects of overall system behaviour under study".	Not mentioned	Least popular simulation method, but it can simulate the interacting and autonomous agents whose behaviours and interactions with their environment are modelled as a set of behavioural rules.	Not mentioned
Simulation optimization	Not mentioned	Solving complicated, stochastic, and mathematically intractable decision problems, without needing many restrictive assumptions. Optimization of a given objective function satisfying some constraints.	Not mentioned	Not mentioned

Continued on next page

Concept / Source	(Kakad et al., 2023)	(Laan et al., 2018)	(Wang, 2023)	(Anderson et al., 2017)
Monte-Carlo simulation	Not mentioned	Not mentioned	"... the second most popular method. MCS is a discrete, static and stochastic simulation method, which is a scheme that applies random numbers to solve certain problems. MCS is usually used to estimate an unknown function ... by repeatedly generating many independent sample paths for each solution."	Not mentioned

Table E.5: *Conceptual matrix of models described in each scientific source*

	(Kakad et al., 2023)	(Laan et al., 2018)	(Wang, 2023)	(Anderson et al., 2017)
Discrete-event simulation	x	x	x	x
Discrete-time simulation	x	x		
Agent-based simulation	x		x	
Simulation optimization			x	
Monte-Carlo simulation			x	

In Table E.6, the search log for the systematic literature review can be seen. The search log contains the date of the search, the database, the search string used including the filters applied in the database, the total hits, and some remarks about the results of the search. In total, seven search strings were applied in two databases.

Table E.6: *Search log of the systematic literature review on selecting a stochastic simulation*

Date	Source	Search string (databases) or search method (other sources)	Total hits	Remarks
02-04-2024	Scopus	TITLE-ABS-KEY ((stochastic) AND (simulat*) AND ("e-health*") AND (capacity)) Filtered from 2000-2024, Limited to English	2	One of the articles is relevant, the other is about technological aspects of e-health applications. Will use broader search terms.
02-04-2024	Scopus	TITLE-ABS-KEY ((mathematical)AND (model) AND ("e-health*") AND (implement*)) Filtered from 2000-2024, Limited to English	21	Too technical or about the practical implementation but not about a capacity model. Sources do not describe a simulation model. No relevant sources found.
02-04-2024	Scopus	TITLE-ABS-KEY ((mathematical AND model) AND ("e-health*") AND (capacity)) Filtered from 2000-2024, Limited to English	6	No relevant sources, so will include multiple search terms for the same key concepts.
02-04-2024	Scopus	TITLE-ABS-KEY ((stochastic OR probabilistic OR variab* OR random) AND (simulat*) AND ("healthcare application" OR "e-health*" OR "m-health" OR "digital health") AND (capacity OR implementation OR optimization)) Filtered from 2000-2024 Limited to English	58	Quite some documents that contain technical aspects such as 5G, wireless networks etc. Search term capacity is too broad.
02-04-2024	Scopus	TITLE-ABS-KEY ((stochastic OR probabilistic OR variab* OR random) AND (simulat*) AND ("healthcare application" OR "e-health*" OR "m-health" OR "digital health") AND (scheduling OR "time capacity" OR staff) AND NOT (5g AND wireless)) Filtered from 2000-2024, Limited to English	13	Most sources not relevant, too much about technology of healthcare applications themselves. Will try the more specialized database.
03-04-2024	PubMed	(((stochastic[Title/Abstract]) AND (simulat*[Title/Abstract])) AND (health*[Title/Abstract])) AND ("time capacity"[Title/Abstract] OR capacity[Title/Abstract]) Filters applied: English, from 2000/1/1 - 2024/4/1, Article language: English	53	A mix of articles that are relevant and articles with too much medical focus. Many useful articles that contain stochastic simulation models.
03-04-2024	PubMed	(((stochastic[Title/Abstract]) AND (simulat*[Title/Abstract])) AND (health*[Title/Abstract])) AND ("capacity"[Title/Abstract] OR "resource*"[Title/Abstract] OR "staff scheduling"[Title/Abstract] OR "allocation"[Title/Abstract]) Filters applied: English, from 2000/1/1 - 2024/4/1, Article language: English	146	Good results, but also a lot of them not relevant. Little focus on staffing in most documents, so those will not be included.

Appendix F Literature about Monte-Carlo simulation

In Table F.1, the results of the literature study about the application of a Monte-Carlo simulation in hospital capacity modelling can be seen.

