Capacity planning model in a home care environment

Master Thesis Industrial Engineering and Management

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These chapters are written as part of the master thesis project in the Master in Industrial Engineering and Management educational program.

Used English translation of Dutch concepts

Wijkzorg = home care nursing

Zorg op afstand = remote care

Specialistische zorg = specialized care

Thuisbegeleiding = home assistance

Verpleegtechnische handelingen = nursing technical care operations.

Preface

Thank you for picking up this report and spending some of your precious time reading or browsing through it. I wrote this report as part of my master's thesis in Industrial Engineering and Management at the University of Twente from May 2022 to Jan 2023 with the Dutch healthcare organisations Sensire and the Slingeland hospital.

This report makes up the final part of almost three years of intense studying in which I found myself more often in the library than outside. More often stressed out than relaxed. Therefore, besides developing all the hard, professional and management skills, I set another intention. I did not want to only dedicate my mental space to writing my master's thesis and get caught up and burnt out in the process. I intended to develop my skills and explore the assignment from a filled cup rather than an empty, stressed-out one. So I filled my cup living a bit of the nomad working live, learning Spanish, improving my German, setting up a small creative business, training for a marathon, yoga, sports and starting therapy. Not because things did not go well but out of curiosity and a better understanding of my behavioural patterns. This filled cup helped me to work on my master's thesis in a balanced, maintainable and productive way which is a first-timer for me. Therefore, this report is not just an academic work but a representation of a process I am proud of.

However, a process is never complete without reflecting and finding points for improvement. A future point of attention is to focus on a practical solution, which was hard due to the strategic level. Another point of attention is improving my communication balancing between all stakeholders and translating Industrial Engineering jargon into understandable language for everyone. By implementing these points of attention, the next time I choose my method, I will be able to more actively ask for help and not hesitate.

I thank Sensire and Slingeland for allowing me to write my master's thesis in both organisations and guiding me from different professional perspectives. Special thanks to my supervisors Yvanka Klein Holte (District Nurse, Sensire) and Gijs Spijkers (capacity manager, Slingeland), for the two weekly meetings in which I always gained new insights and perspectives from different angles. I would also like to thank Gréanne Leeftink, Anne van der Zandt and Erwin Hans for their guidance in a slightly unusual institutional supervisor structure. Gréanne and Anne fell into my research somewhere halfway but provided me with thorough feedback, which I very much thank you for. Finally, I want to thank my family and friends for being there for me and sometimes helping me to keep my cup filled.

Enjoy the read!

Sanne Wopereis
Arnhem, 20 December, 2022

Management summary

Motivation

In the home care environment of Sensire, there is currently no use of methods or models to determine the care need and the corresponding number of home care providers required at an instant in time. This is important because the home care providers form the core of the service Sensire offers. Additionally, better prediction is important due to the expected increase in the elderly and decrease in the workforce. Also, in 2023 Sensire will further implement care-oriented teams (recovery care or chronic care) over regional-oriented teams. This thesis aims to provide insights into the number of home care providers necessary to cover the recovery care from the Slingeland hospital, which helps in better understanding and estimating what the recovery care teams could look like, such as size and regional coverage.

Objective

This research develops a predictive model to provide insight into the number of home care providers Sensire needs at an instant in time and the corresponding care needs from July 2022 to December 2024 to provide care for the recovery patients coming from the Slingeland hospital.

Approach

The problem divides into three sub-problems, as in Figure 1-1. A time series analysis forecasts the number of recovery care clients flowing from the Slingeland hospital into the home care environment of Sensire from July 2022 to December 2024. The forecast functions as an input for an adjusted version of the convolution model of van Berkel et al. (2010) that models the care need corresponding to this inflow over the timeline. The care need then translates into FTEs and home care providers, including indirect hours using various experimental settings such as an absenteeism level of 7%, 9% and 12%, a high and low demand scenario and three different contract scenarios:

- CTSmall: 20% 32-hours, 40% 24-hours, 20% 16-hours and 20% 12-hours
- CTMiddle: 35% 32-hours, 25% 24-hours, 20% 16-hours and 20% 12-hours
- CTLarge: 50% 32-hours, 20% 24-hours, 15% 16-hours and 15% 12-hours

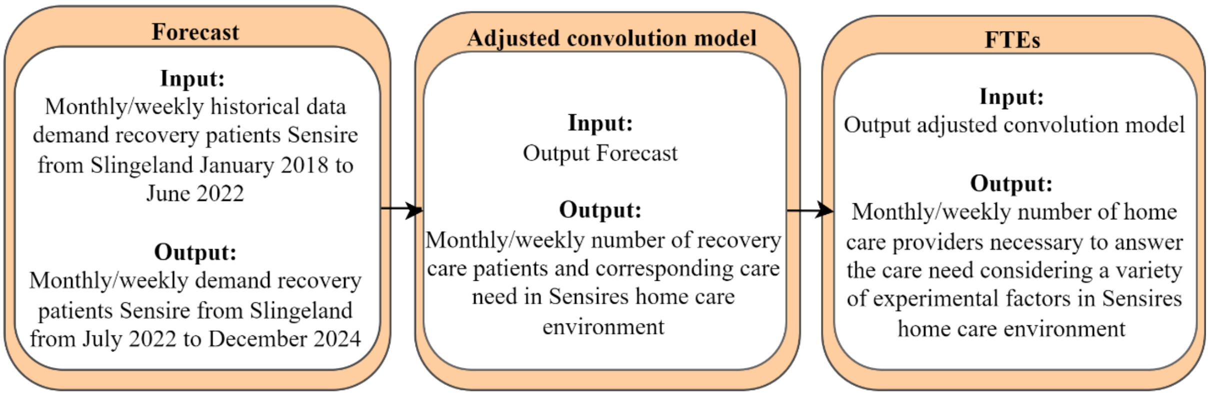


Figure 1-1 research overview

Results

Figure 1-2 shows the results. The number of home care providers needed to cover the recovery patients from the Slingeland hospital to Sensire, considering high demand, are on average between 24-29 home care providers for CTSmall, 23-28 for CTMiddle, and between 20-25 for CTLarge. For the low demand, the number of home care providers needed is between scenario 22-28 CTSmall, between 21-26 home care providers for scenario CTMiddle and between 19-24 for CTLarge. The number of home care providers is calculated based on the number of FTEs using a 95% confidence interval to include uncertainty of the forecasted input data, which the error bars indicate.

The number of home care providers needed is higher at the beginning of the covered period and decreases along the timeline of the covered period since the forecasted number of clients decreases.

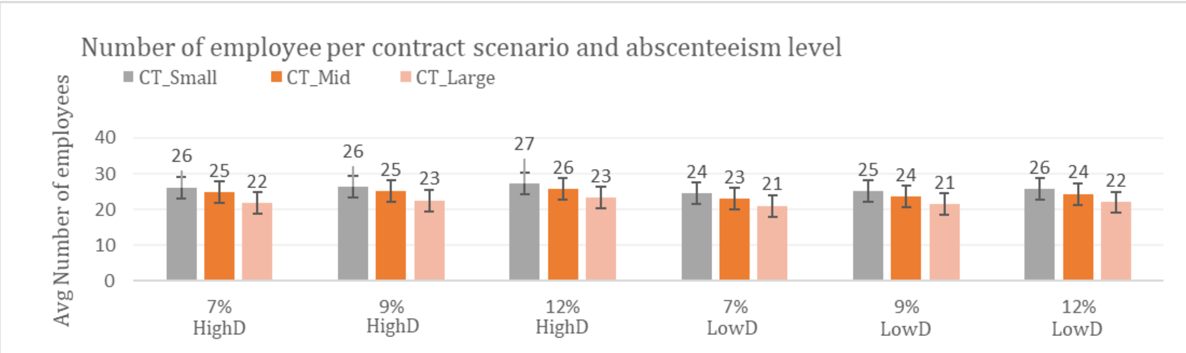


Figure 1-2 Number of employees per contract scenario and absenteeism level

Conclusion

Based on these results, we conclude that the number of home care providers is very case-dependent and, therefore, should be re-evaluated based on absenteeism levels, the current contract scenario and proceeding on the timeline. However, it gives a good strategic guide on which Sensire can steer employing, on average, between 19 and 29 employees with 95% certainty for the entire region to cover the recovery care clients from the Slingeland hospital. In addition, knowing contract configuration and absenteeism levels decreases the 19-29 employee gap. At the time of writing this research, following the LowD, CT_Small and absenteeism of 12% resemble reality which advises employing on average between 24 and 28 home care providers with 95% certainty, of which 20% have a 32-hour contract, 40% a 24-hour contract, 20% a 16-hour contract and 20% a 12-hour contract.

Theoretical contribution

This research contributes to the literature by providing a strategic solution focussing on recovery clients in a home care organization employing a cross-organizational approach in collaboration with the Slingeland hospital. We extend the mathematical convolution model of van Berkel et al. (2010) by using a non-cyclic demand cycle over a cyclic, including calculations of the care need additional to the number of clients and using a regional-based forecast as input.

Practical contribution

The main practical contribution of this research is the insights into the number of home care providers necessary to cover the recovery care from the Slingeland hospital and the effects of absenteeism and contract combination, which gives insight when drafting the new recovery care focussed teams. Some other insights/contributions are the intensified collaboration between Slingeland and Sensire, the effectiveness of implemented interventions, more insight into what to register and how to register, the importance of taking whole system perspectives and a better internal understanding of Operations Research and the possible organizational impact it can have.

Recommendations

We recommend Sensire, in increasing scope, to use the insights from the practical contribution section as a guide in future policy making. Then, expand the calculated number of home care providers for the recovery client stream from the Slingeland stream using the full recovery client stream. Finally, include a whole system perspective on a tactical level to determine future care needs and necessary home care providers. For example, what are the consequences of knee surgery in week 1 in the Slingeland hospital in week 4 for Sensires home care environment. To realize this, improved data exchange or registration is a necessity.

Table of contents

1 Introduction

This research develops a capacity planning model that determines the number of home care providers Sensire needs to cover the care needs of recovery care clients flowing from the Slingeland hospital to the home care environment of Sensire on a strategic level. The capacity planning model forecasts the future number of home care providers. Chapter 1 introduces Sensire, the Slingeland hospital, the problem, the scope and the research questions. Chapter 2 further describes context elements. Next, Chapter 3 contains the literature study. Chapter 4 determines the number of future recovery clients flowing from the Slingeland hospital to Sensire, considering various forecasting methods. Next, Chapter 5 determines the number of clients in care at a time, and their care need using a mathematical convolution model. Then, translating the care need into the number of home care providers considering various experimental settings such as levels of absenteeism and contract combinations. Finally, Chapter 6 contains the conclusion, discussion, further research and recommendations.

In this chapter, Section 1.1 introduces the company this research is subject to and the collaboration with the Slingeland hospital. Next, Section 1.2 describes the Slingeland hospital. Then, Section 1.3 describes the motivation for conducting the research and the research problem. Finally, Section 1.4 describes the research questions.

1.1 About Sensire

This research is conducted at Sensire, a Dutch healthcare organization in the region 'de Achterhoek' and 'de Liemers'. The organization provides various day and night care, nursing, and specialized care. Any form of care is provided at home or in one of their residential care centres. Sensire thrives on letting their clients live their lives as they like ("Leven zoals u wilt") (Over Sensire, 2022). This means Sensire tries to centralize the desires of its clients as much as possible while providing care.

This research focuses on the home care environment, where most clients are 65 years and older**.** Clients receive remote care, specialized care, and home assistance from their homes (Sensire bij u thuis, 2022). Home assistance is out of the scope of this research. Assisted living care consists of all care the client receives at home concerning general daily living tasks (Ministerie van Volksgezondheid, Welzijn en Sport, 2022a). Specialized care focuses on more complex care, for example, conditions such as asthma, dementia, heart failure, and wound treatment (Sensire bij u thuis, 2022). Remote care consists of care delivered through digital means. This form of care enables clients to perform care under guidance. With a team of approximately 1600 home care providers, Sensire provides home care in the entire region.

Sensire has various initiatives and teams focusing on improving care and more efficient and effective capacity management. Sensire uses knowledge from people working on the floors combined with a more academic problem-solving approach to improve the organisation and provide care now and in the future. At the same time, Sensire works towards collaboration with other healthcare organizations to address the regional problems of ageing and migrating adolescents. One of these collaborations is with the Slingeland hospital in Doetinchem.

1.2 About Slingeland hospital

Slingeland hospital has its main location in Doetinchem, covering Bronckhorst-Zuid, Doetinchem, Montferland and Oude IJsselstreek. The Slingeland hospital has a team focussing on capacity management, constantly seeking to improve capacity management, focusing on future healthcare and all related problems and implications while maintaining attention to the quality of care for their patients. Slingeland hospital established an extensive historical patient database. With ageing and migrating adolescents, the management team of Slingeland also seeks to develop overarching collaborations creating one chain from front to end, including not only the hospital but all organizations necessary for the before and after-care or guidance of their patients.

1.3 Research Motivation

This section introduces Sensire's motivation for executing this research.

The effects of ageing, corresponding care needs, and migration of adolescents highly pressure the workforce in the Achterhoek and the Liemers, the region in which Sensire operates. Furthermore, with the increasing healthcare demand and the upcoming outflow of home care providers, there is a need for more efficient and effective planning and scheduling of home care providers, clients, and equipment in home care. Section 2.1 provides more details on existing and upcoming problems in home care. Currently, Sensire has no view of the past, current, and future inflow, duration, re-entry, and outflow of patients in the home care environment. Subsequently, estimating and predicting the capacity needs of the home care providers in the home care environment is challenging, especially now Sensire is redesigning regional teams into care-type-oriented teams.

A problem often has many causes and consequences underlying the problem. Therefore, the cause-and-effect manner of Heerkens et al. (2021) identifies the core problems. Appendix A shows the full problem analysis. Section 1.3.1 summarizes the research problem.

1.3.1 Research problem

Currently, in the home care environment of Sensire, there is no use of methods or models to determine the care need, and the corresponding required number of home care providers. This is important because the home care providers form the core of the service Sensire offers. Additionally, this is important because of the expected increase of older people in the region and their care needs. Therefore, the research focuses on creating a strategic capacity planning model to predict the recovery care client stream from the Slingeland hospital. These clients require more complex care and the care of higher-educated home care providers. Using this focus creates a regional framing because the Slingeland hospital covers only a part of the region Sensire operates. Also, Sensire is currently in the process of redesigning regional teams into care-type-oriented teams. Finally, collaboration with the Slingeland hospital creates an overarching collaboration.

Section 3 shows the results of a literature study discussing current practices. This research adds to the literature because, to the best of our knowledge, the literature does not present a solution focussing on recovery patients in a home care environment involving factors such as: cross-organizational and whole system perspective, region-based forecasts, coverage of the number of caregivers and contract skills, considering a strategic two to five-year level.

We formulated the following research objective:

"To develop a predictive model to provide insight into the number of home care providers Sensire needs at an instant in time from July 2022 to December 2024 to be able to provide care for the recovery patients coming from the Slingeland hospital."

The problem divides into three sub-problems; forecasting demand, modelling the care need at a given time, and translating this into number of home care providers at a given time. Based on the taxonomic classification in healthcare of Hulshof et al. (2012), our problem categorizes as a problem with a focus on capacity dimensioning: matching staff capacity with patient demand, which classifies as a strategic problem. According to Matta et al. (2012), the strategic level focuses on a decision horizon of one to five years, which this research maintains.

Figure 1-1 shows an overview of the steps necessary to answer the research question.

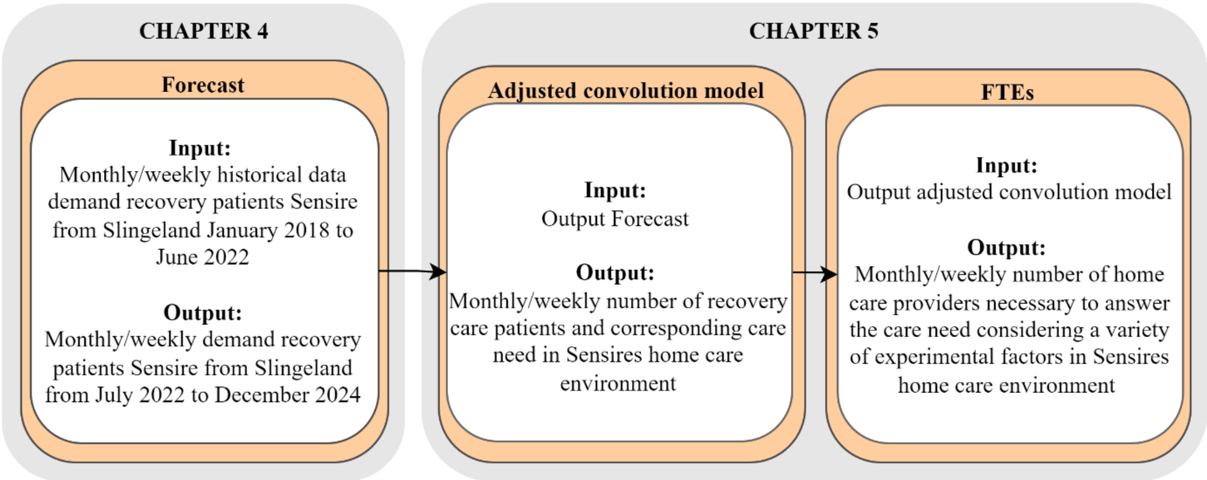


Figure 1-1 Overview of research steps

Forecasting
The incoming care need determines the number of home care providers. To determine the incoming care need, it is necessary to know the incoming number of patients. The goal is to develop a forecast based on historical data from the Slingeland hospital to determine the number of recovery clients flowing into the home care environment of Sensire from the Slingeland hospital.

Modelling the care need
After determining the number of clients flowing in, the next step is determining the corresponding care need translating into time. Care needs have an uncertain nature. Depending on the condition, the number of conditions, gender, age and other social-economic factors, a patient can have different care needs, as further explained in Section 2.3. The goal is to develop a model that calculates the care need at a given time as a consequence of inflowing demand as the forecast determines.

Determining the number of home care providers
After determining the care need, these translate into FTEs and the number of home care providers. Essential here is to consider constraints such as contract types and absenteeism of the home care providers.

1.4 Research questions

The research objective translates into multiple research questions. These are the following:

Chapter 2: Context study

1. What are the current challenges in home care in the Netherlands and the region?
2. What are the relevant stakeholders?
3. How can we characterize the three steps: number of patients flowing from the Slingeland hospital to the home care of Sensire, care need and the corresponding number of home care providers?
    a. What does the demand of patients flowing from the Slingeland hospital to Sensires home care environment look like?
    b. What type of clients, regional origin, conditions and care needs do the clients in the home care environment of Sensire have?
    c. What are the functions with responsibilities, type of contracts and the accumulation of hours of the home care providers of Sensire?

To develop a deeper understanding, the problem is further studied through interviews with key figures and studying internal documents. Additionally, available historical patient data (Slingeland), client data (Sensire), and data about home care providers (Sensire) are obtained internally and studied to get a more thorough understanding of additional factors of influence on the problem.

Chapter 3: Literature study

4. What literature is available on capacity planning models in home care that consider demand forecasting and strategic problems?
5. What models are suitable to use in this research?

This study aims to find appropriate models and methods. Furthermore, the literature study discusses theoretical relevance.

Chapter 4: Forecasting

6. How to forecast the number of recovery clients flowing from the Slingeland hospital to Sensires home care environment?
    a. What methods and elements are necessary to consider in a forecasting study?
    b. What are the problem-specific forecasting elements?
    c. What experimental settings and what-if scenarios are of relevance?
    d. Which method and setting are most suitable for this research?

This research applies the most applicable forecasting methods for the number of recovery clients flowing from the Slingeland hospital to Sensires home care based on adequate validation methods. This research also determines the aggregation level, what-if scenarios and the time frame. Forecasting and validation are done and described using historical patient data (Slingeland).

Chapter 5: Mathematical model

7 How can we develop a mathematical model to determine the care needed at a given time based on the incoming clients as determined in the forecasting study for the what-if scenarios?

8 How does the care need at a given time translate into the need for a number of home care providers?
   a. How many FTEs does Sensire need monthly to cover the care need of recovery patients flowing from Slingeland hospital to the home care environment of Sensire?
   b. To cover the monthly FTEs, what is the impact of a diversity of contracts for the home care providers
   a. What is the impact of absenteeism on the number of home care providers necessary to cover the need of FTEs, including diversity of contracts, as posed in question 8b?

This research uses the forecasted number of clients from the forecasting study to determine the care needed at a given time. Then, translating the care need into the number of FTEs at a given time of interest and experimenting with various settings regarding contract types and levels of absenteeism.

Throughout 4. Forecasting, and 5. the mathematical model, we aim to develop an acceptable, low-risk solution that enables Sensire to capture better patient flows, corresponding care needed, and the number of home care providers. In addition, the model aims to fulfil an advisory role in combining new care-oriented teams enabling comparisons and studying effects for different settings, such as contract types and absenteeism.

Chapter 6: Conclusion, discussion and recommendations

9 What are the conclusion, practical and theoretical implications of our research?
   a. What do we conclude from the research?
   b. What are the implications of the study?
   c. What is the practical contribution of the research?
   d. What is the theoretical contribution of the research?
   e. Based on the research, what will we recommend to Sensire and the Slingeland hospital?
   f. What are the limitations of this study?
   g. What are further options for research?

Based on this research, we write a conclusion describing the effectiveness of the solutions, which form input for the next section, recommendations for Sensire and the Slingeland hospital. The recommendations come with practical implications, implementations and recommendations for further research.

2 Context analyses

This chapter elaborates on the context of the research problem using expert interviews, literature and historical data. Section 2.1 describes the regional problems in home care. Next, section 2.2 describes the home care organization of Sensire. Then, Section 2.3 describes the relevant stakeholders for this research. Section 2.4 describes the demand characteristics. Next, Section 2.5 elaborates on the client's characteristics. Finally, Section 2.6 describes employee characteristics.

2.1 Challenges in home care

This section identifies and explains various current and expected problems in the home care environment of the Netherlands and Sensire, emphasising the importance of this research.

Ageing population
On 1 January 2022, 19.8% of the Dutch population comprised citizens over 65 years, of which 24.8% (4.8% of the Dutch population) were above 80 years old. The pressure of ageing is expected to increase to a level where, in 2040, almost 50% of the Dutch population will be above 65 years compared to the population aged between 20 and 65. From 2025 onwards, there is also an increase in the part of the population aged above 80 years (dual ageing). The estimate is that by 2040 they will make up one-third of the total population aged above 65 years. After 2040 the expectations are that this will stabilize but not decrease until at least 2060 (Centraal Bureau voor de Statistiek, 2022a).

Increasing care needs
With ageing, people in the Netherlands experience more health-related problems. They experience complaints such as long-lasting conditions, infections, malaise, and functional impairment. Additionally, the number of people experiencing their health as being not good in the age group above 75 years is around 50% (Centraal Bureau voor de Statistiek, 2014). Finally, people above 75 years more often experience multi-morbidity. For example, in 2030, 38% of people above 75 years will have more than three conditions (Kennisplein Zorg voor Beter, 2021).

Increasing care needs in the home care environment develop even further because of the governmental stimulants to let older people live in their home environment as long as possible as a result of the personnel shortages in nursing homes (Ministerie van Volksgezondheid, Welzijn en Sport, 2022b).

A consequence of ageing, stimulants of living at home, and the accompanying care needs is an overall increase in care requests. As a result, the care volume in the Netherlands will increase by 4% per year (Kennisplein Zorg voor Beter, 2021).

Region the Achterhoek en the Liemers
The matter of the ageing population and increasing care needs is increasingly visible in the Achterhoek en the Liemers. In the Netherlands, demographic growth concentrates in the Western part (Randstad) of the country around the four largest cities. Primarily adolescents move to these areas resulting in increased ageing in the countryside. From 2035 onwards, an approximated average of over 30% of the population per municipality in 'de Achterhoek' en 'de Liemers' belongs to the age category above 65 years (Planbureau voor de Leefomgeving & Statistische trends, 2019).

Of the employees working in home care in the region 37.5% are 55 years or older (Centraal Bureau voor de Statistiek, 2022c). The retirement age in the Netherlands is 67 in 2022 and is expected to increase only slightly (Ministerie van Algemene Zaken, 2022). Furthermore, a recent report of 8RHK ambassadeurs en Menzis (2020) states that home care providers will decrease in 'de Achterhoek' en 'de Liemers' by 2.7% by 2030.

Another identified trend in 'de Achterhoek' is decreased informal support from the immediate environment. An increase in chronic conditions as a consequence of lifestyle and lagging on digital and reading skills. Moreover, two-third of the population has decreased self-reliance, meaning they struggle with self-management and rely on home care providers (8RHK ambassadeurs, 2020).

Increased work pressure

It is expected that without adopting other practices within healthcare in the Netherlands, there will be a need for 1 out of 4 people working in healthcare by 2040. The work pressure home care providers are experiencing is high and increasing. They result in increased absenteeism and less attention to the patient, which puts pressure on the quality of care (Ministerie van Volksgezondheid, Welzijn en Sport, 2018).

This is reflected in the outstanding vacancies in home care in the Netherlands (Centraal Bureau voor de Statistiek, 2022e) and can also be seen in the region ‘de Achterhoek’ (Centraal Bureau voor de Statistiek, 2022d). Additionally, in 2020 56% of the home care providers working in home care reported experiencing increased work pressure (Centraal Bureau voor de Statistiek, 2021), resulting in an increase in absenteeism (Centraal Bureau voor de Statistiek, 2022b).

2.2 Sensire's home care organization

This section discusses Sensires home care organization and the inflow of clients into the home care environment. Section 2.2.1 explains the home care organization, and Section 2.2.2 elaborates on the inflow of clients.

2.2.1 Home care organization

This section elaborates on the organization of home care at Sensire.

Figure 2-1 depicts the regional home care division. The region covered by Sensire is ‘de Achterhoek’ and ‘de Liemers’ (A). Sensire realizes home care in the region by dividing the region into sub-regions (B). In every sub-region, 6 to 20 district nurses work (C). Every district nurse has a responsible district which, is a municipality or a designated region in the sub-region. Each district nurse has a team of 10 to 20 care providers (D), covering around 30 to 60 clients (E).

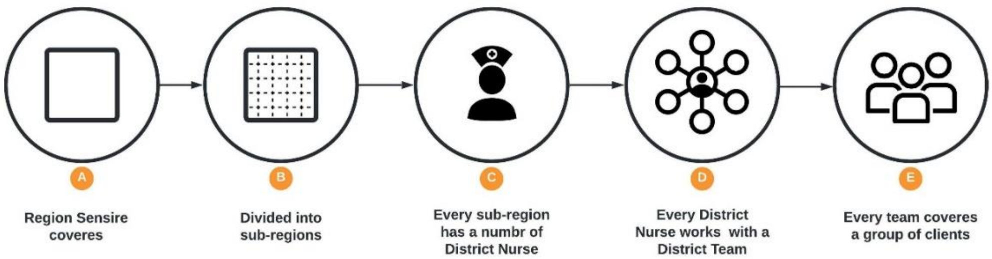


Figure 2-1 Regional division Sensire’s home care

2.2.2 Inflow of clients

This section discusses how clients flow into the home care environment of Sensire.

A client's care request can come through various stakeholders: A hospital in the region (any hospital), general practitioner, social worker, community officer, client, family, rehabilitation department or nursing home.

Figure 2-2 depicts the handling of an incoming care request. A stakeholder sends out a care request (A). Next, the care request arrives at the district nurse (B). The district nurse determines the urgency of the care request based on medical information and other specifics of the care request (C). Then, the district nurse will accept or reject the client and start the process of care deployment (D). Determination of urgency and the decision to accept or reject a client are done based on the experience and professional judgment of the district nurse. When accepted, care will be deployed (E).

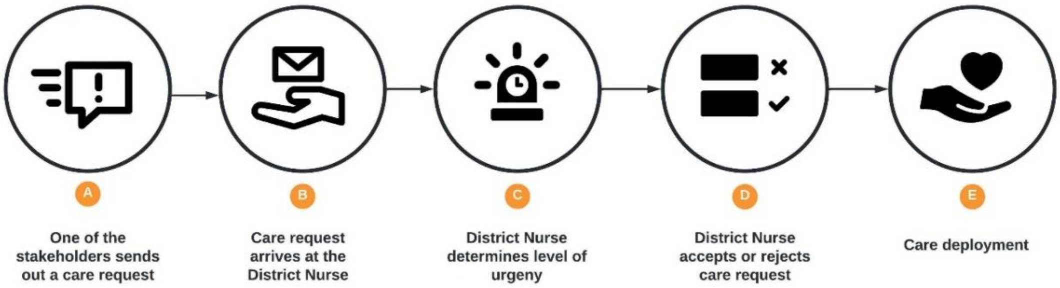


Figure 2-2 Handling incoming care requests Sensire

2.3 Stakeholder

This section describes the most relevant stakeholders for this research: clients, home care providers and collaboration Sensire and Slingeland. Section 2.3.1 explains the client categorization. Next, Section 2.3.2 categorizes the home care providers. Finally, Section 2.3.3 explains the collaboration between Sensire and the Slingeland hospital.

2.3.1 Client categorization

This section discusses the rough client categorization in recovery, chronic, and palliative care used in the home care environment because of their differences in care need.

Recovery care

Recovery care is characterized by clients flowing in and flowing out again in the foreseeable future. They are creating a constant yet variable flow of clients, often from hospitals. This group needs complicated care, which is care in a medical context. Sensire deploys higher responsible home care providers to provide for the care request (which can also consist of general daily living tasks) or short-term required nursing technical care operations. Clients receiving recovery care often receive a ZVW indication (short-term care).

Chronic care

The chronic care group characterizes by clients who are not entirely dependent but will never be able to live without some need for care. They come into care for longer to not flow out again other than when going to a care home or passing away. This group of clients often receives less complicated care, such as help with general daily living tasks such as washing, showering, dressing, and taking medicine. Most of the time, care intensifies with time. Clients receiving chronic care often receive a WLZ indication (long-term care).

Palliative care
Palliative care is care to make the quality of life of people in the last phase of their life as high as possible. Palliative care is characterized by providing physical care and helping with the social and psychological well-being of the patient and the immediate environment. Even though medical care has stopped, this form of care is perceived to occur in a medical context. Higher responsible home care providers, therefore, provide this form of care. Clients receiving palliative care can receive a ZWV and a WLZ indication.

Additional Remarks
The categorizations are rough, and it must be kept in mind that there can be cross-overs between chronic, recovery and palliative care and the ZWV and WLZ indications. For example, the following situations can occur:

- A client with a ZVW indication receiving recovery care can eventually receive chronic care and a WLZ indication.
- Clients with a WLZ indication can receive recovery care when they need complicated short-term care.
- Clients can receive palliative care when they move towards the last phases of their life under their WLZ indication.

Table 2-1 shows the client categorization, definition and occurrence percentage based on Sensires and Slingeland data. Most clients coming from the Slingeland hospital need recovery care, explaining the 77% recovery care clients found in the Data from Slingeland. Since the data of Sensire covers all their clients, the percentage per categorization is more spread.

Table 2-1 Client categorization Sensire and Slingeland (Retrieved from internal documents Sensire and Slingeland)

<table>
<tr><th>Categorization</th><th>Definition</th><th>Data Sensire</th><th>Data Slingeland</th></tr>
<tr><td>Palliative care</td><td>Clients whose reason for going out of care is passing away</td><td>22%</td><td rowspan="2">23%</td></tr>
<tr><td>Chronic care</td><td>Clients receiving care for longer than 84 days (12 weeks) and the reason for going out of care is not passing away</td><td>46%</td></tr>
<tr><td>Recovery care</td><td>Clients who receive care for a period shorter than 84 days (12 weeks), after which they do not receive care for at least three months, and the reason for going out of care is not passing away</td><td>33%</td><td>77%</td></tr>
</table>

2.3.2 Home care provider categorization
This section discusses the types of home care providers.

Table 2-2 presents the abilities and responsibilities of the home care providers. Various home care providers focus on certain care types based on their skills. Therefore, a rough classification between higher and lower responsibilities is possible. Higher responsible home care providers are the providers that completely manage, execute and control the care process, including nursing and nursing technical care operations. They received higher education. Lower responsible home care providers carry out much of the care and sometimes nursing technical care operations but need steering from higher responsible home care providers to guide the process. Appendix D shows percentages per function Sensire wide and for the region considered.

Table 2-2 Function descriptions of home care providers Sensire

Function description	Responsibilities, abilities, and characteristics	Focus care type	Classification
Carers	• Helping clients with general daily living tasks • Approaches the problem from the client's situation • Educated level 3 EQF (European Qualifications Framework)	Chronic care	Lower responsible
Carers IG	• Helping clients with general daily living tasks • Can also execute some nursing technical care operations • Approaches the problem from the client's situation • Acting based on steering from higher responsible home care providers • Educated level 3 EQF	Palliative care and recovery care	Lower responsible
Nurse	• Focuses on executing nursing technical operations • Approaches the problem from the client's perspective as well as a broader, overarching perspective • Is allowed to start up and initiate care • Educated level 4 EQF	Palliative care and recovery care	Higher responsible
District nurse	• Focuses on executing nursing technical operations • Focuses on heavier cases • Approaches the problem from the client's perspective as well as a broader, overarching perspective • Is allowed to start up and initiate care • Functions as the team leader • Focus on following the care content and technological developments • Educated level 6 EQF	Palliative care and recovery care	Higher responsible

2.3.3 Collaboration Sensire and Slingeland

This section introduces Slingeland and the established collaboration for this research between Sensire and the Slingeland hospital.

As explained in Section 2.2.2, Sensire receives care requests from various stakeholders. One of these stakeholders is hospitals such as the Slingeland hospital. The care requests coming into the home care environment of Sensire from Slingeland are patients/clients whose residential locations are in one of the sub-regions 'Bronkchorst', 'Doetinchem,' 'Montferland' and 'Oude IJsselstreek.'

Using historical patient data from the Slingeland hospital concerning the in-flow of clients into Sensires home care together with the internal historical data of Sensire creates an overarching collaboration.

Transfer office
An important hospital department considering this research is the transfer office, which is the bridge between the hospital and care organisations, including the home care environment of Sensire. The nurses working in the transfer office are, together with the nurses on the floor, constantly assessing their patients' status. The two main questions they answer are when they expect the patient to go home and what they need to integrate back into their normal lives. This can take the form of tools that assist the patient when back home, placement in a care home or receiving home care. The transfer office is responsible for arranging care according to the patient's needs. Before consultation with the nurses on the floor, the district nurses scan through patient information, basing their judgement on social economic factors such as gender, condition, age and social network.

2.4 Demand characteristics

This section uses historical client data from the Slingeland hospital from January 2018 to July 2022 that concerns clients flowing into the home care environment of Sensire from the Slingeland hospital. The aim is to explain the demand characteristics via an explanation of the client streams, the observed trends in the various client streams and the performance of a Classical Decomposition. Section 2.4.1 explains the various client streams. Next, Section 2.4.2 explains the identified trend. Finally, Section 2.4.3 performs a Classical Decomposition breaking down the time series.

2.4.1 Client streams

This section discusses the three client streams that make up the total demand flowing into the home care environment of Sensire.

The total demand for the home care environment of Sensire has three origins, as Table 2-3 explains. The total demand for the home care environment of Sensire consists of clients flowing in from the Outpatient Clinic and Clinic into the home care environment of Sensire, plus the number of rejected clients by Sensire.

Table 2-3 Origin patient streams Slingeland hospital to Sensires home care environment

Clinic	Hospital departments where patients receive invasive surgeries. As a consequence, they have to stay in the hospital for more than one day
Outpatient Clinic	Hospital departments where patients receive less invasive surgeries. As a consequence, they leave the hospital on the day of the surgery
Refusals	All patients that Sensire refuses because of lack of available capacity

Considering the strategic nature of this research, an exploratory, descriptive analysis has been performed, plotting the demand for the client streams weekly and monthly to analyse the yearly seasonal effects. This section displays the weekly plots and refers to the appendix for the monthly and additional plots. Some typical time series elements, as Table 2-4 describes, are used to characterize the demand. Table 2-4 contains the cyclic component for completeness; however, the cyclic component is not included in further analyses because of limited data and the unpredictable nature of healthcare and, therefore, even the non-existence of cycles.

Table 2-4 Time series pattern elements

Element	Abbreviation	Explanation
Seasonal	*S*	A variation arises per period (year, month, week) from seasonal factors. For example, there are more incidents of elderly falling in winter because of bad weather, snow and slippery surfaces
Trend	*T*	A trend is a long-term increase or decrease in data, including a changing direction
Cyclic	*C*	A cycle occurs when the data rises and falls with a non-fixed frequency. These are primarily due to economic conditions and related to the business cycle. Usually, the duration is at least two years
Irregular fluctuations	*E*	Any variation left after seasonal, trend and cyclic are removed. These can be completely random or sometimes have some short-term correlation

Clinic

Figure 2-3 shows the weekly demand of the Clinic. The demand shows a decreasing trend, with some but not very visibly, yearly seasonality. There is a lot of variability over the weeks, which does not show a clear constant pattern, increasing the difficulty of predicting patient outflow/inflow behaviour. Additionally, we observe two dips between weeks 16 and 32, 2018. These are a consequence of holidays (increased absenteeism, decreased consultations) in combination with the increased capacity problems that were first encountered in 2017 but not yet resolved in 2018, suggesting a lack of space in Sensires home care environment. Refusals data is not available to further check this. Figure 2-3 shows another dip due to the Corona crisis in weeks 12 to 15 in 2020 due to the immediate postponement of non-urgent consults and surgeries.

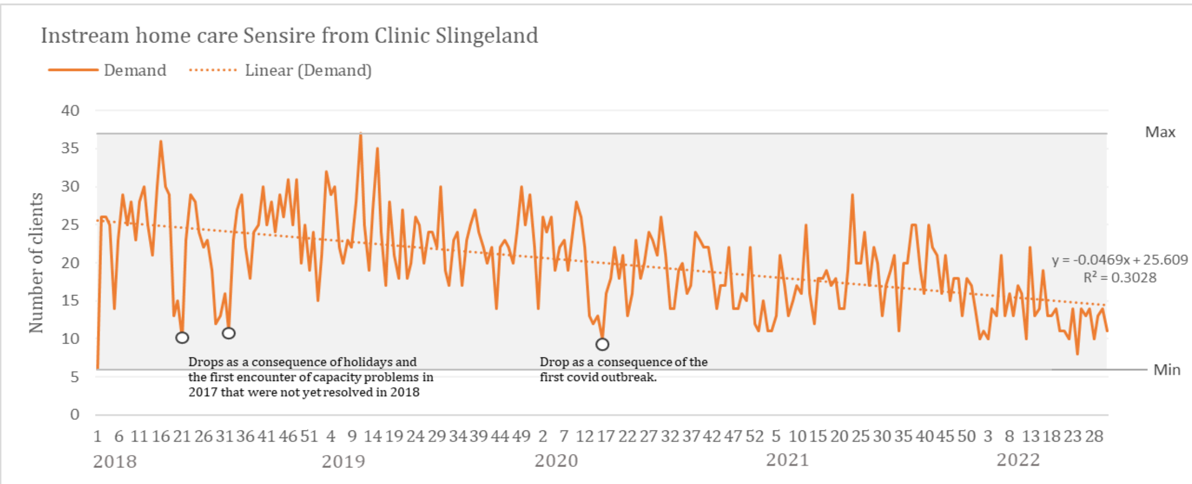


Figure 2-3 Weekly demand from the Clinic Slingeland hospital to Sensires home care environment (Source: retrieved from internal data Slingeland hospital January 2018-July 2022, n = 239)

Outpatient Clinic

Figure 2-4 shows the weekly demand for the Outpatient Clinic. The demand shows a decreasing trend, with some but not very visibly, yearly seasonality. There is a lot of variability over the weeks, which does not show a clear constant pattern, increasing the difficulty of predicting patient outflow/inflow. Three dips in 2018 show the consequences of holidays (increased absenteeism, decreased consultations) in combination with the first encounter of capacity problems in 2017, which remained in 2018. Again these suggest a lack of space in Sensires home care environment. Refusals data is not available to further check this. Also, the figure shows a dip due to the Corona crisis in weeks 12 to 16 in 2020 due to the immediate postponement of non-urgent consults and surgeries.

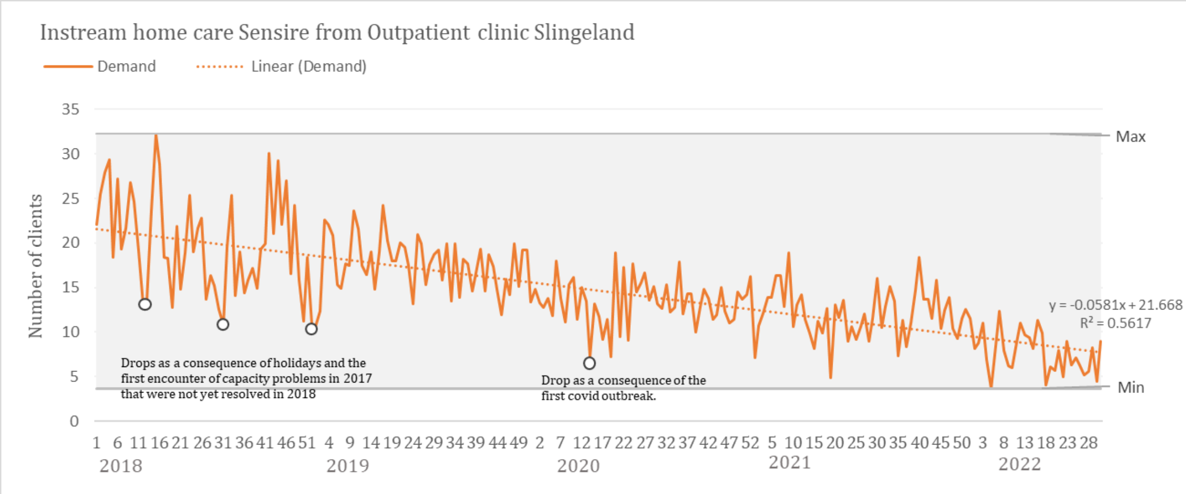


Figure 2-4 Weekly demand from the Outpatient clinic Slingeland hospital to Sensires home care environment (Source: retrieved from internal data Slingeland hospital January 2018-July 2022, n = 239)

Refusals

Refusals have been a trend in the past years, and observations of refusals are only available from January 2019 to July 2022. Figure 2-5 shows the monthly Refusals. The Refusals show no clear seasonality, no clear trend and high variable behaviour, increasing the difficulty of forecasting. In March, April and May 2022, a drop in refusals directly corresponds to the drops observed in the Clinic and Outpatient Clinic. Due to the immediate postponement of non-urgent consults and surgeries, the requests for Sensire's home care environment decreased, decreasing the number of refusals. In September, there was a rise in the number of refusals due to the Corona crisis, which is a consequence of increased absenteeism, potentially because of increased work stress due to the covid outbreak. Another reason is the active role of Sensire in the Corona hotel, where home care providers of Sensire worked, decreasing the number of home care providers in the home care environment of Sensire and pressuring the workforce.

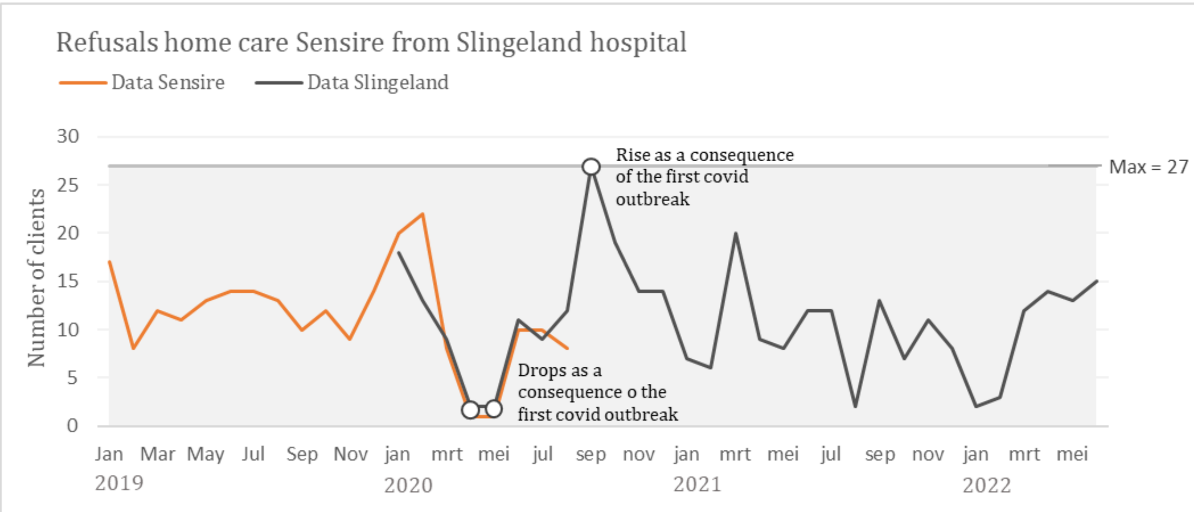


Figure 2-5 Number of monthly refusals by Sensire flowing from the Slingeland hospital (Source: retrieved from internal data Slingeland hospital January 2020- June 2022, n = 30 and internal data Sensire January 2019-Augustus 2020, n = 20)

2.4.2 Trend explanation

This section explains the decreasing trend in demand from the Clinic and the Outpatient Clinic flowing into the home care environment of Sensire.

Considering the upcoming increased ageing, as Section 2.1 elaborates on, we expect the number of clients flowing into the home care environment of Sensire to increase. However, Section 2.4.1 shows a decrease in clients flowing into the home care environment of Sensire from the Outpatient Clinic en Clinic from Slingeland. We further analysed this decreasing trend and found the following causes:

- There is a decrease in the number of Outpatient Clinic visits per week (Appendix G-1).
- The share of Sensire as a home care provider has decreased, especially since the end of 2021, due to increased competition in the home care field that focuses on technical nursing actions (confident internal document). Additionally, the increased number of Refusals makes the Slingeland hospital look elsewhere to satisfy their demand.
- The establishment of interventions for the Outpatient Clinic and Clinic are successful (eye surgeries, knee and hip surgeries) (Appendix G-2 andAppendix G-3). Interventions aim to decrease the inflow into the home care environment via better preparation of clients before the surgery or reorganization of the aftercare. Sensire and Slingeland work together on the implementation of more of these interventions.