Table F.1: *Literature about Monte-Carlo simulation*

Title	Author(s)	Stochastic input parameters	Simulation size	Data sources	Sensitivity analysis used?
An eConsultant versus a hospital-based outpatient consultation for general (internal) medicine: a costing analysis	Job et al.	Input parameters drawn from a distribution based on the data collected or assumptions, lognormal service times	10000 iterations	12-month retrospective patient activity data for the period 2020–2021	Yes
Cost-effectiveness of memantine in community-based Alzheimer's disease patients: An adaptation in Spain	Antonanzas et al.	Priori distributions such as beta, dirichlet and lognormal	10000 iterations	Epidemiological data	Yes
The societal impact of implementing an at-home blood sampling device for chronic care patients: patient preferences and cost impact	Lingervelder et al.	Input parameters represented by a distribution to acquire probabilistic values	10000 iterations	Online survey results	Yes
Economic evaluation of tiotropium and salmeterol in the treatment of chronic obstructive pulmonary disease (COPD) in Greece	Maniadakis et al.	Transitions between states, exacerbation probabilities and resources utilisation are assigned distributions	5000 iterations	Clinical trials, resource utilisation and cost data from a Greek university hospital	Yes

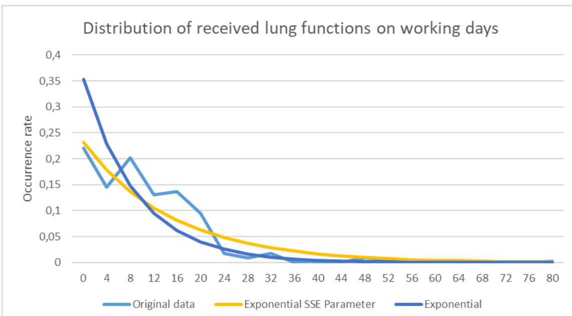
Appendix G Questionnaire about time spent on e-health care

This is a translated version of the questions asked to six healthcare professionals about the time spent on e-health care. The questions are originally posed in Dutch.

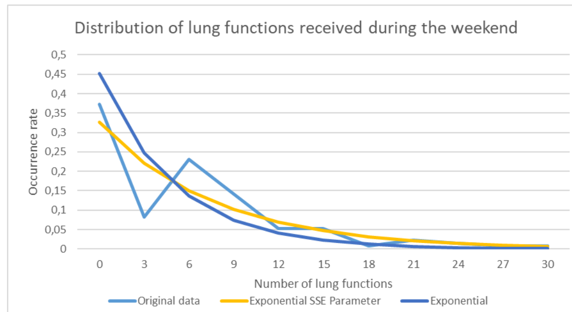
1. [Open question] What is your function within the asthma e-health team?
2. [Closed multiple choice question] Do you sometimes assess a lung function?
3. [Open question] What percentage of the sent lung functions do you assess in an average week?
4. [Open question] How much time do you need on average to assess a lung function?
5. [Open question] How much time do you need on average to **read** a text from a patient about for example complaints?
6. [Open question] About how many patients on average per week do you need to consult with other healthcare professionals? And with who do you discuss?
7. [Open question] How much time does this consult take on average when it is needed?
8. [Open question] How much time do you on average need to **send** a chat after a patient sent a **lung function** or **question**?
9. [Open question] How many inactive patients do you contact on average per week?
10. [Open question] How much time do you need on average to **send** a chat to a patient who **did not log something for a long time** in the app?
11. [Open question] With how many of those inactive patients do you call on average per week?
12. [Open question] How much time does calling 1 patient take on average?
13. [Closed multiple choice question] Do you sometimes put e-health updates in HiX as part of the monthly monitoring?
14. [Open question] How much time does it on average take to place an update about 1 patient?
15. [Open question] Are there other things you would like to share about the spent time on e-health care that are not taken into account yet in this questionnaire?

Appendix H Data analysis parameter optimisation

From the data analysis in Section 4.1 it follows that all lung functions received, chats received and chats sent are exponentially distributed. To optimise the distribution fitting, an optimised parameter has been calculated by minimising the Sum of Squares Error (SSE) with the Excel Solver. Since running the simulation with the original parameter resulted in results that are more comparable with the dataset than running the simulation with the optimised parameter, we have chosen to implement the original parameter in the simulation model. In Figures H.1, H.2 and H.3 the results of the distribution fitting with the optimised parameters as stated in Table H.1 can be seen. These seem to fit well with the data. However, in Table H.2 it can be seen that the calculation of the total time spent deviates from the original data.

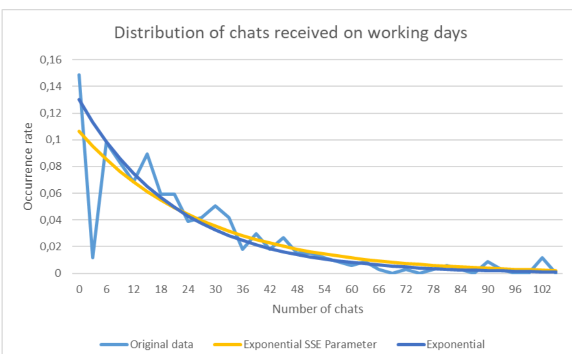


(a) *Distribution of lung functions received on weekdays per patient per day (Lambda = 0.0654, n=854, January 2023 to May 2024)*

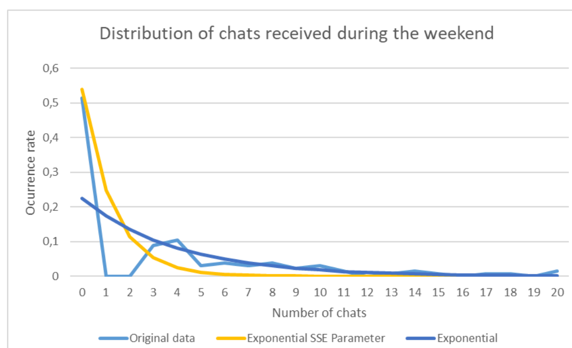


(b) *Distribution of lung functions received on the weekend per patient per day (Lambda = 0.1297, n=197, January 2023 to May 2024)*

Figure H.1: *Lung function input distributions*



(a) *Distribution of chats received during weekdays for 100 patients (Lambda = 0.0368, n=2219, January 2023 to May 2024)*



(b) *Distribution of chats received during the weekend for 100 patients (Lambda = 0.7741, n=166, January 2023 to May 2024)*

Figure H.2: *Received chat distributions*

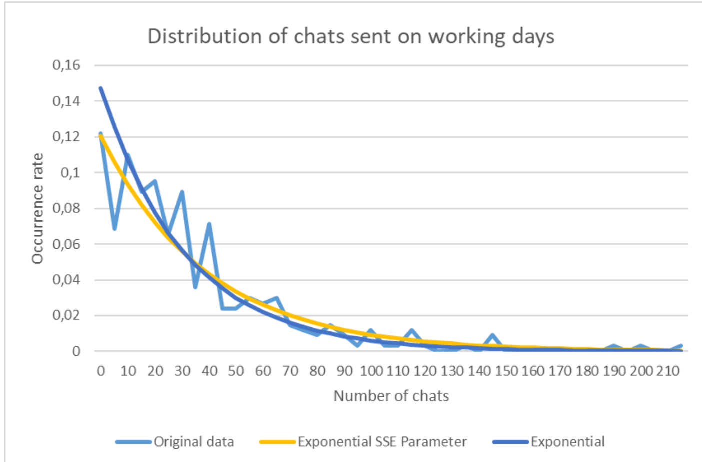


Figure H.3: *Distribution of chats sent during weekdays for 100 patients (Lambda = 0.0256, n = 3127, January 2023 to May 2024)*

Table H.1: *Parameters used for the exponential distribution*

Parameter	**Value optimised with SSE**
Lambda lung functions received on working days	0,0654
Lambda lung functions received in the weekend	0.1297
Lambda chats received on working days	0.0368
Lambda chats received in the weekend	0.7741
Lambda chats sent on working days	0.0256

Table H.2: *Simulation results compared with data for 40 patients*

Time spent by healthcare professional	**Data results (hours per week)**	**Simulation results (hours per week)**
Total time Pediatricians	0,251	0,285
Total time Specialist nurse	1,550	2,083
Total time Technical physicians	2,121	3,956
Total time Asthma nurse	2,296	3,158

Appendix I Graphs of time spent on working days

In Figures I.1, I.2 and I.3 the total time spent per working day can be seen for the pediatrician, specialist nurse and technical physician respectively.