Based on the causes, the decrease in clients flowing into the home care environment of Sensire is valid. The decreasing trend of recovery care clients from the Slingeland hospital means that the increasing number of elderly does not reflect in this client stream. Therefore we observe a decrease in necessary home care providers to cover the care need of the recovery care client stream from the Slingeland hospital. Consequently, the expected increase in clients in Sensire's home care environment can come from either a different recovery care client inflow or a different client group, such as chronic care clients. Home care providers of Sensire confirm this since the recovery care client group is a relatively "young" client group, and chronic care concerns higher-age clients.

2.4.3 Trend breakdown: Classical Decomposition

This section discusses the results of a Classical Decomposition. A Classical Decomposition breaks down the time series: demand of the Clinic, Outpatient Clinic and the Refusals into their time series elements, as Table 2-5 shows.

Performing a Classical Decomposition reveals the time series components of the demand that are not identified or not established by looking at the plots. Establishing certainty on the time series components is important because these are essential in demand analyses and when making decisions on the forecasting method in Section 2.4.3. This section performs a Classical Decomposition for the demand of the Outpatient Clinic, the Clinic, Outpatientclinic&Clinic combined and the Refusals. Refusals are analysed separately because they do not follow a trend and show high variable behaviour. Chosen is a multiplicative decomposition because of the increasing or decreasing trend (Section 2.4.1) and the seasonal variability range, which seems to be proportional to $T_t + C$ (Appendix G-14 to E-18). A multiplicative model adds the elements as follows: $Z_t = S_t * T_t * C_t * E_t$, where t is an indication of time. The multiplicative classical composition is performed using monthly and weekly observations. Table 2-5 presents results focussing on trend and seasonality. The decomposition shows yearly seasonality. However, it does not indicate strong seasonality. All sorts of demand display residuals. However, a lack of data on the refusals makes the decomposition into seasonal and residual elements impossible. Therefore, Table 2-5 does not include residuals.

Table 2-5 Multiplicative Classical Decomposition performed on the demand

	Trend	Seasonal	Figures
Outpatient Clinic	Decreasing Weekly obs. : y = -0.0528x + 20.182 Monthly obs. : y = -1.0116x + 86.739	Yearly seasonality	Appendix G-8 to Appendix G-13
Clinic	Decreasing Weekly obs. : y = -0.0494x + 25.013 Monthly obs. : y = -0.9307x + 109.01	Yearly seasonality	Appendix G-14 to Appendix G-19
Outpatient Clinic & Clinic	Decreasing Weekly obs. : y = -0.1022x + 45.192 Monthly obs. : y = -1.9423x + 195.75	Yearly seasonality	Appendix G-20 to Appendix G-25

2.5 Client characteristics

This section discusses the variety of characteristics incoming clients in home care can have based on various historical datasets with data obtained between January 2019 to July 2022. Additionally, one dataset contains data from December 1969 to July 2022. The datasets consider all regions because of data scarcity. For the same reason, clients receiving a ZWV and a WLZ are included. Section 2.5.1 provides general client characteristics using the three care need pillars in Table 2-6. Then, Section 2.5.2 further categorizes the recovery care client group using the NZA questionnaire.

Table 2-6 Care needs pillars Sensire

Length Care Period	Indicating the length of a care period in days. Expressed in minimum, average and maximum
Average time per care moment	Indicates the average time spent per care moment in minutes, expressed in minimum, average and maximum
Average moments per week	Indicates the average care moments per week. This variable is strongly correlated with the length of care period and expressed in minimum, average and maximum

2.5.1 General

This section discusses the inflow per municipality, the overall spread of age, and the care need pillars, as presented in Table 2-6, providing a general overview. Appendix B contains detailed analyses.

The largest inflow for clients of Sensire is from the area Slingeland covers. This makes the collaboration between Sensire and Slingeland essential. With age, the number of clients and overall care needs increases around 50 and decreases around 90. Care required depends on the condition or action, age, gender, and the number of conditions therefore, it is necessary to include these factors as much as possible. The length of a care period ranges between 1 day and 1082 days. The number of moments in a care period ranges between 1 moment and 187 moments. The average minutes per care minute ranges between 10 and 790 minutes. Looking at the age, length of a care period, and the number of moments and minutes per period, we see a high variability which complicates predictions and estimations of the number of clients' care needed and the resultingly necessary number of home care providers.

We seek to reduce variability, focussing on recovery care clients to make better predictions and estimations. As a result, we can better indicate the number of clients, care needed and necessary home care providers. Recovery care clients are no more than 84 days in care, which reduces the variability of the length of a care period from a maximum of 1082 days to 84 days and consequently the number of moments. Various home care providers state that the care coming with recovery care clients is also more predictable since many common medical procedures result in a similar care need question. For example, the common knee or hip surgery almost always results in some help with general daily living tasks and wound care unless there are severe complications. In such cases, home care is necessary but does not deviate significantly from client to client. In conclusion, recovery care is more predictable and, therefore, more steerable and predictable.

2.5.2 NZA

This section describes the data obtained via the NZA (Nederlandse Zorg Autoriteit) questionnaire conducted at Sensire from October 2021 to April 2022. Sensire considers the NZA questionnaire as a reliable data source.

The NZA is a Dutch organization that checks whether health insurance companies and other healthcare organizations follow the rules. They aim for people to receive the care they have the right to and fulfil an advisory role for the government (Rijksoverheid, 2022). To do so in a home care environment, they use the NZA questionnaire, which covers various areas of concern, focussing on the client's current condition, self-reliance, and expected progression. A low score indicates a 'good' situation with a lot of self-reliance. A higher score indicates a decrease in these factors. Areas covered are expected progression, multi-morbidity, general daily living tasks, medication usage, social network, psychological functioning, memory, and resilience. Finally, it indicates what kind of chronic conditions the clients have and what technical nursing operations are required. For this research, we focus on the latter two using NZA historical data from October 2021 to April 2022. To determine the usability, we performed a detailed analysis of the NZA, on which appendix C elaborates.

We use the information from the NZA analyses focussing on the care need pillars from Table 2-6 to, in consultation with Sensire, further define recovery care client groups since including all social economic factors determining clients' paths is unrealistic considering time and data. As from Table 2-3, recovery care clients have fewer than 85 days of care. Table 2-7 shows the definition of these groups. This deviation is important because the three groups have different increasing care needs: No_NT, One_NT and Mult_NT. No_NT makes up the largest part of the total demand and has the lowest care needs, and according to various home care providers is very predictable. However, groups One_NT and Multp_NT are still significantly large and have a larger care need. For example, the average minutes per month for group One_NT compared to group No_NT are 1.5 times more. Additionally, the average minutes per month for group Mult_NT compared to group No_NT are 2.7 times more. Therefore, not dividing into groups can underestimate the actual care needed. According to home care providers, the increase in One_NT is due not only to the more complicated nursing technical action but also because a nursing technical action means some help with general daily living tasks. On the other hand, the even higher increase for the Mult_NT comes not only from the execution of various nursing technical actions but moreover from the significant decrease in the self-reliance of clients as a consequence of decreased health. Consequently, the care need increases for all tasks, including general daily living tasks. Additionally, these clients suffer more often from multi-morbidity. An example is a client needing injections and a probe before knee surgery. In the execution of these actions, the home care providers full-filled a supporting role. However, after the knee surgery, the client's self-reliance decreased significantly, and the client was unable to perform the actions and general daily living tasks without help.

Table 2-7 Group definition of recovery care patients

Group	Definition	Additional remark	Perc.
No_NT	Recovery care patients only receive help with general daily living tasks that receive no Nursing Technical actions	Can also suffer from a chronic condition	70.39%
One_NT	Recovery care patients receive one Nursing Technical action	Can also receive ADL or suffer from a chronic condition	25.75%
Mult_NT	Recovery care patients receive multiple Nursing Technical actions	Can also receive ALD or suffer from a chronic condition	3.86%

2.6 Home care provider characteristics

This section further describes contract hours, absenteeism, holidays and travel hours using the home care provider categorization established in Section 2.3.2. Section 2.6.1 discusses the various contract hours. Then, Section 2.6.2 explains how the hours accumulate.

2.6.1 Contract hours

This section describes the contract types of relevant home care providers based on an internal document with all home care providers employed at Sensire on 24 June 2022.

Figure 2-6 displays the functions and the most common type of contracts Sensire wide per function. The most common contracts are the same for the region, only differentiating slightly. The number of hours in the contracts increases with the responsibilities of the functions (Appendix D-8 toAppendix D-16). This directly correlates with the tasks the home care providers of the functions are responsible for. Carers, Carers IG and Nurses work most mornings and evenings (broken shift) according to their clients' availabilities and preferences for general daily living tasks etc. For these functions having 36-hour contracts would mean working seven days a week. District Nurses have additional jobs in the districts with a more organizational function and are therefore less bounded to the morning and evenings, allowing them to have larger contracts. These broken-shifts increase the demand for home care providers to fill the shifts.

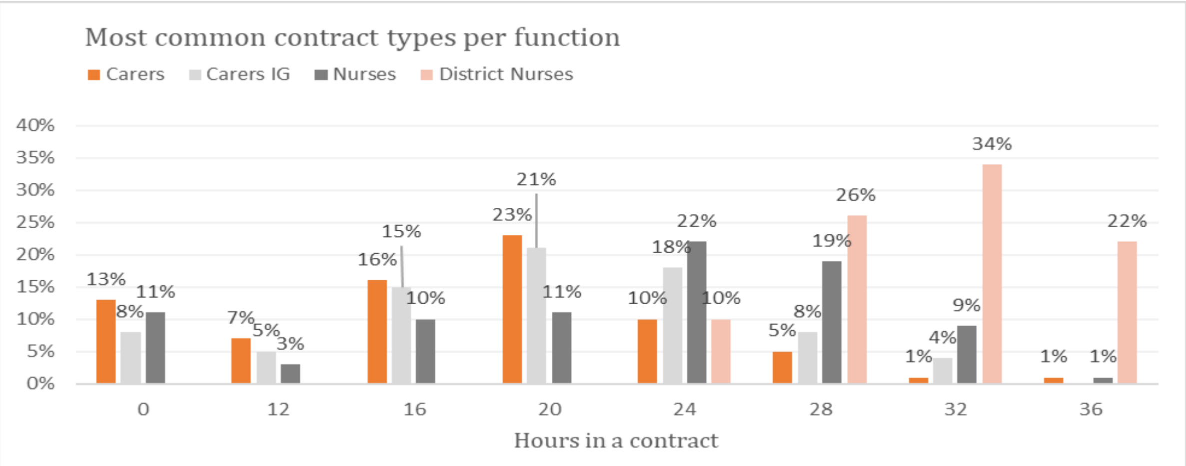


Figure 2-6 Most common contract types per function (Source: internal employee data Sensire 24-06-2022, n = 1097)

2.6.2 Accumulation hours

This section explains how the hours within the contract accumulate.

To track performance KPIs (Key Performance Indicators), contracts divide into categories where the hours correspond to specific tasks. The total hours within a contract divide into the following categories: direct care, indirect care, travel time, absenteeism and leave of absence. Table 2-8 shows the definition of the contract accumulation categories.

Table 2-8 Contract accumulation categorization

Direct care	**Hours of actually delivered care to a client**
Indirect care	Hours that consider care that is not directly delivered to the client, such as planning, meetings and training, which are not travel hours
Travel time	Hours that are dedicated to travelling from and to clients
Absenteeism	Hours that concern sickness of home care providers
Leave of absence	Hours for holidays or maternity leave

2.6.3 KPIs

This section gives an overview of general performance using KPIs: plus/min hours, absenteeism, travel time, productivity and effectivity using historical datasets from January 2021 to week 28, 2022. Appendix E provides the full analyses.

Table 2-9 KPI explanation

KPI	**Definition**
Plus/min hours	Plus hours are the hours that home care providers work outside their contract hours. Min hours are the hours that a home care provider works less than their contract hours
Absenteeism	Hours a home care provider is not able to work, such as sickness or leaves of absence
Productivity	Productivity is the number of direct hours compared to the total number of hours, which includes absenteeism, travel time, and leaves of absence
Effectivity	Effectivity is the number of direct hours compared to the total number of hours, excluding absenteeism and leave of absence, because these are factors out of influence

Table 2-9 presents the definition of the different KPIs. There has been an overall increase in plus/min hours between -6% and 16% and absenteeism between 7.1% and 16.9% over the last few years. The absenteeism over the last years is significant, exceeding the 8.9% benchmark of Sensire. We observed productivity for the region that is slightly below Sensire's average, explained by the high level of absenteeism. The region's productivity is between 55% and 65%, which is below Sensire's average. Effectivity in the region fluctuates between 75% and 85%. Productivity and effectivity do not significantly increase or decrease. The increase in plus hours and absenteeism indicates increased work pressure. According to Sensire business management consultation, working a lot of plus hours increases overall absenteeism, as Section 2.1 refers to. Exceeding the benchmark for absenteeism and productivity indicates increased work pressure.

3 Literature study

This chapter discusses the literature related to the research problem. Our research problem categorizes as a strategic resource capacity planning problem, which concerns case mix planning, capacity dimensioning and workforce planning (Hulshof et al. 2012). In the context of our research, this is the prediction of the clients and their care needs (demand) and matching this to home care providers (resources) on a strategic level. Several elements are of interest to perform a literature search on which this chapter's sections refer to. We focus this literature study on operation research literature in a healthcare setting, gathering relevant information, identifying previous work and how this research contributes to the literature. Section 3.1 covers the predictive element of a literature search on demand forecasting. Then, Section 3.2 covers the capacity dimensioning of home care providers according to demand performing a literature search on capacity planning. Section 3.2.2 covers the strategic and cross-organizational elements focusing the literature search on strategic capacity planning models and whole-system perspectives. Section 3.3 explores options for further research. Finally, Section 3.4 concludes this research.

3.1 Demand forecasting

This section discusses demand forecasting, starting with a general introduction to demand forecasting, after which we focus on regular interval time series. Next, section 3.1.1 discusses various approaches to demand forecasting. After creating focus, Section 3.1.2 describes key activities of regular time series, after which Section 3.1.3 discusses various regular time series models.

3.1.1 Demand forecasting approaches

This section discusses various approaches to demand to forecast.

Forecasting concerns predicting the future as accurately as possible given all the information available, including understanding contributing factors, data availability and whether the forecast affects the things we are trying to forecast. Again, various approaches are available from the literature.

Hare et al. (2008) developed a deterministic multi-state Markov model of the HCC systems model. The model predicts the future client counts for various community care services, including home care providing a strategic direction plan. The model can run up to 29 years past its initial start date of April 2002, correctly reproducing the total community care clients count for each month within a 5% marge and often within 2%. Though their research focusses on a strategic predictive model and includes community care, amongst which is home care, there are a couple of limitations in the context of our research. The model predicts future clients and not future service loads, aggregates on a higher level and is limited in the types of demographics used in model predictions. Eggink et al. (2015) describe a micro-simulation model suitable for forecasting the use of publicly funded long-term elderly care. The focus of their research is on changes in care caused by changes in the size or composition of the population, which is something that is currently happening in the healthcare system of the Netherlands. Elderly care defines as care for individuals with ages above 30. Though they make a reasonable estimate, the study period is very long (> 25 years), and results further on the horizon are uncertain. The study, thus, functions more as an evaluation guide on policy measures.

Mathematical models and simulation studies are usable as forecasting methods. However often applied on a higher aggregation level, focusing on the evaluation of settings. A common use manner for more detailed forecasting is time series forecasting. Time series is a collection of observations made sequentially through time. During this research, we have access to detailed information on the past inflow of patients to the home care environment of Sensire, and therefore we focus on time series forecasting. More specifically, regular interval time series forecasting. The remainder of this chapter uses two books on forecasting from Chatfield & Chris Chatfield (2001) and Hyndman & Athanasopoulos (2018) unless otherwise stated.

3.1.2 Forecasting activities

This section describes the forecasting activities that involve a forecasting study.

Problem definition, gathering information and exploratory analyses

The problem definition involves merely understanding the application of the forecast, done through interviews and data understanding. Data understanding comes via collecting and analysing data. Looking in the data for patterns, trends, seasonality, cycles and outliers.

Choosing and fitting the model

Choosing the model depends on the availability of historical data, relationships between forecast and explanatory variables, application of the forecast and expertise of the forecaster. Commonly two or three protentional models are compared, and parameters are estimated.

Usage and evaluation

Once the model is chosen and parameters are estimated, the model is used to make forecasts. The factual accuracy of the model can only be evaluated after data becomes available. Necessary here is documentation of the model and the results, as well as assumptions as a means of justification.

3.1.3 Regular interval time series methods

This section introduces various regular interval time series methods.

Simple methods

Simple methods mainly serve as benchmarks rather than the method of choice. For example, the average method assumes that the forecasts of all future values are equal to the average of the historical data. The naïve method sets all forecast values to be the value of the last observation. The seasonal naïve method does the same but uses the final observed value from the season of the former year. Next, the drift method is a variation of the naïve method allowing the forecast to increase or decrease over time where the amount of change over time (drift) is set to be the average change seen in the historical data. Finally, the Classical Decomposition method grasps the following time series components: trend, period, seasonality and residuals.

Time series regression models

Time series regression models assume that the time series of the forecast variable Y has a linear relationship with the predictor variable X. Simple linear regression believes there is a linear relationship between the forecast variable Y and a single predictor variable X. Multiple linear regression assumes the same and only uses multiple predictor variables. Finally, nonlinear regression includes non-linearity by transforming the linear forecast variable Y and/or the predictor variable X before estimating the regression model.

Exponential smoothing models
Forecasts produced using exponential smoothing methods are weighted averages of past observations, with the weights decaying exponentially as the observations get older. It is one of the most used forecasting methods and generates reliable forecasts quickly and for a wide range of time series. Simple exponential smoothing forecasts data with no clear trend or seasonal pattern. Two commonly known trend methods are Holt's linear trend method which is an extension of the simple exponential smoothing but allows trends. Holt-Winter's seasonal method is an extended linear trend method which also captures seasonality. Holt-Winter differentiates between the additive case and the mixed case. The additive case is preferred when the seasonal variations are roughly constant throughout the series. The mixed case is selected when the seasonal variations changes in proportion to the series' level.

ARIMA models
Arima models aim to describe the autocorrelation in the data. Autoregressive models describe the variable of interest using a linear combination of past values. The moving average model uses past forecast errors in a regression-like model.

Advanced methods
For completeness, mentioned here is the field of advanced methods. Besides previously mentioned methods, a wide variety of advanced methods combine techniques or provide extensions on existing techniques in numerous ways. Therefore, advanced methods are not subject to this research.

3.2 Capacity planning models

This section describes the achievements and limitations of various models that predict staff capacity in a healthcare setting. Section 3.2.1 discusses various capacity planning models in a healthcare setting other than a hospital. Then, Section 3.2.2 dives deeper into these capacity planning models focussing on strategic problems and whole system perspectives.

3.2.1 Capacity planning models
This section describes capacity planning models in a healthcare setting other than a hospital.

We found two sources which discuss capacity planning and calculating staff capacity in a healthcare setting other than a hospital. First, Rodriguez et al. (2015) focus on staff capacity planning, calculating the number of personnel required to ensure the activity of a home health care centre. They propose a two-stage integer linear stochastic programming approach using various demand scenarios that consider one experimental factor at a time. The best results, 70% of the problems reaching the optimal solution, are found for the scenario that deviates the geographical demand using a uniform distribution. Then, Shehadeh et al. (2022) developed a two-stage stochastic optimization methodology to predict the number of caregivers to hire (predict staffing capacity) and their allocation to types of services for each day (capacity allocation). They included randomness and uncertainty for customer demand and duration. A tactical planning horizon of 30, 90 and 180 days is used, and the objective is to minimize the total costs of over and under-staffing. The experiments yielded good results and applications for practice. However, the experiments were performed based on basic demand.

Though in our research investigating different demand scenarios is of importance, it is hard to describe reality using demand scenarios that only integrate one factor at a time while including limited uncertainty. Also, we would like to add staff capacity predictions and include care need estimations to our research. Some other limitations of these works are the lack of focus on home care, strategic level, cross-organizational whole system perspectives, capacity dimensioning based on future demand and including social and economic factors.

3.2.2 Strategic capacity problems and whole system perspectives

This section further focusses on capacity problems in a healthcare environment that focusses on strategic problems with a cross-organizational whole-system perspective.

Esensoy & Carter (2018) adopt a strategic perspective with a three to five years timespan. Their paper presents a system dynamics simulation for assessing healthcare transformation policies involving alterations to patient pathways and service levels. They adopt a whole system perspective, including emergency departments, acute care, long-term care homes, home and community care, etc. The model includes detailed information such as age, sex, clinical condition, source and destination. However, the model does not include demand forecasts. Therefore, the model presented should be treated as part of a policy analyses toolkit along with other tools such as qualitative models, demand and supply forecasts and economic analyses. Additionally, the case studies presented in the paper using the model do not include a case study in a home care environment.

Another research that looks into the possibilities of the whole system's perspective, also referred to as overarching solutions, is from VanBerkel et al. (2010). They provide an overview of the relationships between major hospital departments and describe how researchers account for these relationships. Again, mentioning the importance of a holistic view because confining model scopes to a single department makes researchers overlook the complex relationships in healthcare. VanBerkel et al. (2010) take a whole system perspective, enabling a flexible time line, layering departments, accounting for various relationships between them and enabling problem-specific adjustments. Again, though this research does not include home care specifically, home care is, in essence, an extension of the hospital system where the patients is the one factor linking the hospital with home care.

Van Gameren & Woittiez (2005) take a strategic perspective and a whole system perspective determining transitions between care provisions demanded by the dutch elderly. However, they provide macro-level insights. Then, Zhang et al. (2012) include strategic-level research (timespan of 10 to 20 years) and combine several operations research and statistical methods. The developed methodology sets long-term capacity planning over a multiyear planning horizon for the frail elderly population. Although the study takes an overarching perspective, they do not include this in their model.

Additionally, they focus on long time chronic care. Finally, Recently Zychlinski et al. (2020) take an overarching perspective analyzing the flow between hospitals and geriatric institutions to improve their joint operation. Though they merely focus on the hospital side of the problem, it only uses analytical models and focuses on geriatric care.

3.3 Research trends

In addition to identified limitations of existing literature in this research, we did a literature search on identified research trends in healthcare from an operation management perspective.

Hulshof et al. (2012) emphasize strategic level and overarching solutions as options for further research. Their research states that there are limited examples of strategic models in the literature and even fewer models that consider cross-department or cross-organizational interactions to capture the whole care process. However, an integrated approach is beneficial but not straightforward due to conflicting objectives. Williams et al. (2021) discuss other further research options. They synthesize work on modelling the application of frail and elderly patients from an Operations Research and Management Sciences (OR/MS) perspective, identifying the gaps for future studies. They highlight the need for research to focus on the entire pathway for a patient, where research focuses on the patient's movement between care locations. Focussing on hospitals and how they feed into community care services allows for integrated care systems. Finally, a research opportunity is to consider a sudden rise in frail and elderly patients. A side note is that the research only focused on the elderly over 65 years and did not include all OR/MS approaches. However, it provides valuable insights into further research possibilities.

Additionally, Armadàs et al. (2021) explore the literature on home care operations management strategic problems and gives guidance for potential research. For example, considering global demand forecasting, they suggest a research direction to focus on patient location forecasting using either an individual-based or region-based approach. For capacity planning, they recommend heuristic methods that provide the number of caregivers, type of contract, skills, outsourced services, etc., using forecasting models as input. However, they do not specify further details on these methods or the inclusiveness of overarching solutions.

3.4 Conclusion literature study

This section describes the conclusion of the literature study. Section 3.4.1 concludes the literature study. Based on this conclusion. Section 3.4.2 provides and motivates an approach to further this research.

3.4.1 Conclusion literature study

This section provides the conclusion of the literature study.

Demand forecasting

There are various approaches to demand forecasting, such as deterministic Markov models, microsimulation, and time series forecast. Mathematical models and simulation studies are usable as forecasting methods, however often applied on a higher aggregation level focusing on the evaluation of specific settings. A common use of more detailed forecasting is time series forecasting which is the focus of the remainder of this part of the literature search.

Time series forecasts have a couple of key activities:

- Problem definition, gathering information and exploratory analyses
- Choosing and fitting the model
- Usage and evaluation

A couple of regular interval time series methods are simple methods that often function as a benchmark. Then, time series regression models assume a linear relationship between predictor and forecast. Exponential smoothing methods use weighted averages, decreasing the weight when an observation gets older. Exponential smoothing methods can include trend and seasonality patterns in their forecasts. Finally, Arima models use autocorrelation as the main driver.

Capacity planning models

This literature study shows a lot of solutions for capacity planning problems in a healthcare environment other than hospitals employing various elements such as stochastic programming, tactical planning, strategic planning, simulations, policy evaluations, demand scenarios, overarching solutions and whole system perspectives. However, the available literature has a variety of limitations in the context of this research: literature considering strategic solutions covers a very far time horizon (over ten years), and there is a focus on predicting the number of clients or staff without considering service load, focussing on only one experimental factor, limited uncertainty included or very high levels of aggregation (population level). Additionally, research is either very specific for a client/patient group or highly aggregated. Also, though cross-organizational and whole-system perspectives are available in the literature, no literature is available considering a hospital-home care relationship.

Research trends

The literature shows a variety of research opportunities which include: whole system perspectives, cross-department or cross-organizational, usage of individual-based or regional-based forecasting, use of forecasting as input for models, focus on strategic models, researching the increase in elderly, overarching solutions that include multiple methods, considering the number of caregivers and type of contract skills and outsourced services.

3.4.2 Approach and motivation

To the best of our knowledge, the literature does not discuss a solution focussing on recovery clients in a homecare environment that involves numerous factors. Such as:

- A cross-organizational, whole-system perspective
- Usage of individual-based or region-based forecast as an input
- Covering the number of caregivers and type of contract skills
- Considers a strategic (two to five-year) level
- Overarching solutions that include multiple methods

Therefore, we try to fill the gap with this research by focusing on the case discussed in Section 1.3.1. and previously mentioned points. We are using a forecast study and application of an adjusted version of the convolution model of VanBerkel et al. (2010).

Motivation forecast method

This research focuses on a problem where, as from Section 2.4.3, demand has trend and seasonality. Therefore the Holt-Winters mixed method seems most suitable, which grasps trends and seasonality. However, considering the strategic nature of this research and long-term predictions, there is an inevitable matter of inaccuracy in the prediction. Therefore, exploring a simple method is valuable as a means of comparison and trade-off between complexity and uncertainty. A suitable simple method is a classical multiplicative decomposition because of the ability to grasp the time series elements.

Motivation convolution model

To calculate the number of recovering clients at a time and the corresponding care need, this research uses an adjusted version of the convolution model of Van Berkel et al. (2010). Van Berkel et al. (2010) take a whole system perspective, enabling a flexible timeline, layering departments, accounting for various relationships between them, and implementing problem-specific adjustments, making it suitable for our research. We extend the model from a hospital application to a cross-organizational application between the Slingeland hospital and Sensire. The original model uses a cyclic demand cycle. However, this research deals with a non-cyclic demand cycle. Adjustments are implemented accordingly. Then, this research extends the model to calculate the corresponding care need instead of only dealing with the number of clients or patients. Finally, instead of using a schedule as input, this research extends the model using a forecast.

4 Forecasting future recovery client demand

This chapter describes the forecasting process to predict the future demand of recovery clients flowing into the home care environment of Sensire over the period Jul-2022 to Dec-2024 based on historical patient data from Slingeland hospital covering the period Jan-2018 to Jun-2022 which is the initial step of this research as from Figure 1-1. Section 4.1 discusses the forecasting method and elements. Next, Section 4.2 discusses the data-specific forecasting design. Then, Section 4.3 discusses the results and chooses a preferred method. Finally, Section 4.4 concludes this chapter. This chapter uses the two sources, Chatfield & Chris Chatfield (2001) for the Holt-Winters forecasting procedure and Hyndman & Athanasopoulos (2018) for the Classical Decomposition, validity, outliers, accuracy, prediction intervals and training and test set unless otherwise stated.

4.1 Forecasting method and elements

This section discusses the elements needed to execute the forecasting study. Section 4.1.1 explains the forecasting methods. Next, Section 4.1.2 explains the necessary elements to execute the forecasting study.

4.1.1 Forecasting methods

Classical Decomposition

The classical decomposition, as Section 2.4.3 explains, breaks down an observed value Z_t in an estimate of the seasonality S_t, Trend T_t, cycle C_t and irregular fluctuations E_t. The Classical Decomposition uses these components to make a forecast Z_{t+k} where k is the time to forecast ahead. Appendix H explains the details, including formulas to perform a forecast using the Additive and Multiplicative Classical Decomposition, excluding the cycle elements as stated in Section 2.4.3. Even though we establish in Section 2.4.3 that the multiplicative case seems most appropriate, using both cases enables comparison and confirmation of previous choices.

Holt-Winters method

The Holt-Winters method breaks down an observed value Z_t in an estimate of the level n_t (average value in the time series), estimate of the trend b_t and the estimate of the seasonality f_t. The Holt-Winters method uses this breakdown to make a forecast Z_{t+k} where k is the time forecasted. Just as with the Classical Decomposition, the Holt-Winters method knows a mixed (multiplicative) and additive case which follows the same rule and reason for application. Appendix J explains the details, including formulas. Necessary using the Holt-Winters method is to optimize the parameters α, β and γ on the training set of which Section 4.1.2 explains more. The parameters can take a value between 0 and 1. α corresponds to the level, β corresponds to the trend and γ corresponds with the smoothness of seasonality. For all the parameters a value close to 0 indicates that older values in the time series have more weight. A value close to 1 means that current values in the time series have more weight.

Decomposition validity

To determine the validity of the methods, performing a decomposition validity on the errors is necessary. The errors are the difference between forecasted values and the actual observed demand values ($e_t = Z_t - \hat{Z}_t$). The decomposition validity consists of a 'Test to the Expected Values of the Errors' (must have) and the 'Error Autocorrelation Coefficient' (Nice to have). The 'Expected Values of the Errors' checks if the forecast is biased by proving statistically if the 'Expected Value of the Errors' $E(e_t)$ = 0 (additive case) and $E(e_t)$ =1 (mixed/multiplicative cases) with 95% significance. The 'Error Autocorrelation Coefficient' checks whether the errors correlate with a 95% confidence interval. When there is a correlation, the estimates of the elements still contain useful information.

4.1.2 Explanation forecasting elements

This section discusses forecasting elements to consider when performing a forecast.

Aggregation level

Table 4-1 presents aggregation approaches. Aggregation summarizes observed demand vertically or horizontally. For example, Bottom-up, Top-down and Hybrid are horizontal aggregation approaches.

Table 4-1 Aggregation level

Method	Explanation	Benefit
Vertical aggregation	Aggregation within a dataset	Greater accuracy, more stable time series patterns
Horizontal aggregation	Aggregation across datasets	
• Bottom-up	Combines individual forecasts	Better capture differences in demand. As a consequence, seasonality
• Top-down	Uses aggregated data to create forecasts	Greater accuracy and more stable time series patterns
• Hybrid approach	Combination of Bottom-up and Top-down	Ability to apply advantages of the bottom-up or top-down method on certain datasets

Outliers

Outliers are observations that do not perform as the other observations in the time series. Because outliers can influence the forecast, it is important to identify and, when necessary, remove outliers. We use two statistical tests: IQR (Inter Quartile Range) and the Z-score. The Z-score is more sensitive for outliers (Appendix H, formula 1 and 2). After identifying outliers, a second opinion is necessary to establish whether the outlier is true or performs according to a seasonal trend or has an underlying cause.

Forecast timespan

A forecast considers a predetermined timespan in line with desired results and the nature of the problem (operational, tactical, strategic).

Error measures

To determine the forecasting method performance, errors are measured ($e_t = Z_t - \hat{Z}_t$). Table 4-2 shows the focus an error measure can have. Standard statistical measures allow for comparison within datasets however, to compare among datasets, normalization is necessary using relative measures. The aim is to approach an accuracy of 100%, meaning an error of 0%.

Table 4-2 Error measures: bias and variability

Focus measure	Explanation	Standard/relative	Appendix H
Bias	Systematic over or underestimation most of the time due to the forecasting method	Standard measure Relative measure	Formula 3 Formula 7
Variability	Random, unpredictable errors most of the time due to data	Standard measure Relative measure	Formula 4, 5 Formula 8

Training and test set

To determine an experiment's accuracy, the data divides into a training set and a test set. Table 4-3 shows the definition. According to Hyndman & Athanasopoulos (2018), a good rule of thumb is assigning 80% of your data to the training set and 20% to the test set.

Table 4-3 Training and test set

Set	Explanation
Training set	Trains the method, when necessary, optimize the parameter while minimizing the accuracy values.
Test set	A forecast is performed over the test data with the established parameters from the training set. Accuracy is measured again and indicates how well the forecast performs.

Prediction interval

Since forecasts have an uncertain nature establishing prediction intervals is necessary to indicate the accuracy of the forecast. The prediction intervals give a range in which the forecasted value lies. Calculating prediction intervals is commonly done with 80% or 95% prediction intervals. The further in the future the value lies, the higher the forecast uncertainty and, consequently, the wider the prediction intervals. Appendix H formula 9 calculates the upper and lower bound for the prediction interval. Appendix H formulas 10 and 11 calculate the standard deviation for the Holt winters case based on Yar & Chatfield (1990). Finally, appendix H formula 12 calculates the standard deviation of the forecasts for the Classical Decomposition, which uses the seasonal naïve method, as Hyndman & Athanasopoulos (2018) mention.

4.2 Forecasting design

This section presents the data-specific design for the forecast using the general non-data-specific information as Section 4.1 provides. The forecast input is the historical data from the Outpatient Clinic, clinic and the refusals as Section 2.4 presents. Section 4.2.1 presents the data-specific forecasting elements. Section 4.2.2 establishes the what-if scenario. Finally, Section 4.2.3 combines forecasting elements and the what-if scenarios into the experimental design.

4.2.1 Data-specific forecasting elements

This section presents the data-specific forecasting elements. Table 4-4 summarises the data, objective and background as discussed in previous sections.

Table 4-4 Data-specific forecasting elements

Element	Approach	Explanation
Vertical aggregation	• Weeks • Months	The ability to capture seasonality within the year but still high-level aggregation given the strategic nature of the research and, therefore needlessness to provide daily forecasts
Horizontal aggregation	Approach 1: Bottom-up • Outpatient Clinic • Clinic • Refusals	Focusses on the consequences of seasonality via better capturing differences in demand
	Approach 2: Hybrid a) Top-down • Outpatient clinic • Clinic b) Bottom-up • Outpatient Clinic & Clinic • Refusals	Aggregating the Outpatient Clinic and Clinic because both contain similar yearly seasonality and a decreasing trend

Outliers	Eight outliers are identified, of which the 2018 week 1 and 2021 week 40 are considered true outliers and removed from the data using the mean of previous and consequent observations.	These observations are not the result of seasonality compared to previous and successive years, nor are they part of an increasing or decreasing trend. Appendix L presents the full analyses
Timespan forecast	July-2022 to Dec-2024 (2.5 years timespan)	• Strategic nature of this research and in consultation with Sensire. • The data does not cover more than three years back • Increased inaccuracy of forecasting a longer period in an uncertain environment
Error measure	Relative measures: MAPE	Comparison performance between datasets requires normalized measures. Therefore, MAPE is the most intuitive for the interpreter (Zotteri et al., 2005)
Training set	Weekly aggregation: Week 1-2018 to week 52-2021 Monthly aggregation: Jan-2018 to Dec-2021	80% of data is assigned to the training set
Testing set	Weekly aggregation: Week 1-2022 to week 26-2022 Monthly aggregation: Jan-2022 to Jun-2022	20% of data assigned to the testing set
Prediction interval	80% and 95%	

4.2.2 What-if scenarios

This section discusses the two what-if scenarios established in consultation with Sensire. What-if scenarios establish possible future situations given a forecast has uncertainty.

Section 2.4.1 mentions that the total demand consists of the Outpatient Clinic, Clinic and Refusals. This research establishes two trends, in consultation with Sensire, for the Refusals, which result in two what-if scenarios. Figure 4-1 shows the monthly aggregation level's high and low scenarios. Appendix L-1 shows the figure for the weekly aggregation level. These trends for the refusals are a projection of the expectation and do not use a forecasting method because of limited data and incoherent high variable behaviour of the refusals.

The high scenario expects refusals to rise. As Section 2.1 elaborates, the number of elderly in the region will rise in the next years, and care demand will increase. Therefore, in combination with a decrease in the workforce, one expectation is that the number of refusals will rise, as the high scenario indicates. The low scenario expects refusals to stay approximately the same. The reasoning is that though the number of elderly will rise and the workforce decreases, the current focus on the more efficient arrangement of care processes would result in around the same number of refusals. Efficient arrangement of care processes consists of increased collaboration between care organisations and a different working approach, such as the interventions in Section 2.4.2 explain.

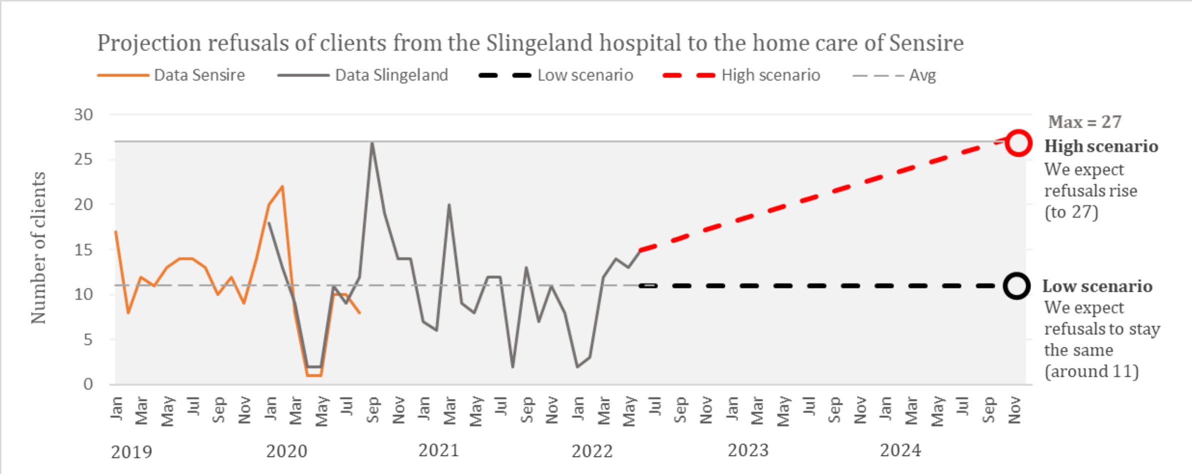


Figure 4-1 Projection refusals of clients from the Slingeland hospital to the home care of Sensire (Source: retrieved from internal data Slingeland hospital January 2020- June 2022, n = 30 and internal data Sensire January 2019-Augustus 2020, n = 20)

4.2.3 Experimental design

This section discusses the experimental settings and the corresponding experimental design to determine the most suitable forecast settings for forecasting the demand from the Clinic and Outpatient Clinic based on common sense and accuracy measures. After the performance of the experimental design, this research chooses the preferred method to perform the actual forecast. Figure 4-1 shows the expected prediction for the behaviour of the refusals, which is added later to the forecast of the demand for the Clinic and the Outpatient Clinic. The experimental design considers the following factors:

- **Method**
  - Classical Decomposition
    - Additive
    - Multiplicative
  - Holt-Winters Method
    - Additive
    - Mixed
- **Forecast levels (includes what-if scenarios in Refusals)**
  - Outpatient Clinic
  - Clinic
  - Outpatient Clinic & Clinic
- **Horizontal aggregation**
  - Weekly
  - Monthly

Example: one experiment trains and tests on weekly aggregated historical data of the Outpatient Clinic using the Classical Decomposition Multiplicative method. Another experiment trains and tests the Outpatient Clinic & Clinic monthly aggregated data using the Holt-Winters Additive method.

Appendix H contains the full experimental design for the forecast.

4.3 Forecast results

This section discusses all results. Section 4.3.1 discusses the experimental design results and chooses the preferred forecasting settings. Next, Section 4.3.2 performs and discusses the forecast. Then, Section 4.3.3 performs an additional validation step.

4.3.1 Results experimental design

This section shows and discusses the most important results of the experimental design. Appendix O shows the full results of the forecast experiments.

Table 4-5 shows the best results per setting using the MAPE for the monthly aggregation level. Appendix N shows all the results, including other accuracy measures. We assume that a MAPE<5% is accurate, a MAPE between 5% and 25% is low but acceptable, and a MAPE>25% is not acceptable. The general expectation is that the MAPE of the test set is higher than the MAPE of the training set since the training data is something the model tunes to and is familiar with. In addition, the test data consists of new data points and indicates how well the model performs.

Table 4-5 shows that the Classical Decomposition achieves the best results for the training set. However, the Holt-Winter method achieves the best accuracy for the test set (lower MAPE). To better understand the behaviour of the forecast beyond the MAPE, we plot the best-performing experiment for the Classical Decomposition and the Holt-Winters.

Figure 4-2 presents the actual and forecasted demand from January 2018 to June 2022 for the Holt-Winter monthly aggregated mixed case. The forecast overfits (high variability) from January 2019 to June 2020 before the model captures the time series. This period makes up a large part of the training set, explaining the unexpectedly lower accuracy (higher error) for the test set compared to the training set. The variance also reflects this, with a variance of 756.8 for the training set and 66.2 for the test set, suggesting the forecast performs better on the test set than on the training set. Then, we observe γ = 1.00 which means more emphasizes on more recent observations in the time series towards the end of the observations in the training set considering seasonality. Figure 4-2 shows no visible bias indicating that the Holt-Winters captures trend and level well.

Increasing the size of the training set gives the forecast a longer 'warm-up' period however decreases the size of the test set. Trying out experimental setting four, but now with a training/test ratio of 90%/10% instead of 80%/20%, results in higher accuracy for the training set of 16.04%. The longer training set enables the forecast to grasp trend, level and seasonality better. However, it decreases the accuracy for the test set to 15.76%. Note here that this would leave a small testing set of n=6. All previous mentioned show the effects of a small dataset. The forecasting method needs time to grasp the time series, and before further finetuning the forecast, the training set is cut off, unable to grasp further details.

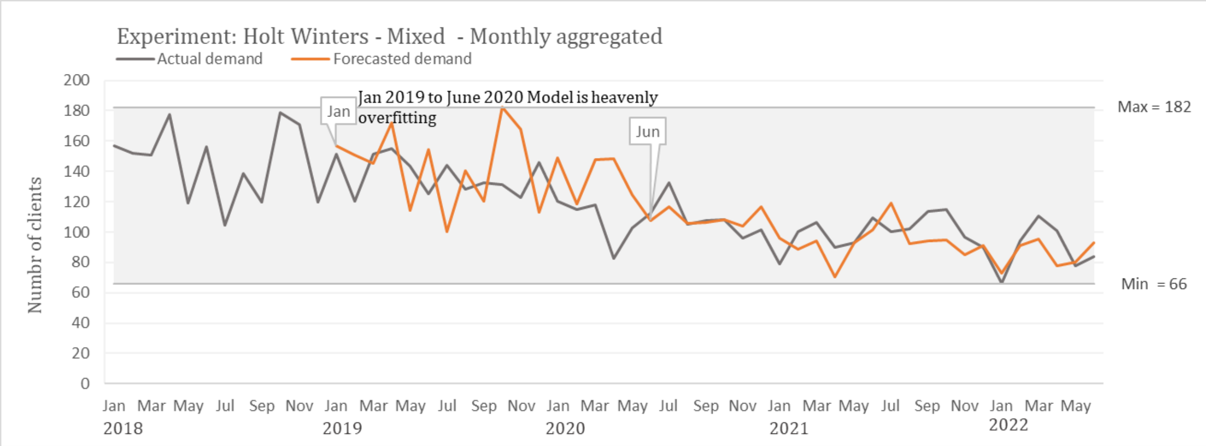


Figure 4-2 Results experiment: Holt-Winters - Mixed - Monthly aggregated

Figure 4-3 presents the actual and forecasted demand from January 2019 to June 2022 for the Holt-Winter monthly aggregated mixed case. The forecasts underfit from January 2018 to June 2019 before the model can capture the time series. However, slight underfitting of the forecast continues, and the model cannot grasp the complexity of the actual demand. The error correlation reflects that there is still information on the decomposition available. Again, we observe the consequences of a small dataset. The forecasting method needs time to grasp the time series, and before further finetuning the forecast, the training set is cut off, unable to grasp further details. Figure 4-3 shows no visible bias indicating that the Classical Decomposition captures trend and level well.

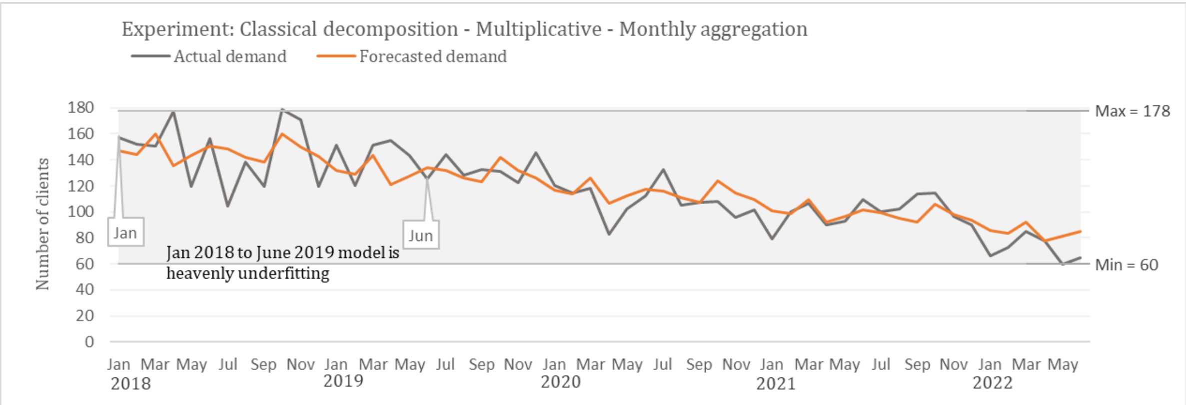


Figure 4-3 Results experiment: Classical Decomposition - Multiplicative - Monthly aggregated

Table 4-5 presents the monthly aggregation results, which we use to further compare the Classical Decomposition with the Holt-Winters method. The training set performs better for the Classical Decomposition as a consequence of the slight underfitting in comparison to the highly overfitting behaviour of the Holt-Winters. However, the Holt-Winters case performs better for the test set, meaning the continued underfitting of the Classical Decomposition simplifies the forecast too much, resulting in lower accuracy (higher error). Suggesting that to grasp a certain level of detail, the Holt-Winters case is a better fit.