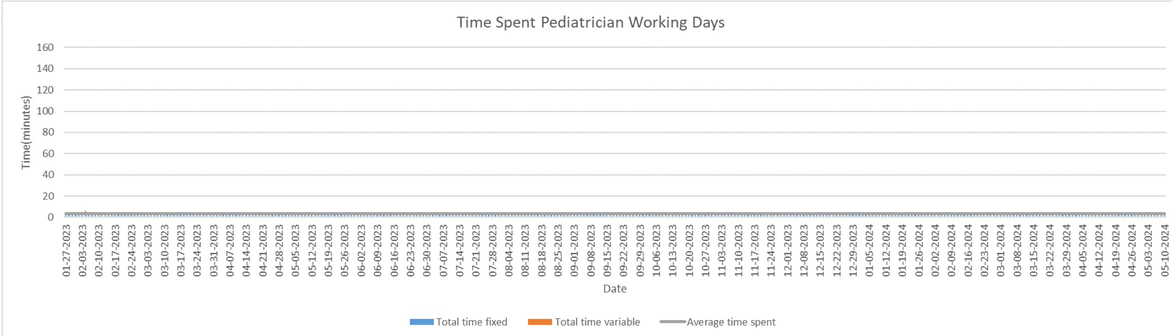


Figure I.1: *Time spent divided in fixed time and variable time per working day for the pediatrician*

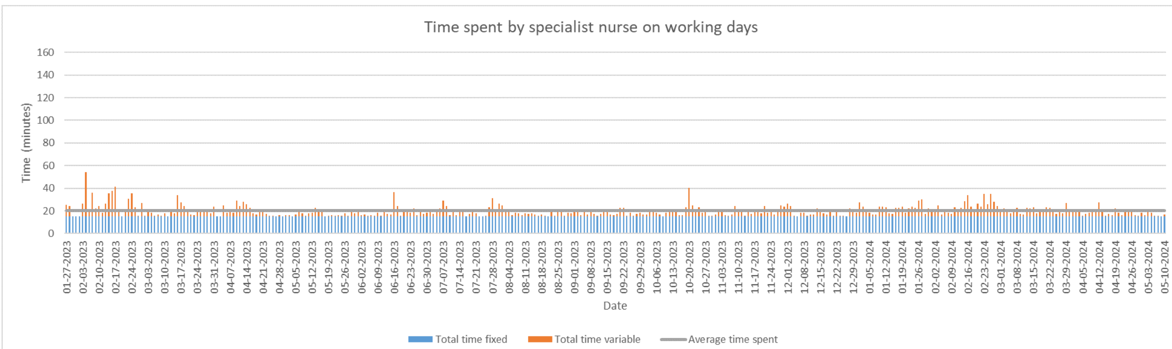


Figure I.2: *Time spent divided in fixed time and variable time per working day for the specialist nurse*

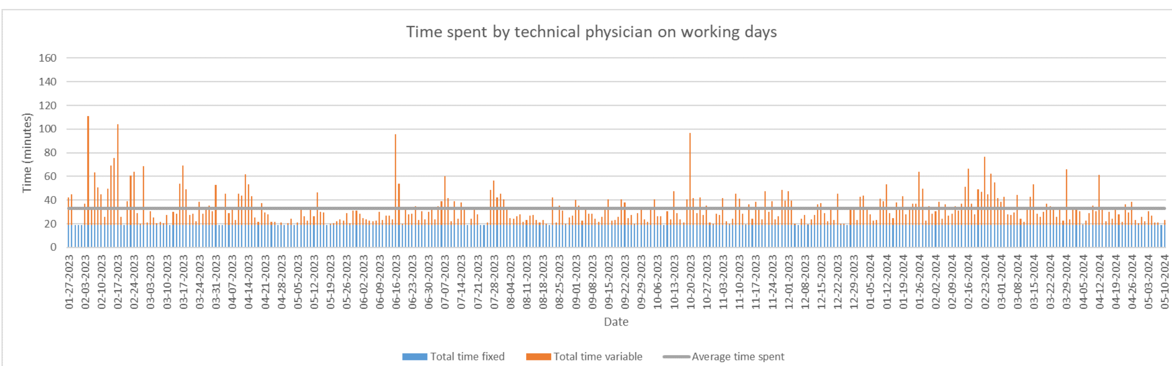


Figure I.3: *Time spent divided in fixed time and variable time per working day for the technical physician*

Appendix J VBA source code

```
Attribute VB_Name = "Module1"
Option Explicit

'Author: Lydia Mak
'Made for IEM Bachelor Thesis Project
'Last update: 03/07/2024

Public NrPatients As Long
Public NumDays As Integer
```

```
Public Years As Integer
Public NumberLF() As Long
Public NumberChatsReceived() As Long
Public NumberChatsSent() As Long
Public TotalTime() As Double
Public RandomYear As Integer
Public Iterations As Integer
Public WarmUpYears As Integer

Sub Main()

'Only update values at the end of the code execution
Application.ScreenUpdating = False

Dim ws As Worksheet
Set ws = Worksheets("Dashboard")

'Give values to public variables
NrPatients = ws.Cells(3, 3)
NumDays = 365
Years = ws.Cells(4, 3)
WarmUpYears = ws.Cells(5, 3)
Iterations = ws.Cells(6, 3)
RandomYear = WarmUpYears + Int((Years - WarmUpYears) / 2)

'Error handling
If Years < 1 Then
    MsgBox ("The number of years must be higher or equal to 1")
    Exit Sub
End If

If WarmUpYears >= Years Then
    MsgBox ("The Run-Length must be at least 1 year higher than the Warm-Up period, but can not be higher than 89 years.")
    Exit Sub
ElseIf Years > 89 Then
    MsgBox ("The Run-Length must be at least 1 year higher than the Warm-Up period, but can not be higher than 89 years.")
    Exit Sub
End If

If RandomYear < WarmUpYears Then
    MsgBox ("The graph plots a year within the warm-up period. For more reliable results, choose a higher number of years.")
End If

Randomize 'Re-seed the random number generation, only has to be done once

'Delete previous output and charts from the worksheet
ws.Range("F4:H7").Clear
If ws.ChartObjects.Count > 0 Then
    ws.ChartObjects.Delete
End If

'Formatting
Range("E2:H8").Borders(xlDiagonalDown).LineStyle = xlNone
Range("E2:H8").Borders(xlDiagonalUp).LineStyle = xlNone
With Range("E2:H8").Borders(xlEdgeLeft)
    .LineStyle = xlContinuous
    .ColorIndex = 0
    .TintAndShade = 0
    .Weight = xlThin
End With
With Range("E2:H8").Borders(xlEdgeTop)
    .LineStyle = xlContinuous
    .ColorIndex = 0
    .TintAndShade = 0
    .Weight = xlThin
End With
With Range("E2:H8").Borders(xlEdgeBottom)
    .LineStyle = xlContinuous
```

```
    .ColorIndex = 0
    .TintAndShade = 0
    .Weight = xlThin
End With
With Range("E2:H8").Borders(xlEdgeRight)
    .LineStyle = xlContinuous
    .ColorIndex = 0
    .TintAndShade = 0
    .Weight = xlThin
End With
Range("E2:H8").Borders(xlInsideVertical).LineStyle = xlNone
Range("E2:H8").Borders(xlInsideHorizontal).LineStyle = xlNone

'Call the different subs
Arrivals
CalculatingTimeSpent
MakeHistogram

Application.ScreenUpdating = True

End Sub


Function RandomExponential(Lambda As Double) As Double

Dim RandomNumber As Double

RandomNumber = Rnd() ' Draw a random number between 0 and 1

RandomExponential = (-1 / Lambda) * Log(1 - RandomNumber)

End Function

Sub Arrivals()

Dim LambdaLFWorkingDays As Double
Dim LambdaLFWeekend As Double
Dim LambdaChatsRecWorkingDays As Double
Dim LambdaChatsRecWeekend As Double
Dim LambdaChatsSentWorkingDays As Double
Dim NumberDayOfWeek As Integer
Dim Days() As Long
Dim d As Long
Dim i As Long
Dim DayNumber As Long 'Counter to keep track of the DayNumber over all years
Dim it As Long
Dim NrLFIterations() As Integer
Dim NrChatsReceivedIterations() As Integer
Dim NrChatsSentIterations() As Integer
Dim NrLF As Integer
Dim NrChatsRec As Integer
Dim NrChatsSent As Integer

ReDim Days(1 To NumDays * Years)
ReDim NumberLF(1 To NumDays * Years)
ReDim NumberChatsReceived(1 To NumDays * Years)
ReDim NumberChatsSent(1 To NumDays * Years)
ReDim NrLFIterations(1 To Iterations)
ReDim NrChatsReceivedIterations(1 To Iterations)
ReDim NrChatsSentIterations(1 To Iterations)