Table 4-5 Best forecasting results monthly aggregation

Exp.	Method	Decomposition	Horizontal	MAPE Training	MAPE Test
Monthly aggregated					
1	Classical Decomposition	Multiplicative	Outpatient Clinic & Clinic	10.25%	14.53%
2		Additive	Outpatient Clinic &Clinic	10.37%	14.36%
3	Holt-Winters	Mixed	Clinic	18.89%	14.67%
4		Mixed	Outpatient Clinic & Clinic	16.85%	**11.54%**

Forecasting method choice

Since the test set indicates how well an actual forecast performs, better accuracy on the test set is more important. We, therefore, choose experiment 4 of Table 4-5 with a MAPE of 16.85% for the training set and a MAPE of 11.54% for the test set. The parameter this method uses is α = 0.13, β = 0.07, γ = 1.00 indicating there is more emphasis on the level and the trend of older values in the time series. Additionally, the high gamma value indicates the time series smoothness of the seasonal component, which emphasizes more recent values. This explains why it took some time for the times series to grasp seasonality. Though the monthly aggregated forecast performs the best, for this research, it is also of interest to consider a weekly forecast since the forecast of this section functions as an input for the mathematical model in Section 5. The best-performing experiment for the weekly aggregation level is the Classical Decomposition combining the Clinic and Outpatient Clinic data with a MAPE of 13.68% on the training set and 21.23% on the test set. Both cases favour the multiplicative/mixed case, as we identified in Section 2.4.3. The increase in accuracy (decreased error) for the monthly aggregation is notable. Monthly aggregation is a higher aggregation level, resulting in greater accuracy and a more stable time series, as Table 4-1 explains.

4.3.2 Forecast

This section performs the forecast using the total demand (Clinic, Outpatient Clinic and Refusals), implementing the Holt-Winters multiplicative method for the monthly aggregated demand and the Classical Decomposition mixed method for the weekly aggregated demand. Figure 4-4 and Figure 4-5 show the results of the forecast of the HighD (high demand scenario) for the monthly and weekly aggregation, including the 80% and 95% prediction intervals. Appendix L-1 and Appendix L-2 show the results of the LowD (low demand scenario) for the monthly aggregation and weekly aggregation. The LowD and HighD scenario trend is downward, where the minimum attained value changes. For example, the HighD monthly aggregation has a minimum of 60 compared to a minimum of 44 for the LowD. Likewise, the HighD weekly aggregation has a minimum of 9 compared to a minimum of 5 for the LowD, which are quite significant differences for the demand scenarios. We see the forecasts have yearly seasonality showing the same pattern in 2023 and 2024 for the monthly and weekly aggregation levels. The monthly forecasts show less seasonality towards the end because of the γ = 1.00 flattening the seasonality component which indicates less variability in the future demand.

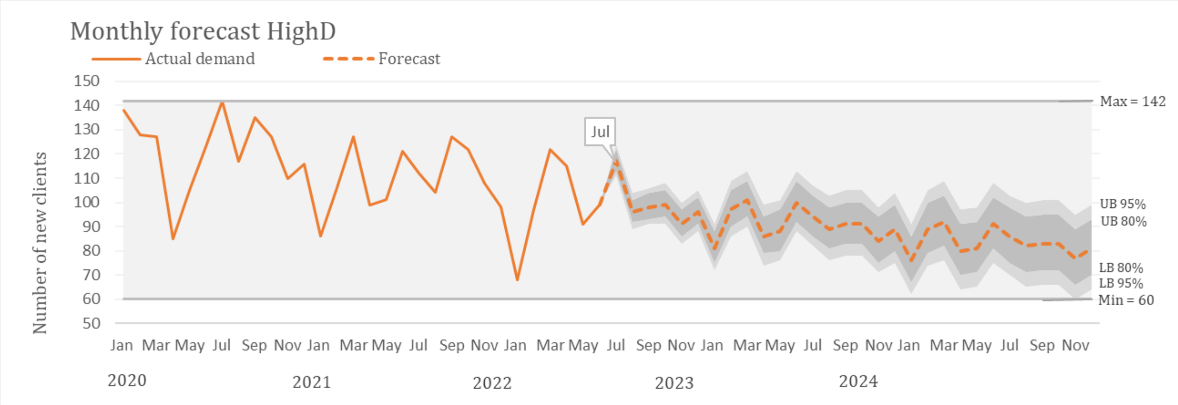


Figure 4-4 Monthly forecast HighD (n=60)

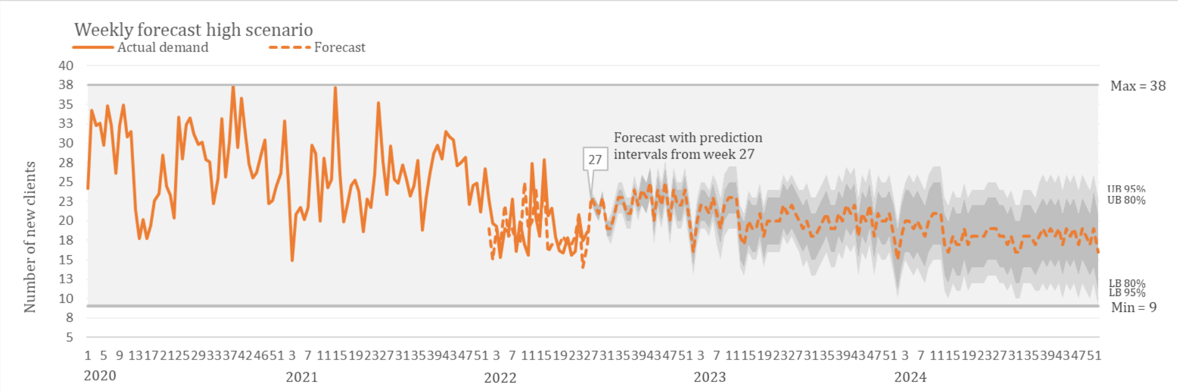


Figure 4-5 Weekly forecasts HighD (n=258)

4.3.3 Additional validation step

This section discusses an additional validation step. The forecast in this research starts in July 2022 and covers 2.5 years. Towards the end of this research, a couple of months past such that an additional validation step is possible using the actual data from July 2022 to November 2022 (week 27-2022, to week 44-2022).

Figure 4-6 shows a plot of the actual demand with the weekly forecasted demand for the LowD scenario. The fit is not perfect however matches the general behaviour. We found a MAPE of 25%, which is within the 25% margin meaning that the forecast performs within established accuracy measures. However, the MAPE for the high case is 27%, which exceeds the 25% benchmark, suggesting the LowD scenario is more accurate. Moreover, we observe from the figure that the forecast cannot grasp the highly variable behaviour of the actual demand pattern, probably indicating underfitting of the model, as also discussed in Section 4.3.1.

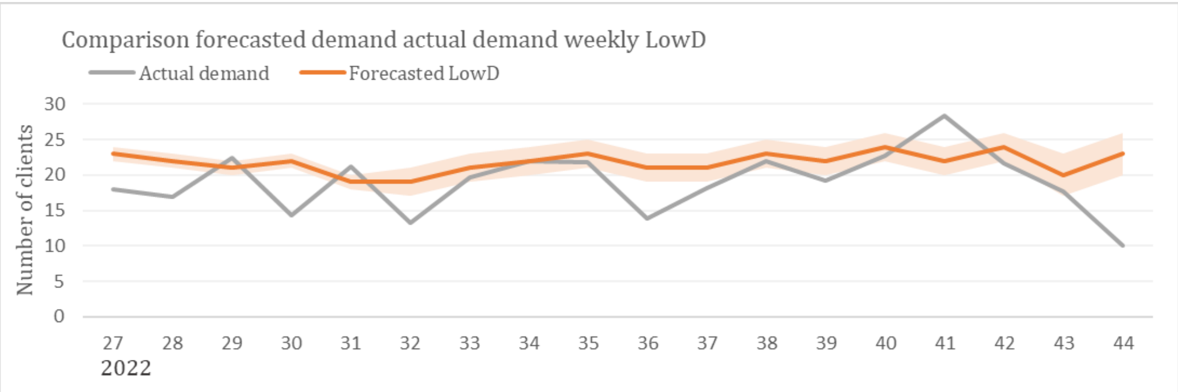


Figure 4-6 Comparison of forecasted demand and actual demand weekly LowD

We want to draw attention to a couple of points regarding this validation. The difference between the HighD scenario and the LowD is small during this period. Differences become more significant only later in the timeline. Over the evaluated period in this section, LowD performs better than HighD. However, this can change since changes between the scenarios become more significant when progressing on the timeline. Second, Figure 4-7 plots the actual demand, including refusals with the forecasted LowD without refusals, and shows a better fit with a MAPE of 19% than the LowD with refusals which indicates that the effects of the refusals are, at this stage of the forecast, insignificant. Appendix P-4 shows the results for the monthly aggregated case, which shows better accuracy due to aggregation. The MAPE for the LowD scenario is 17%, the HighD scenario is 14%, and without the refusals is 10%.

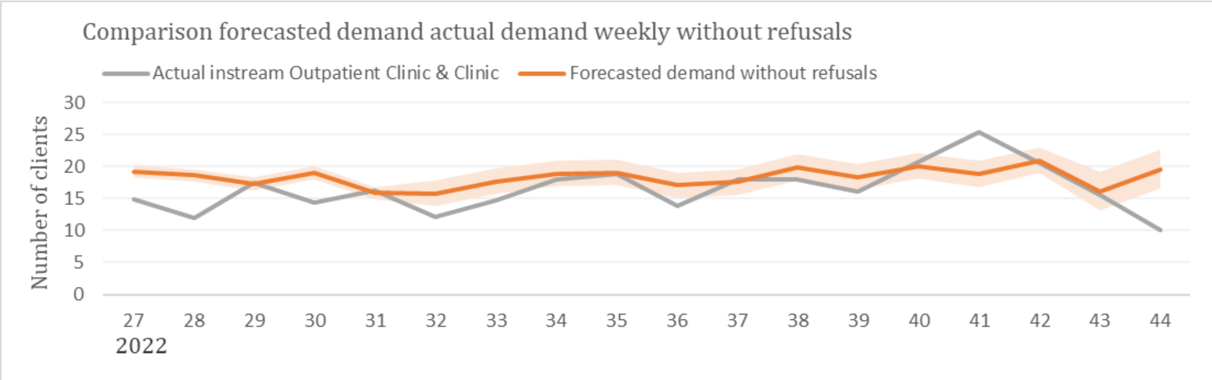


Figure 4-7 Comparison forecasted LowD with actual demand without refusals

4.4 Forecasting conclusion

This chapter described the forecasting process to predict the future demand of recovery clients flowing into the home care environment of Sensire over the period Jul-2022 to Dec-2024 based on historical patient data from the Slingeland hospital covering the period Jan-2018 to Jun-2022. The demand divides, as Section 2.4 discusses, into the demand of the Outpatient Clinic, Clinic and Refusals.

Due to the Refusals' highly variable and unpredictable behaviour, a forecast on this part of the demand is impossible. Therefore, in consultation with Sensire, we choose to project future refusals establishing two scenarios. A LowD scenario where refusals stay the same and a HighD scenario where refusals rise.

For the Outpatient Clinic and Clinic forecast, we tested the performance of the Classical Decomposition method and the Holt-Winters method while using various experimental factors, as Section 4.2.3 discusses. We choose to use the MAPE as an accuracy measure to indicate the performance of an experiment. We assume that a MAPE<5% is accurate, a MAPE between 5% and 25% is low but acceptable, and a MAPE>25% is not acceptable.

The Holt-Winters multiplicative case with the Outpatient Clinic and Clinic data combined and monthly aggregation performed the best, reaching a MAPE of 16.85% for the training set and 11.54% for the test set using the following parameters: α = 0.13, β = 0.07, γ = 1.00. Indicating more emphasis on the level and the trend of older values in the time series and flattening the seasonality of the time series with an emphasis on more recent observations.

Because the forecast functions as an input for Section 5, we also considered a weekly aggregation case. The best-performing method for the weekly aggregated data is the Classical Decomposition Multiplicative method combined with the Clinic and Outpatient Clinic data, attaining a MAPE of 13.68% for the training set and 21.23% for the test set.

The last step is to combine the forecast for the Clinic and Outpatient Clinic with the LowD and HighD scenarios for the refusals. The LowD and HighD scenarios show a decreasing trend, variable behaviour over the weeks and months and yearly seasonality. Since forecasts carry uncertainty, every predicted value on the timeline has a 95% confidence interval that widens along the timeline. For example, the inflow for the monthly HighD in March 2023 lies with 95% certainty between 90 and 110 and, in November 2024, between 60 and 100. The HighD scenario monthly aggregation has a minimum of 60 compared to a minimum of 44 for the LowD. The HighD scenario weekly aggregation has a minimum of 9 compared to a minimum of 5 for the LowD scenario. Indicating the scenarios are quite different towards the end of the projected timeline.

An additional validation step shows that the forecast yields good results for the LowD, with a MAPE for the HighD of 27% and LowD of 25% for the weekly case and a MAPE of 17% for the HighD of 17% and LowD of 15%. Except for the weekly HighD scenario, all perform below the 25% benchmark. At this point, including the refusals seems to result in worse results which could indicate refusals do not result in significant differences. Excluding the refusals results in a MAPE of 19% for the weekly and 10% for the monthly cases.

5 Determining the number of home care providers

This chapter answers how many home care providers Sensire needs to respond to the care need coming with the constant yet variable monthly and weekly inflow of recovery clients from the Slingeland hospital. We do so by experimenting with different contract types and levels of absenteeism. Section 5.1 explains the model used. Section 5.2 discusses relevant experimental settings. Section 5.3 discusses the results. Section 5.4 concludes this chapter.

5.1 Model explanation

This section explains the model to determine the number of home care providers Sensire needs. Section 5.1.1 overviews the necessary steps using a conceptual model scheme based on Figure 1-1. Then, Section 5.1.2 generally explains the adjusted convolution model. Section 5.1.3 explains the mathematical details of the adjusted convolution model to derive the number of clients at a point in time. Then, section 5.1.4 explains the extension to the adjusted convolution model to calculate the care need at a point in time. Finally, Section 5.1.3 explains how to translate the care need into FTEs and the number of home providers.

5.1.1 Conceptual model

This section explains the conceptual model, and Figure 5-1 shows the steps.

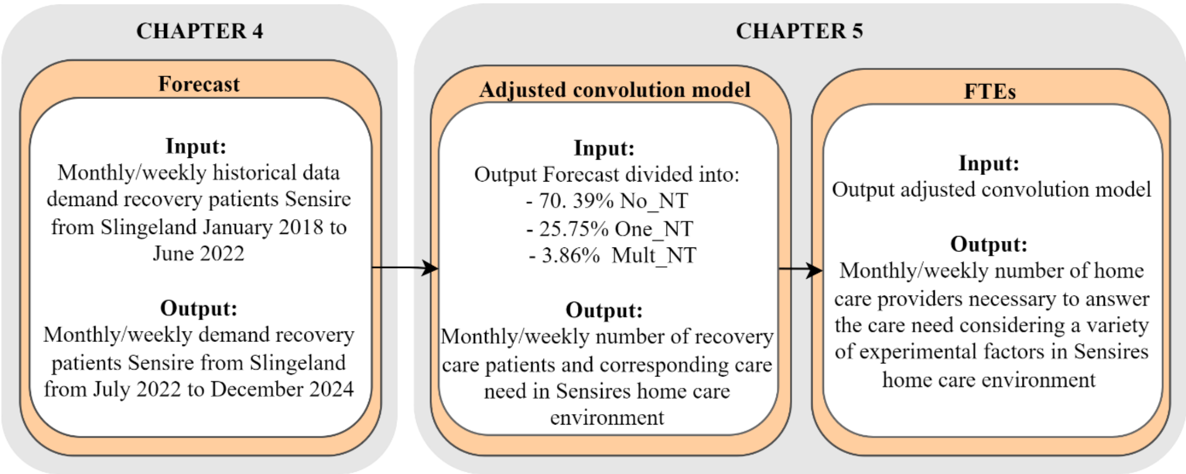


Figure 5-1 Conceptual model scheme

The forecast output divides into the weekly/monthly demand for three groups, No_NT, One_NT and Mult_NT, from Table 2-7. The three groups form the input for the adjusted convolution model that calculates the total number of recovery care patients and their corresponding care need at a point in time, as Sections 5.1.2 - 5.1.4 further explain. These outputs function as input for the last part, which concerns calculating the number of home care providers to cover the care need, including settings such as absenteeism and various contract combinations.

5.1.2 Adjusted convolution model

This section gives a general explanation of the adjusted convolution model.

To determine the care need at a point within the period July 2022 - December 2024, this section uses an adjusted version of the convolution model of van Berkel et al. (2010) because the model allows, as Section 3.4.2 explains, a whole system perspective, flexible time line, layering departments, accountment for various relationships and problem specific adjustments.

Accordingly, we make the following problem-specific adjustments:

- We are extending the model from a hospital application to a cross-organizational application between the Slingeland hospital and Sensire.
- We implement a non-cyclic demand cycle instead of the original cyclic demand cycle. Appendix Q-1 shows a figure of the non-cyclic demand cycle.
- We extend the model to calculate the number of clients and the corresponding care need instead of only the number of clients. Section 5.1.3 elaborates on the adjusted convolution model to calculate the number of clients at a point in time. Section 5.1.4 elaborates on extensions to calculate the care need at a point in time. A point in time for this research is a month or a week from July 2022 to December 2024.
- Instead of using a schedule as input, we use a forecast as input.

5.1.3 Adjusted convolution model: Number of clients

This section explains the mathematical model for the adjusted convolution model to calculate the number of clients at a designated point in time. We first explain the sets, parameters (inputs) and variables of the formulas used.

Sets

m	*time in months/weeks m = {1, 2, 3, …, M}*
j	*group j = {1, 2, …, J}*
q	*time a demand block q is executed q = {1, 2, 3, …, Q}*
n	*number of months/weeks after the execution of a demand block* $b^{j,q}$ *n= {0, 1, …* L_j*}*
x	*number of clients receiving care*

Parameters

L_j	*the maximum length of stay for group j*
$b^{j,q}$	*demand block executed at time q from group j*
$P^j(n)$	*the probability that a client from group j stays n months/weeks*
$c^{j,q}(x)$	*probability for x demand in block j, q (assignment of this probability via a normal distribution using the lower bound, mean, upper bound and standard deviation as an input)*
τ	*the largest value of x with a positive probability resulting from the formula*

Variables

d_n^j	*the probability that a client from group j is discharged n months/weeks after flowing in*
$h_n^{j,q}(x)$	*probability distributions that n months/weeks after a demand block q of client group j x clients are still in recovery*
$h_m^{*j,q}(x)$	the *probability distribution that the number of recovering clients as a consequence of demand block j,q is x at time m.*
$H_m(x)$	the *probability that in month/week m, there are x clients in recovery*
H_m	*number of patients in recovery at time m*

Formulas
Using the defined variables and parameters, we first calculate the probability distributions for one demand block using formulas 1 and 2.

Formula 1 calculates the probability of discharge of a client from group j in a month/week, dividing the probability of staying of a client of group *j* at time *n* by the probability of staying longer but no longer than the maximum established months/weeks L_j. The outcome of formula 1 increases the probability of discharge over time *n* since the longer a client is in the system, the higher the probability the client leaves the system. In the last possible *n,* the probability of discharge is one since a client always leaves the system in the last month/week.

Formula 2 calculates the probability distribution that *n* months/weeks after a demand block *q* of client group *j*, *x* clients are recovering. To calculate the probability of *x* clients in recovery, in other words, *x* clients not discharged, we calculate all combinations of *x* clients in recovery over *k=x* to $k=c^{j,q}(x)$ which is the maximum number of clients that flows into block *q*. At *n=0*, no clients discharge therefore $h_n^{j,q}(x) = c^{j,q}(x)$. However, when *n* proceeds, clients discharge at *n* and *n-1,* leaving numerous combinations on how to reach the probability of *x* clients in the system at time *n*. $\sum_{k=x}^{C^{j,q}} \binom{k}{x}$ Calculates all combinations *x* from *k* where the maximum *k* is the maximum demand in block *q* since to have *x* clients in the system at *n*, you need at least or more than *x* clients at *n-1*. $\left(d_{n-1}^{j}\right)^{k-x}$ Represents the probability of discharge for *k-x* clients at *n-1*. $\left(1 - d_{n-1}^{j}\right)^{x}$ Represents the probability of no discharge for *x* clients at *n-1*. $h_{n-1}^{j,q}(k)$ Represents the probability that there where at least *k* clients at *n-1*.

(1) $$d_n^j = \frac{P^j(n)}{\sum_{k=n}^{L_j} P^j(k)}$$

(2) $$h_n^{j,q}(x) = c^{j,q}(x) \qquad n = 0$$

$$h_n^{j,q}(x) = \sum_{k=x}^{C^{j,q}} \binom{k}{x} (d_{n-1}^j)^{k-x} (1 - d_{n-1}^j)^x \, h_{n-1}^{j,q}(k) \qquad otherwise$$

After determining all the one demand blocks for *j, q* and *n* formulas 3 and 4, calculate the full demand cycle. Formula 3 calculates the impact of block $b^{j,q}$ on the number of recovering clients in month/week *q*. So when taking a block $b^{1,3}$ as an example, given the current time $m = 5$, then $h'^{1,3}_5(x) = h_{5-3}^{1,3}(x)$ which is $h_2^{1,3}(x)$ because $m = 5$ is two months after the execution of the demand block. Figure 2 shows the adjusted non-cyclic demand cycle from *h* to *h*.* Appendix Q-2 shows a figure of how h transfers to *h*.* Then, formula 4 calculates all the convolutions over *j* and *q,* deriving probability functions for every *x* at time *m*.

(3) $$h{*}_m^{j,q}(x) = h_{m-q}^{j}(x) \qquad q \le m < L^j + q$$

$$h{*}_m^{j,q}(x) = \mathbf{0} \qquad otherwise$$

$\mathbf{0}$ means $h_m^{j,q}(0) = 1$ and all other probabilities $h_m^{j,q}(l) = 0, l > 0$

(4) $$H_m(x) = h_m^{*1,1}(x) * \ldots * h_m^{1,Q}(x) * h_m^{*2,1}(x) * \ldots * h_m^{*I,Q}(x)$$

Now $H_m(x)$ represents the probability of *x* patients in month/week *m*. Formula 5 calculates the expected number of clients in recovery at time *m.*

(5) $$H_m = \sum_{x=0}^{\tau} x \cdot H_m(x)$$

Settings sets and parameter derivation

The maximum for specific sets depends on whether the model calculates on a monthly or a weekly basis. Table 5-1 shows these settings. As previously mentioned, this convolution model application uses a non-cyclic demand. A warm-up period is, therefore, necessary to arrive at a steady state system. Since the maximum length of stay of recovery care patients is 84 days, the probability of still being in the system after 84 days is 0. The warm-up period is, therefore, 84 days which is 12 weeks and three months. The m and q in Table 5-1 include these.

Table 5-1 Weekly or monthly specific sets

Sets	Weekly	Monthly	Further description
m	M = 144	M = 33	July 2022 to December 2024 contains 132 weeks or 30 months. Including the warm-up period results in 144 weeks and 33 weeks
j	J = 3	J = 3	No_NT, One_NT, Mult_NT
q	Q = 144	Q = 33	July 2022 to December 2024 contains 132 weeks or 30 months. Including the warm-up period results in 144 weeks and 33 weeks
n	L_j = 12	L_j = 3	84 days is 12 weeks or three months

The parameter data derived from the NZA questionnaire data from Sensire November 2021-March 2022 with 4857 data points combined with the dataset on efficacy March 2019-March 2022 with n = 49795. The dataset was filtered on recovery care patients (receiving less than 84 days of care), leaving 1999 data points.

5.1.4 Adjusted convolution model: Care need

This section explains the mathematical adjusted convolution model to calculate the care needed at a point in time.

Section 5.1.3 explains that the model extends into a model to calculate the care need (in hours) at a time. The general approach is the same as in section 5.1.3. However, it is necessary to add a step between formulas (2) and (3) that translates $h_n^j(x)$ the probability distributions that n months/weeks after a demand block of client group *j x* clients are still in recovery into the number of minutes/hours/days. Additionally, the following parameters and variables have to be added or changed.

Sets

t — *care need in minutes/hours/days t = {1, 2, 3, …, T}*

Parameters

$f_n^j(t)$ — *probability distribution of t hours of care per month/week is dependent on group j and month/week n after a client flows in*

Variables

$F_n^j(t)$ — *probability distributions that n months/weeks after a demand block of client group j t hours of care are still in recovery*

$h_m^{*j,q}(t)$ — the *probability distribution that the number of hours of care as a consequence of demand block j,q is t at time m.*

$H_m(t)$ — the *probability that in month/week m, there are t hours of care in recovery*

H_m — *number of hours in recovery at time m*

$h_n^{j,q}(x)$ and $f_n^j(t)$ combine into $F_n^j(t)$. For example, $h_1^{1,12}(3)$ = 0.2 means that there are 3 clients in the system, which all have a probability function for the care need $f_1^1(t)$. To arrive at $F_1^1(t)$ we multiply the probability of having 3 clients $h_1^{1,12}(3)$ with the convolution $(f_1^1(t) * f_1^1(t) * f_1^1(t))$.

We then replace (3), (4) and (5) with (6), (7) and (8)

$$(6) \qquad h^{*}{}_{m}^{j,q}(t) = F_{m-q}^{j}(t) \qquad\qquad q \le m < L^j + q$$

$$h^{*}{}_{m}^{j,q}(x) = \mathbf{0} \qquad\qquad otherwise$$

$\mathbf{0}$ means $h_m^{j,q}(0) = 1$ and all other probabilities $h_m^{j,q}(l) = 0, l > 0$

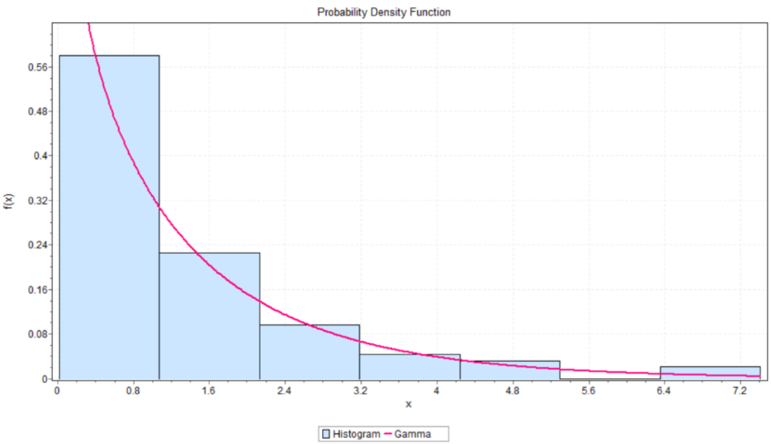
$$(7) \qquad H_m(t) = h_m^{*1,1}(t) * \dots * h_m^{1,Q}(t) * h_m^{*2,1}(t) * \dots * h_m^{*J,Q}(t)$$

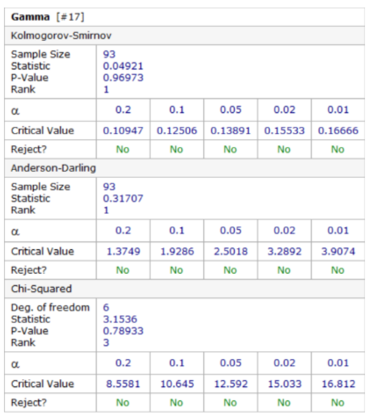
Now $H_m(t)$ represents the probability of t hours of care in month/week m. Formula 5 calculates the expected number of hours in recovery at time m.

$$(8) \qquad H_m = \sum_{x=0}^{\tau} x \cdot H_m(x)$$

Sets and parameter derivation

The settings stay the same as in Section 5.1.3. However, we have to derive the parameter $f_n^j(t)$. Probability distribution of the hours of care per month/week for group j, n months/weeks after clients inflow. The monthly case needs 12 probability distributions (j=3*n=3). The weekly case needs 36 probability distributions (j=3*n=12). After dividing the data into these groups, the first step is removing outliers using the Z-score as in Appendix K. Then, EasyFit software (Softonic, 2021) derives the probability distributions. The software uses three goodness-of-fit tests: Kolgomorov Smirnov, Anderson Darling and the Chi-Square test. Snedecor & Cochran (1989) states that the value of the chi-square test statistic depends on how the data is binned and, therefore, should be an alternative to the Anderson-Darling and Kolmogorov Smirnov goodness of fit tests. According to Razali & Yap (2009), the Anderson-Darling test gives more weight to the tales, which is irrelevant for this research because we cut off the tails. The Kolmogorov Smirnov, therefore, is the focus goodness of fit test for finding the probability distribution and their parameters where H_0 : the data follows the distribution. The aim is to not reject with at least an α = 0.02. Figure 5-2 shows a distribution plot and Goodness of fit test from EasyFit. Appendix R shows all the probability distribution derivations.





Gamma [#17]					
Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	93 0.04921 0.96973 1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.10947	0.12506	0.13891	0.15533	0.16666
Reject?	No	No	No	No	No
Anderson-Darling					
Sample Size Statistic Rank	93 0.31707 1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	No	No	No	No	No
Chi-Squared					
Deg. of freedom Statistic P-Value Rank	6 3.1536 0.78933 3				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	8.5581	10.645	12.592	15.033	16.812
Reject?	No	No	No	No	No

Figure 5-2 Determination probability distribution using EasyFit

After determining the distributions and their parameters, the next step is calculating the probabilities for every t value. Since in some distributions, a very high t value still has a positive probability, which would significantly increase the model's running times, the max t value is set to the max value as found in the dataset, which differs for the monthly or the weekly aggregation level.

5.1.5 Home care providers Sensire

The last step of the model is to translate the number of clients and their care needs into the number of home care providers. The care need translates into the number of FTEs to cover the care need. However, the number of FTEs to cover the care need does not directly translate into actual needed FTEs since we deal with indirect hours and absenteeism.

Indirect hours and absenteeism

Section 2.6.2 states that the effectivity deviates between 75% and 85%. Since effectivity does not include absenteeism, the percentage of indirect hours deviates between 15% and 25%. Including these percentages is necessary to arrive at the actual needed FTEs. However, this 15% to 25% gives a slightly skewed perception. District nurses only have an effectivity percentage of 30% since they have less direct contact with clients. Therefore, in consultation with Sensire, we choose a percentage of indirect hours of 20%. To arrive at the actual needed FTEs, excluding absenteeism, multiply the number of FTEs to cover the care need by 1.2. Additional to indirect hours, we have to include a factor for absenteeism. Absenteeism includes as an experimental setting. Section 5.2.3 explains which settings this research considers.

Contract configuration

The number of home care providers depends on the configuration of contracts. For example, a higher percentage of 34-hour contracts compared to 20-hour contracts results in a lower need for home care providers than the other way around. Therefore, contract configuration includes an experimental setting. Section 5.2.3 elaborates further on which contract combinations this research considers.

5.2 Experimental design

This section explains all experimental settings considered in determining the care need, the number of clients and the home care providers. Section 5.2.2 provides an overview of the experimental settings. Next, section 5.2.3 further explains the experimental settings this research considers when calculating the number of clients and their care needs. Next, section 5.2.4 further explains the experimental settings for calculating the number of home care providers. Finally, section 5.3.4 further explains the settings considered in the sensitivity analyses.

5.2.1 Overview experimental settings

This research divides the experimental parameters into three sections, as in Figure 5-1. Table 5-2 presents parameters corresponding with the adjusted convolution model, which considers determining the care need and the number of clients. Section 5.2.2 provides a detailed explanation.

Table 5-3 presents parameters corresponding to the determination of home care providers. Section 5.2.3 provides a detailed explanation. Table 5-4 presents parameters corresponding with the sensitivity analyses. Section 5.2.4 provides a detailed explanation.

Table 5-2 Experimental settings: determination of care need and number of clients

Experimental setting: determination of care need and number of clients	
Experimental setting	**Abbrevation**
Scenarios	
• Low demand	LowD
• High demand	HighD
Aggregation level	`
• Monthly	Month
• Weekly	Week
Care need per month/week	
• Probability density function	Pdf
• Average	Avg

Table 5-3 Experimental settings: determination of home care providers

Experimental setting: determination of home care providers	
Experimental setting	**Abbreviation**
Absenteeism	
• 7%	7%
• 9%	9%
• 12%	12%
Contract type	
• Small (small number of large contracts)	CTSmall
• Middle (more number of large contracts)	CTMid
• Large (a lot of larger contracts)	CTLarge

Table 5-4 Experimental settings: sensitivity analyses

Experimental settings: sensitivity analyses	
Experimental settings	**Abbrevation**
Scenario	
• Low demand	LowD
• High demand	HighD
Length of Stay	
• Increase staying shorter, decrease staying longer	LoS
Care need	
• increase at the beginning, decrease at the end	CareN

5.2.2 Experimental parameters number of clients and care need

This section discusses the experimental settings used to determine the care need and the number of clients from Table 5-2.

The questions the experimental settings of this section answer are:

1) What is the impact of demand scenarios on the care need and number of clients?
2) What is the impact of the aggregation level, weekly and monthly, on the care need and the number of clients?
3) What is the impact of the way of determination of the care need on the care need?

Scenarios

Section 4.2.2 establishes and explains the two scenarios. In the LowD scenario, the number of refusals stays approximately the same, and in the HighD scenario, the expectation is that the number of refusals increases.

Aggregation level
Section 4 performs a forecast for the monthly aggregated case as well as the weekly aggregated case. The monthly aggregated case performs better. However, the forecast functions as an input for the adjusted convolution model of this research section and monthly aggregation levels could result in a loss of details on the care need. Section 4.4, therefore, concludes with the forecast method for the monthly aggregation level as well as the weekly aggregation level. Using both as experimental settings allows comparison.

Determination of the care needed per month/week
The data this section uses provides the care needed in the following matter: hours per period. For example, client X receives 4.8 hours of care in 80 days. The adjusted convolution model needs the hours of care per week or month as input. We considered various options, of which Appendix S presents a detailed explanation and selected two options to include as experimental settings. One option uses the probability density function as an input determining the care need as follows: The care need is determined per group and month/week in care, where the amount of care in a month or week corresponds to the number of days spent in that specific month/week. Note here that depending on the period this person is in care one observation splits into multiple observations. The second option uses the average care need as input.

5.2.3 Experimental settings home care providers Sensire
This section discusses the experimental settings used to determine the number of home care providers from Table 5-3.

The questions the experimental settings of this section answer are:
1) How many FTEs does Sensire need monthly to cover the care need of recovery clients flowing from Slingeland hospital to the home care environment of Sensire, including indirect hours?
2) What is the impact of absenteeism on the number of home care providers necessary to cover the need for FTEs?
3) To cover the monthly FTEs, what is the impact of a diversity of contracts for the home-care providers, including different levels of absenteeism, as posed in question 2?

Level of absenteeism
Section 2.6.2 shows the minimum level of absenteeism of 7% in week 1 2021 – week 28 2022, the maximum level of absenteeism for the region is 14%. Therefore, the desired level of absenteeism within Sensire is 7%. However, from the data, this level is often higher. Therefore, in consultation with Sensire, two higher levels of 9% and 12% are considered of interest as experimental settings.

Contract combinations
The possible combinations for contracts are endless. However, in consultation with Sensire, we choose the most common contract types (32, 24, 16 and 12 hours) to consider for the experiments. Table 5-5 shows three ways of combining these contracts. The CTSmall represents the current situation with a few 32-hour contracts. Section 2.6.2 discusses that many smaller contracts result from the general practice of helping clients in the mornings or evenings (broken shifts). Therefore, working 32-hour contracts would mean working seven days a week. However, Sensire tries to change this general practice by normalizing receiving care during hours other than the morning or evening hours. The desired contract situation for Sensire is CTLarge. Since this is a significant step in the 32-hour contracts, CTMid includes as an in-between step. It is important to include smaller contracts to make the teams more agile.

Table 5-5 Contract combinations

	32 hour	24 hour	16 hour	12 hour
CTSmall	20%	40%	20%	20%
CTMiddle	35%	25%	20%	20%
CTLarge	50%	20%	15%	15%

5.2.4 Sensitivity analyses

To test the robustness of the model in addition to the experimental design, as Sections 5.2.2 and 5.2.3 explain, the execution of sensitivity analyses is important. Based on the results from the experimental design, we chose a couple of scenarios of interest to perform sensitivity analyses. The sensitivity analysis analyses the impact of potential future changes of independent variables on the model. More specifically, what percentage of change in the independent variables makes the chosen scenario outcomes not hold anymore.

We considered the following to determine the settings of interest for this sensitivity analysis as from Table 5-4:

- With its corresponding increase in care need, the ageing population could result in more clients flowing in, included in the LowD and HighD scenarios.
- The implementation of various interventions that redesign the care processes resulted in a decrease in recovery care patients/clients flowing from the Slingeland hospital to Sensire's home care environment, included in the LowD and HighD scenarios.
- The implementation of more interventions to decrease the care need for the home care environment of Sensire to decrease the LoS and CareN.

5.3 Results

This section discusses the results. Section 5.3.1 shows the results for the number of clients. Section 5.3.2 shows the results for the care need. Section 5.3.3 closes this section with a discussion of the number of home care providers' results.

5.3.1 Number of clients

This section compares the number of clients using the monthly and weekly aggregation and HighD and LowD cases.

As expected, the number of clients at a designated time follows a decreasing trend, as the forecasted demand. Besides following the same trend, the number of clients also follows the same seasonal pattern as the forecasted demand, meaning that not only the inflow of recovery care clients decreases but as well the total number in care. Figure 5-3 shows the monthly aggregated high-demand case plot. The same seasonal pattern is a consequence of the same probabilities used at every point. The probability of staying one, two or three months in, for example, January 2023 is the same as when a client would flow in in May 2024. Logically, the number of recovering clients in care is higher than the forecasted demand since a client can stay up to three months in the system. Appendix T-1 to Appendix T-8 shows the plots of the number of clients over time for the other cases that show the same behaviour.

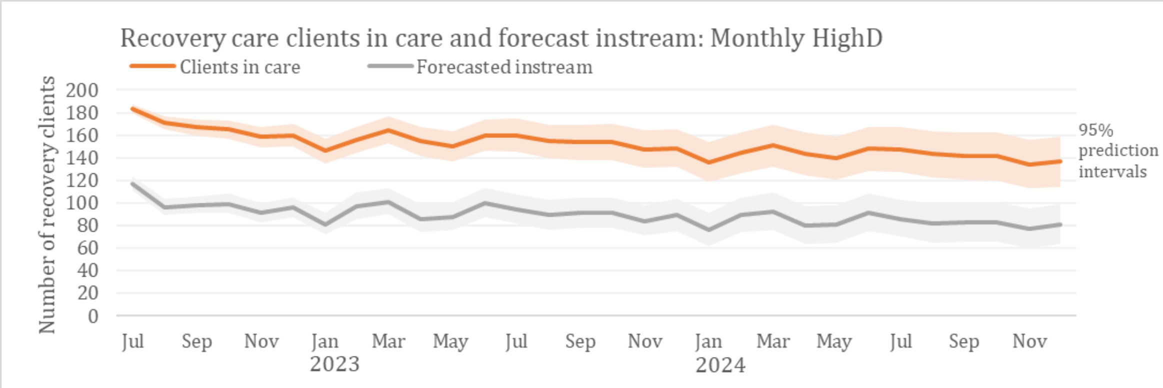


Figure 5-3 Number of recovery clients with forecasted demand: monthly high

5.3.2 Care need

This section discusses the results of the care need using the calculated number of FTEs, including indirect care. The experiments consider two options to determine the care need, Pdf and Avg, and two aggregation levels, Weekly and Monthly, as Section 5.2 discusses.

Pdf and Avg

Figure 5-4 shows the two options to determine the care need for the HighD and the LowD monthly case. Section 5.2.1 explains that Pdf determines the care need, deriving probability functions from the data, and Avg uses the average care need as input. The figure shows that option Pdf shows a higher need for FTEs than option Avg because of the better ability to capture variable behaviour since full probability functions function as an input. However, as expected, they lay close to each other. Where in the beginning, the HighD and the LowD for the Pdf and the Avg follow their path, we see further in the figure that the LowD of the Avg case and the LowD of the Pdf case approach each other. The same goes for the HighD case of the Avg and the HighD of the Pdf. The difference between the Pdf and the Avg becomes almost parallel, meaning the differences between the HighD and the LowD and the difference in Pdf and Avg are insignificant.

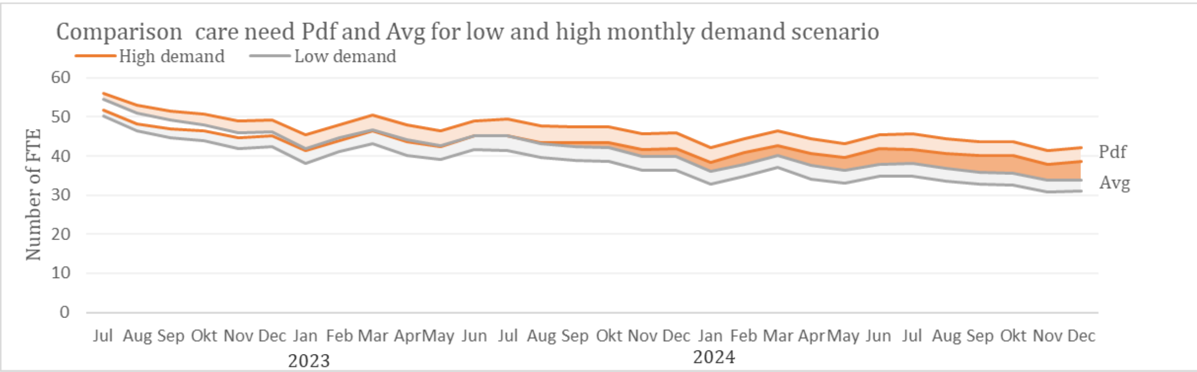


Figure 5-4 Comparison determination care need option Pdf and Avg for the LowD and HighD monthly scenario

We can further argue this because when we plot the confidence intervals for the two most different cases, HighD Pdf and the LowD Avg, we can see from Figure 5-5 that the confidence intervals overlap. Appendix T-9 andAppendix T-10 show the same behaviour for the weekly case. However, the difference between the HighD pdf and the LowD further on the timeline (for example, December 2024) is 11 FTEs, which is quite a difference. Therefore, further looking into the best option is necessary.

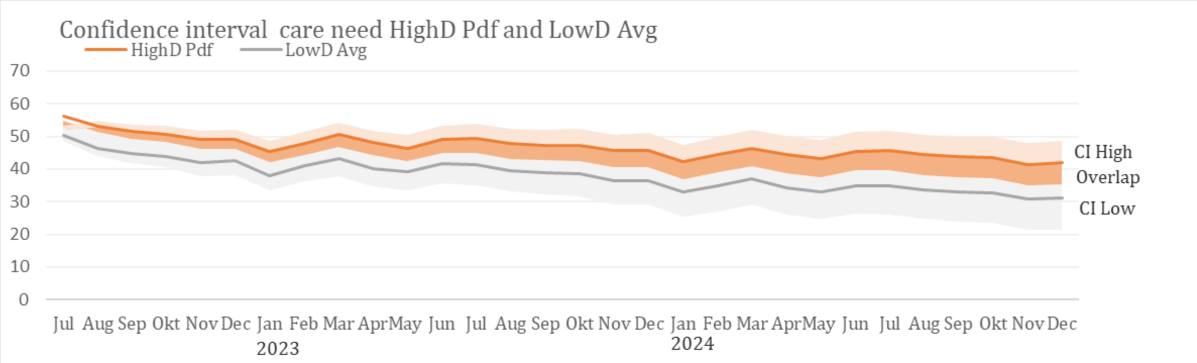


Figure 5-5 Confidence interval care needs HighD Pdf and LowD Avg

Weekly and monthly aggregation level

Besides options Pdf and Avg, we also considered a weekly and monthly aggregation level for the HighD and LowD scenarios to determine the care needed. The monthly observation splits into four separate observations (monthly care need/4) to analyse the difference. The expectation is that the monthly observations are approximately the same as the weekly observations, as Figure 5-6 shows. However, we observe a slightly higher number of FTEs for the weekly case, explained by the higher batches of clients that flow out at once in the monthly aggregation case, resulting in a lower weekly average. Appendix T-11 shows the same results for the Avg case. The difference between the split monthly FTE demand and weekly FTE demand emphasizes the importance of a certain level of detail, such as aggregation on a weekly level over monthly.

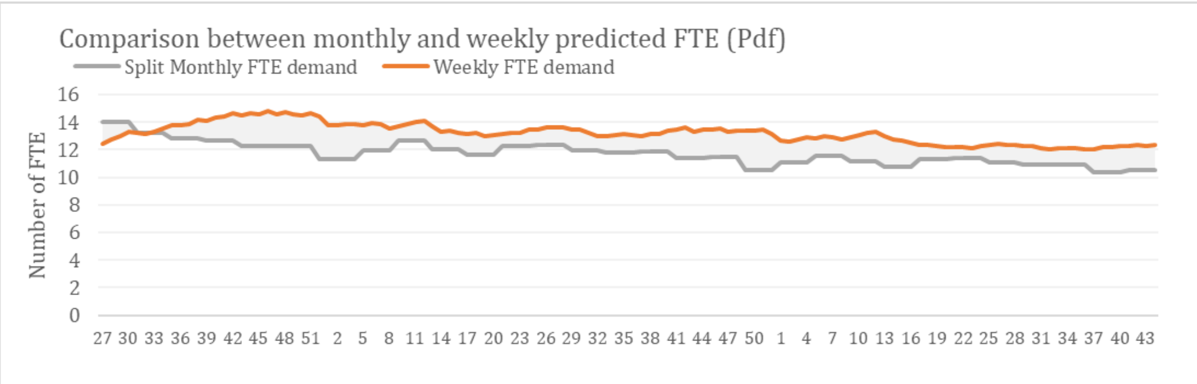


Figure 5-6 Comparison between monthly and weekly predicted FTEs

5.3.3 Home care providers Sensire

This section discusses the number of home care providers Sensire needs considering different absenteeism levels and contract combinations. We choose to from now on analyse using the weekly aggregation level since this is also the reflection level Sensire uses internally and, as Section 5.3.2 explains, better grasp reality.

Effect difference of absenteeism and number of FTE

Figure 5-7 shows a plot of the level of absenteeism for the HighD and LowD scenarios. As expected, the number of FTEs needed to cover the care is higher, with a higher absenteeism level. We can observe from this figure that the level of difference stays consistent throughout the entire period. Figures 5-7 and 5-8 show that the average difference between 7% absenteeism and 12% absenteeism is 0.62 FTE for the LowD scenario and 0.66 FTE for the HighD scenario. The absenteeism difference seems to make a small difference, considering the number of hours spread over teams in the entire region. However, an FTE difference of 0.62 is a number that steers on easily.

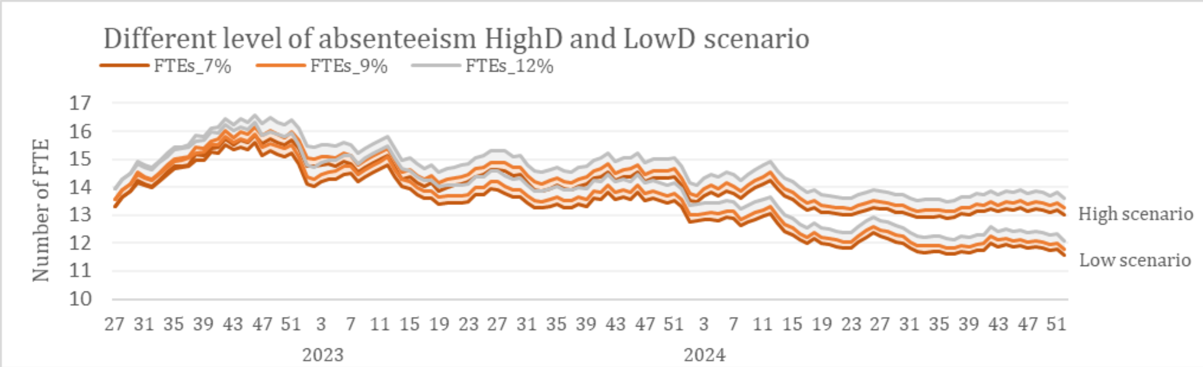


Figure 5-7 Different levels of absenteeism high and LowD

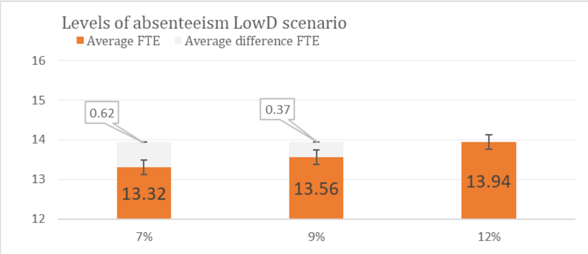


Figure 5-8 Levels of absenteeism LowD scenario

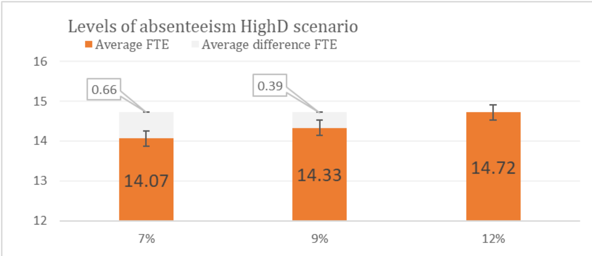


Figure 5-9 Levels of absenteeism HighD scenario

Effect of contract scenario and absenteeism level

This section discusses the effect of the contract scenario and absenteeism level, looking at the average number of home care providers necessary to answer the care need over the projected period. Considering the different contract scenarios and absenteeism levels, we see from Figure 5-10 that CTLow needs more home care providers to respond to needed FTE care than scenarios CTMiddle and CTLarge. The same yields for CTMiddle over CTLarge. This is a direct and logical consequence of the increase in 32-hour contracts and a decrease in smaller contracts. The difference between CT_Small and CT_Middle is, at most, 1. The difference between CT_Small and CT_Large is 3 or 4 and becomes less towards the end of the projected period.

The level of absenteeism shows the same behaviour as in the previously discussed section, and between the 7% and 9% cases, there is at most one home care provider difference, with the same yields for the 9% to 12% cases. In this figure, we also see that the largest differences in the number of home care providers come with changing the contract levels over the change in absenteeism, meaning that steering on the contract levels results in better estimations.

The results base on the forecast, which carries uncertainty which the error bars from Figure 5-10 indicate with a 95% confidence interval. Generally, the upper bound is 2 or 3 employees higher than the average, and the lower bound is 2 or 3 employees lower. At the beginning of the projected period, this is less, and towards the end, these become higher because of the increased uncertainty. For example, CT_Small, 7%, HighD needs with 95% certainty between 24 and 28 employees, with a gap close to zero at the beginning of the projected period. HighD and LowD for the CT_Small 7% needs, with a 95% certainty, between 22 and 28 employees. Though the gap is larger, this is a number Sensire can steer on since the type of contract combinations, and absenteeism level is retrievable from internal data.

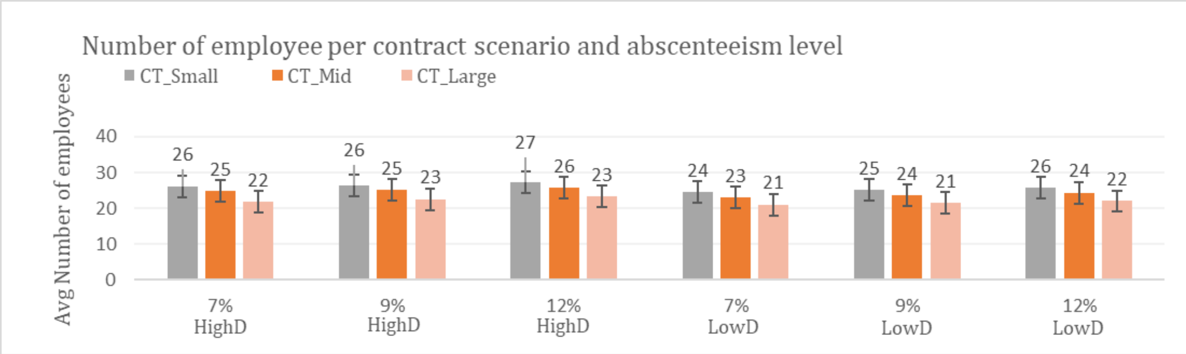


Figure 5-10 Number of employees per contract scenario and absenteeism level

Deviation number of FTEs compared to contract scenarios

Figure 5-11 shows the percentage of FTE dedicated to a specific contract type compared to the percentage of employees that eventually covers that contract type, for example, to have 50% of your contracts filled by 32-hour contracts. 64% of your FTEs assigns to 32-hour contracts. As stated before, necessary is a certain level of agility. Therefore, keeping an eye on the part assigned to smaller contracts is of interest since too few smaller contracts decrease agility. For example, taking the LowD, 7% absenteeism with CTLarge from Figure 5-10, the total need for employees is 21. Figure 5-10 shows that 15% of employees would have a 16 or 12-hour contract for four home care providers. Spread over the entire region, considering there are around 20 teams, would mean less than one home care provider with a small contract and therefore decreased agility which is something to consider and avoid.

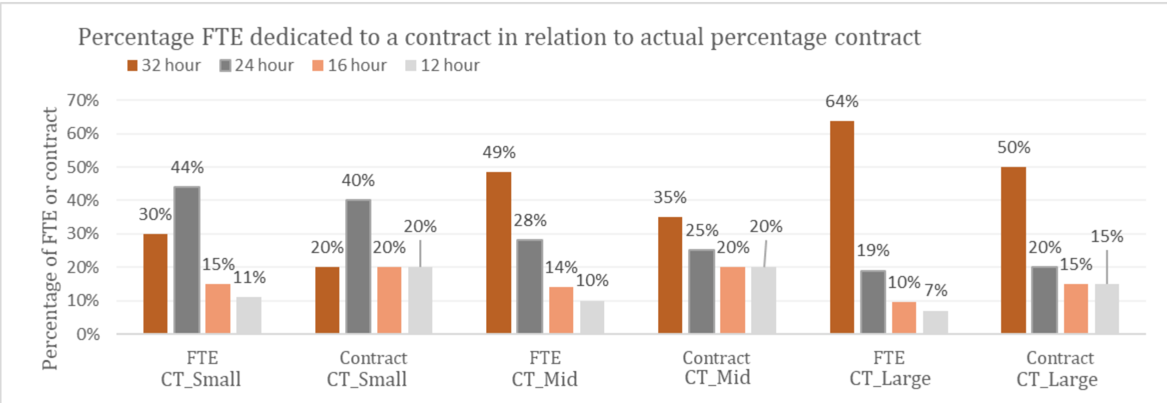


Figure 5-11 Percentage FTE dedicated to a contract with an actual percentage per contract

5.3.4 Validation results

This section validates the outcomes.

Data suitable for validation are the number of clients receiving care in a week, the number of hours delivered per week, and the number of FTEs per week by Sensire, all data available. However, the level of detail meaning recovery care from the Slingeland hospital is not extractable from this data, and only region-specific information is available. Using percentages yielded extremely high outcomes for the number of hours of care delivered and the number of clients, a consequence of including all sorts of care and flows. Since no direct access to data validates the outcomes, this research considers three options. Beginning with common sense and validated forecasts to evaluate the number of clients in the system. Then, average care per client per week and expert validation to validate the outcomes for the total care need.

Common sense

Section 4.3.3 explains the forecast's validation, which retrieves good results. Therefore, the forecasted input in our model can function as a validation for the mathematical model. Figure 5-12 shows the predicted weekly inflow and the number of recovery clients in care. For the HighD weekly case, the weekly inflow lies between 17 and 26 clients with a 95% confidence interval. Given that a client can stay a maximum period of 12 weeks and the probability of staying longer becomes smaller towards the tail, the number of clients between 100 and 140 seems realistic.

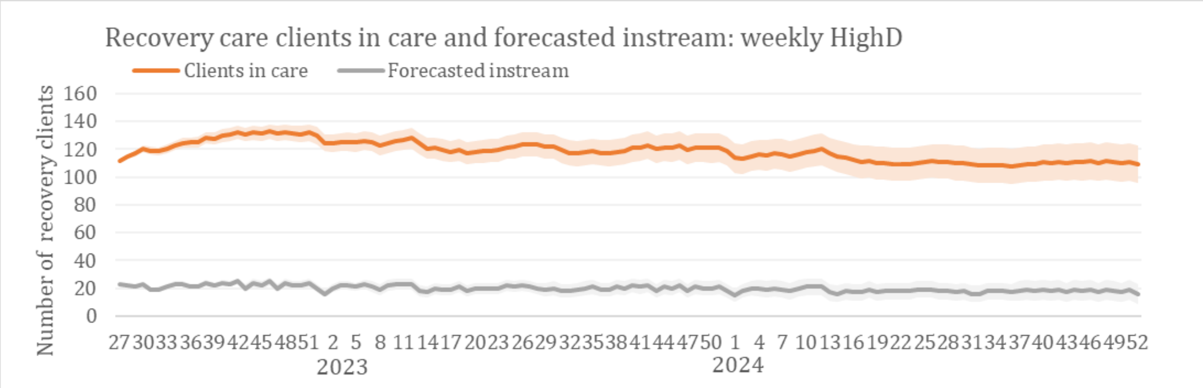


Figure 5-12 Recovery care clients in care and forecasted inflow: weekly HighD

Average hours of care per client per week

From the data of Sensire, it is possible to retrieve the regional average hours of care per week per client over weeks 28 to 44, which is 3.4 hours per client per week. From the model, it is also possible to retrieve the same for the Pdf and the Avg, which are 3.7 and 3.3 hours of care per client per week. These averages lie close to each other, especially the 0.1 difference for the Avg case compared to the data of Sensire. The Pdf and the data of Sensire differ by 0.3 hours per client per week which is 18 minutes. Considering a client often receives multiple moments of care per week, for example, 3, this means only a difference of 6 minutes per moment per client per week which is insignificant.

Expert validation

Because the average hours of care per client per week comes from the bulk data, which includes chronic and palliative care and all different sources, expert validation makes up the last part of this validation. The initial response is the difficulty of giving a specific answer because district nurses often schedule according to moments, so x minutes per moment. Since, as previously discussed, a difference of 0.3 hours results in a difference of only 6 minutes per moment, it is hard to give a specific answer. The general response is that 3.7 seems quite high but would be realistic or even more for the first couple weeks in care, and the Pdf seems more realistic. After the first couple weeks, the care of a client would become less, and the Avg seems more realistic. However, the model deals with new clients at every point with a higher care need, making the Pdf seem the most realistic option.

5.3.5 Sensitivity analyses

To test the robustness of the model, a sensitivity analysis analyses the impact of potential future changes on the model's independent variables.

There are potential future changes to consider when determining the factors to include in the sensitivity analyses for the recovery care patients flowing from the Slingeland hospital to Sensires home care environment. First, the ageing population with their corresponding increase in the need for care. However, via various implemented interventions that redesign the care processes, there is a decrease in recovery care patients/clients flowing from the Slingeland hospital to Sensire's home care environment. Also, more interventions to decrease the care need for the home care environment of Sensire are ready for implementation. As a consequence of all just mentioned, Table 5-6 shows the considered independent variables and the explanation.

Table 5-6 Independent variables considered in the sensitivity analyses

Independent variable	Explanation
LowD and HighD	Included in the LowD scenario and HighD scenario in previous sections
LoS (Length of Stay)	• Increasing the probability of staying shorter (first 50%) • Decreasing the probability of staying longer (last 50%)
CareN	• Decrease the mean of the probability functions of the care needs per week and client group • Recalculate the standard deviation with the new mean • Decrease the variance such that the care need decreases more on the tails

The sensitivity analysis uses a 5% step and then a 10% step for the LoS, the Care need and a combination of analyzing changes in the necessary hours of care per week and the number of clients in care per week. Figure 5-13 shows the results for the sensitivity analyses of the HighD weekly case changing the LoS probabilities. We see that already 5% change results in a difference. The other sensitivity analyses in Appendix U-1 to Appendix U-10 show the same behaviour. The difference between the original LoS and the 5% decreased LoS from Figure 5-13 is, on average, 8 hours of care. On average, the difference between the original and the 10% decreased LoS from Figure 5-13 is 20 hours. Though this suggests the original solution does not hold anymore in the grand scheme, these differences are insignificant, especially considering the strategic nature of this research. A difference of 20 hours is 1-2 FTEs difference for an entire region, does not change the eventual necessary number of employees per team significantly and still enables good steering, which means the model is robust for change in the context of this research.

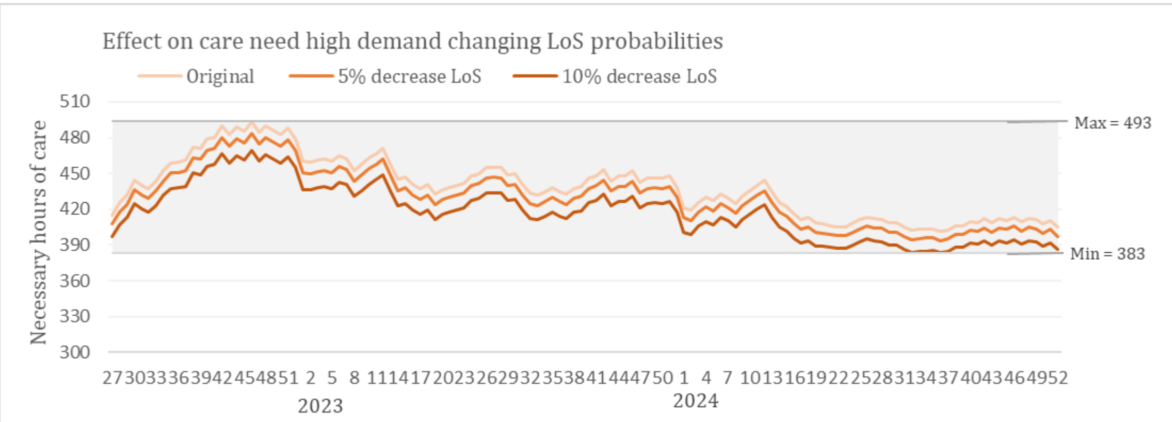


Figure 5-13 Effects on care need high demand changing LoS probabilities

5.4 Conclusion on the number of home care providers

This research focussed on calculating the number of home care providers Sensire needs to cover the care needs coming with the recovery care clients from the Slingeland hospital from July 2022 to December 2024. An adjusted convolution model calculates the number of clients in care and the corresponding care needs at a designated time for various settings.

We considered three different contract scenarios:

- CTSmall: 20% 32-hours, 40% 24-hours, 20% 16-hours and 20% 12-hours
- CTMiddle: 35% 32-hours, 25% 24-hours, 20% 16-hours and 20% 12-hours
- CTLarge: 50% 32-hours, 20% 24-hours, 15% 16-hours and 15% 12-hours

As well as three levels of absenteeism: 7%, 9% and 12%.

The number of home care providers needed to cover the recovery patients from the Slingeland hospital to Sensire, considering HighD, are on average between 24-29 home care providers for CTSmall, 23-28 for CTMiddle, and between 20-25 for CTLarge. For the LowD, the number of home care providers needed is between scenario 22-28 CTSmall, between 21-26 home care providers for scenario CTMiddle and between 19-24 for CTLarge. The number of home care providers is calculated based on the number of FTEs using a 95% confidence interval to include uncertainty of the forecasted input data. The level of absenteeism causes the differences for every scenario. Finally, the number of home care providers needed is higher at the beginning of the covered period and decreases along the timeline of the covered period since the number of clients decreases.

These results are based on the weekly forecasted demand and probability functions to determine the care need. However, when experimenting with settings in the model, it became clear that a certain level of detail is necessary to grasp real-life complexity and make results more realistic, which experts emphasized as well. Therefore, the first option, Pdf, to determine the probability functions of the care need using complete probability functions, seems to grasp better details of the model over option Avg, which uses averages. The same goes for the aggregation level, where the weekly case grasps greater detail than the monthly aggregation level, which is also the evaluation and operation level that Sensire employs.

Based on these results, we conclude that the eventual number of home care providers is very case-dependent and should be re-evaluated based on absenteeism levels, the current contract scenario and proceeding on the timeline. However, it gives a good strategic guide on which Sensire can steer employing between 19 and 29 employees with 95% certainty for the entire region to cover the recovery care clients from the Slingeland hospital. Knowing contract configuration and absenteeism levels decreases the 19-29 employee gap. At the time of writing this research, following the LowD, CT_Small and absenteeism of 12% resemble reality. Which advises employing between 24 and 28 home care providers with 95% certainty, of which 20% have a 32-hour contract, 40% a 24-hour contract, 20% a 16-hour contract and 20% a 12-hour contract. Finally, the model is sensitive to input changes which concern the CareN and the LoS. However, the outcomes of these changes are insignificant in the grand scheme of things, and therefore the model is robust considering the strategic nature of this research.

6 Conclusion, discussion and recommendation

This chapter concludes the research. Section 6.1 concludes the research. Next, Section 6.2 gives recommendations for Sensire and Slingeland hospital. Then, 6.3 further discusses the outcomes. Finally, Section 6.4 describes further research based on the outcomes.

6.1 Conclusion

Considering an increase of elderly in the region, a decrease in the workforce and the new structure of teams into care-oriented teams, the aim of this research was as follows:

"Develop a predictive model to provide insight into the number of home care providers Sensire needs at an instant in time in the next 2.5 years to be able to provide care for the recovery patients coming from the Slingeland hospital."

To answer the research statement, the problem divides into three sub-problems as from Figure 1-1. Starting with a time series analysis, forecasts the number of recovery care patients flowing from the Slingeland hospital into the home care environment of Sensire. The forecast functions as an input for a mathematical model that models the care need corresponding to this inflow over the projected timeline. Finally, the care need is translated into necessary home care providers using various experimental settings.

6.1.1 Forecast conclusion

The forecast considered the Classical Decomposition additive and multiplicative case and the Holt-Winters additive and mixed case using historical patient data from the Slingeland hospital of the Outpatient Clinic and Clinic from January 2018 to June 2022. The forecast considers various aggregation levels using January 2018 to December 2021 as the training set and testing the error on the test set from January 2022 to June 2022. A MAPE < 5% is accurate, a MAPE between 5% and 25% is low but acceptable, and a MAPE > 25% is low and not acceptable.

The Holt-Winters multiplicative case with the Outpatient Clinic and Clinic data combined and monthly aggregation performed the best, reaching a MAPE of 16.85% for the training set and 11.54% for the test set using the following parameters: α = 0.13, β = 0.07, γ = 1.00. The parameters indicate more emphasis on the level and the trend of older values in the time series and flattening the seasonality of the time series.

Because the forecast functions as an input for the mathematical model, we also considered a weekly aggregation case. The best-performing method for the weekly aggregated data is the Classical Decomposition Multiplicative method combined with the Clinic and Outpatient Clinic data, attaining a MAPE of 13.68% for the training set and 21.23% for the test set.

The forecast covers these methods for HighD and LowD scenarios that find their origin in the projected refusals from July 2022 to December 2024. The minimum for the monthly HighD is 60, and LowD is 44. The minimum for the weekly HighD is 9, and LowD is 5. The general trend of the historical data is decreasing due to applied interventions and less invasive surgeries. Additionally, the historical data shows variable monthly/weekly behaviour and yearly seasonality. Consequently, the forecast shows these as well. Since forecasts carry uncertainty, we included a 95% confidence interval that widens along the timeline.

An additional validation step over July 2022 to November 2022 yields good results for the LowD, with a MAPE for the HighD of 27% and LowD of 25% for the weekly case and a MAPE of 17% for the HighD of 17% and LowD of 15%. Except for the weekly HighD scenario, all perform below the 25% benchmark. At this point, including the refusals seems to result in worse results which could indicate refusals do not result in significant differences. Excluding the refusals results in a MAPE of 19% for the weekly and 10% for the monthly cases.

6.1.2 Mathematical model conclusion

The forecasts function as an input for the mathematical model, which calculates the number of clients at a designated time and the corresponding care need. These then translate into FTEs and the number of home care providers using various settings, such as contract types and levels of absenteeism. We considered a 7%, 9% and 12% level of absenteeism, a HighD and LowD scenario and three contract configurations as follows:

- CTSmall: 20% 32-hours, 40% 24-hours, 20% 16-hours and 20% 12-hours
- CTMiddle: 35% 32-hours, 25% 24-hours, 20% 16-hours and 20% 12-hours
- CTLarge: 50% 32-hours, 20% 24-hours, 15% 16-hours and 15% 12-hours

The number of home care providers needed to cover the recovery patients from the Slingeland hospital to Sensire, considering HighD, are on average between 24-29 home care providers for CTSmall, 23-28 for CTMiddle, and between 20-25 for CTLarge. For the LowD, the number of home care providers needed is between scenario 22-28 CTSmall, between 21-26 home care providers for scenario CTMiddle and between 19-24 for CTLarge. The number of home care providers is calculated based on the number of FTEs using a 95% confidence interval to include uncertainty of the forecasted input data. The level of absenteeism causes the differences for every scenario. Finally, the number of home care providers needed is higher at the beginning of the covered period and decreases along the timeline of the covered period since the forecasted number of clients decreases.

Based on these results, we conclude that the number of home care providers is very case-dependent and, therefore, should be re-evaluated based on absenteeism levels, the current contract scenario and proceeding on the timeline. However, it gives a good strategic guide on which Sensire can steer employing between 19 and 29 employees with 95% certainty for the entire region to cover the recovery care clients from the Slingeland hospital. Knowing contract configuration and absenteeism levels decreases the 19-29 employee gap. At the time of writing this research, following the LowD, CT_Small and absenteeism of 12% resemble reality. Which advises employing between 24 and 28 home care providers with 95% certainty, of which 20% have a 32-hour contract, 40% a 24-hour contract, 20% a 16-hour contract and 20% a 12-hour contract.

The model is sensitive to input changes which concern the CareN and the LoS. However, the outcomes of these changes are insignificant in the grand scheme of things, and therefore the model is robust considering the strategic nature of this research.

6.1.3 Practical contribution

This research is the first within the Sensires' home care environment executed from an Industrial Engineering and Management perspective. The direct practical contribution of the outcomes of this research is the insights into drafting new recovery care focussed teams and the effects on these of combining different contract types. In 2023, Sensire will implement care-oriented teams (recovery or chronic care) over regional teams. Gaining better insights into the number of home care providers necessary to cover the recovery care from the Slingeland hospital (which is a large party) helps in better estimating what these recovery care teams could look like, such as size and regional coverage. Besides the main contribution, the research also provides various other valuables, such as the intensified collaboration between Slingeland and Sensire. Then various insights such as the effectiveness of implemented interventions, more insight into what to register and how to register and the importance of taking whole system perspectives and the challenges ahead.

6.1.4 Theoretical contribution

This research contributes to the literature by providing a strategic solution focussing on recovery patients in a home care organization employing a cross-organizational approach collaborating with a hospital, which to the best of our knowledge, the literature does not discuss. Then, this research combines two different techniques. A regional-based forecast functions as an input for a mathematical model. This research extends the mathematical convolution model of van Berkel et al. (2010) in three ways. First, the original model uses a cyclic demand cycle. However, this research deals with a non-cyclic demand cycle, and adjustments are made accordingly. Second, this research extends the model to calculate the corresponding care need instead of only dealing with a number of clients or patients. Finally, instead of using a schedule as input, this research extends the model using a forecast.

6.2 Recommendations Sensire and Slingeland

This research explores how to build new recovery care and chronic care-focused teams. Moreover, it indicates specifically the recovery care patient stream from the Slingeland hospital to the home care environment of Sensire for the region: Montferland, Doetinchem, Oude Ijsselstreek and Bronckhorst. However, many assumptions are necessary, and data availability and reliability are common issues in this research. From the sensitivity analyses, it became clear that the model is sensitive to changes in the Length of Stay and the care needed. However, not significant considering the strategic scope of this research. Additionally, the eventually needed number of home care providers on the projected timeline is very case-dependent and, therefore, should be re-evaluated based on absenteeism levels, the current contract scenario and proceeding on the timeline. Based on the results, we have recommendations for Sensire and the Slingeland hospital, which we divide into three levels forming a roadmap increasing the scope as follows, insights of this research, including the entire recovery care client stream, aiming for a whole system perspective in collaboration with Slingeland and other organisations.

Use insights from this research

The current situation that seems most realistic at this point is the LowD, CT_Small and a 12% absenteeism. Which advises employing between 24 and 28 home care providers on average over the projected timeline with 95% certainty, of which 20% have a 32-hour contract, 40% a 24-hour contract, 20% a 16-hour contract and 20% a 12-hour contract. We advise Sensire to use this as a broad indication for drafting the care-oriented teams keeping in mind these results only cover the recovery care clients from the Slingeland.

Besides the results, this research found other insights along the way, such as:

- The decreasing trend of the recovery care clients/patients
- The successful implementation of various interventions, as found in the data
- Importance of specific elements in data registrations (what and how to register) to produce reliable research outcomes from an operational research perspective
- Increased understanding of the operational research perspective enables an increased understanding of the potential contribution of operational research
- Ability to narrow the scope for future research, creating more accuracy and impact, for example, considering a more tactical level.

Recovery care client stream

We advise further research on the number of clients and the corresponding care needed for the full recovery client stream so that results are more implementable. Potentially on a more tactical level to increase the reliability of the outcome and include a district level since they behave differently.

Whole system perspective

We recommend Sensire and Slingeland continue pursuing their collaboration and include more healthcare organisations focussing on a whole-system perspective to tackle the increasing elderly and decreasing workforce in the region since care organisations form a chain. For example, what are the consequences of knee surgery in week 1 in the Slingeland hospital in week 4 for Sensires' home care environment.

6.3 Discussion

In this section, we want to draw the readers' attention to the drawbacks of our research and, thus, potential room for improvement.

6.3.1 General Discussion

This research was the first step within Sensire in applying operation research and a first step toward further collaboration between Sensire and Slingeland. Consequently, this research deals with first-time issues, such as lack of information and registration, data availability and sharing. Therefore, we had to scope the research: the recovery care patients flowing from the Slingeland hospital to the home care environment of Sensire.

Then, this research makes two significant classifications: the classification in recovery care, palliative care and chronic care clients. Second, the deviation of the recovery care clients into groups No_NT, One_NT and Mult_NT. These classifications are necessary to come to results and simplify real-life complexity. However, as the words "simplify real-life complexity" imply, this is not the same reality. In reality, patients/clients belong to multiple or separate non-common groups.

Additionally, there is a returning theme of limited data, which has its cause in how and what to register. The research uses the limited datasets available and combines these to the best ability keeping as much information as correct as possible. Section H provides the assumptions necessary regarding this.

We would have liked to take a whole system perspective, which could have been possible by coupling the data that national privacy regulations made impossible. Ideally, researching the entire patient-to-client flow starting in the hospital and ending in the home care environment of Sensire is of interest, taking an actual whole system perspective. Finally, this research does not consider many social-economic factors due to a lack of data, such as social network, living with a person, previous conditions/vulnerability and gender. These points were visibly important in the transfer office and the districts. Transfer and district nurses would base their judgement on these points, which provided a good care estimate. Also, Brailsford & Schmidt (2003) states the importance of including social and economic factors in models to increase the accuracy and reliability of outcomes.

6.3.2 Forecast specific discussion

There is always uncertainty when performing forecasts. Even when perfectly executing a forecast, there is inevitable inaccuracy because of the unpredictability of future events. A rule of thumb is the further the forecasts, the higher the uncertainty. When performing forecasts, inaccuracy can appear all along the way via data choices, decomposition errors, wrongly choosing the forecast method, wrong removal of outliers, aggregation inaccuracy and biases, wrong validation methods etc. Therefore, it is very important to keep this in consideration. Especially when considering a strategic problem and the forecasting timespan is relatively long (Jul-2022 to Dec-2024) and data is limited, which we will elaborate on in consecutive paragraphs.

Inaccuracy also arises projecting the number of refusals to the future because the scenarios are only argued based on expert knowledge. Additionally, the trend for both scenarios is projected to be linear. However, the behaviour of the Refusals is not. Additionally, the assumption on the MAPE is a point of uncertainty. The literature does not establish specific benchmarks on what values of the MAPE are accurate, low accurate but acceptable and low accurate but unacceptable. These numbers are a matter of perspective; one person may or may not find 20% acceptable or unacceptable.

We already tipped briefly on the lacking information within the data. However, there are also the consequences of small datasets. We notice that accuracy measures are relative to size, with a decreasing accuracy for the test set when the testing points went down. Also, the importance of enough data points in the training and test sets. According to Hyndman & Athanasopoulos (2018), the test set should be at least 20% of the training set we maintained. However, the test set should be at least as large as the maximum forecast horizon required. The latter is something we could not maintain. A larger dataset will likely enable the forecasting method to grasp trends better, level and seasonality resulting in more reliable forecasts and accuracies.

Finally, the choice of method can be a point of discussion. The number of forecasting methods available is numerous. Based on the identified forecasting elements, this research uses the Holt-Winters and Classical Decomposition methods, but other methods might be more appropriate. For example, the Linear Holt method resulted in better accuracy measures. However, the method does not use a seasonality component resulting in poor forecasts. Additionally, the strategic nature of this research complicates making exact forecasts, and a bias due to uncertainty is inevitable.

6.3.3 Mathematical model-specific discussion

We start this section by discussing the choice for the mathematical convolution model. Initially, we wanted to use a simulation study because changes in the system happen when an event occurs, the interaction between entities is considered irrelevant, the aim is to evaluate possible scenarios, there is a strong need for a dynamic environment, a high level of variability and the need to track individuals. However, in the set-up phase of the simulation, it became clear that the level of detail and hourly/daily tracking of individuals often found in simulation studies are not necessary for the strategic aim of this research. Therefore, the adjusted convolution model enabled us to do all previously mentioned on a higher level except for tracking specific individuals through the system. However, it enables us to model the care need of specific individuals (clients).

Then, we want to discuss some of the simplifications of real-life complexity in the model. We tried to include some considerations in simplifying real-life in our experiments, such as the aggregation level (weekly and monthly) and determining the care need (options Pdf and Avg). However, many simplifications remain. For example, taking the level of absenteeism as a constant, data shows that absenteeism fluctuates throughout the year, the deviation of the clients into three groups and the choice only to consider the possibilities of three contract types. The previously mentioned also ties into the simplification of the contract scenarios. This research analyses three contract scenarios. However, many deviations from these are possible. However, we do not think these factors significantly decrease the quality of this research considering the strategic nature and the established prediction intervals that indicate the uncertainty.

6.4 Further research

This section discusses further options for research.

With an eye on the projected implementation of care-oriented teams (recovery care or chronic care) over regional teams, this research provides an exploration and indication of the number of recovery clients and the care need flowing from the Slingeland hospital to the home care environment of Sensire specifically. However, further research on the number of clients and the corresponding care needed for the full recovery or chronic client stream would be of interest, including a district level, since districts behave differently. Additionally, focus on recovery care over chronic care since this is a more predictable form of care.

Then, research a different way of classification. The classification in groups No_NT, One_NT, and Mult_NT was necessary to obtain reliable results with the available data. However, it simplifies real-life complexity a lot. For example, based on working in the transfer office takes into account social-economic factors such as social network, living with a person, previous conditions and gender are relevant. This is also supported by literature such as Brailsford & Schmidt (2003), who incorporate more human behaviour via social-economic factors. However, information needs to be available and extractable.

Also, a point of further research is taking a whole system perspective since certain hospital procedures directly influence the demand for care in the home care environment. But also, certain procedures by general practitioners influence hospitals or home care environments. An example of interest is knowing the effects of knee surgery in the Slingeland hospital on the care need in the home care environment in Sensire. The convolution model is suitable to extend in this manner. However, it is necessary to track a patient/client through the system; therefore, national regulations regarding privacy need adjustment, or unambiguous registration of where a client comes from and what the previous treatment was within the home care environment of Sensire is a necessity.

This research provides a strategic-level solution. The further on the projected timeline, the more uncertainty a time series analysis carries. Therefore, together with the inevitable variable behaviour of healthcare, it could be advisable to shorten the projected timespans and explore a more tactical level for which the convolution model is also suitable. When shortening the projected period exploring different time series models can be of interest since our current method slightly under fits, which can have its cause in the method.

Then, including more validation, especially for the convolution model, with better registration of just mentioned specifics, such as where a client comes from or previous treatments, this ties into a very important returning theme: researching the manner of registration. What information to register and how to register the information in an unambiguous way that enables reliable data. Increasingly important since the convolution model shows sensitivity to changes in the input data.

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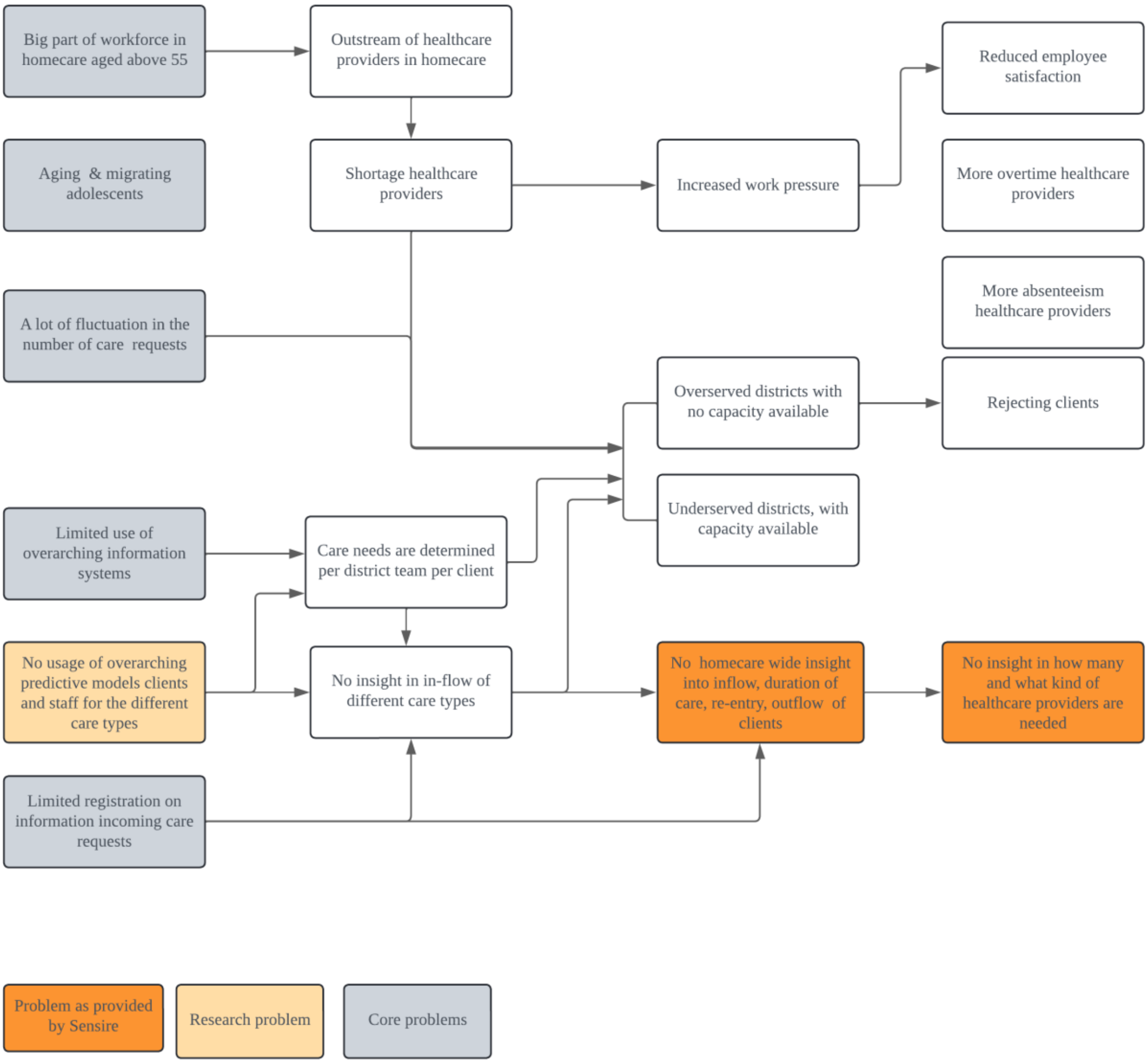
Appendix

A. *Problem analyses*

A problem often has many causes and consequences underlying the problem. Therefore, the cause-and-effect manner of Heerkens et al. (2021) is employed to identify core problems. This appendix discusses all the core problems except the research problem, Section 1.3.1 presents.



Appendix A-1 Problem cluster

Ageing and migration of adolescents
The ageing population and adolescent migrating behaviour are societal problems on a much larger scale than Sensire's home care and out of the influence of Sensire alone. Therefore, dealing with these facts is necessary to structure the organization accordingly. Therefore, the age and migration of adolescents are out of this research's scope.

A lot of fluctuation in care requests
The inflow of care requests fluctuates highly, which can only be influenced to a certain degree but needs high-level overarching solutions where care organizations work together. The problem is not the focus of this study because it needs a significant structural change to integrate the various information. However, as discussed in Section 1.3.1, the research problem aims for more overarching solutions through collaboration in which possibly the desire is to aim for decreasing fluctuations.

Limited use of overarching information systems
In the home care environment of Sensire, overarching systems are limited. Care requests arrive at the district nurse, coming from a variety of stakeholders through the use of various means. For example, hospital A uses other information systems to convey information and communicate with the district nurses than hospital B. Consequently, in some regions, the district nurse must deploy multiple information systems in addition to email and phone. Moreover, this happens on a district level, making it impossible to get an overview on a higher region-wide level.

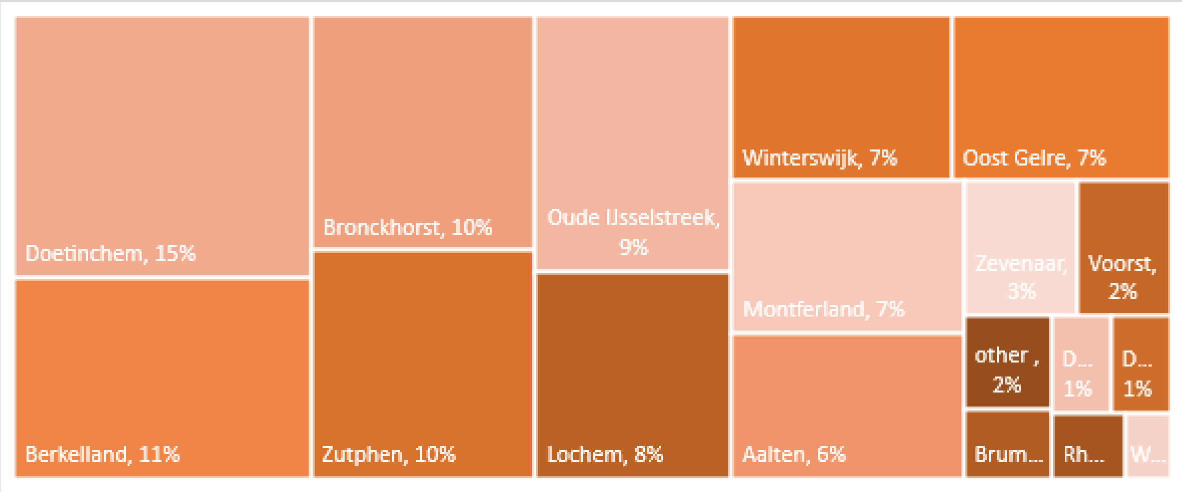
Sensire uses information systems to convey/receive information, not for active collaboration and integrating information from organizations such as hospitals and home care. This problem is not the focus of this study because it needs a significant structural change to integrate the various information streams and systems. As previously mentioned, the research problem discussed in Section 1.3.1, aims for more overarching solutions through collaboration.

Limited registering information care request
No information is registered when a care request arrives at the district nurse. Therefore, no information is available on the type of care request, inflow source, urgency level, acceptance/rejection, and motivation for accepting/rejecting. The problem is considered out of scope because the district nurses already experience that they have to register a lot of information in their limited time, the level of urgency of this problem and the degree of depth desired for this research. However, this problem will form the core of the recommendations for Sensire.

B. Client characteristics

Inflow per municipality

We observe that the inflow of clients from the municipalities is spread relatively equally with no outliers other than 'Doetinchem'. This is a logical consequence because Doetinchem locates in one of the most prominent cities of 'de Achterhoek.' Looking at the area covered by Slingeland (Doetinchem, Bronckhorst, Oude IJsselstreek, and Montferland), we observe that 41% of the inflow of clients comes from this area, making up a large part of the total inflow of Sensire (Appendix B-1).



Appendix B-1 Percentage inflow per municipality

Age

From Figure 0-1, we observe that the inflow of clients is centralized around the age of 88 with a steeper slope towards the higher ages and a more gradient slope towards the younger generations. Every age between 0 and 120 is covered, making the age difference between the youngest and older clients large. Additionally, there are more female than male clients at younger and older ages.