i = 0
For i = 1 To NumDays * Years
    Days(i) = i
Next i

'Lambdas derived from means of historical data
LambdaLFWorkingDays = 0.10902
LambdaLFWeekend = 0.200182
LambdaChatsRecWorkingDays = 0.04615
LambdaChatsRecWeekend = 0.253136
```

```
LambdaChatsSentWorkingDays = 0.03181

DayNumber = 1
d = 0

For d = 1 To Years * NumDays

    NumberDayOfWeek = ((Days(d) - 1) Mod 7) + 1

    NrLF = 0
    NrChatsRec = 0
    NrChatsSent = 0

       For it = 1 To Iterations

            'The day of the week (1 = Monday, 2 = Tuesday, ... , 7 = Sunday)
            'Check if it is a working day or weekend
            If NumberDayOfWeek <= 5 Then 'Working day
                'Use the RandomExponential function to find an arrival rate
                'The Lambda is based on 100 patients, so divide by 100 and multiply
    with NrPatients
                NrLFIterations(it) = (RandomExponential(LambdaLFWorkingDays) / 100) *
    NrPatients
                NrChatsReceivedIterations(it) = (RandomExponential(
    LambdaChatsRecWorkingDays) / 100) * NrPatients
                NrChatsSentIterations(it) = (RandomExponential(
    LambdaChatsSentWorkingDays) / 100) * NrPatients
            Else 'Weekend
                NrLFIterations(it) = (RandomExponential(LambdaLFWeekend) / 100) *
    NrPatients
                NrChatsReceivedIterations(it) = (RandomExponential(
    LambdaChatsRecWeekend) / 100) * NrPatients
                NrChatsSentIterations(it) = 0
            End If

            NrLF = NrLF + NrLFIterations(it)
            NrChatsRec = NrChatsRec + NrChatsReceivedIterations(it)
            NrChatsSent = NrChatsSent + NrChatsSentIterations(it)

       Next it

    NumberLF(DayNumber) = NrLF / Iterations
    NumberChatsReceived(DayNumber) = NrChatsRec / Iterations
    NumberChatsSent(DayNumber) = NrChatsSent / Iterations

    DayNumber = DayNumber + 1

Next d

End Sub


Sub CalculatingTimeSpent()

Dim InputTimes() As Double
Dim Role As Integer '(1 = pediatrician, 2 = specialist nurse, 3 = technical physician,
 4 = asthma nurse)
Dim TimeSpent As Integer '(1 = assessing lung function, 2 = reading chat, 3 =
    discussing patient, 4 = sending chat, 5 = calling patient, 6 = writing e-health
    update, 7 = extra time)
Dim t As Long
Dim r As Long
Dim i As Long
Dim SumTotalTime As Double
Dim PercentageLFAssessed() As Double
Dim NrPatientsDiscuss() As Double
Dim PercentageChatsSent() As Double
Dim PercentageChatsRead() As Double
Dim NrInactivePatientsCall() As Double
Dim NrEhealthUpdates() As Double
Dim DayNumber As Long
```

```
Dim TotalTime() As Double
Dim ConfidenceInterval As Double
Dim MeanTotalTime As Double
Dim SumOfSquaresError As Double
Dim SampleSize As Integer
Dim SampleVariance As Double
Dim SampleDeviation As Double
Dim ConfidenceLevelValue As Double
Dim LFTime As Double
Dim ChatReadTime As Double
Dim DiscussTime() As Double
Dim ChatSentTime As Double
Dim CallPatientTime() As Double
Dim EhealthUpdateTime() As Double
Dim ExtraTime() As Double
Dim LFTimeSum() As Double
Dim ChatReadTimeSum() As Double
Dim ChatSentTimeSum() As Double
Dim FTENeeded As Double

'Variable values
Role = 4
TimeSpent = 7
ConfidenceLevelValue = 1.96 'Value for a 95% Confidence Interval

'Dimensioning the arrays
ReDim LFTimeSum(1 To Role) As Double
ReDim ChatReadTimeSum(1 To Role) As Double
ReDim ChatSentTimeSum(1 To Role) As Double
ReDim DiscussTime(1 To Role)
ReDim CallPatientTime(1 To Role)
ReDim EhealthUpdateTime(1 To Role)
ReDim ExtraTime(1 To Role)
ReDim InputTimes(1 To TimeSpent, 1 To Role)
ReDim TotalTime(1 To Role, 1 To Years * NumDays)
ReDim PercentageLFAssessed(1 To Role)
ReDim NrPatientsDiscuss(1 To Role)
ReDim PercentageChatsSent(1 To Role)