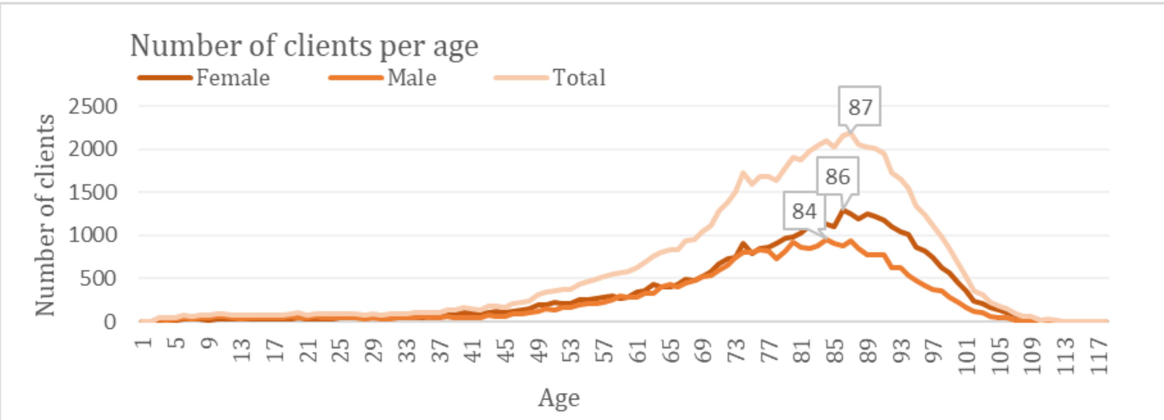
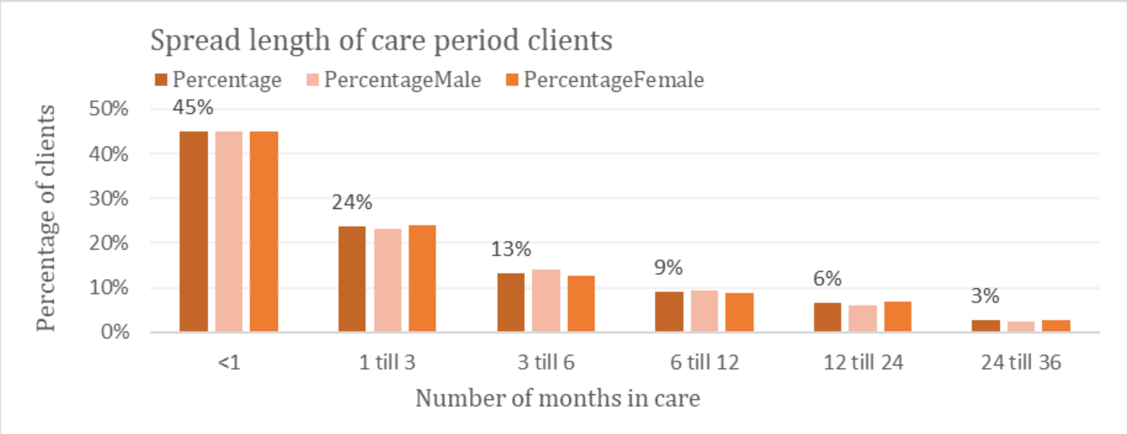
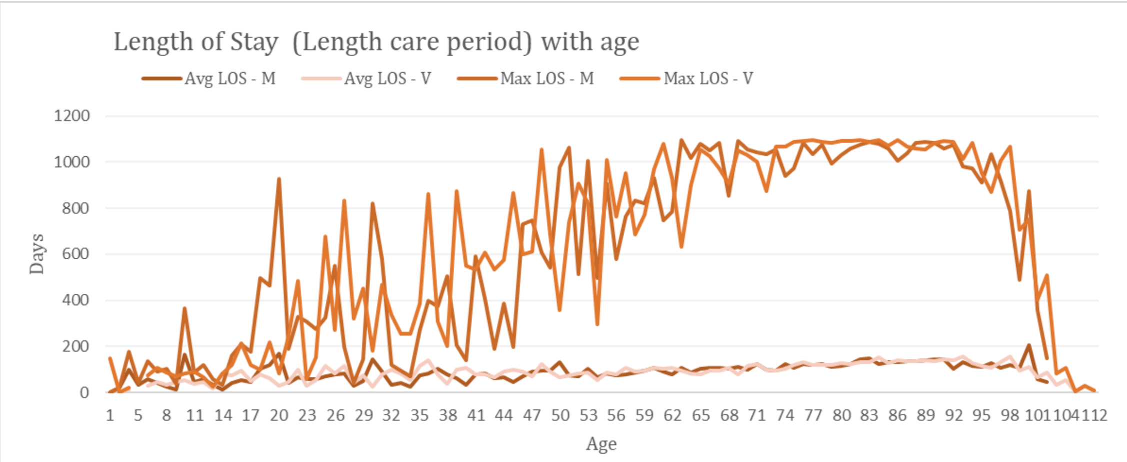


Figure 0-1 Age home care clients Sensire (Source: retrieved from internal client data Sensire, n = 70493)

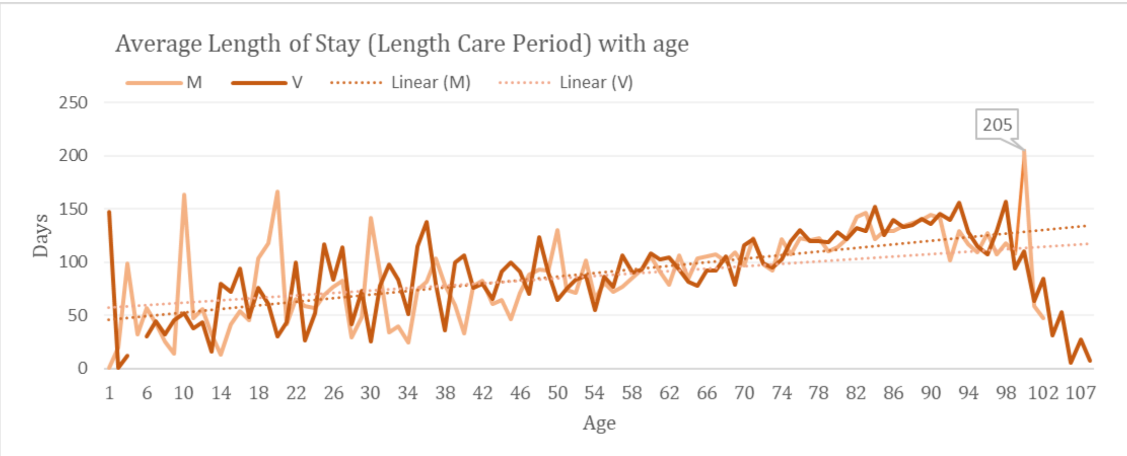
Length care period
Looking at the pillar Length of care period, 45% of clients are treated for less than a month. 37% for a period between one and six months, and the last 18% receive care for more than six months with a maximum of 3 years with a decreasing trend. Looking per gender (only female, only male) gives the same percentages (Appendix B-2). Looking at the Length of a care period corresponding to age, there is an increasing trend starting at an average of 60 days and increasing to an average care period of 100 days over age. After the age of 98, there is a drop in the average length of care periods. The average length of a care period increases slightly more for a male than a female with age (Appendix B-3, Appendix B-4).



Appendix B-2 Spread length care period (differentiated for gender)



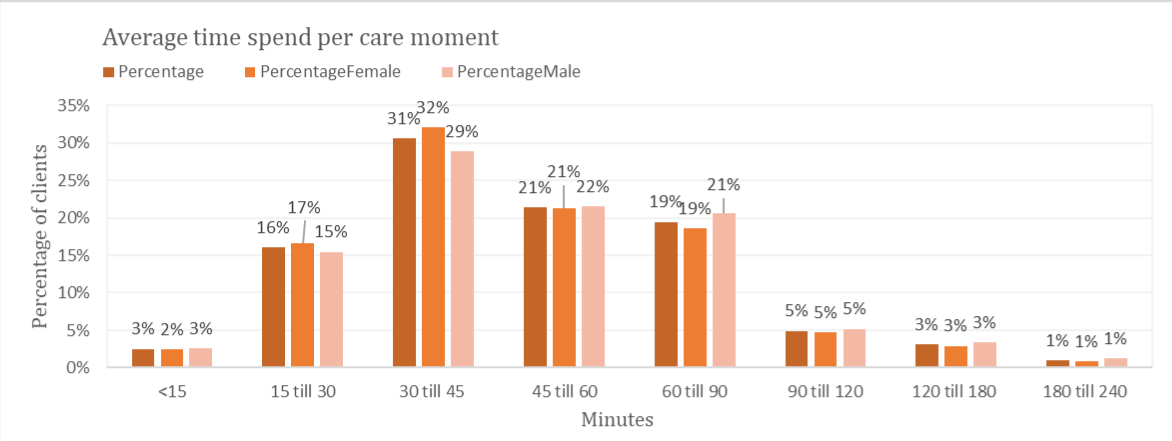
Appendix B-3 Length of a care period, age and gender



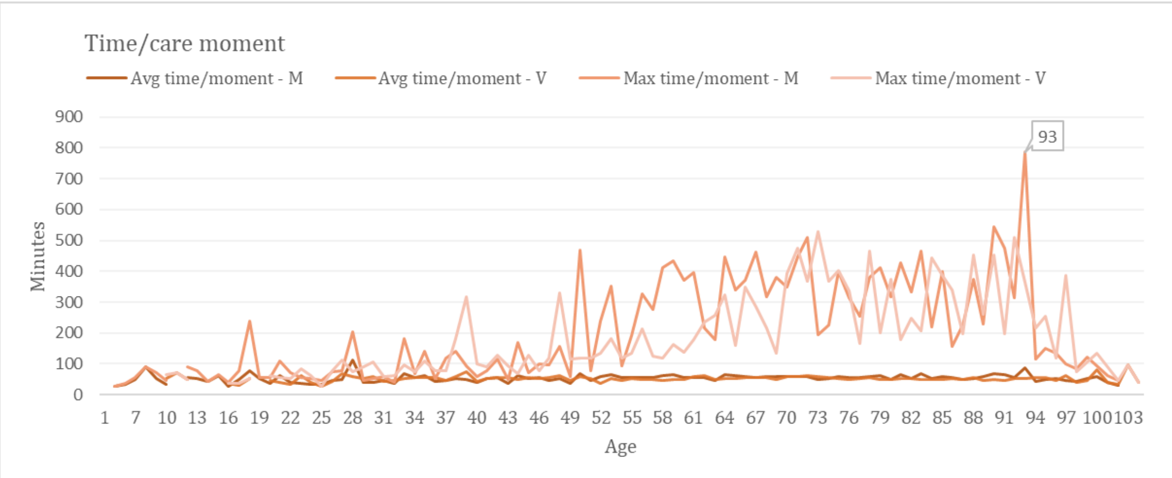
Appendix B-4 Average length of a care period, age and gender

Average time per care moment

31% of the clients receive an average of between 30 and 45 minutes of care per care moment. The percentage of clients receiving 15 to 30 mins care is 16% and decreases to 3%, where clients, on average, receive less than 15 minutes of care. 40% of the clients receive, on average, between 45 and 90 minutes of care per moment. This further decreases to 1%, where clients receive three to four hours of care per care moment. An occasional client is receiving, on average, more than 4 hours of care due to intensified 24-hour care. Looking per gender (only female, only male) gives almost the same percentages (Appendix B-5). Again we can observe an increasing trend of average time spent per care moment with age, but this time only slightly, deviating around 50 minutes, dropping after the age of 98 (Appendix B-6).



Appendix B-5 Average time per care moment per gender

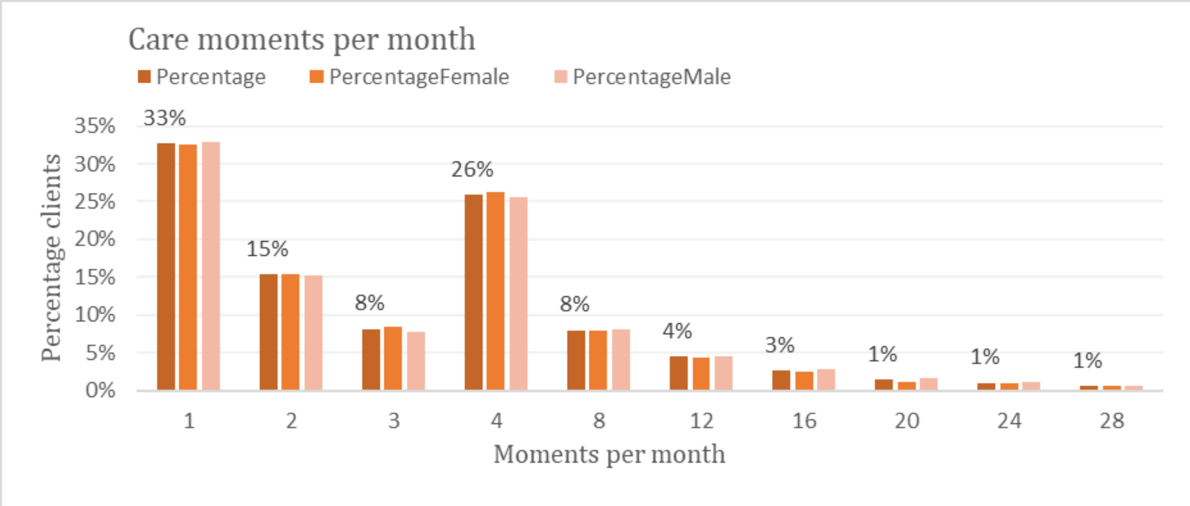


Appendix B-6 Average time per care moment, age and gender

Care moments per week

26% of the clients receive one moment of care per week, and 22% receive less than this. 16% of the clients receive two times of care per week, further decreasing to 1% of clients receiving eight moments of care per week. Looking per gender (only female, only male) gives the same percentages (Appendix B-7).

The trends identified for the three care need pillars are reflected by the area Slingeland covers (Bronckhorst, Doetinchem, Montferland, Oude IJsselstreek). However, there is a bit more fluctuation.

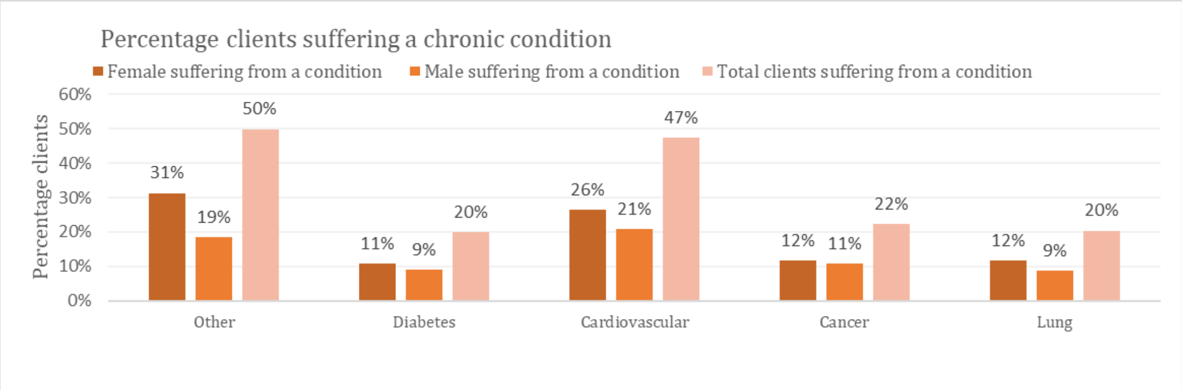


Appendix B-7 Spread care moments gender

C. NZA analyses

Chronic condition

86% of the clients suffer from a form of chronic condition. 54% suffer from one chronic condition, 46% suffer from multi-morbidity, 34% have two, and 12% suffer from more than two conditions (Appendix C-4). Appendix C-1 shows the conditions and the percentage of people suffering from this condition. Also, the total subdivides in what percentage are male and female. There are overall more females. However, looking per gender (only female or male) gives the same percentages per condition as the total. Furthermore, the percentages per condition change with the number of chronic conditions. For example, when having two chronic conditions, the percentage of clients suffering from cardiovascular disease is higher than when having one chronic condition (Appendix C-5). Also, with age, the number of chronic conditions increases (Appendix C-6), and the average age of people receiving home care suffering from chronic conditions is 77.

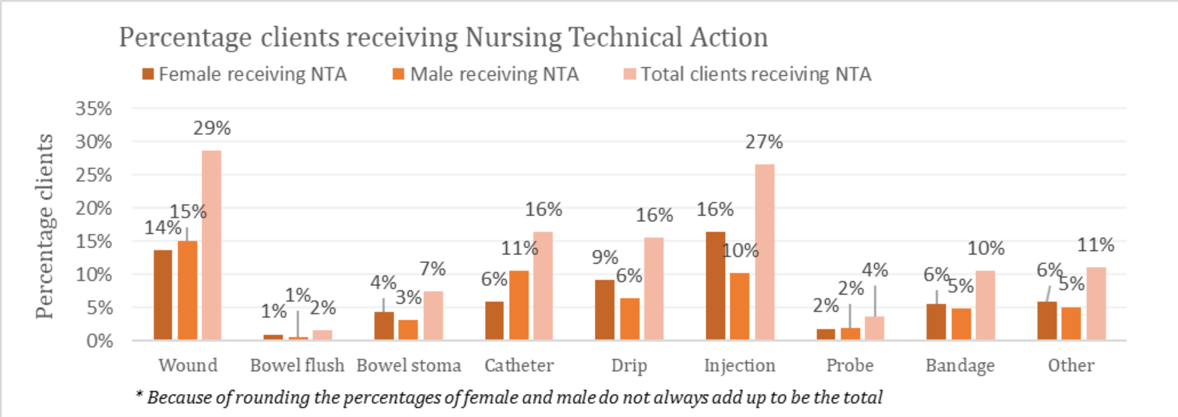


Appendix C-1 Percentage chronic conditions clients Sensire (Source: retrieved from NZA questionnaire data Sensire November 2021-March 2022, n = 4857)

With chronic conditions, the number of conditions, gender and age come different care needs. Though the averages are relatively close for the different care needs, the maximums deviate considerably per chronic condition (Appendix C-10, Appendix C-12, Appendix C-14). Care needs increase when clients suffer from 1 to 3 conditions, after which they decrease when clients suffer from 4 or 5 conditions. Additionally, the care needs differentiate per condition and gender (Appendix C-11, Appendix C-13, Appendix C-15). For example, the length of a care period is longer for females with a lung condition than for males. The average time per care moment is almost the same for females as for males, but females receive more moments of care per week for all conditions except diabetes.

Nursing technical action

28% of the clients receive a nursing technical care operation. 82% receive one technical care operation, 15% receive two care operations, and 3% receive more than 2 with a maximum of five care operations (Appendix C-16). Appendix C-2 shows the nursing technical actions and their percentage of occurrence. Also, the total subdivides in what percentage are male and female. There are overall more females. However, looking per gender (only female, only male) gives the same percentages per condition as the total (Appendix C-16). Also, based on age, the probability of a certain action changes. For example, the probability of receiving a drip is higher at a younger age than receiving a catheter (Appendix C-22, Appendix C-23). The average age of clients receiving nursing technical actions is 73.



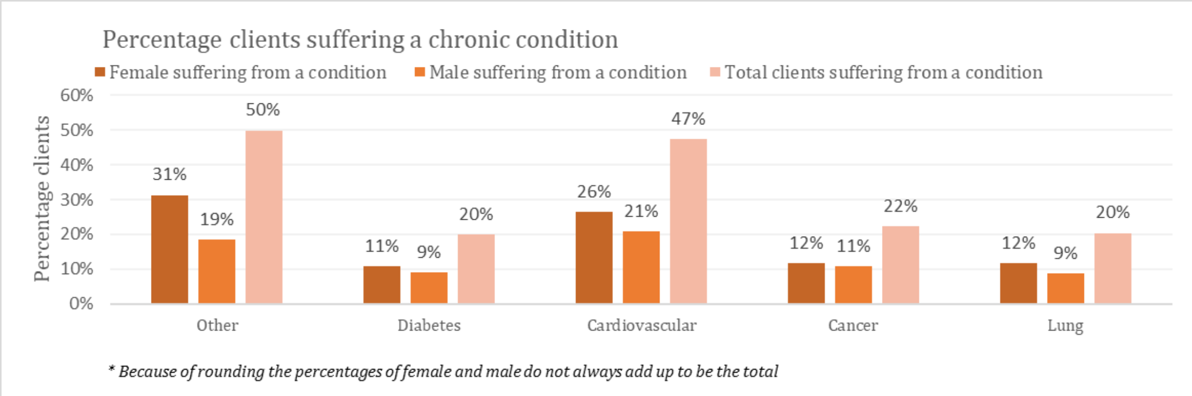
Appendix C-2 Percentage nursing technical actions per client Sensire (Source: retrieved from NZA questionnaire data Sensire November 2021-March 2022, n = 4857)

The nursing technical actions, number of actions, gender, and age result in different care needs. The averages are relatively close for the different care needs except for time per care moment which differentiates. The averages and maximums deviate considerably per nursing technical action. (Appendix C-24, Appendix C-26, Appendix C-28). Care needs increase with the number of nursing technical actions, especially the average time per care moment (Appendix C-20, Appendix C-21).

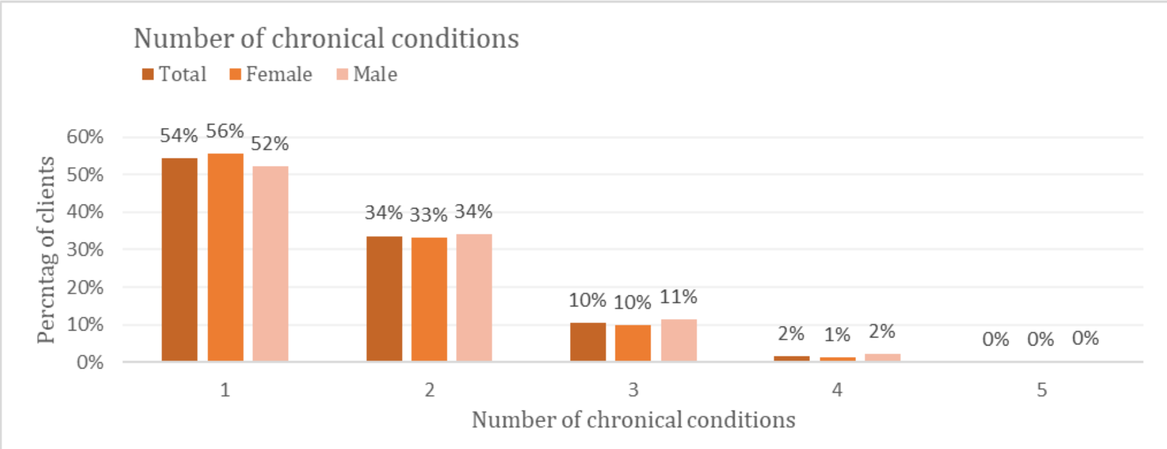
Additionally, care needs differentiate per condition and gender (Appendix C-25, Appendix C-27, Appendix C-29). For example, the length of a care period is longer for females receiving help with a bowl stoma and for males receiving an injection. In addition, the average time/care moment differentiates, females often receive more moments per week.

General daily living tasks

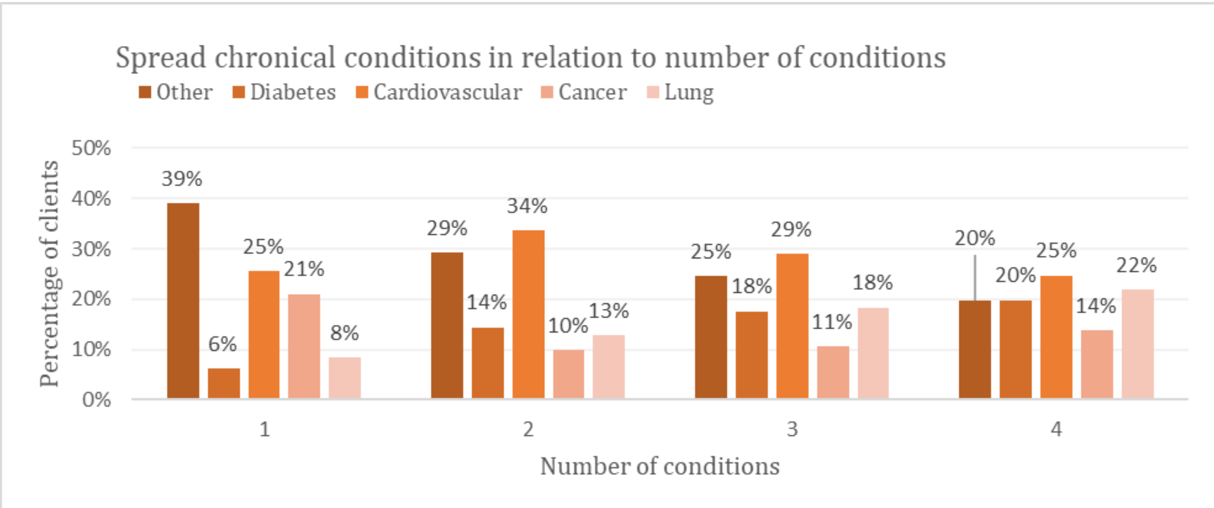
The NZA questionnaire asks clients to rate their self-reliance on a scale from 1 to 4 for the following general daily living tasks: washing/showering, dressing, eating and drinking, and going to the bathroom. A score of 1 means that the client can execute a task themselves, and a score of 4 means they cannot. The assumption is that a client needs help with general daily living tasks if one of the sub-general tasks is rated higher than 2. 53% of the clients need help with one of the daily living tasks. 7% only need help with daily living tasks, 92% need help with daily living tasks while suffering from a chronic condition, and 2% need help with daily living tasks while receiving some form of nursing technical care. The care needs vary per daily living tasks (Appendix C-30 toAppendix C-32).



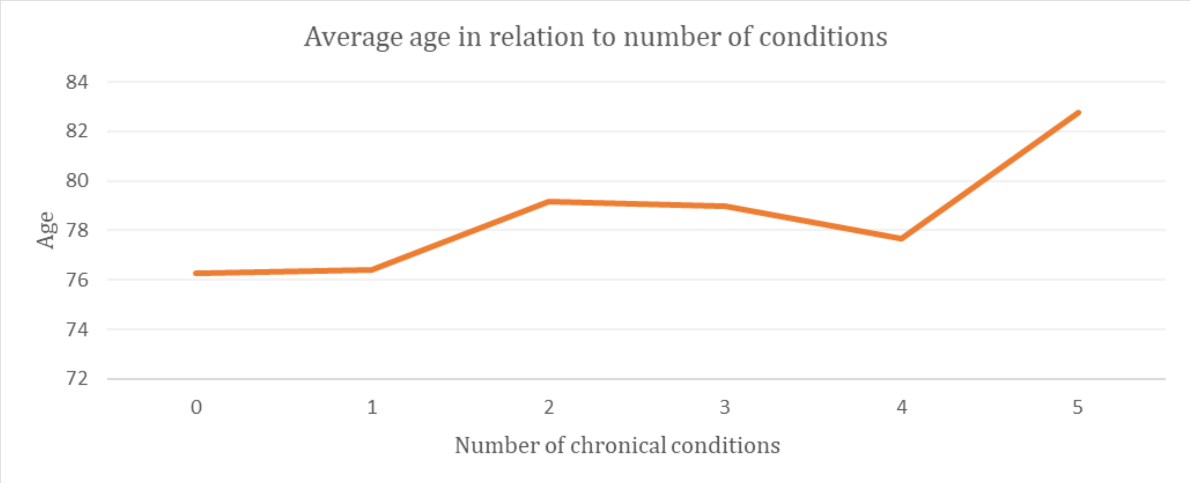
Appendix C-3 NZA, chronic conditions and gender



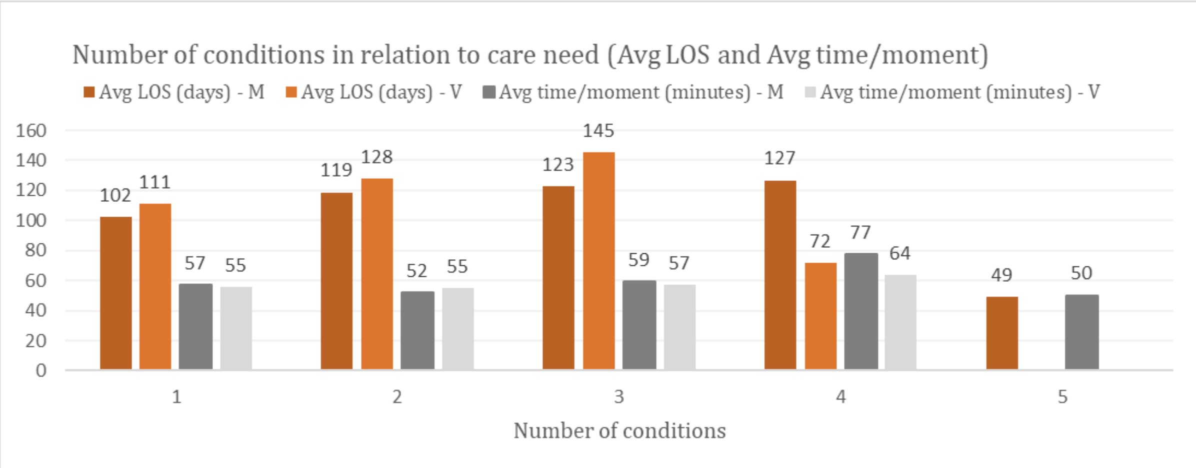
Appendix C-4 NZA, number of chronic conditions and gender



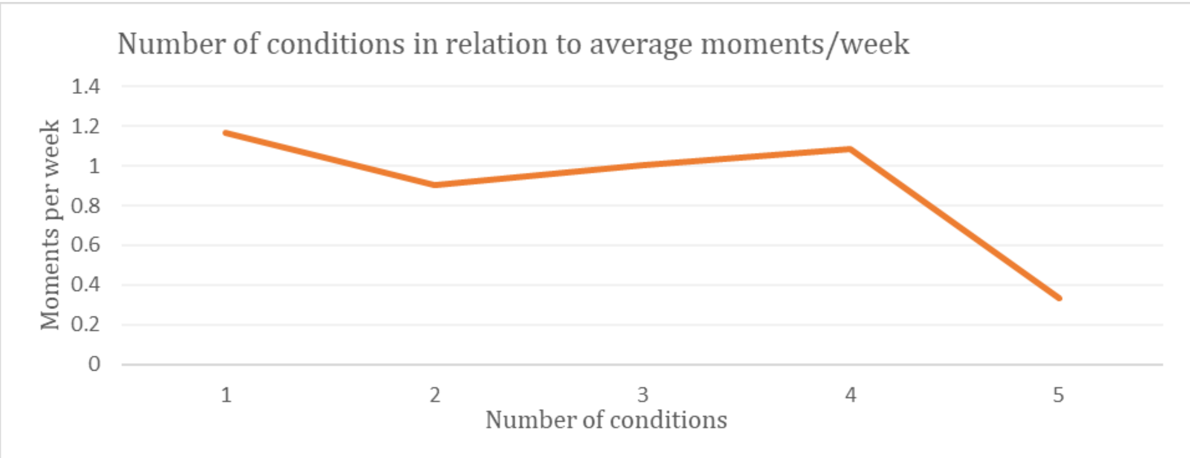
Appendix C-5 Number of chronic conditions and sort condition



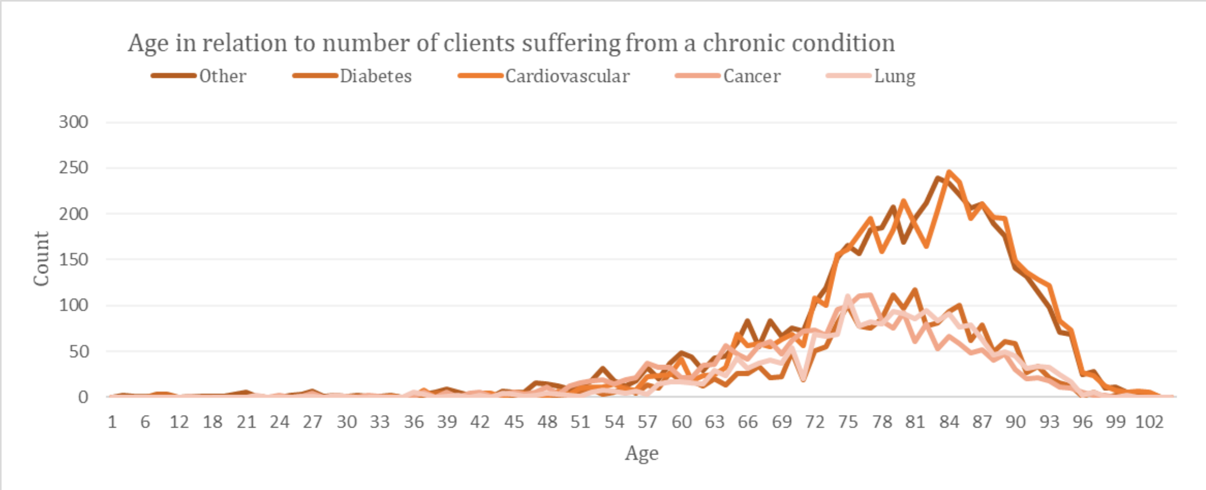
Appendix C-6 Number of chronic conditions and age



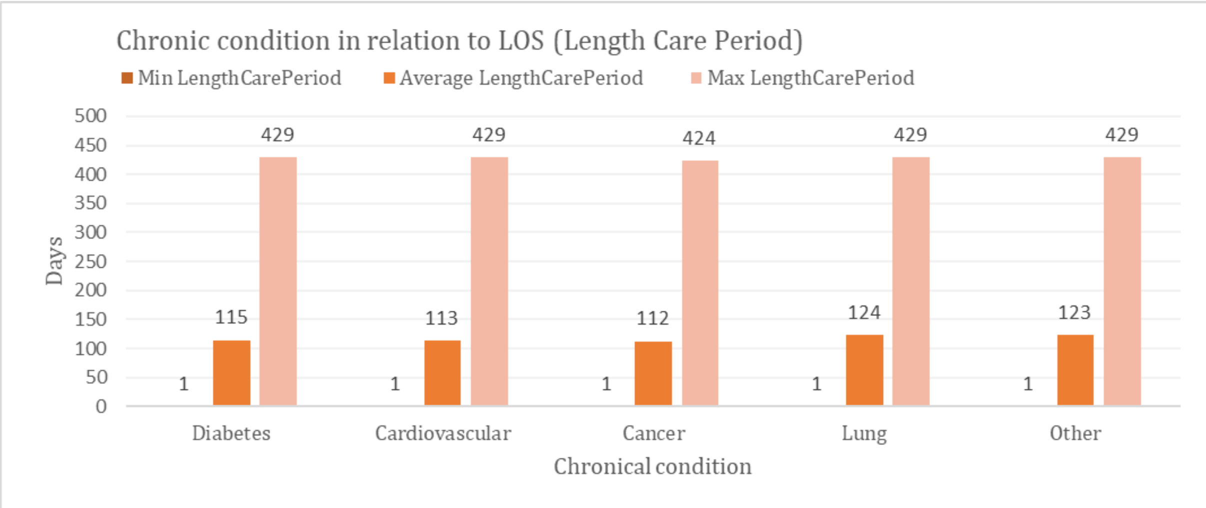
Appendix C-7 Number chronic conditions and care need - Avg LengthCarePeriod, Avg time/care moment



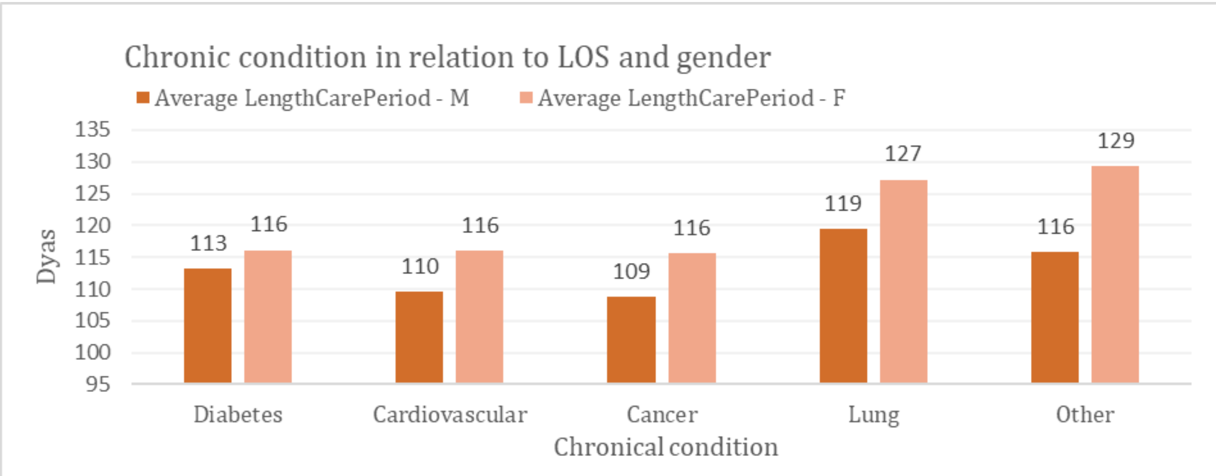
Appendix C-8 Number of chronic conditions and care need - average moments per week



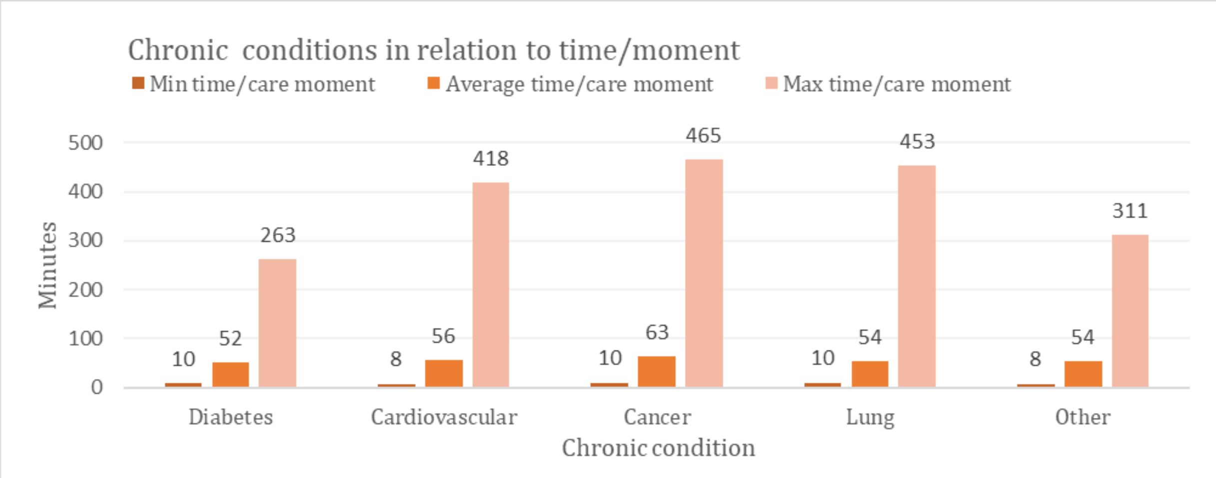
Appendix C-9 Chronic conditions and age



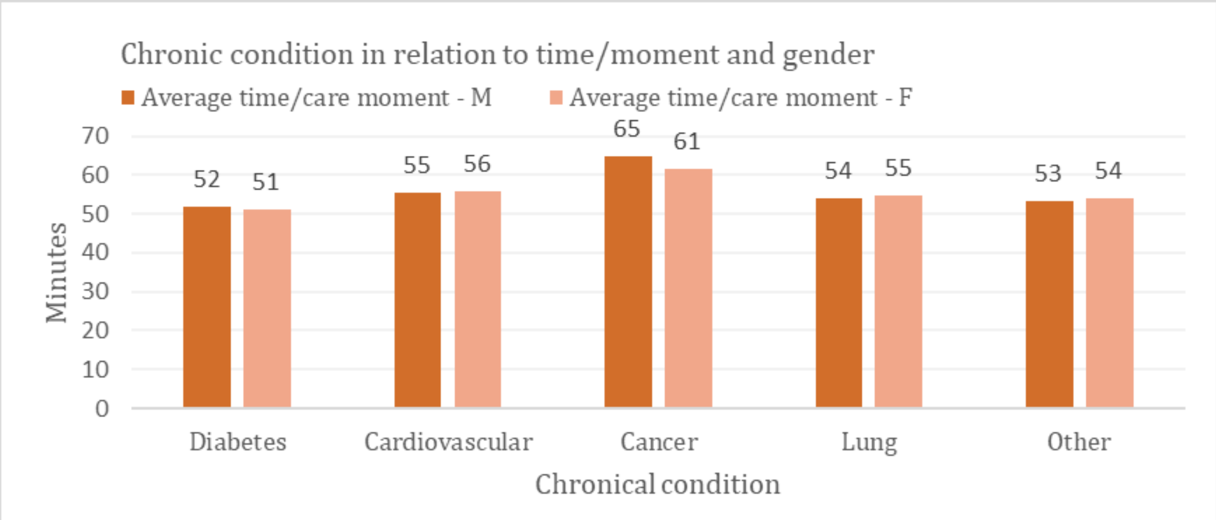
Appendix C-10 Chronic condition and LengthCarePeriod



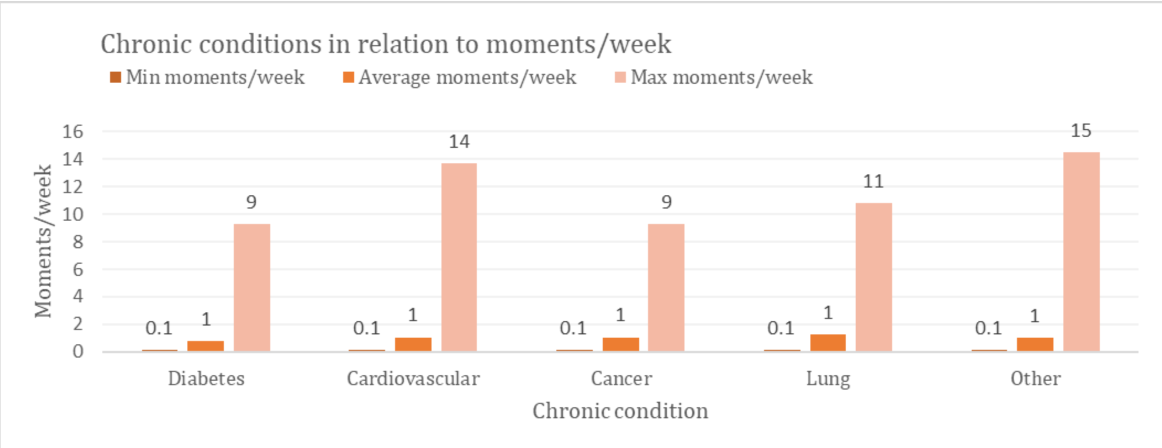
Appendix C-11 Chronic condtions -Avg LengthCarePeriod and gender



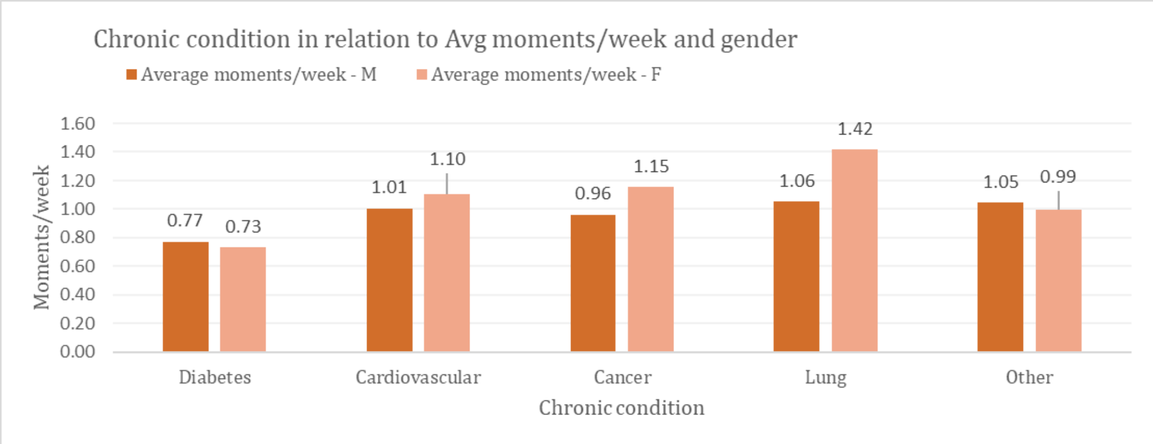
Appendix C-12 Chronic conditions and Time/Care moment



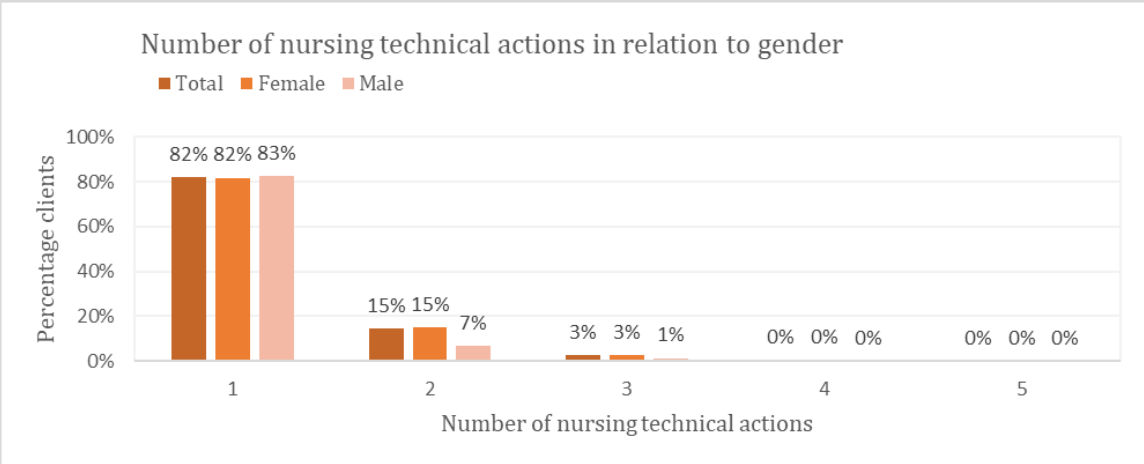
Appendix C-13 Chronic conditions - Avg Time/care moment and gender



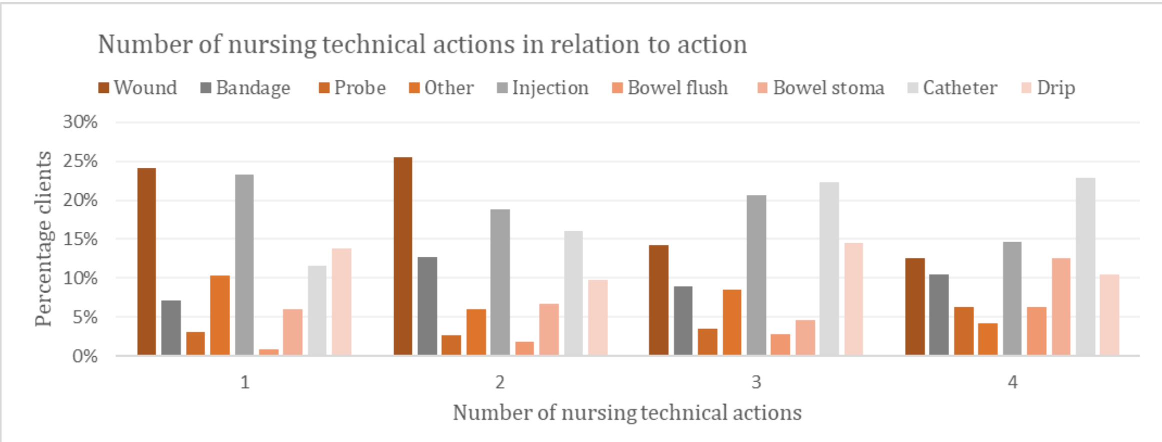
Appendix C-14 Chronic conditions and Moments/Week



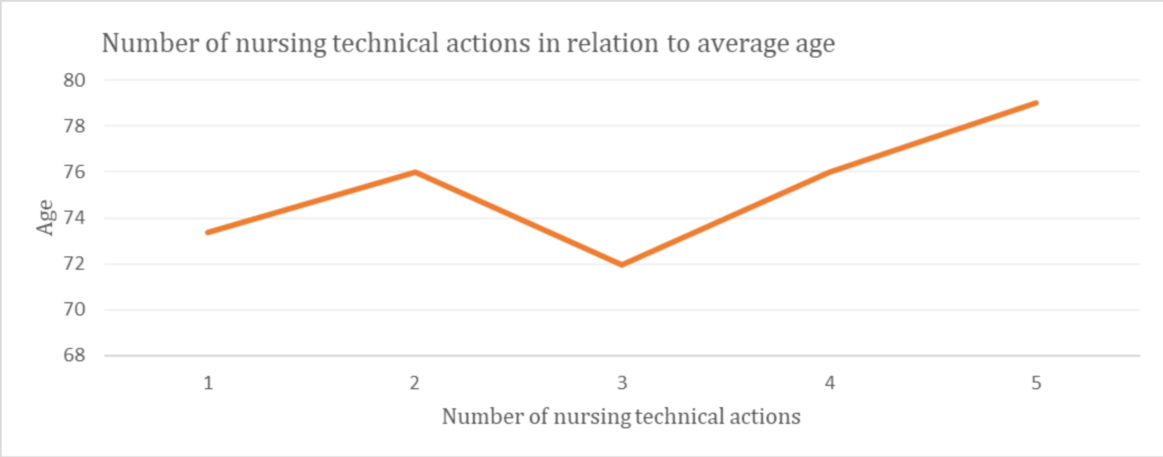
Appendix C-15 Chronic conditions – Avg Moments/week and gender



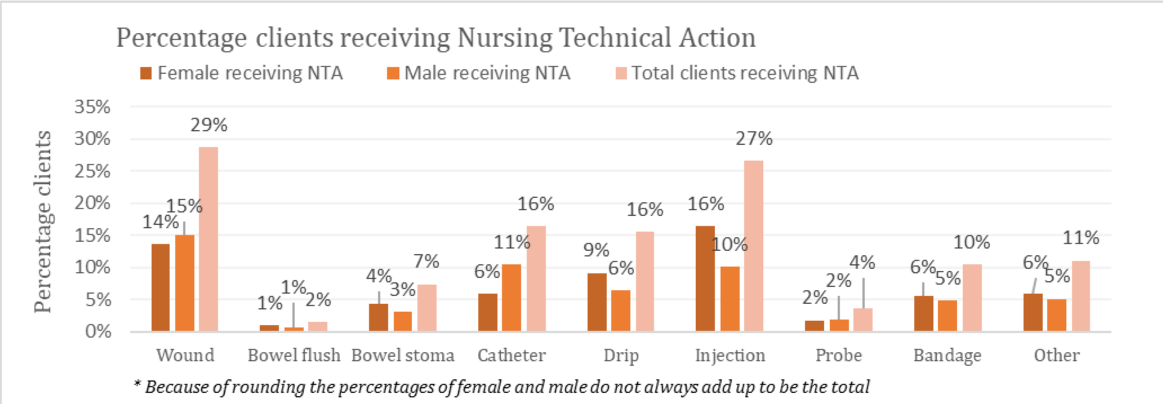
Appendix C-16 Number of nursing technical actions and gender



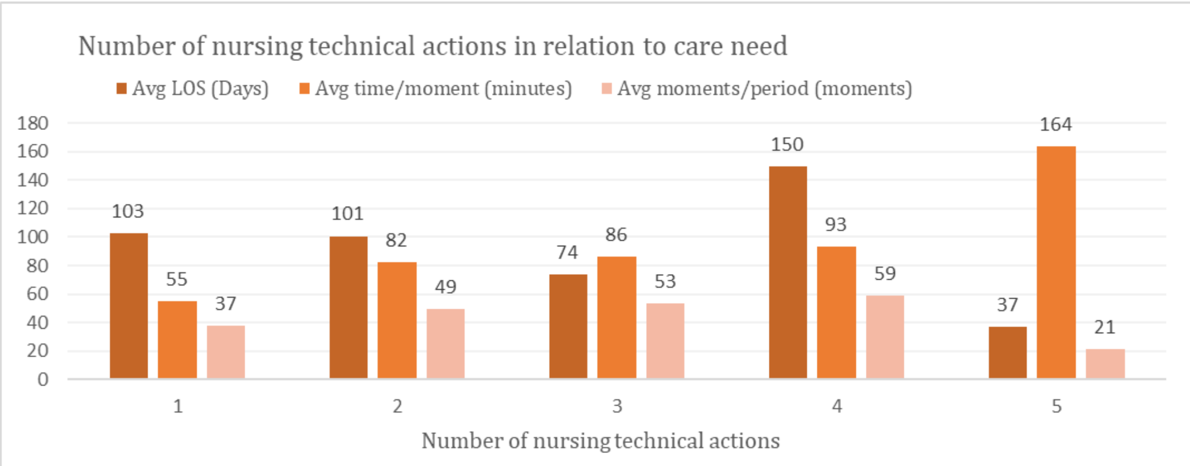
Appendix C-17 Number of nursing technical actions and action



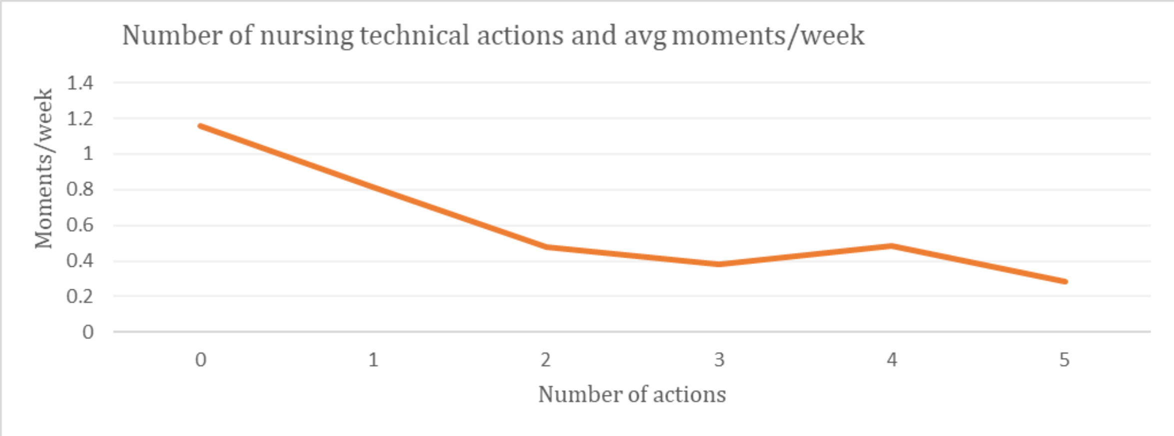
Appendix C-18 Number of nursing technical actions and age



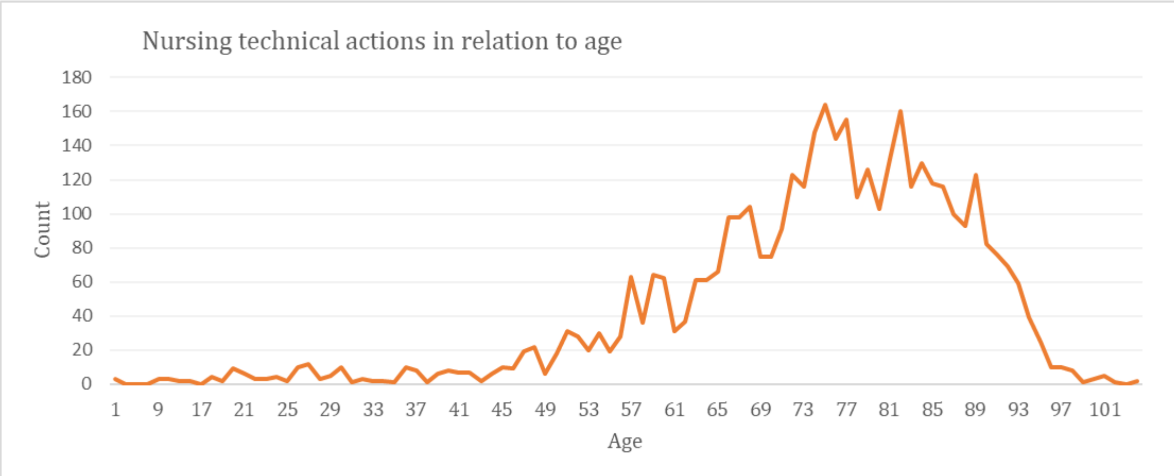
Appendix C-19 Percentage per nursing technical actions and gender



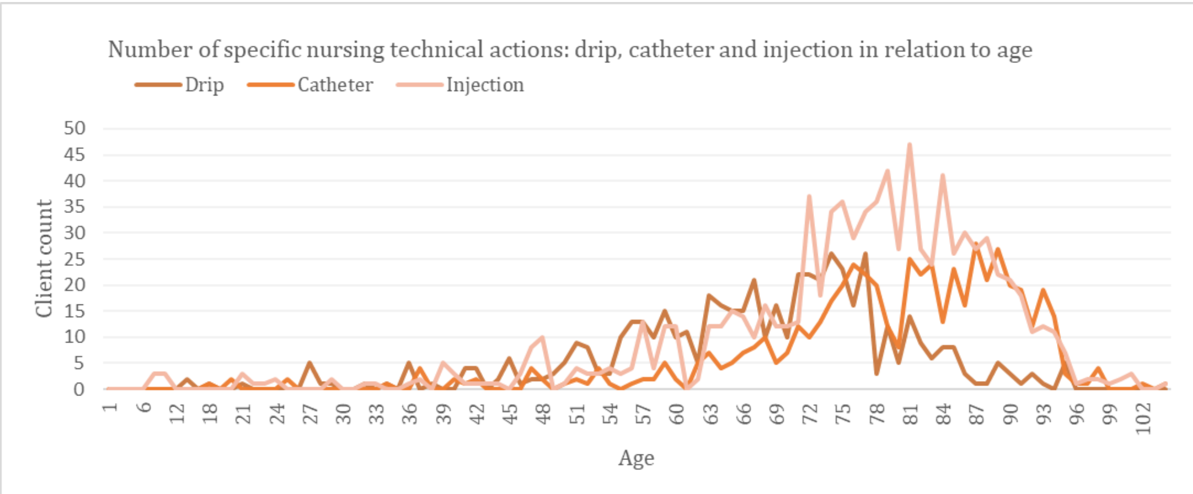
Appendix C-20 Number of nursing technical actions and care need - LengthCarePeriod & Average Time/care moment



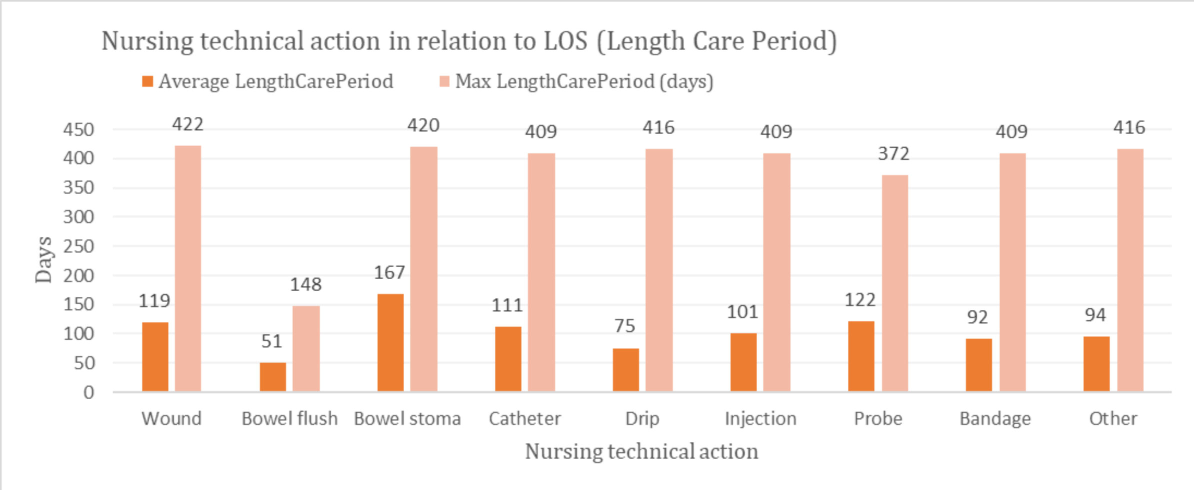
Appendix C-21 Number of nursing technical actions and care need average moments/period



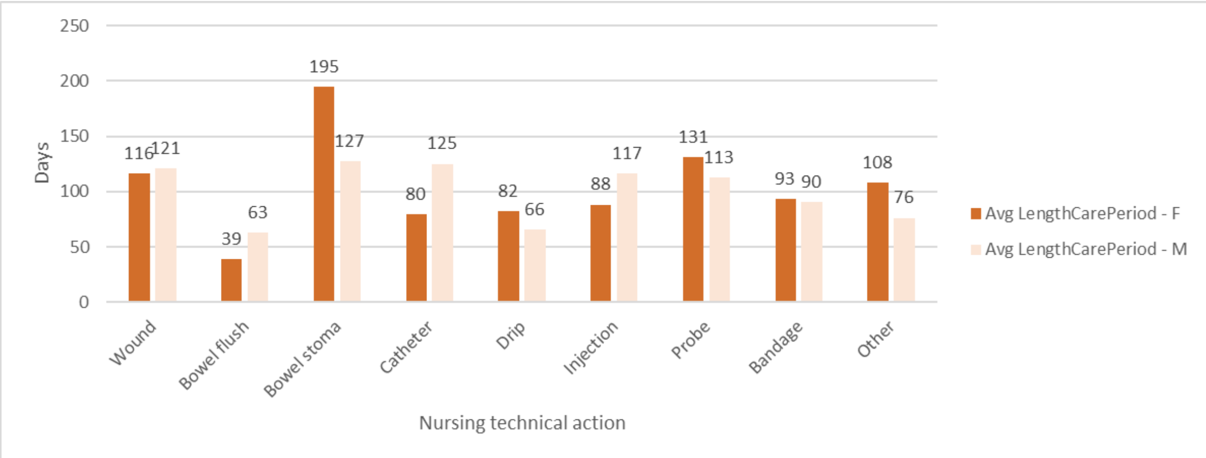
Appendix C-22 Total number of nursing technical actions and age



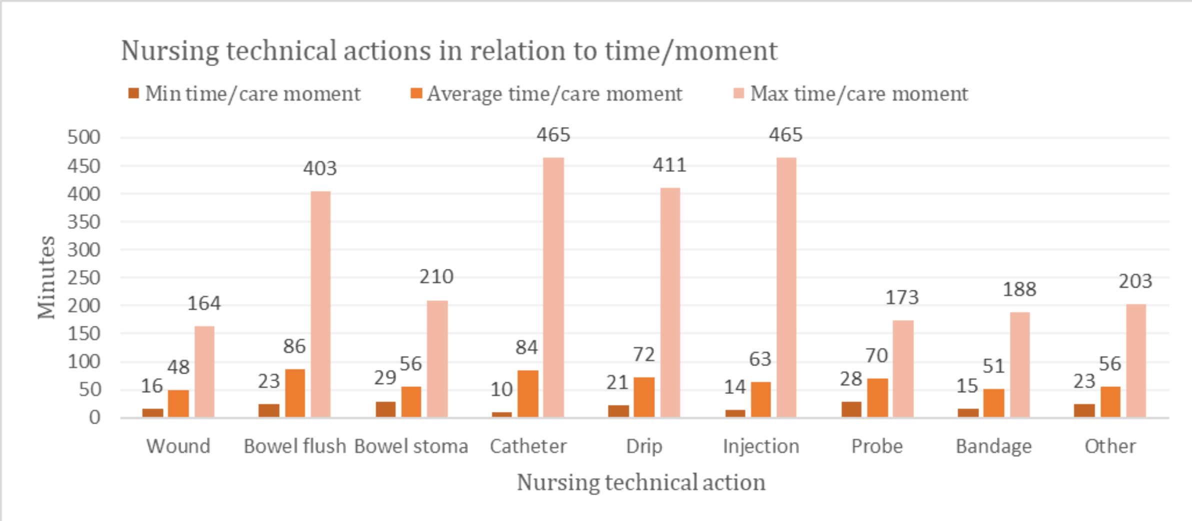
Appendix C-23 Number of nursing technical actions Drip, Catheter and injection with age



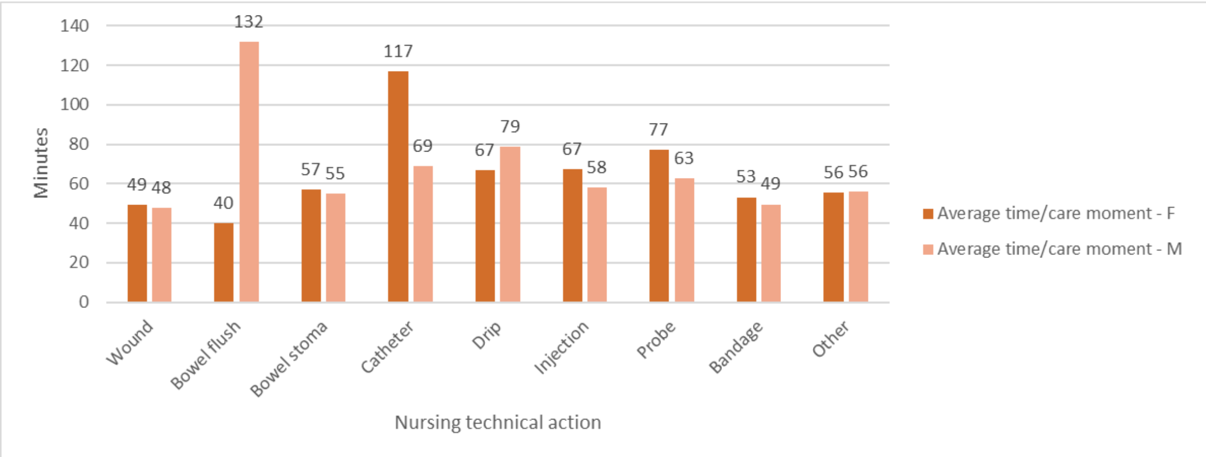
Appendix C-24 Nursing technical actions – LengthCarePeriod



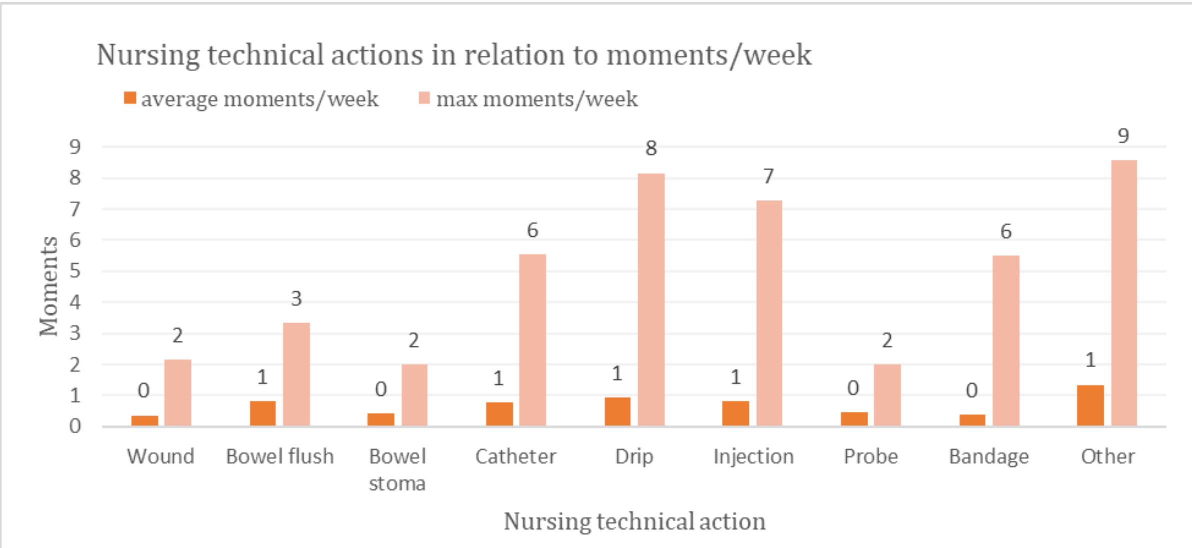
Appendix C-25 Nursing technical actions, LengthOfCare period and gender



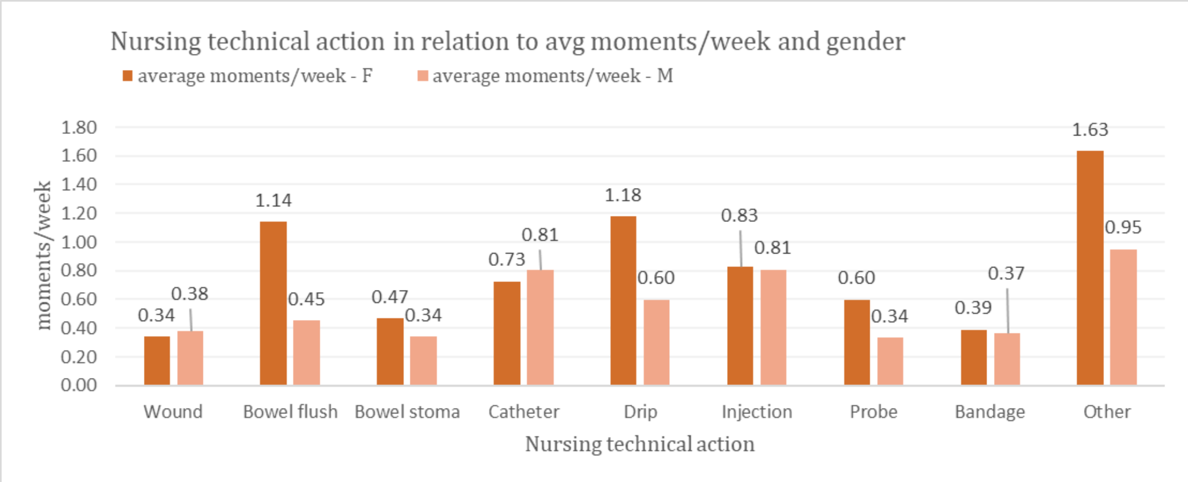
Appendix C-26 Nursing technical actions and time/care moment



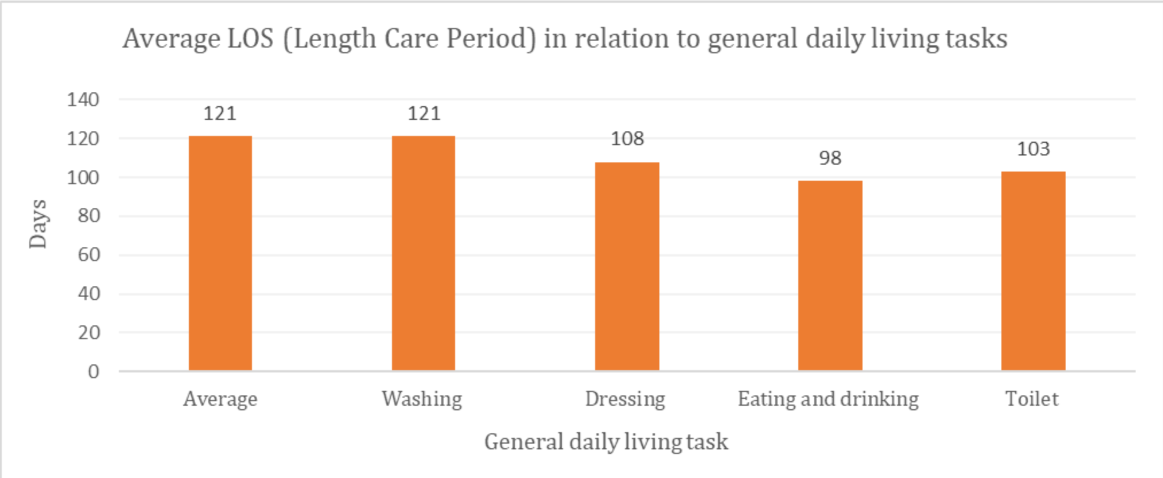
Appendix C-27 Nursing technical actions - Avg time/care moment and gender



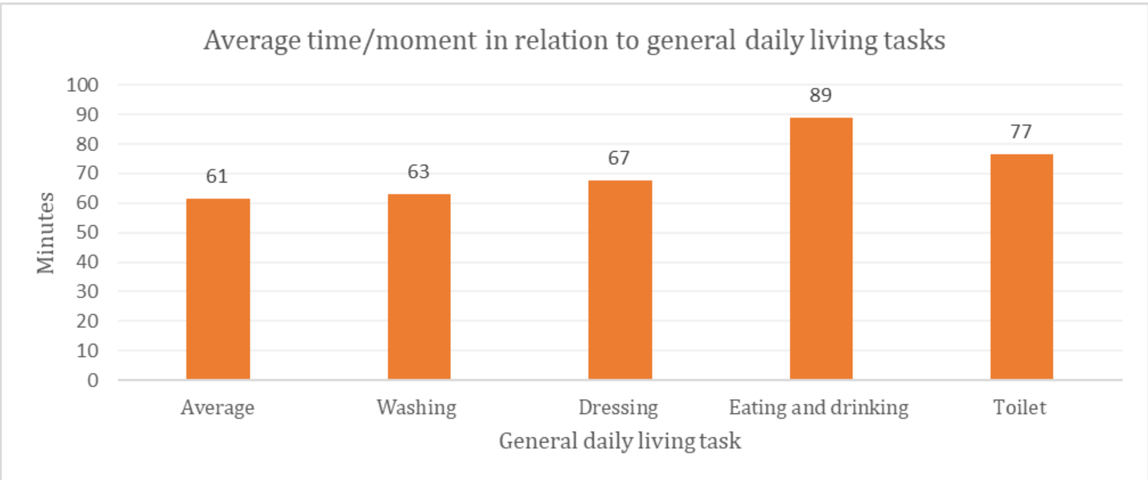
Appendix C-28 Nursing technical actions and moments/week



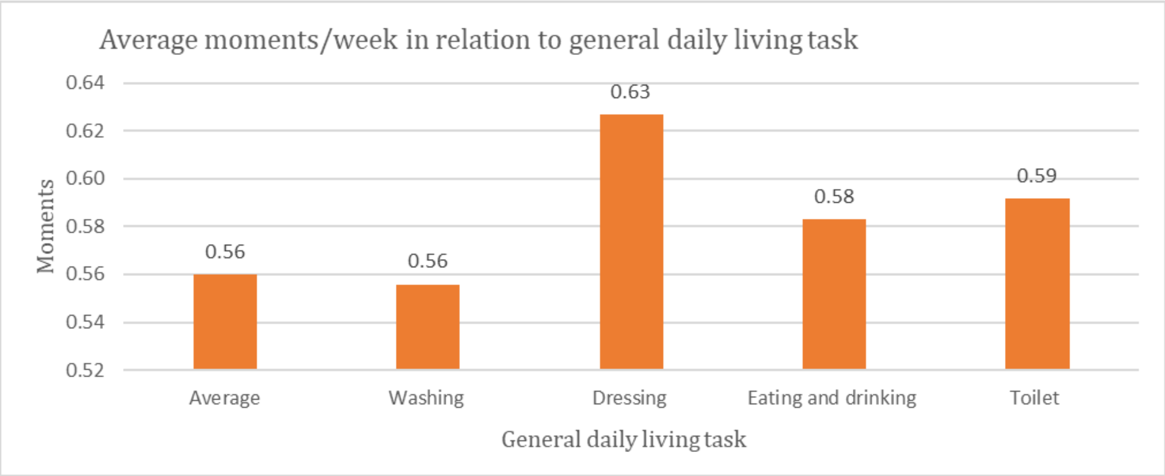
Appendix C-29 Nursing technical actions - Avg moments/week and gender



Appendix C-30 General daily living tasks - Avg LengthCarePeriod



Appendix C-31 General daily living task avg time/care moment



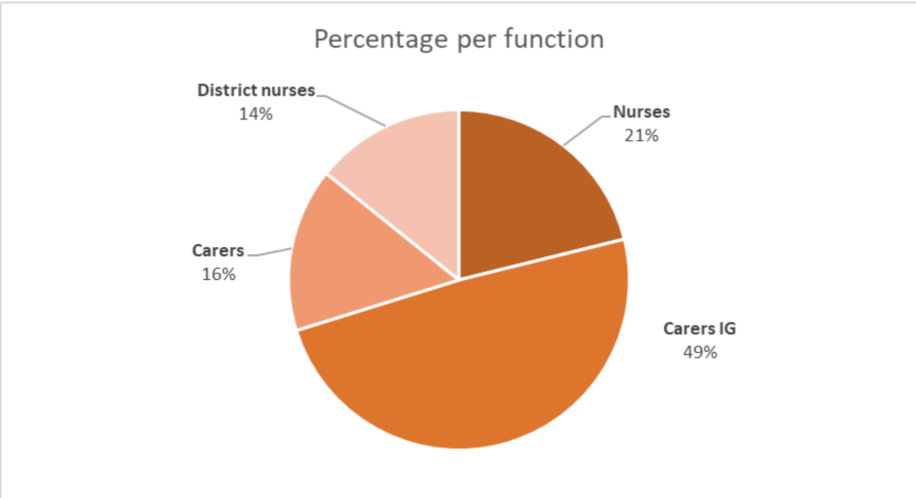
Appendix C-32 General daily living tasks - Avg moments/week

D. Home care provider characteristics

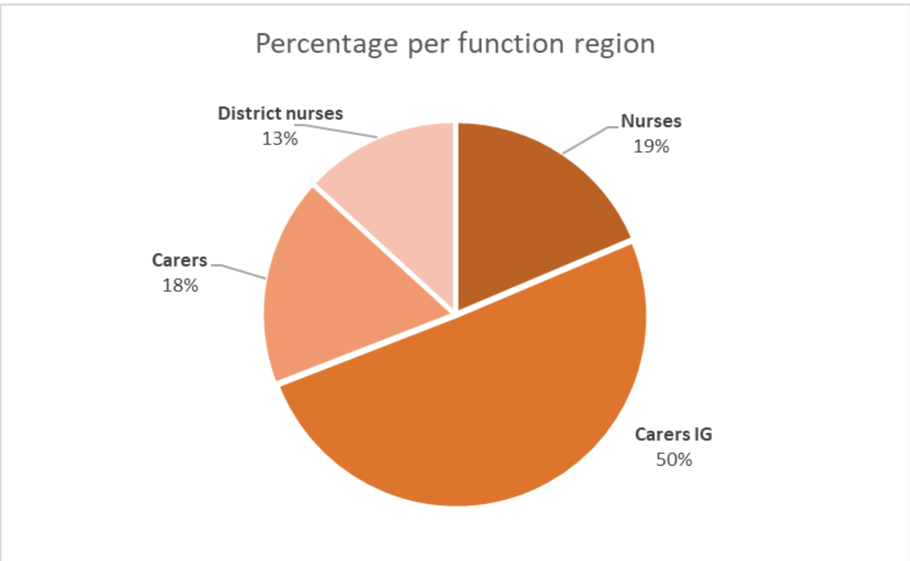
Table 0-1 shows the percentage of home care providers per function for the total (from 1970 onwards) and the percentage inflow per function over the last ten years. The Carers IG make up almost half of the employees, after which the Nurses, Carers and last, the District Nurses. Regional data reflects the percentage of home care providers per function of the Sensire-wide data. In the last ten years, the inflow of carers has been very little, and the inflow of Nurses increased (Appendix D-1 to Appendix D-4).

Table 0-1 Percentage of home care providers employed by Sensire per function (Source: internal employee data Sensire 1970 – 2022, n =1097)

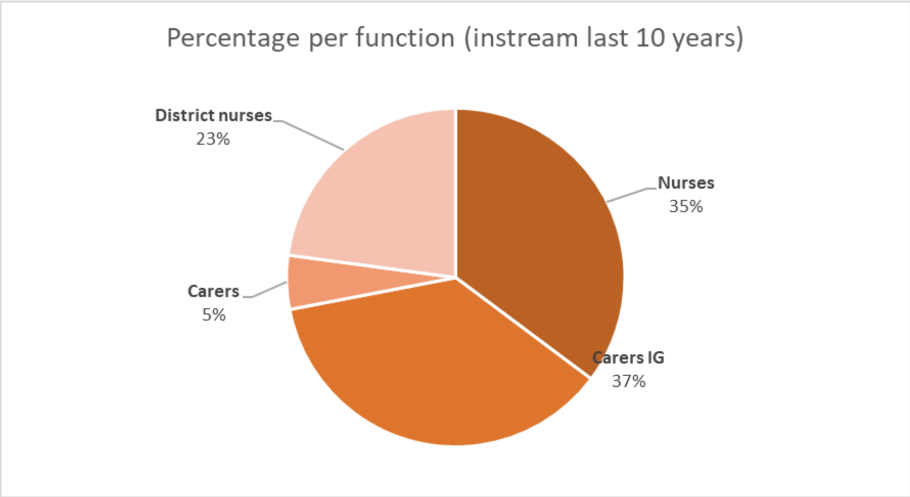
	Sensire		**Region**	
	Total	Last ten years	Total	Last ten years
Carers	16%	5%	18%	4%
Carers IG	49%	37%	50%	38%
Nurses	21%	35%	19%	35%
District Nurses	14%	23%	13%	23%



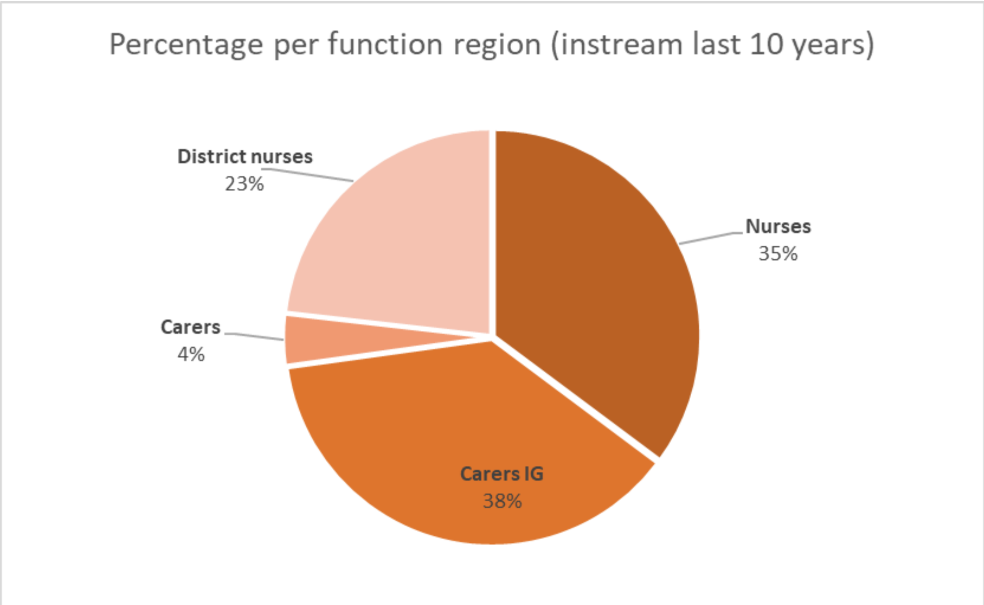
Appendix D-1 Percentage per function Sensire wide



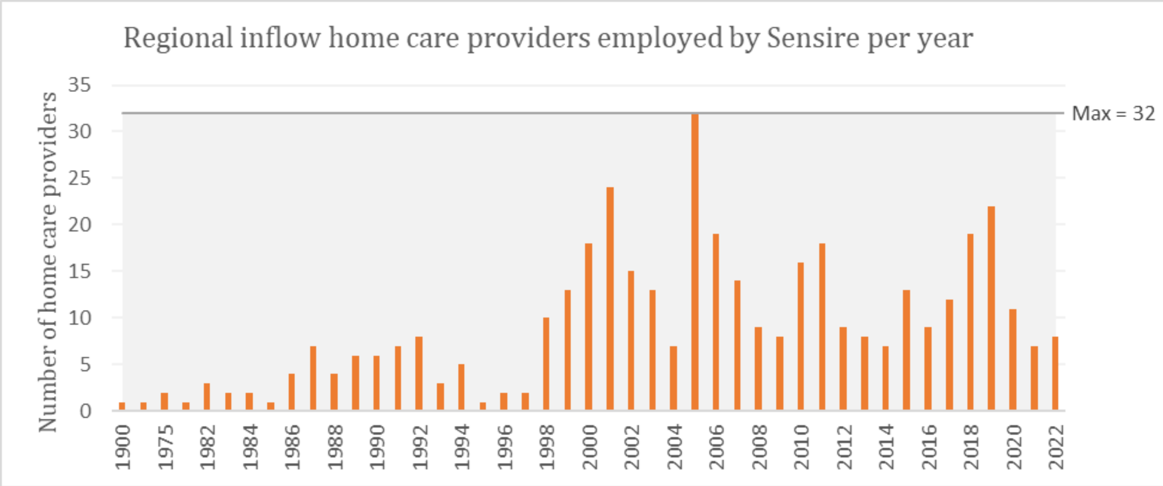
Appendix D-2 Percentage per function regional



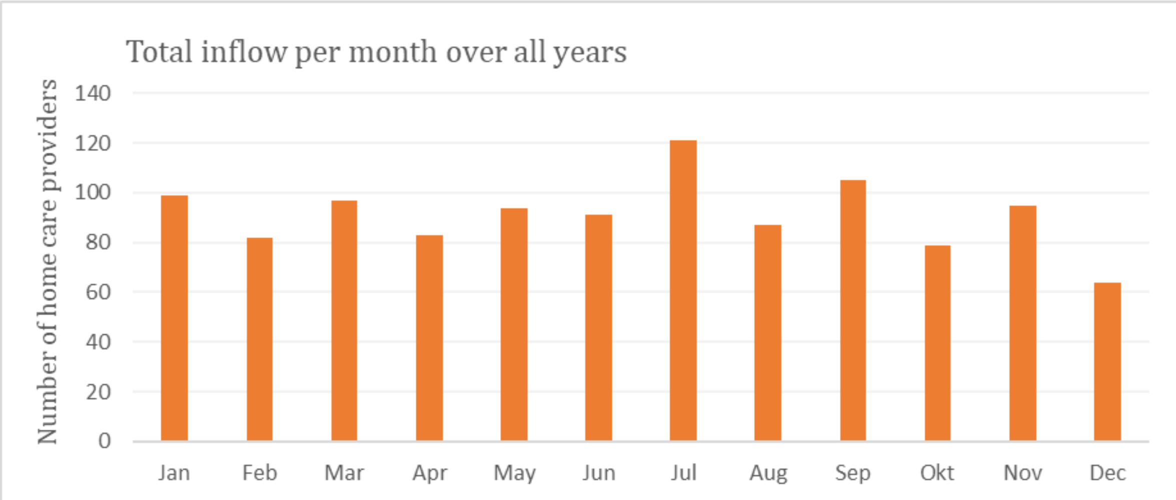
Appendix D-3 Percentage per function inflow last 10 years (2012-2022) Sensire wide



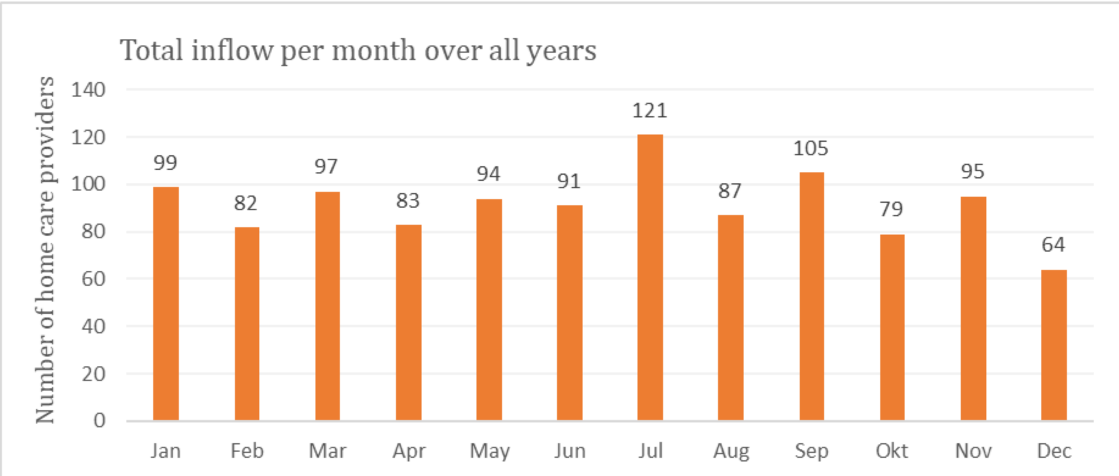
Appendix D-4 Percentage per function inflow last 10 years (2012-2022) regional



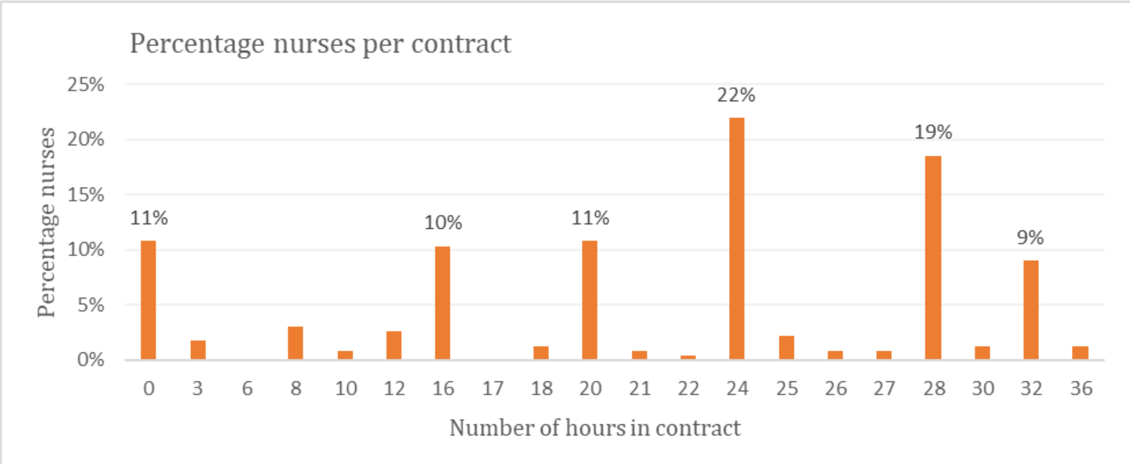
Appendix D-5 Inflow home care providers per year regional



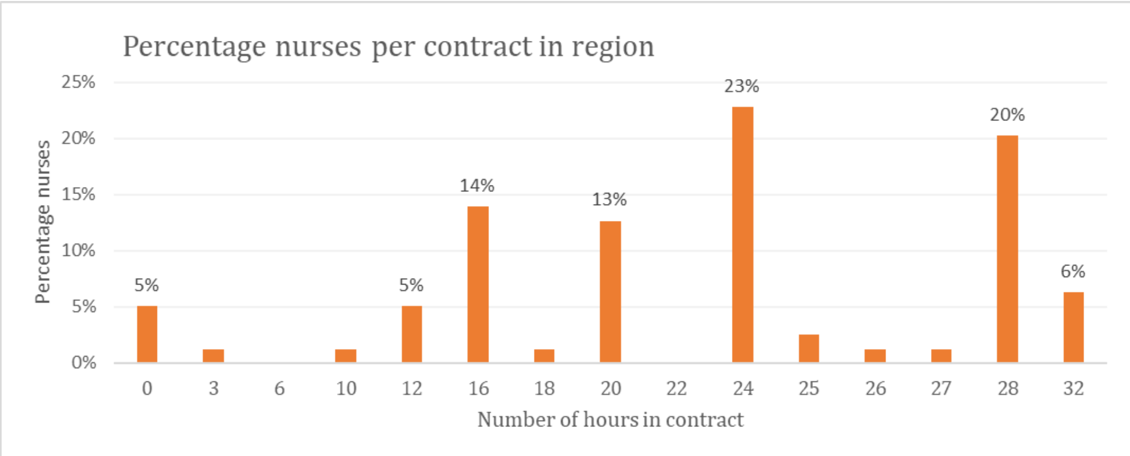
Appendix D-6 Total inflow per month Sensire



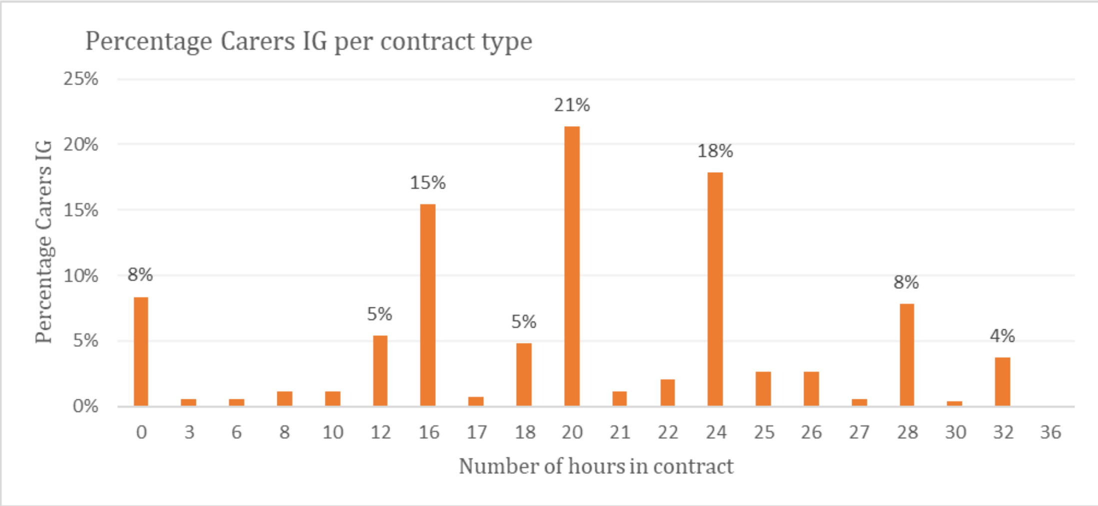
Appendix D-7 Total inflow per month regional