ReDim PercentageChatsRead(1 To Role)
ReDim NrInactivePatientsCall(1 To Role)
ReDim NrEhealthUpdates(1 To Role)

r = 0
i = 0
For r = 1 To Role
    For t = 1 To TimeSpent
        InputTimes(t, r) = Worksheets("Dashboard").Cells(t + 11, r + 2).Value
        'Debug.Print "InputTimes(" & t & "," & r & "): " & InputTimes(t, r)
    Next t
Next r

'Filling the arrays (with values from table of questionnaire results)
PercentageLFAssessed(1) = 0
PercentageLFAssessed(2) = 0.25
PercentageLFAssessed(3) = 1
PercentageLFAssessed(4) = 0.1
NrPatientsDiscuss(1) = (2 / 40 * NrPatients) / 7  'Per day
NrPatientsDiscuss(2) = (5 / 40 * NrPatients) / 7
NrPatientsDiscuss(3) = (4 / 40 * NrPatients) / 7
NrPatientsDiscuss(4) = (4 / 40 * NrPatients) / 7
PercentageChatsSent(1) = 0.0003
PercentageChatsSent(2) = 0.0444
PercentageChatsSent(3) = 0.3655
PercentageChatsSent(4) = 0.5898
PercentageChatsRead(1) = 0.05 'Does not count up to 1, because there is overlap in who
     reads what
PercentageChatsRead(2) = 0.2
PercentageChatsRead(3) = 0.4
PercentageChatsRead(4) = 0.7
NrInactivePatientsCall(1) = (0 / 40) * NrPatients / 7 'Per day
NrInactivePatientsCall(2) = (1 / 40) * NrPatients / 7
```

```
NrInactivePatientsCall(3) = (0 / 40) * NrPatients / 7
NrInactivePatientsCall(4) = (1 / 40) * NrPatients / 7
NrEhealthUpdates(1) = (0 / 40 * NrPatients) / 7  'Per day
NrEhealthUpdates(2) = (1 / 40 * NrPatients) / 7
NrEhealthUpdates(3) = (3 / 40 * NrPatients) / 7
NrEhealthUpdates(4) = (1 / 40 * NrPatients) / 7

r = 0
i = 0
'Initialise the total time array
For r = 1 To Role
    For i = 1 To Years * NumDays
        TotalTime(r, i) = 0
    Next i
Next r


'Time spent not dependent on DayNumber
For r = 1 To Role
    DiscussTime(r) = NrPatientsDiscuss(r) * InputTimes(3, r) 'Per day
    CallPatientTime(r) = NrInactivePatientsCall(r) * InputTimes(5, r) 'Per day
    EhealthUpdateTime(r) = NrEhealthUpdates(r) * InputTimes(6, r) 'Per day
    ExtraTime(r) = InputTimes(7, r) 'Per day
    Debug.Print "Discuss time " & r & " is " & DiscussTime(r) * 7
    Debug.Print "Calling time " & r & " is " & CallPatientTime(r) * 7
    Debug.Print "E-health update time " & r & " is " & EhealthUpdateTime(r) * 7
    Debug.Print "Extra time " & r & " is " & ExtraTime(r) * 7
Next r


'Time spent dependent on DayNumber
'First calculate the time in minutes per day, then transform that to hours per weeks
For r = 1 To Role
    SumTotalTime = 0
    DayNumber = 1

        For i = WarmUpYears * NumDays To Years * NumDays
            LFTime = PercentageLFAssessed(r) * NumberLF(DayNumber) * InputTimes(1, r)
            ChatReadTime = PercentageChatsRead(r) * NumberChatsReceived(DayNumber) * InputTimes(2, r)
            ChatSentTime = PercentageChatsSent(r) * NumberChatsSent(DayNumber) * InputTimes(4, r)
            TotalTime(r, DayNumber) = LFTime + ChatReadTime + DiscussTime(r) + ChatSentTime _
            + CallPatientTime(r) + EhealthUpdateTime(r) + ExtraTime(r)

            LFTimeSum(r) = LFTimeSum(r) + LFTime
            ChatReadTimeSum(r) = ChatReadTimeSum(r) + ChatReadTime
            ChatSentTimeSum(r) = ChatSentTimeSum(r) + ChatSentTime

            SumTotalTime = SumTotalTime + TotalTime(r, DayNumber)

            DayNumber = DayNumber + 1

        Next i

    'Print the total time on the Dashboard
    Worksheets("Dashboard").Cells(r + 3, 6) = Round(SumTotalTime / 60 / ((DayNumber) / 7), 3) 'Average time in hours per week

    'For determining the Confidence Interval
    MeanTotalTime = SumTotalTime / (Years * NumDays - WarmUpYears * NumDays)
    DayNumber = 1 'Reset

    For i = WarmUpYears * NumDays To Years * NumDays
        SumOfSquaresError = SumOfSquaresError + (TotalTime(r, DayNumber) - MeanTotalTime) ^ 2