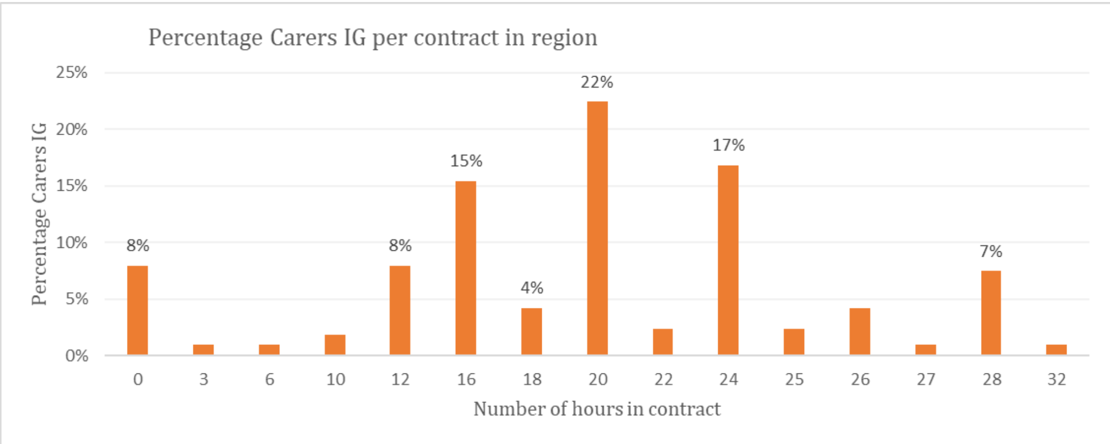


Appendix D-8 Percentage of nurses per contract type

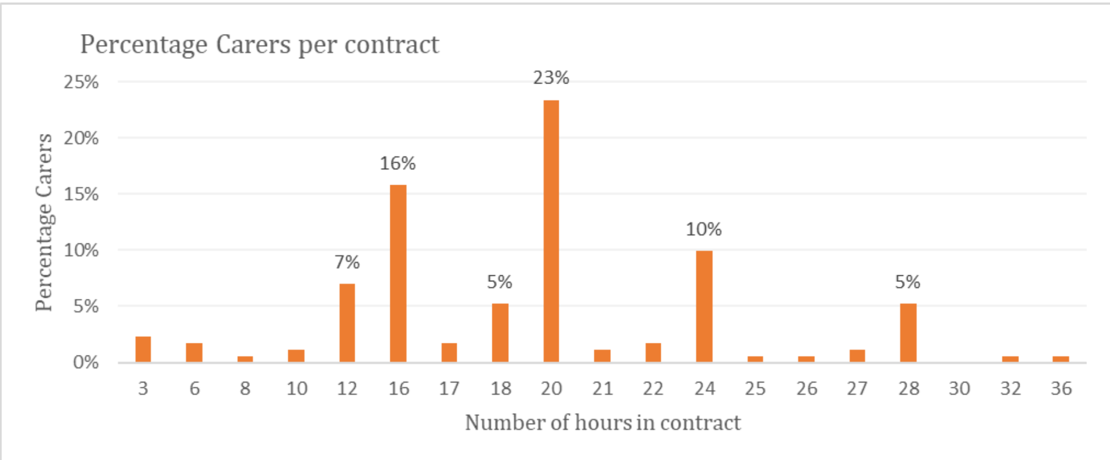


Appendix D-9 Percentage of nurses per contract type regional

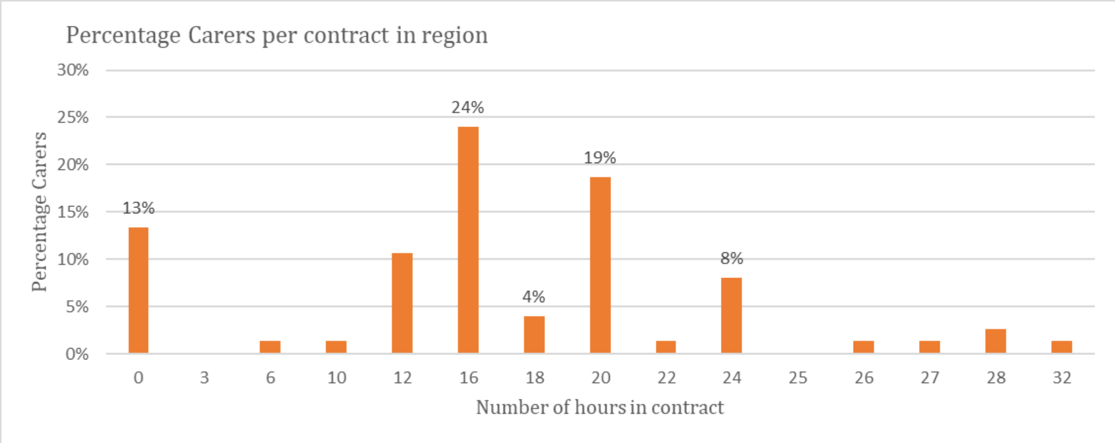




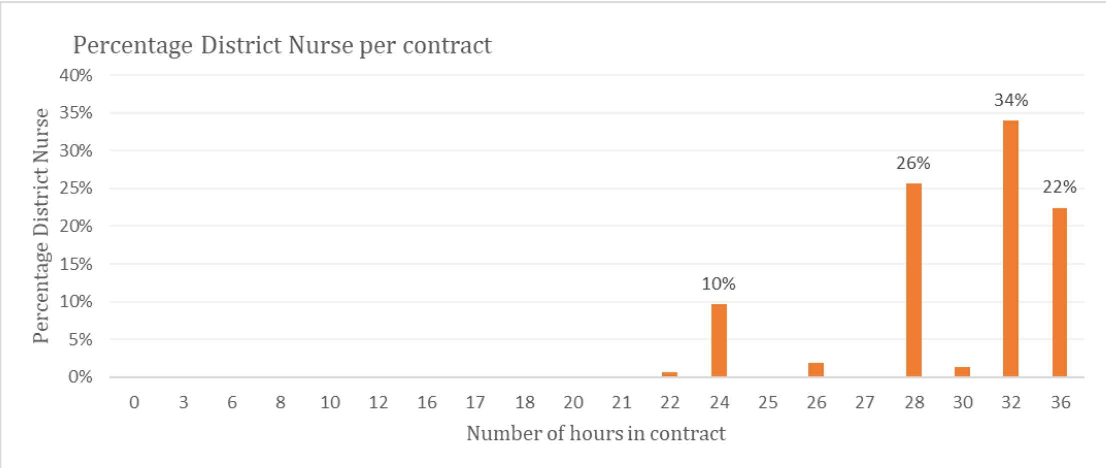
Appendix D-10 Percentage Carers IG per contract type regional



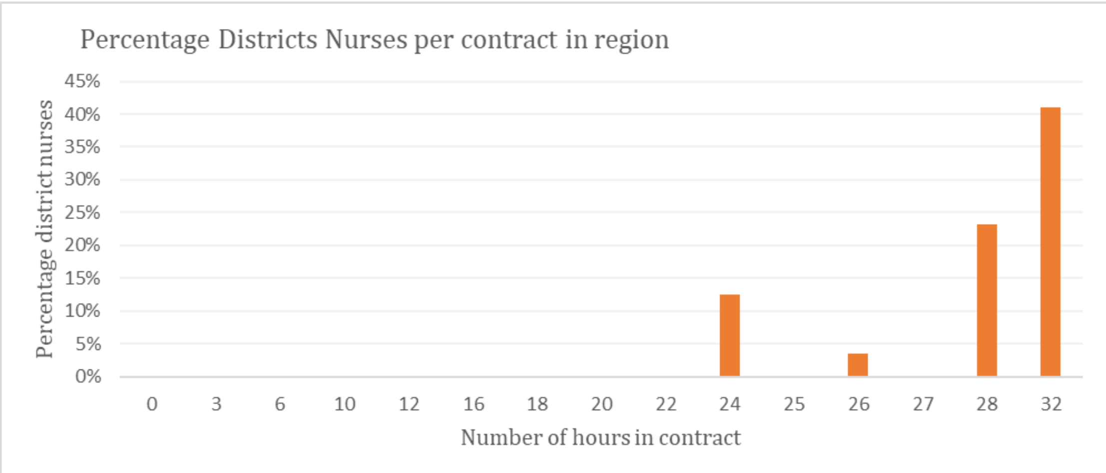
Appendix D-11 Percentage carers per contract type



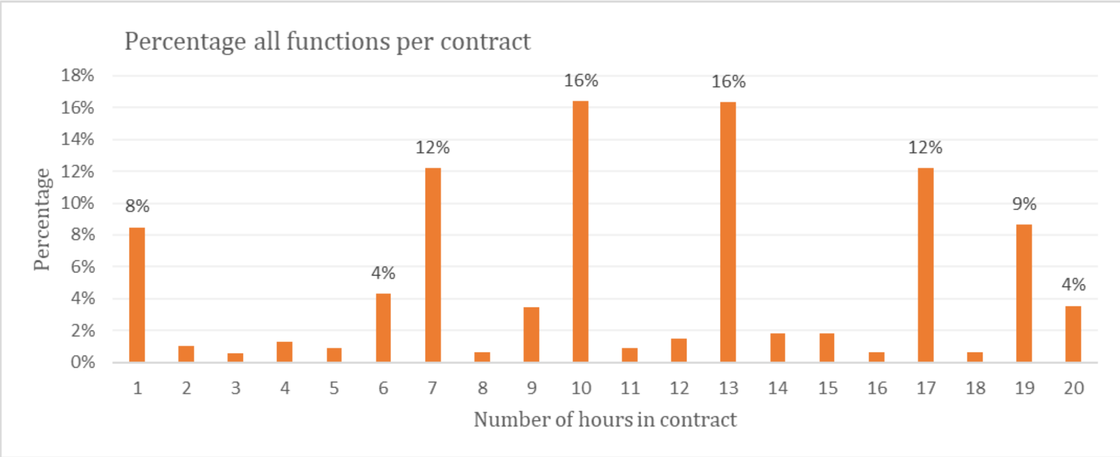
Appendix D-12 Percentage carers per contract type regional



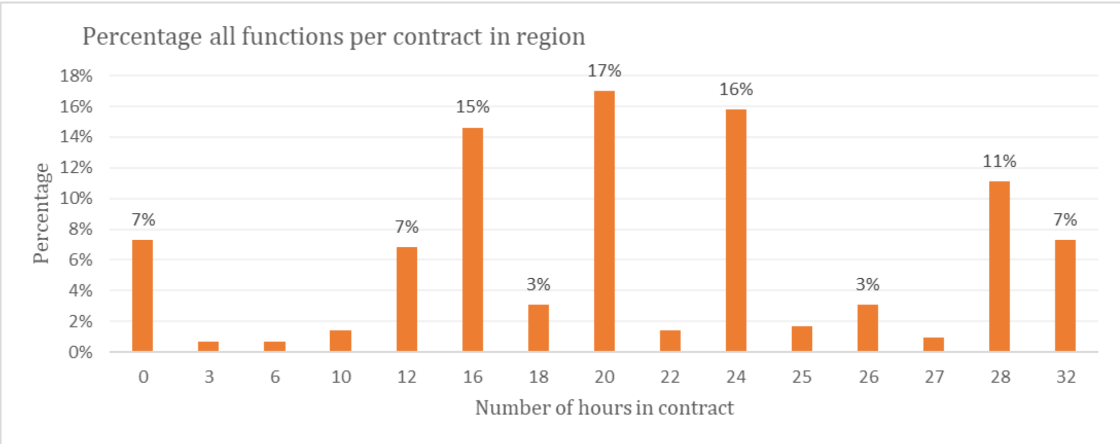
Appendix D-13 Percentage of District Nurses per contract type



Appendix D-14 Percentage District Nurses per contract type regional



Appendix D-15 Percentage of all functions combined per contract type



Appendix D-16 Percentage of all functions combined per contract type regional

E. KPI analyses

Plus/min hours
Plus hours are the hours a home care provider works outside their contract hours. Min hours are the hours that a home care provider works less than their contract hours. Plus/min hours is the percentage that a home care provider worked too much or too little. A positive number indicates plus hours a negative number indicates min hours. The benchmark is a maximum percentage of 8%. The average plus/min hours within Sensire and the region are almost similar. Except for the last weeks of 2021, they balanced around 6%, with a max of 16% and a minimum of -6%. The 8% benchmark is exceeded in the middle of 2021 and most of 2022. Looking at the districts in the region, Doetinchem shows more significant outliers for the plus hours and the min hours, especially for 2022. The other districts in the region follow the mean with slight deviations here and there (Appendix E-1 and Appendix E-2).

Absenteeism
Absenteeism has been increasing over the years. The Sensire-wide averages reflect in the regional averages (Appendix E-3). However, the current Sensire-wide benchmark, a maximum of 8.9% absenteeism, is exceeded a lot. The districts Doetinchem and Montferland always exceed the average. Montferland exceeds the averages in the middle of 2021 and 2022, fluctuating between 15% and 20%. The district Oude Ijsselsteek follows the average except for 2022. Only the district Bronckhorst is below the average, fluctuating around 5% over the years. Figure 0-2 shows the level of absenteeism over the years for the region and the Sensire-wide average.

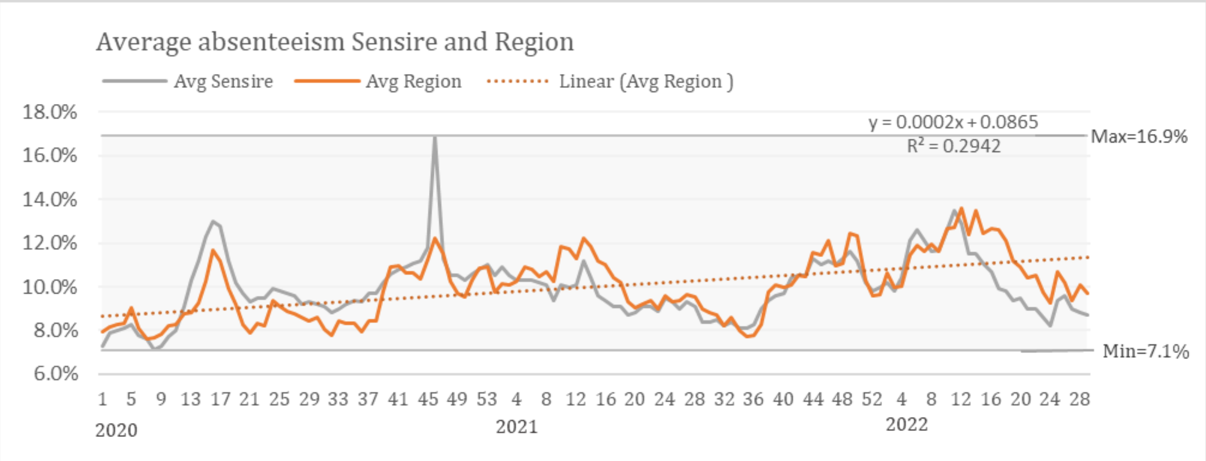
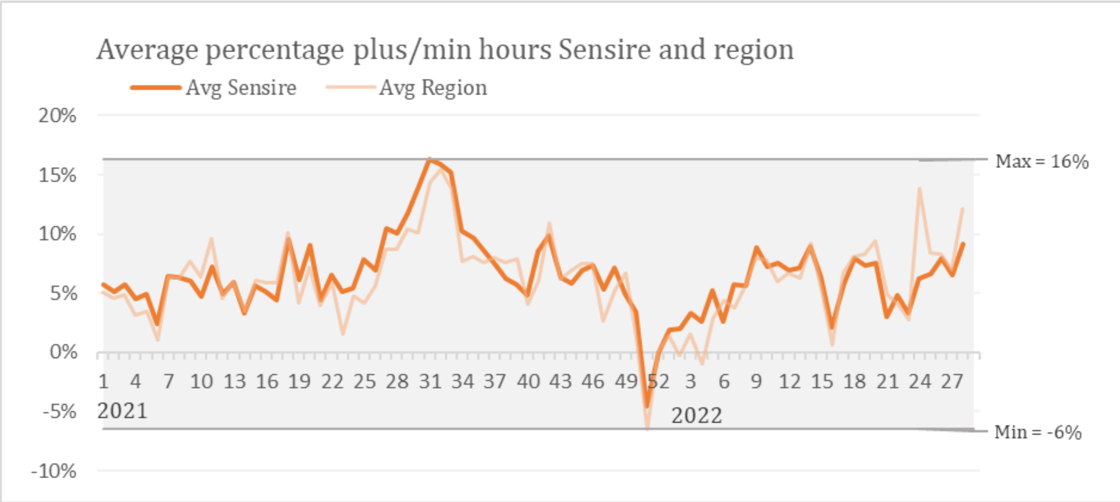
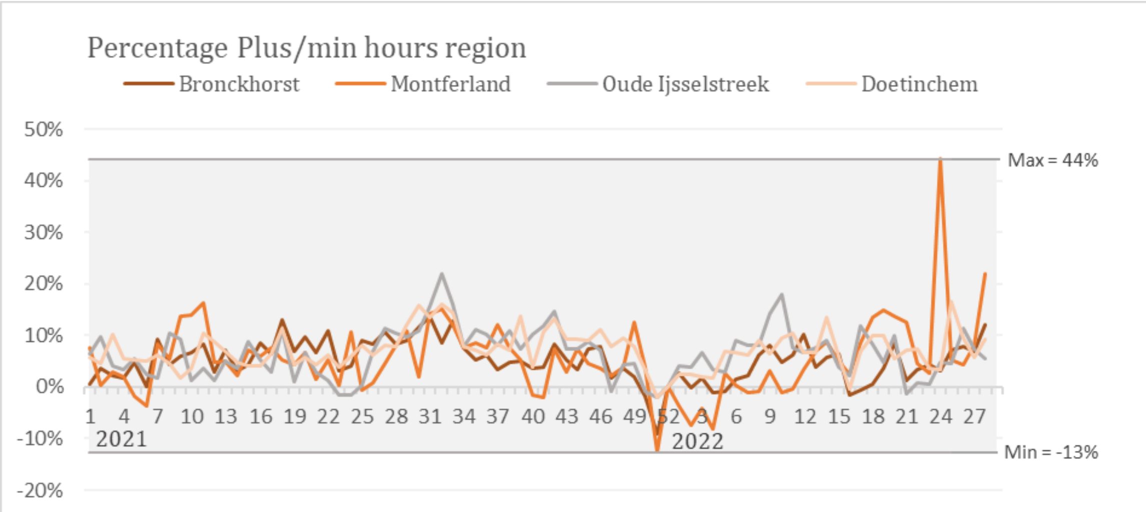


Figure 0-2 Absenteeism employees Sensire in the region (Source: internal employee data Sensire)

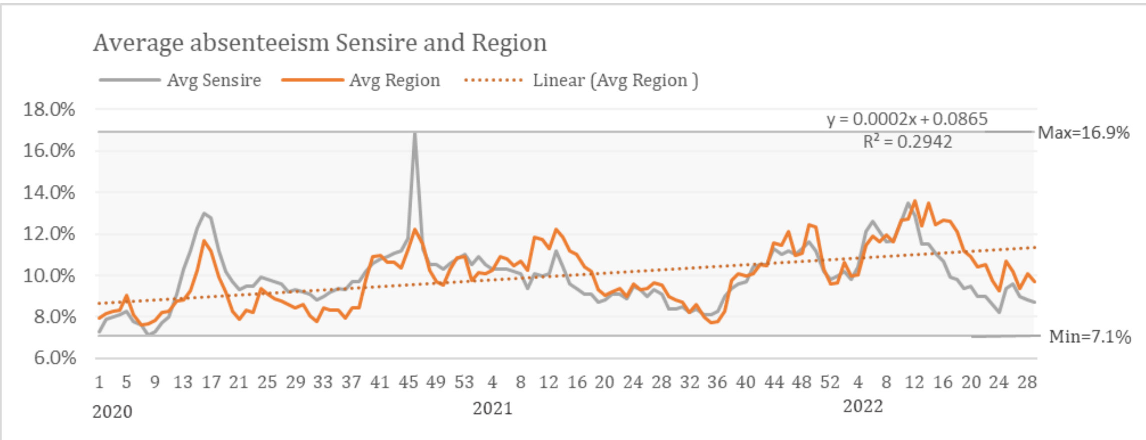
Productivity and effectivity
Productivity is the number of direct hours compared to the total number of hours, which includes absenteeism, travel time, and leaves of absence. Effectivity is the number of direct hours compared to the total number of hours, excluding absenteeism and leave of absence, because these are factors out of influence. The benchmark is a minimum of 77%. The higher the percentage for productivity and effectiveness, the better. As a logical consequence, the effectivity is higher than the productivity. Focussing on productivity. The average productivity for the region is slightly below Sensires' average. The productivity of the district bronckhorst exceeds the Sensire wide average for productivity. Montferland and Doetinchem are slightly below, and the Oude IJsselstreek is below the Sensire wide average. There is no increase or decrease, and the average productivity fluctuates between 55% and 65% (Appendix E-5). Effectivity follows the same pattern Sensire wide, the region and for the districts. However, it fluctuates between 75% and 85% (Appendix E-6 and Appendix E-7).



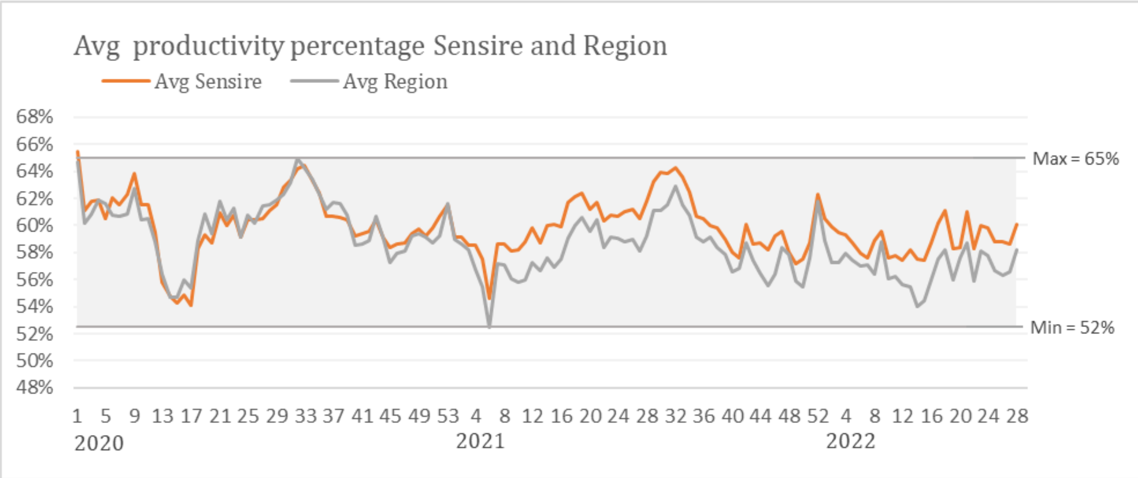
Appendix E-1 Average plus/min hours Sensire and region



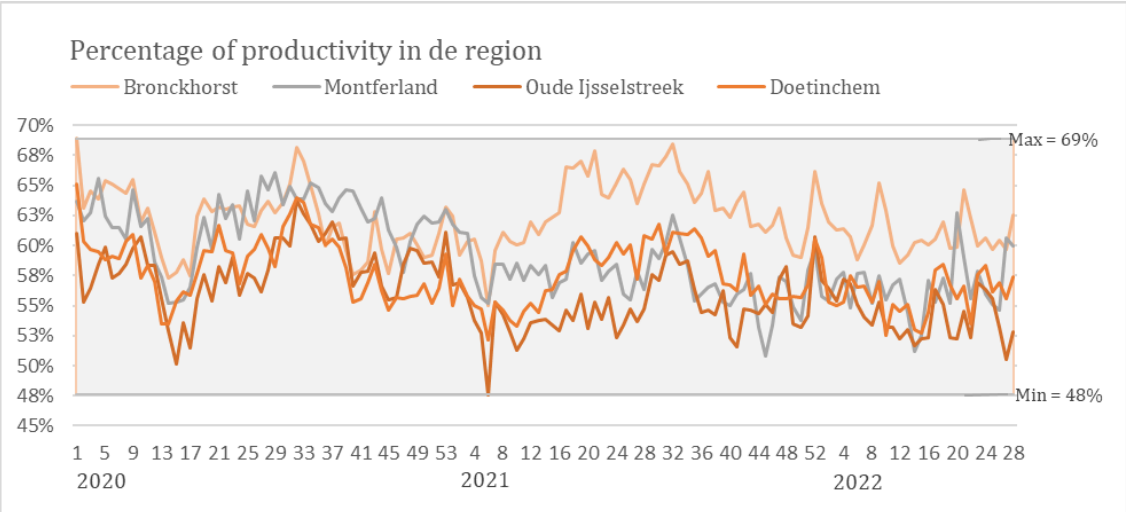
Appendix E-2 Average plus/min hours, regional breakdown



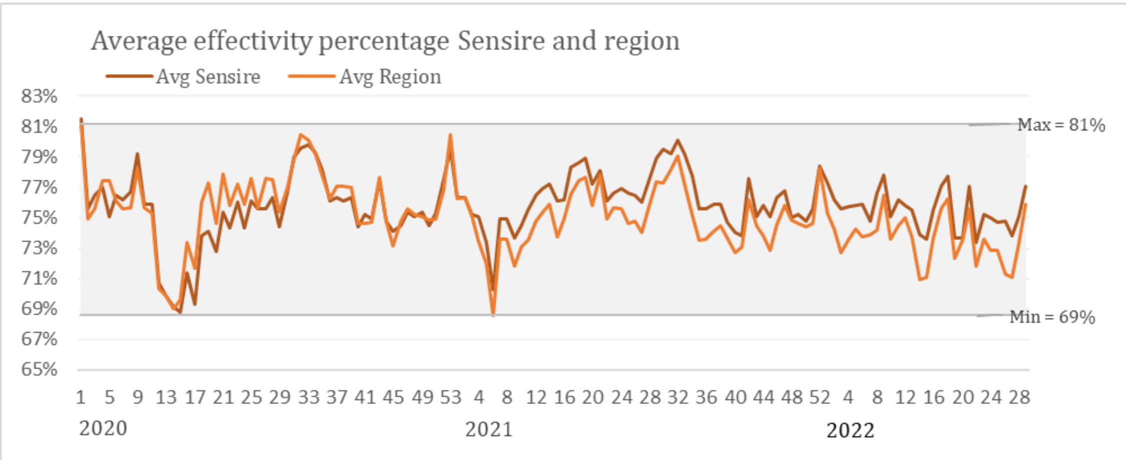
Appendix E-3 Average absenteeism Sensire and region



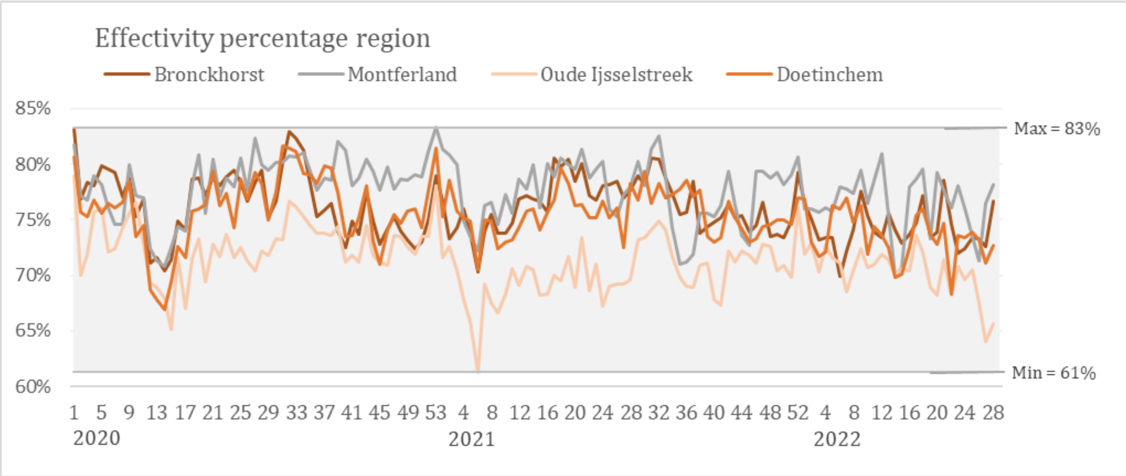
Appendix E-4 Average productivity percentage Sensire and Region



Appendix E-5 Productivity regional



Appendix E-6 Average effectivity Sensire and region



Appendix E-7 Effectivity in the region

F. Systematic literature review hybrid capacity models

The literature study on hybrid capacity models uses PubMed, Google Scholar, en Scopus as search engines. The main question answered is the availability of demand forecasting and capacity planning models in home care on a strategic level. To get a better understanding of available literature for home care, first, a search is performed with various combinations using the keywords:

- "home care"
- "capacity planning"
- "demand forecasting"

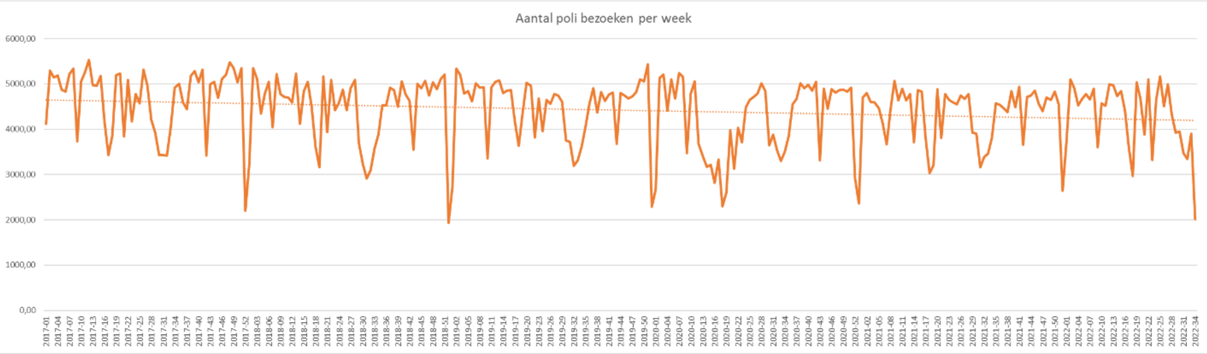
The keywords are combined in the following search string for google scholar: "home care"and "capacity planning" and "demand forecasting". The PubMed database uses the following search strings: "home care" [Title/Abstract] AND "capacity planning" [Title/Abstract], and "home care" [Title/Abstract] AND "demand forecasting" [Title/Abstract]. After performing the search in this manner and lacking strategic focussed papers, we performed another search that included the key-word "strategic". Appendix F-1 shows the results. A one-step backward search was performed, and the following 16 papers were selected based on title, abstract and scanning the paper:

- (Castaño & Velasco 2020)
- (Méndez-Fernández et al. 2020)
- (Yalçındağ et al. 2016)
- (Cappanera en Scutellà 2021)
- (Hare et al. 2008)
- (Rodriguez et al. 2015)
- (Eggink et al. 2015)
- (Shehadeh et al. 2022)
- (Esensoy & Carter 2018
- (VanBerkel et al. 2010)
- (Hulshof et al. 2012)
- (Williams et al. 2021
- (Armadàs et al. 2021)
- (Gameren & Woittiez 2005)
- (Zhang et al. 2012)
- (Zychlinski et al. 2020)

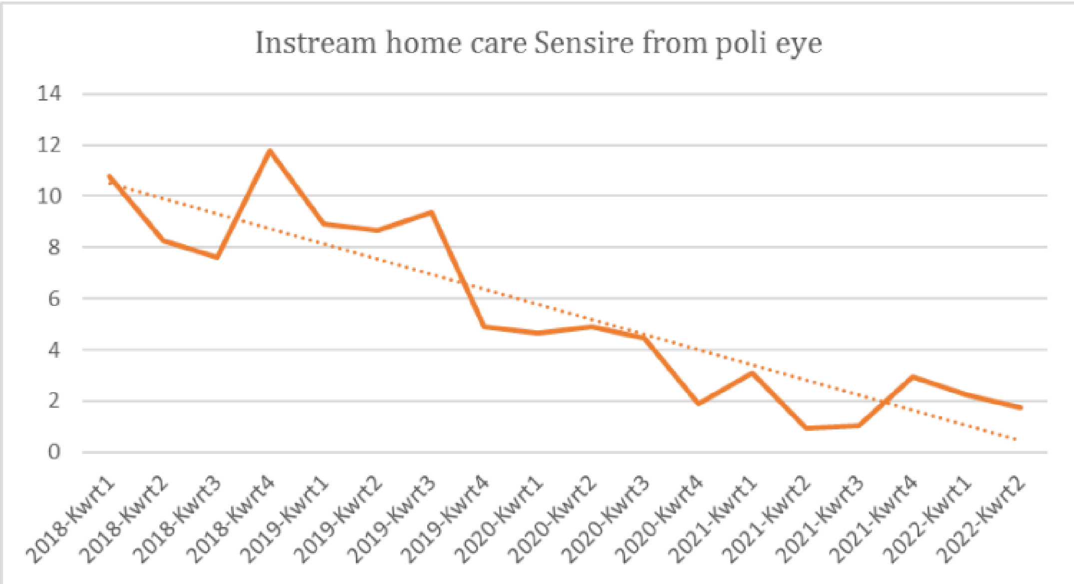
	Without "strategic"	With "strategic"
Google Scholar		
"home care" and "capacity planning" and "demand forecasting".	80	68
PubMed		
"home care" [Title/Abstract] AND "capacity planning" [Title/Abstract]	5	1
"home care" [Title/Abstract] AND "demand forecasting" [Title/Abstract]	1	0

Appendix F-1 Used literature search terms Google Scholar and PubMed

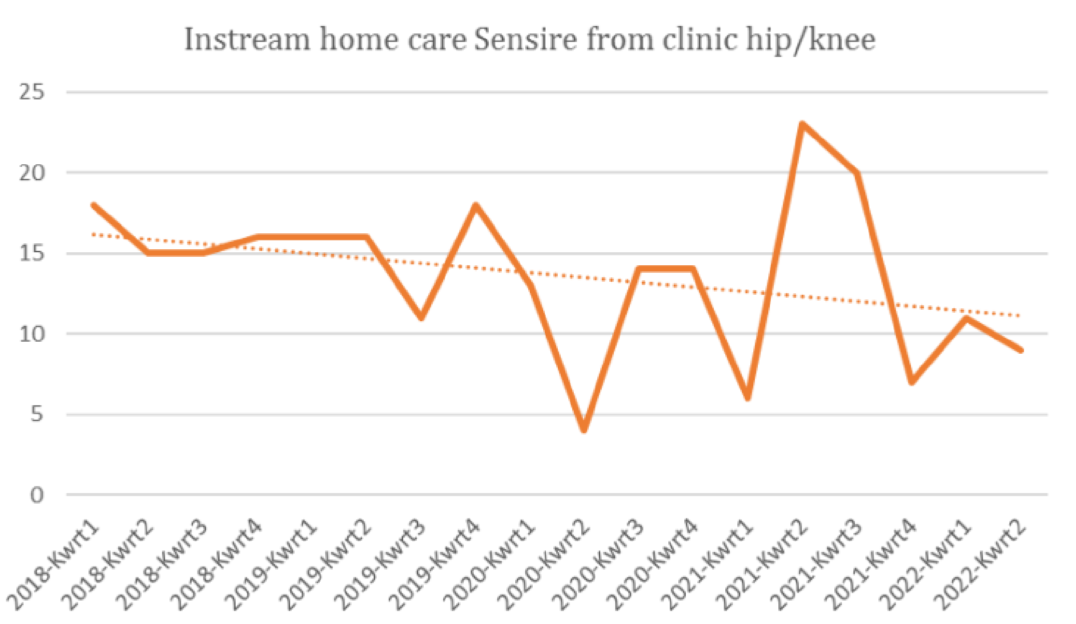
G. Demand characteristics



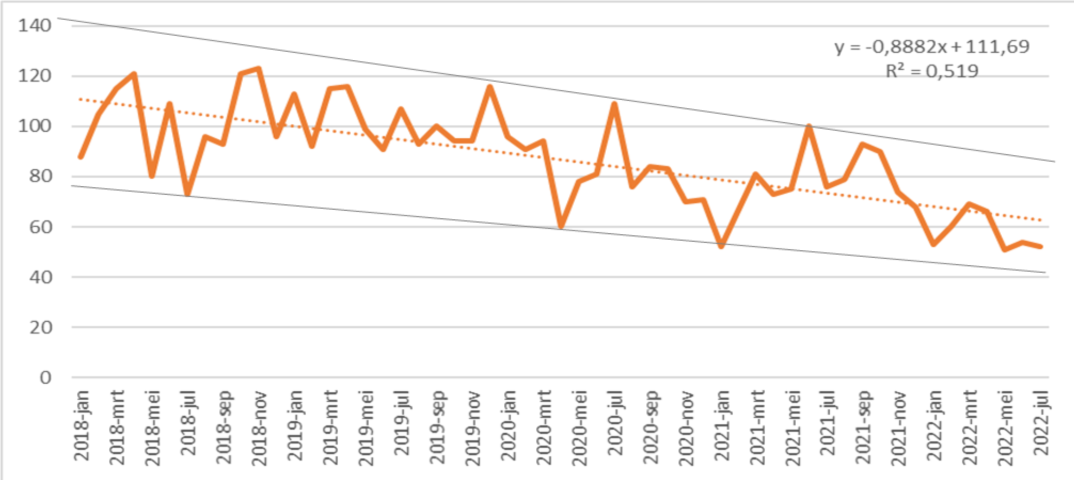
Appendix G-1 Decrease the number of Outpatient Clinic visits



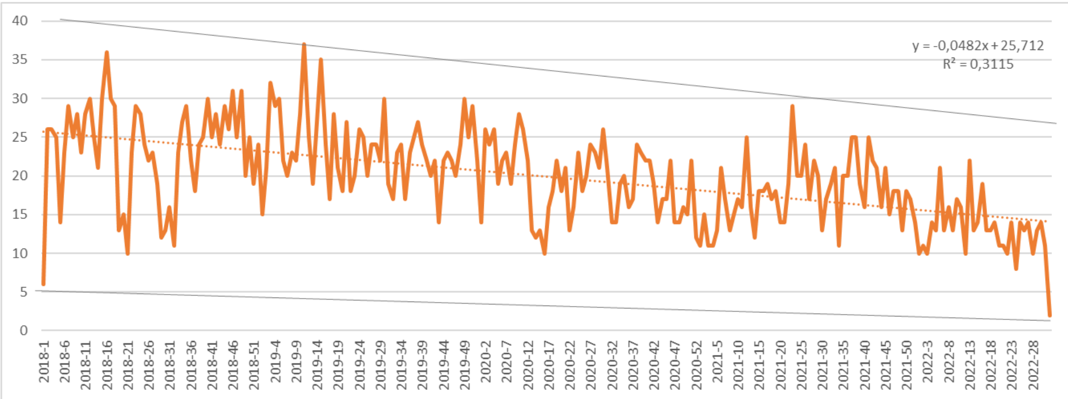
Appendix G-2 Inflow home care from Clinic hip/knee



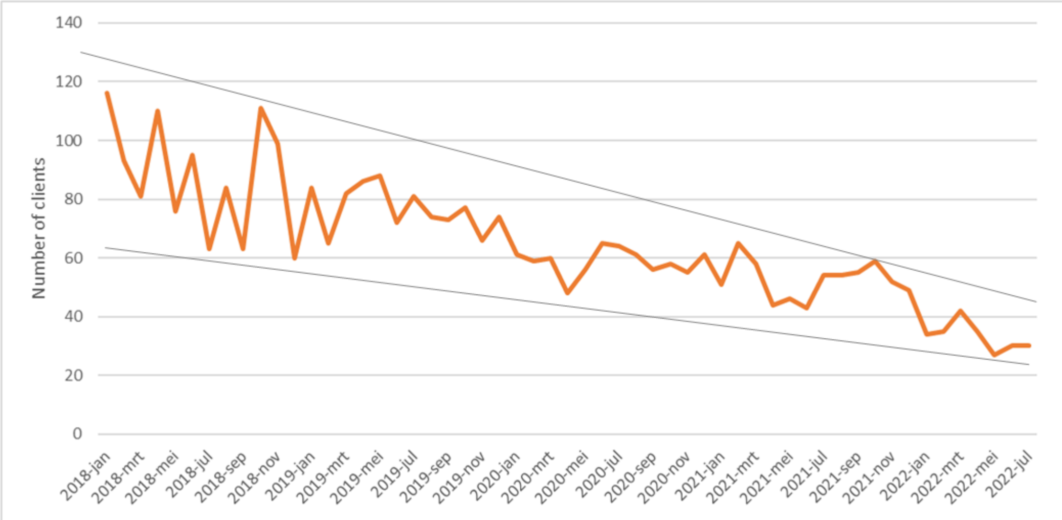
Appendix G-3 Inflow home care from Outpatient Clinic eye



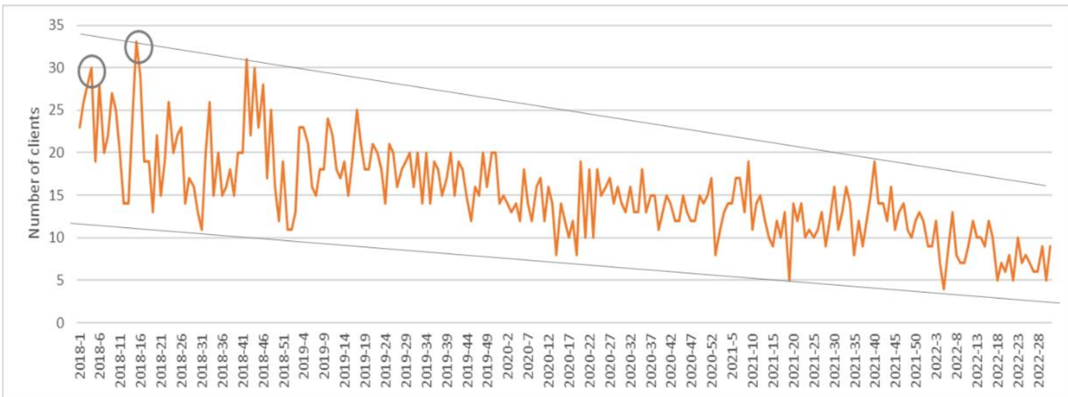
Appendix G-4 Choice for multiplicative classical decomposition monthly observations Clinic



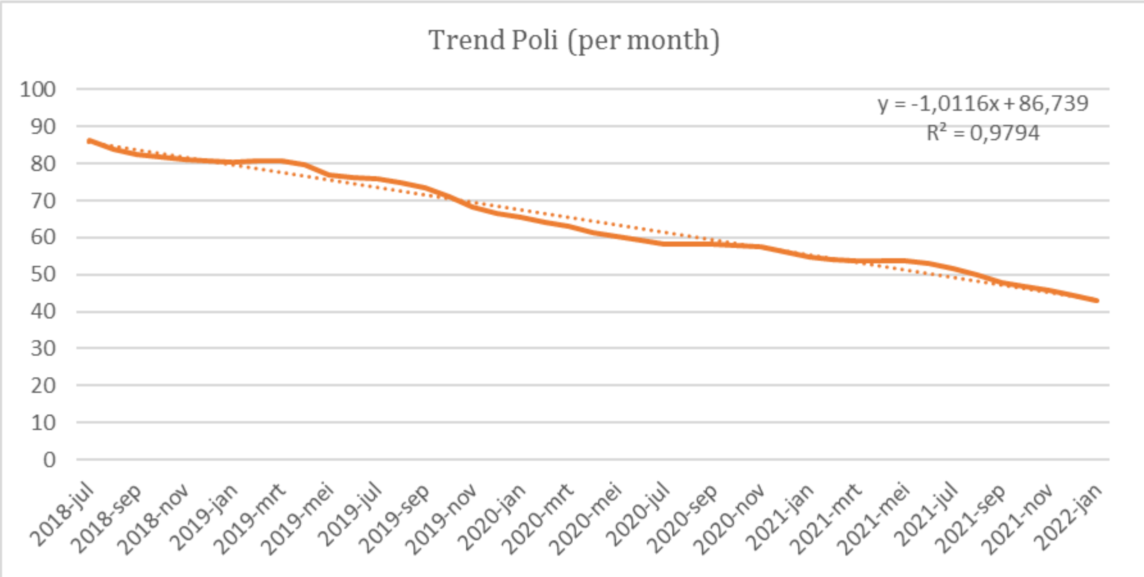
Appendix G-5 Choice for multiplicative classical decomposition weekly observations Clinic