        DayNumber = DayNumber + 1
    Next i

    SampleVariance = SumOfSquaresError / (Years * NumDays - WarmUpYears * NumDays)
```

```
    SampleDeviation = Sqr(SampleVariance)
    SampleSize = Years * NumDays - WarmUpYears * NumDays
    ConfidenceInterval = ConfidenceLevelValue * (SampleDeviation / SampleSize)

    'Print the confidence interval
    Worksheets("Dashboard").Cells(r + 3, 7) = "+/- " & Format(ConfidenceInterval, "
    0.0000")

    'Print number of FTE's needed
    FTENeeded = (SumTotalTime / 60 / ((DayNumber) / 7)) / 36
    Worksheets("Dashboard").Cells(r + 3, 8) = Round(FTENeeded, 2)

Next r

End Sub

Sub MakeHistogram()

Dim x() As Double
Dim y_LF() As Double
Dim y_ChatsReceived() As Double
Dim y_ChatsSent() As Double
Dim i As Long
Dim ws As Worksheet
Dim rng_LF As Range
Dim rng_ChatsReceived As Range
Dim rng_ChatsSent As Range
Dim chartObj As ChartObject

' Reference the "Dashboard" worksheet
Set ws = Worksheets("Dashboard")

' Set the range where the chart output needs to be
Set rng_LF = ws.Range("B20:H38")
Set rng_ChatsReceived = ws.Range("J2:U18")
Set rng_ChatsSent = ws.Range("J20:U38")

' Initialize arrays
ReDim x(1 To NumDays)
ReDim y_LF(1 To NumDays)
ReDim y_ChatsReceived(1 To NumDays)
ReDim y_ChatsSent(1 To NumDays)

' Populate arrays with data
For i = 1 To NumDays
    x(i) = i
    y_LF(i) = NumberLF(NumDays * RandomYear + i)
    y_ChatsReceived(i) = NumberChatsReceived(NumDays * RandomYear + i)
    y_ChatsSent(i) = NumberChatsSent(NumDays * RandomYear + i)
Next i

'The Lung function chart
Set chartObj = ws.ChartObjects.Add(Left:=rng_LF.Left, Width:=rng_LF.Width, Top:=rng_LF
    .Top, Height:=rng_LF.Height)
With chartObj.Chart
    .ChartType = xlColumnClustered

    If .SeriesCollection.Count = 0 Then .SeriesCollection.NewSeries

    With .SeriesCollection(1)
        .XValues = x
        .Values = y_LF
    End With

    .HasTitle = True
    .ChartTitle.Text = "Lung Functions Received per Day"
    .HasLegend = False
    .Axes(xlCategory, xlPrimary).HasTitle = True
    .Axes(xlCategory, xlPrimary).AxisTitle.Text = "Days"
    .Axes(xlValue, xlPrimary).HasTitle = True
    .Axes(xlValue, xlPrimary).AxisTitle.Text = "Count"
```

```
End With

'The Received Chats chart
Set chartObj = ws.ChartObjects.Add(Left:=rng_ChatsReceived.Left, Width:=
    rng_ChatsReceived.Width, Top:=rng_ChatsReceived.Top, Height:=rng_ChatsReceived.
    Height)
With chartObj.Chart
    .ChartType = xlColumnClustered

    If .SeriesCollection.Count = 0 Then .SeriesCollection.NewSeries
    With .SeriesCollection(1)
        .XValues = x
        .Values = y_ChatsReceived
    End With

    .HasTitle = True
    .ChartTitle.Text = "Chats Received per Day"
    .HasLegend = False
    .Axes(xlCategory, xlPrimary).HasTitle = True
    .Axes(xlCategory, xlPrimary).AxisTitle.Text = "Days"
    .Axes(xlValue, xlPrimary).HasTitle = True
    .Axes(xlValue, xlPrimary).AxisTitle.Text = "Count"
End With

'The Sent Chats chart
Set chartObj = ws.ChartObjects.Add(Left:=rng_ChatsSent.Left, Width:=rng_ChatsSent.
    Width, Top:=rng_ChatsSent.Top, Height:=rng_ChatsSent.Height)
With chartObj.Chart
    .ChartType = xlColumnClustered

    If .SeriesCollection.Count = 0 Then .SeriesCollection.NewSeries

    With .SeriesCollection(1)
        .XValues = x
        .Values = y_ChatsSent
    End With

    .HasTitle = True
    .ChartTitle.Text = "Chats Sent per Day"
    .HasLegend = False
    .Axes(xlCategory, xlPrimary).HasTitle = True
    .Axes(xlCategory, xlPrimary).AxisTitle.Text = "Days"
    .Axes(xlValue, xlPrimary).HasTitle = True
    .Axes(xlValue, xlPrimary).AxisTitle.Text = "Count"
End With

End Sub
```