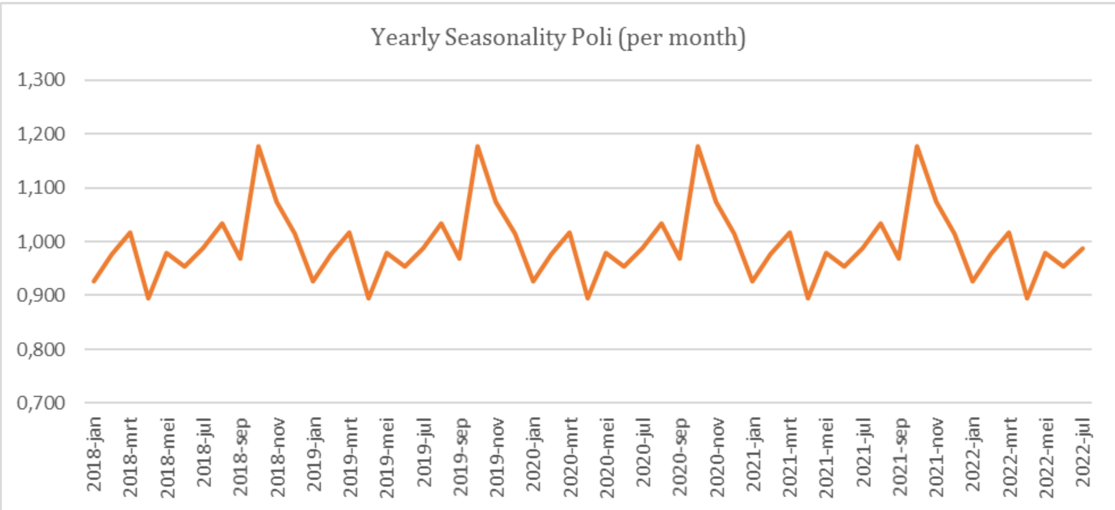
Appendix G-6 Choice for multiplicative classical decomposition Outpatient Clinic monthly observations



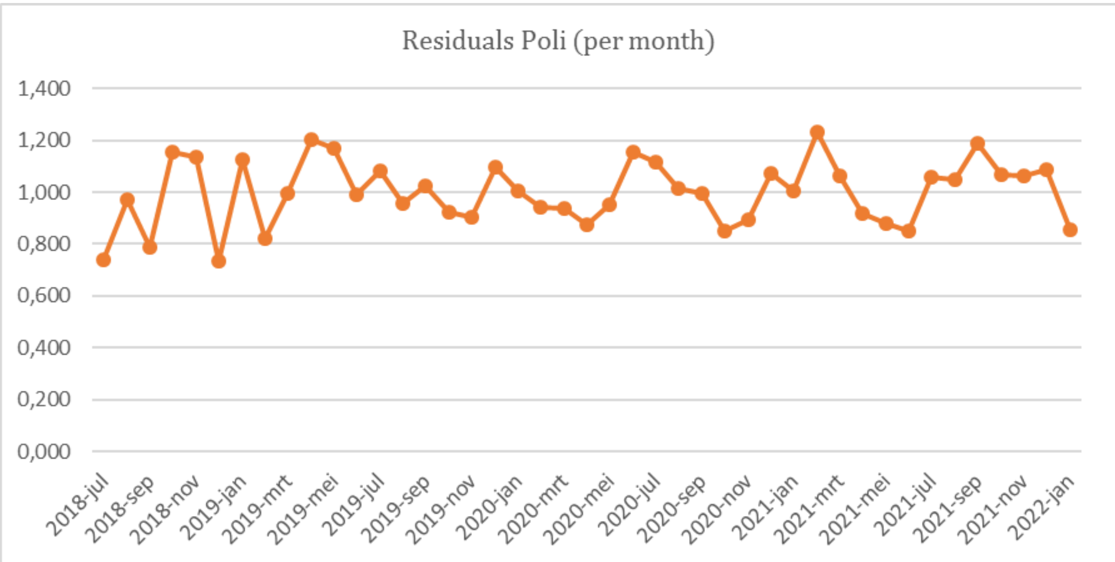
Appendix G-7 Choice for multiplicative classical decomposition Outpatient Clinic weekly observations



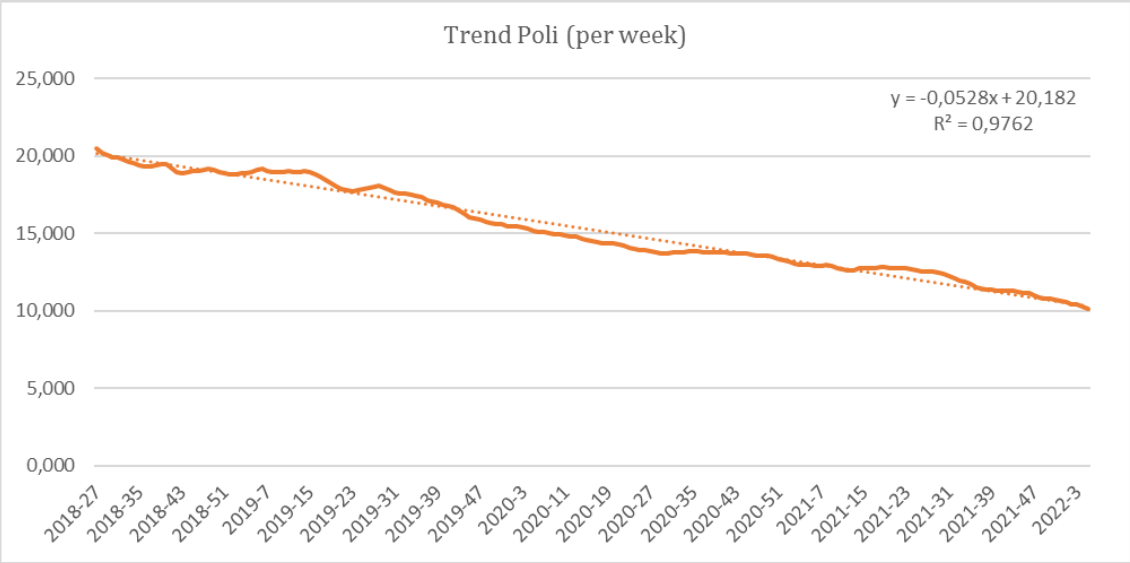
Appendix G-8 Trend demand Outpatient Clinic (Per month)



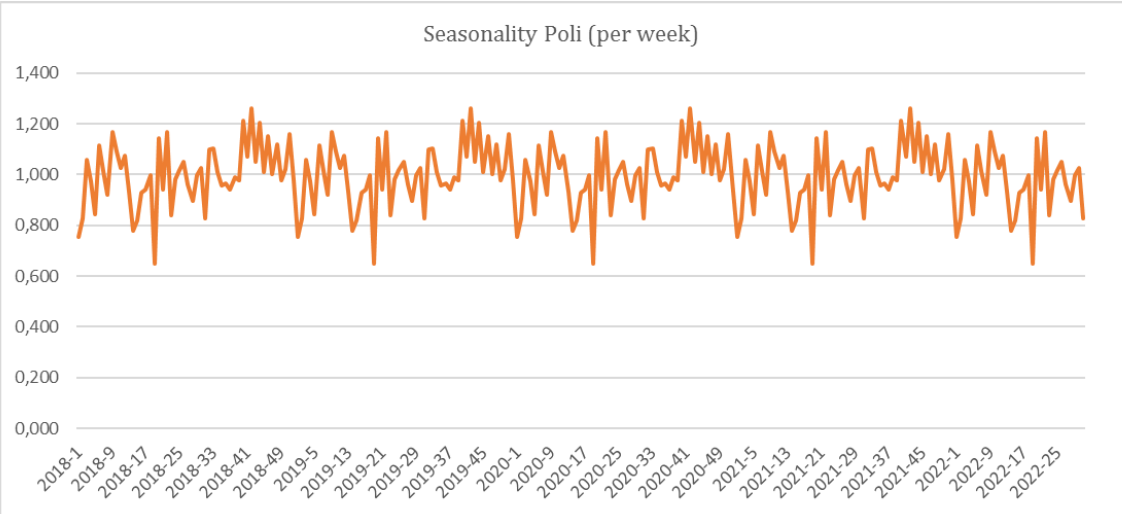
Appendix G-9 Seasonality demand Outpatient Clinic (per month)



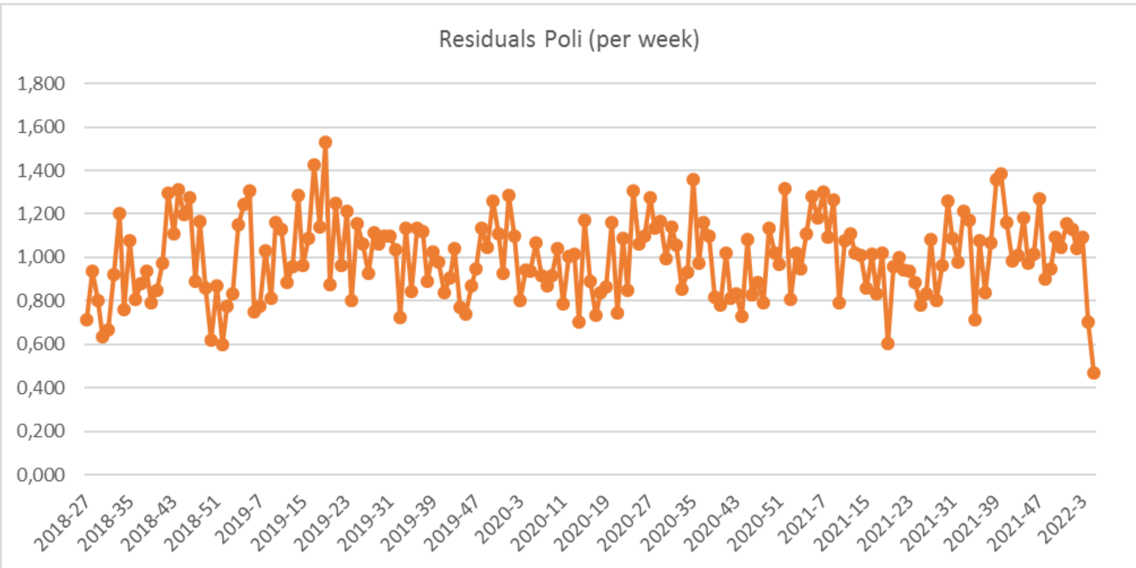
Appendix G-10 Residuals demand Outpatient Clinic (per month)



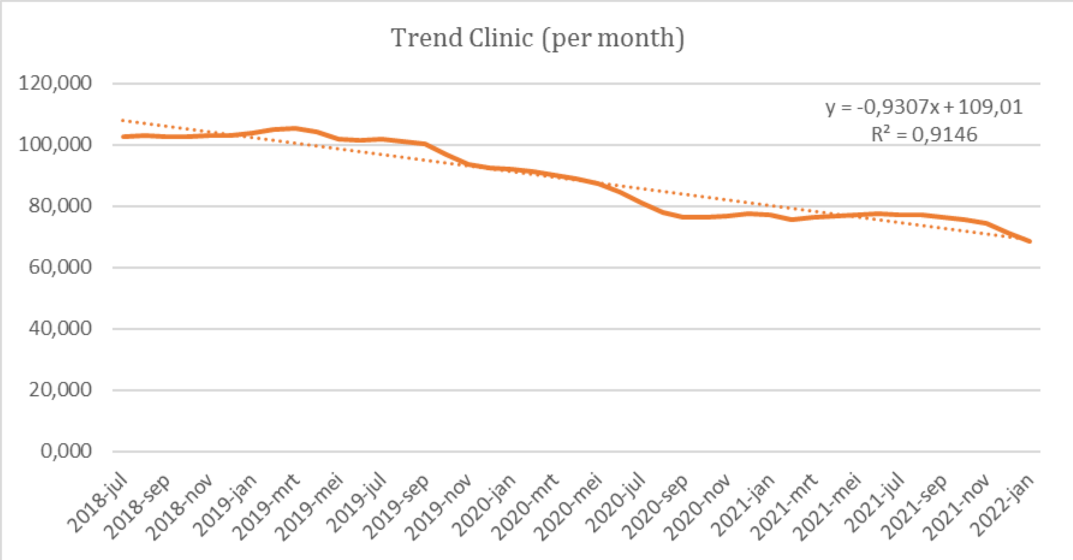
Appendix G-11 Trend demand Outpatient Clinic (per week)



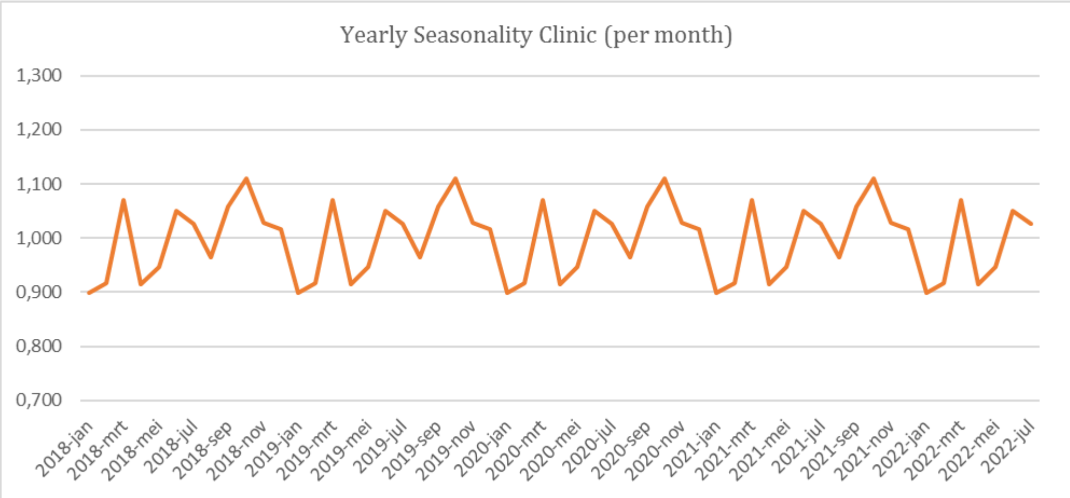
Appendix G-12 Seasonality demand Outpatient Clinic (per week)



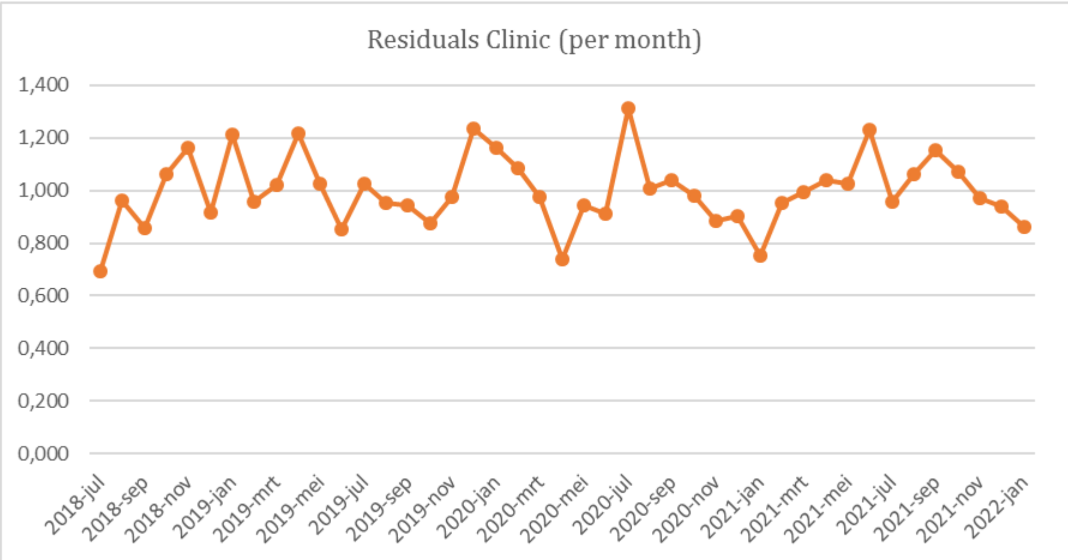
Appendix G-13 Residuals demand Outpatient Clinic (per week)



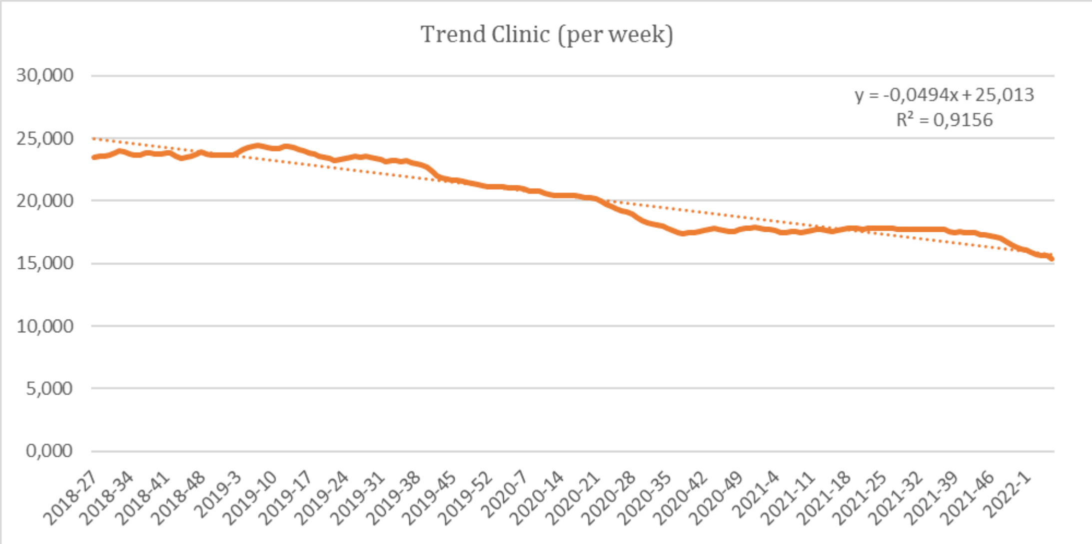
Appendix G-14 Trend demand Clinic (per month)



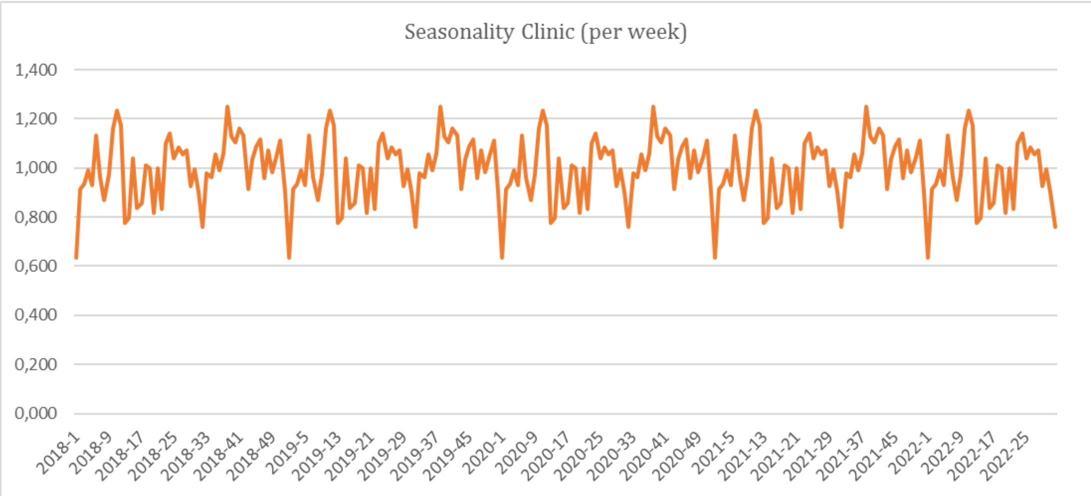
Appendix G-15 Seasonality demand Clinic (per month)



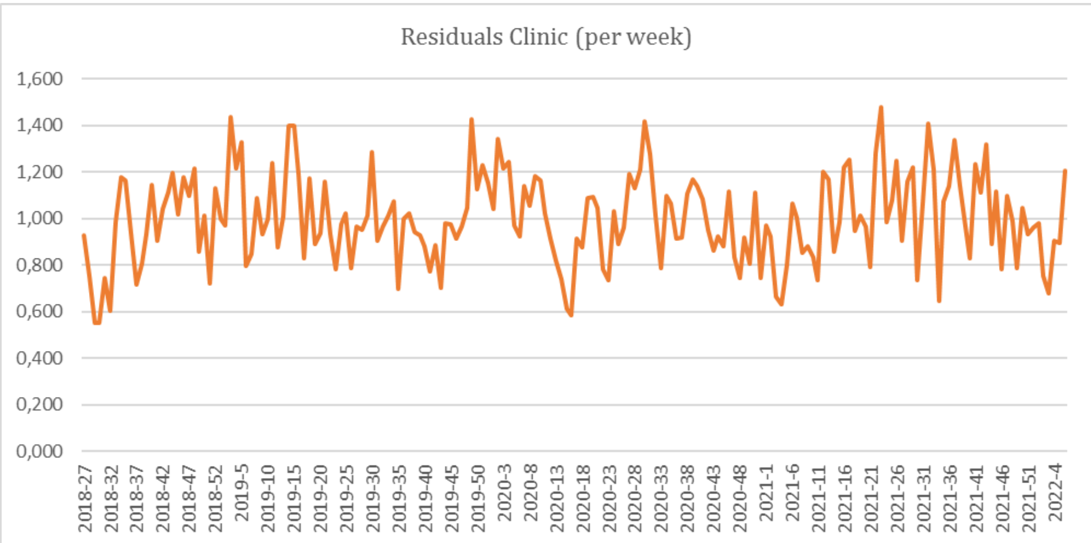
Appendix G-16 Residuals demand clinic (per month)



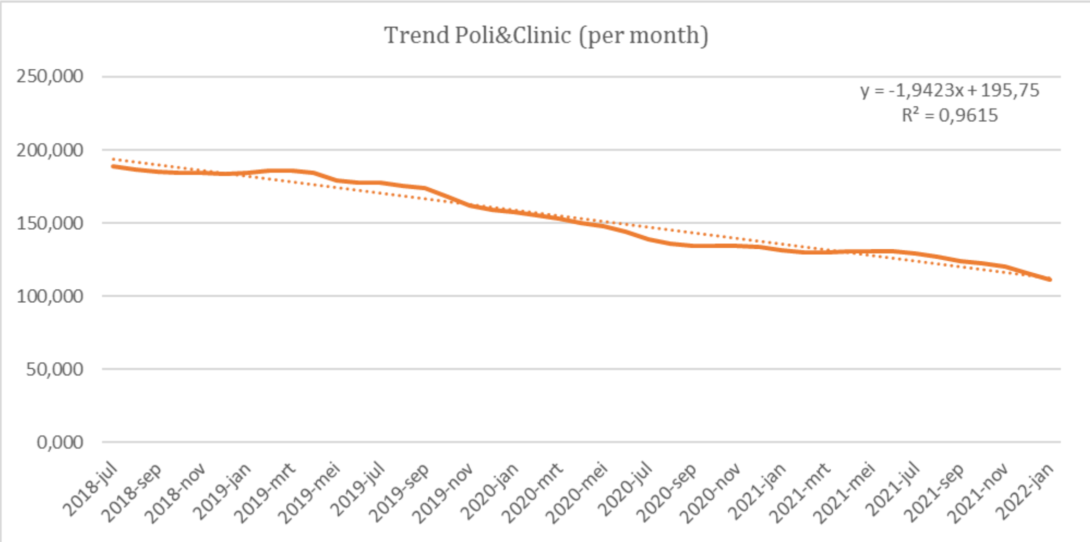
Appendix G-17 Trend demand Clinic (per week)



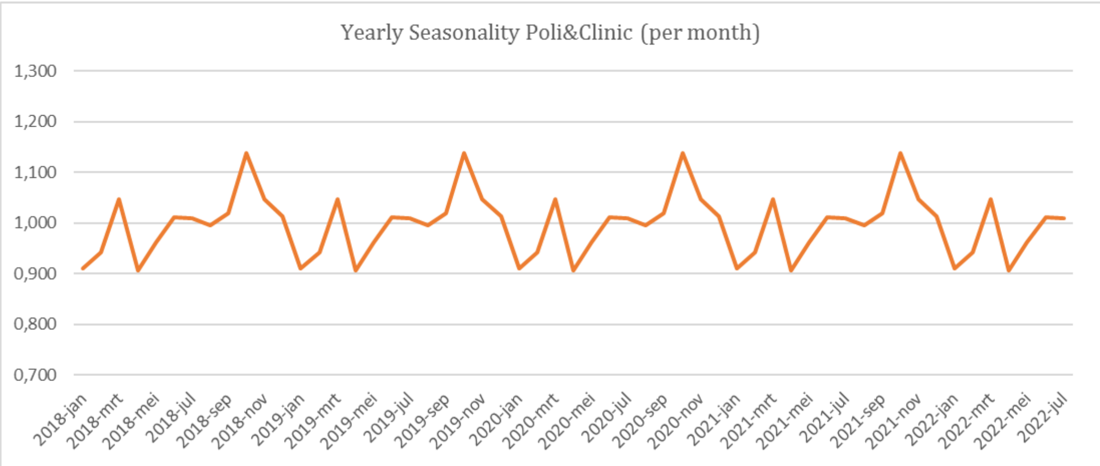
Appendix G-18 Seasonality demand Clinic (per week)



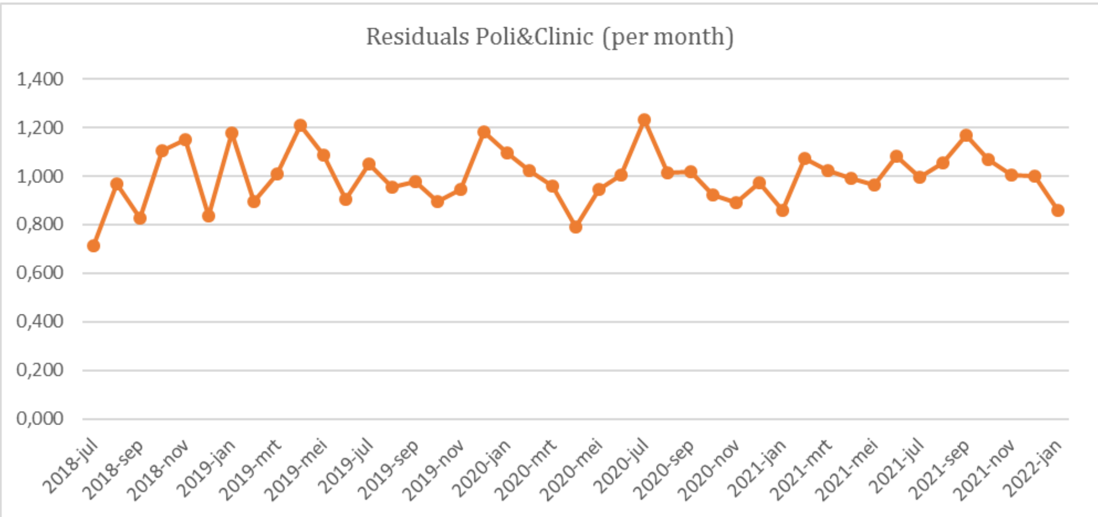
Appendix G-19 Residuals demand Clinic (per week)



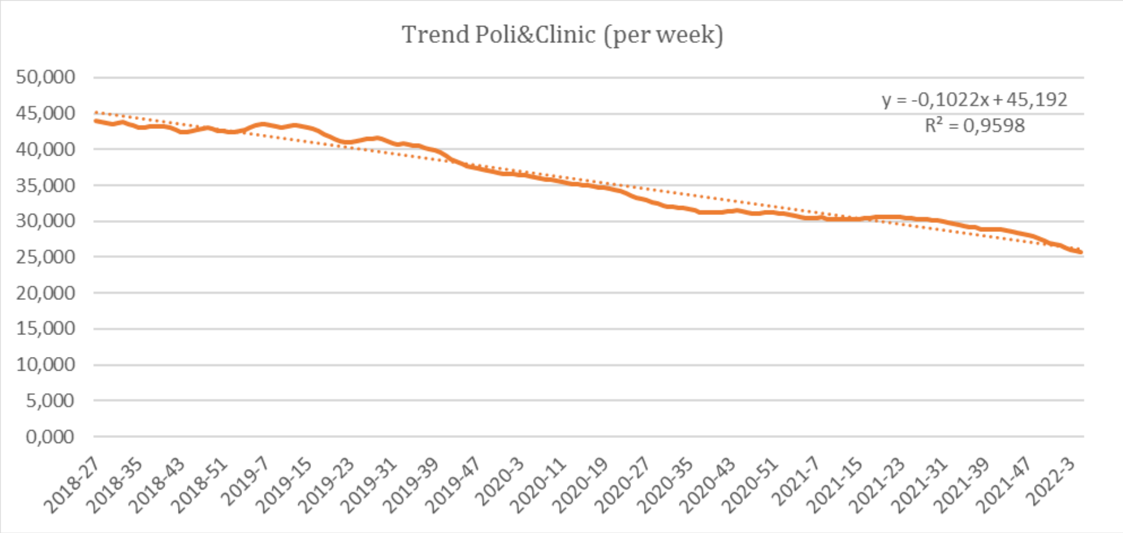
Appendix G-20 Trend demand Outpatient Clinic & Clinic (per month)



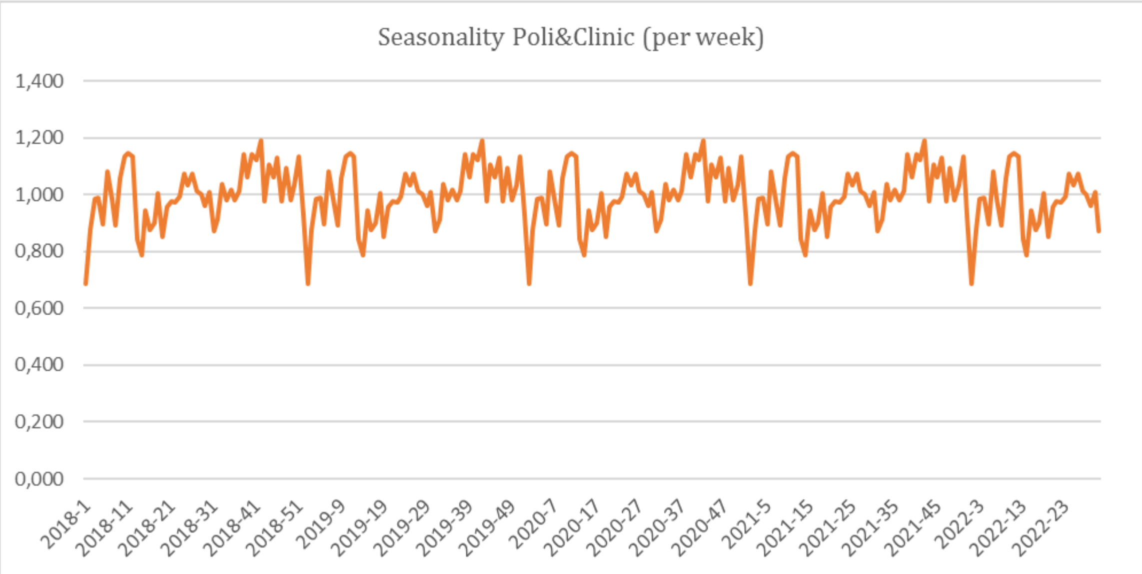
Appendix G-21 Seasonality demand Outpatient Clinic & Clinic (per month)



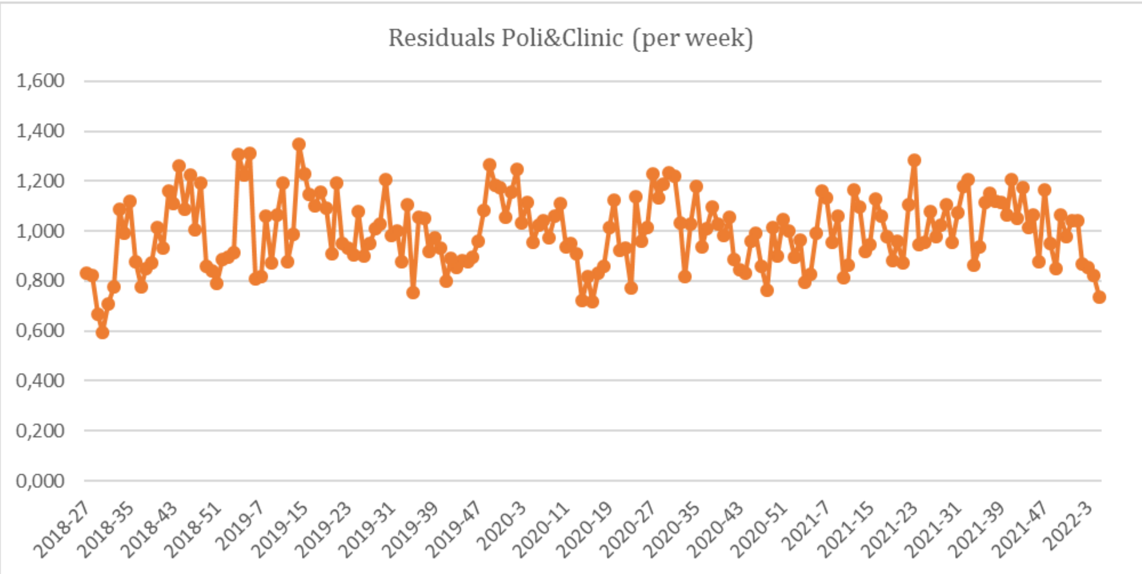
Appendix G-22 Residuals demand Outpatient Clinic & Clinic (per month)



Appendix G-23 Trend demand Outpatient Clinic & Clinic (per week)



Appendix G-24 Seasonality demand Outpatient Clinic & Clinic (per week)



Appendix G-25 Residuals demand Outpatient Clinic & Clinic (per week)

H. Assumptions

Assumptions data analyses

1. The care need analyses consider only the actual, registered care and not the estimations done at the beginning of deploying a care period because these are incorrect and do not even come close to the actual care need.
2. The analyses for the client classification use a very limited dataset.
3. A new care period starts when a patient comes into care and goes out of care again. In this analysis, the patient is considered to be a new patient.
4. The analyses only consider the relevant functions for this research: Carers, Carers IG, Nurses and District Nurses, excluding other functions such as interns.
5. Analyses concerning employees use average Sensire-wide benchmarks for the KPIs. However, the districts have different benchmarks in line with the district's overall performance. Therefore, this analysis only used the average Sensire-wide benchmark for comparison.

Forecast assumptions

6. The out-flow from the Outpatient Clinic of Slingeland to Sensire is 48% based on the 48% of the out-flow identified in the data of the Clinic
7. The 77% recovery patients of the Clinic are assumed based on the 77% recovery care patients identified in the Outpatient Clinic data.
8. Assumed normality for the performance of statistical tests
9. The Low and high scenarios for the refusals are an expectation based on expert knowledge. Therefore they are an assumption on the number of forecasts in the future.
10. A MAPE < 5% is accurate, a MAPE between 5% and 25% is low but acceptable, and a MAPE > 25% is low and not acceptable.
11. Not including the cycle element
12. Normally distribution of forecasting errors

Adjusted convolution model assumptions

13. Probability density functions of the care need (based on data)
14. Cutting off the probability density functions at the max and normalizing these.
15. Establishing the input parameters for the adjusted convolution model (based on data)
16. The normal distribution between the min and max of the prediction interval around the mean of the forecast using the standard error as the standard deviation to calculate the probability for some clients at a designated point in time.
17. Take into account data that covers the entire region of Sensire to maintain as much of the limited data as possible.
18. The level of absenteeism is a constant parameter.
19. Indirect hours are 20% of the hours included as an factor 1.2 over the calculated FTE based on the care need.

I. Forecasting: Classical decomposition

Additative case	Multiplicative case	
$\boldsymbol{M_t = \frac{\frac{Z_{t-\frac{s}{2}}}{2} + \ldots + Z_t + \ldots \frac{Z_{t+\left(\frac{s}{2}\right)}}{2}}{s}}$		Calculate trend-cycle element via moving averages for an even seasonal component s. An even seasonal component means that the number of periods t in a season s is an even number (Also possible for an uneven seasonal component)
$\boldsymbol{T_t = at + b}$		Calculate trend element via linear regression. (a = intercept, b = slope)
$\boldsymbol{r_t = Z_t - M_t}$	$r_t = \frac{Z_t}{M_t}$	Calculate seasonality with irregular fluctuations
$\boldsymbol{S_i = \frac{1}{K}(r_{tn} + r_{tn+N} + \cdots + r_{tn+(K-1)N})}$		Calculate seasonal component
$\boldsymbol{\mu_{S_t} - 2\sigma_{S_t} \leq r_t \leq \mu_{S_t} + 2\sigma_{S_t}}$		Eliminate r_t when placed outside the interval.
$\boldsymbol{\sum_{n=1}^{N} S_n = 0}$	$\sum_{n=1}^{N} S_n = N$	Validate, if validation is not satisfied, recalculate the seasonal component.
$\boldsymbol{xf = \frac{N}{\sum_{n=1}^{N} S_n}}$		Calculate seasonal adjustment
$\boldsymbol{E_t = r_t - S_t}$	$E_t = \frac{r_t}{S_t}$	Calculate irregular fluctuations
$\hat{Z}_t = \boldsymbol{T_t + S_t}$	$\hat{Z}_t = T_t * S_t$	Composes the elements of forecasting $\hat{Z}_t$.

J. Forecasting: Holt-Winters

Additive case		
Initialization		
$\boldsymbol{n_s = Z^* = \frac{1}{s} * \sum_{t=1}^{s} Z_t}$		Level
$\boldsymbol{b_s = 0}$		Trend
$\boldsymbol{f_j = Z_j - Z^*}$	$(j = 1, \dots, s)$	Seasonality
Estimate		
$\boldsymbol{n_t = \alpha * (Z_t - f_{t-s}) + (1 - \alpha) * (n_{t-1} + b_{t-1})}$	$0 \le \alpha \le 1$	Level
$\boldsymbol{b_t = \beta * (n_t - n_{t-1}) + (1 - \beta) * b_{t-1}}$	$0 \le \beta \le 1$	Trend
$\boldsymbol{f_t = \gamma * (Z_t - n_t) + (1 - \gamma) * f_{t-s}}$	$0 \le \gamma \le 1$	Seasonality
Forecast		
$\hat{Z}_{\boldsymbol{t}}(\boldsymbol{k}) = (\boldsymbol{n_t} + \boldsymbol{b_t} * \boldsymbol{k}) + \boldsymbol{f_{t+k-s}}$	$k = 1, 2, \dots, s$	1 season ahead
$\hat{Z}_{\boldsymbol{t}}(\boldsymbol{k}) = (\boldsymbol{n_t} + \boldsymbol{b_t} * \boldsymbol{k}) + \boldsymbol{f_{t+k-2s}}$	$k = s + 1, s + 2, \dots, 2s$	2 seasons ahead
$\hat{Z}_{\boldsymbol{t}}(\boldsymbol{k}) = (\boldsymbol{n_t} + \boldsymbol{b_t} * \boldsymbol{k}) + \boldsymbol{f_{t+k-3s}}$	$k = 2s + 1, \dots, 3s$	3 seasons ahead
Mixed case		
Initialization		
$\boldsymbol{Z^* = \frac{1}{s} * \sum_{t=1}^{s} Z_t}$		Level
$\boldsymbol{b_s = 0}$		Trend
$\boldsymbol{f_j = \frac{Z_j}{Z^*}}$	$(j = 1, \dots, s)$	Seasonality
Estimate		
$\boldsymbol{n_t = \alpha * \left(\frac{Z_t}{f_{t-s}}\right) + (1 - \alpha) * (n_{t-1} + b_{t-1})}$	$0 \le \alpha \le 1$	Level
$\boldsymbol{b_t = \beta * (n_t - n_{t-1}) + (1 - \beta) * b_{t-1}}$	$0 \le \beta \le 1$	Trend
$\boldsymbol{f_t = \gamma * \left(\frac{Z_t}{n_t}\right) + (1 - \gamma) * f_{t-s}}$	$0 \le \gamma \le 1$	Seasonality
Forecast		
$\hat{Z}_{\boldsymbol{t}}(\boldsymbol{k}) = (\boldsymbol{n_t} + \boldsymbol{b_t} * \boldsymbol{k}) * \boldsymbol{f_{t+k-s}}$	$k = 1, 2, \dots, s$	1 season ahead
$\hat{Z}_{\boldsymbol{t}}(\boldsymbol{k}) = (\boldsymbol{n_t} + \boldsymbol{b_t} * \boldsymbol{k}) * \boldsymbol{f_{t+k-2s}}$	$k = s + 1, s + 2, \dots, 2\,s$	2 seasons ahead
$\hat{Z}_{\boldsymbol{t}}(\boldsymbol{k}) = (\boldsymbol{n_t} + \boldsymbol{b_t} * \boldsymbol{k}) + \boldsymbol{f_{t+k-3s}}$	$k = 2s + 1, \dots, 3s$	3 seasons ahead

K. Forecasting: Outliers, accuracy, prediction interval, what-if scenarios

Outliers

1 $Q1 - (1{,}5 * (Q3 - Q1)) \leq observed\ demand\ \leq Q3 + (1{,}5 * (Q3 - Q1))$

2 $-3\ \leq\ \frac{\mu - Z_t}{\sigma}\ \leq 3$

Accuracy measures

Standard statistical measures:

3 $Mean\ Error$: $ME\ =\ \frac{\sum_{t=1}^{n} e_t}{n}$

4 $Mean\ Absolute\ Error$: $MAE\ =\ \frac{\sum_{t=1}^{n} |e_t|}{n}$

5 $Mean\ Squared\ Error$: $MSE\ =\ \frac{\sum_{t=1}^{n} e_t^2}{n}$

Relative measures:

6 $Percentual\ Error$: $PE_t\ =\ \left(\frac{Z_t - \hat{Z}_t}{Z_t}\right) * 100$

7 $Mean\ Percentual\ Error$: $MPE\ =\ \frac{\sum_{t=1}^{n} PE_t}{n}$

8 $Mean\ Absolute\ Percentual\ Error$: $MAPE\ =\ \frac{\sum_{t=1}^{n} |PE_t|}{n}$

Prediction interval

9 $Upper\ and\ lower\ bound$: $\hat{Z}_{\boldsymbol{t}}(k)\ \pm\ z_{\alpha/2} *\ \sigma_k$

Standard deviation errors Holt winters

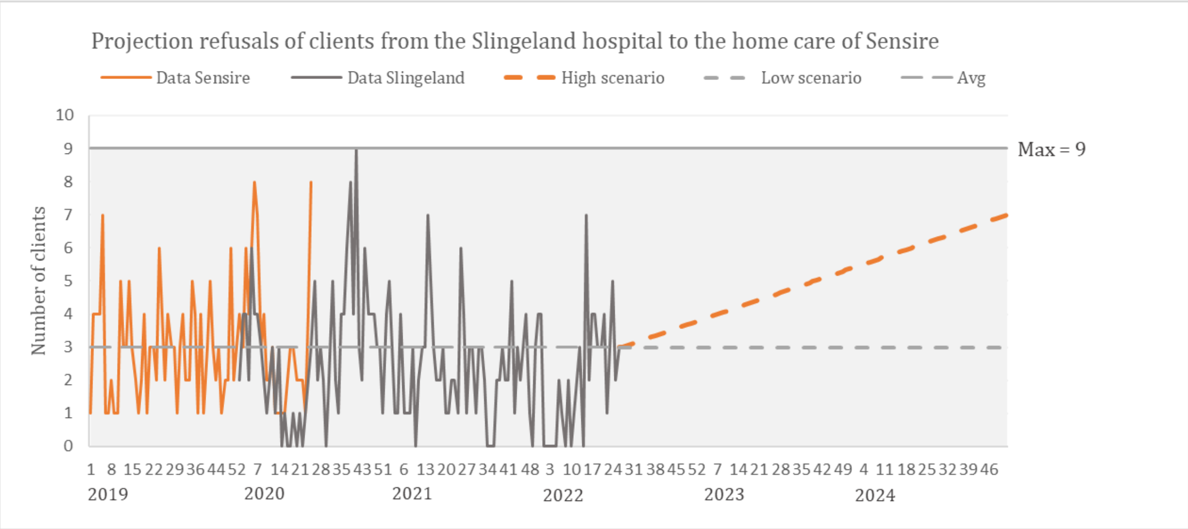
10 $\sigma_k\ =\ \sigma_e *\ \sqrt{1 +\ \sum_{i=1}^{k-1} \mathrm{U}_i^2}$

11 $\mathrm{U}_i\ =\ \alpha(1 + \beta_i)$ $\qquad where\ s \neq i - 1$
$\mathrm{U}_i\ =\ \alpha(1 + \beta_i) +\ \gamma(1 - \alpha)$ $\qquad where\ s = i - 1$

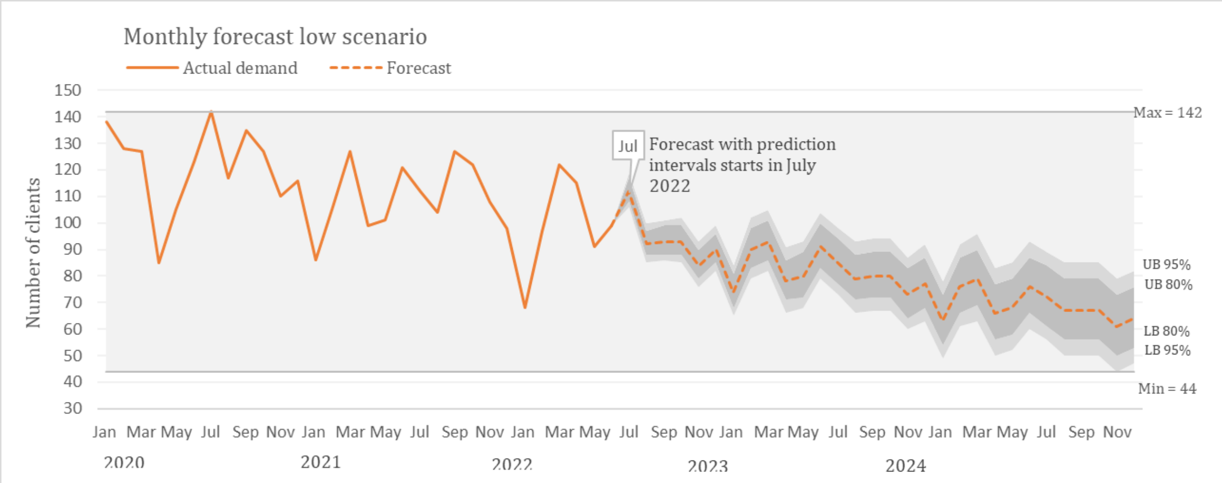
Standard deviation errors Classical Decomposition

12 $\sigma_k\ =\ \sigma_1 *\ \sqrt{k + 1}$

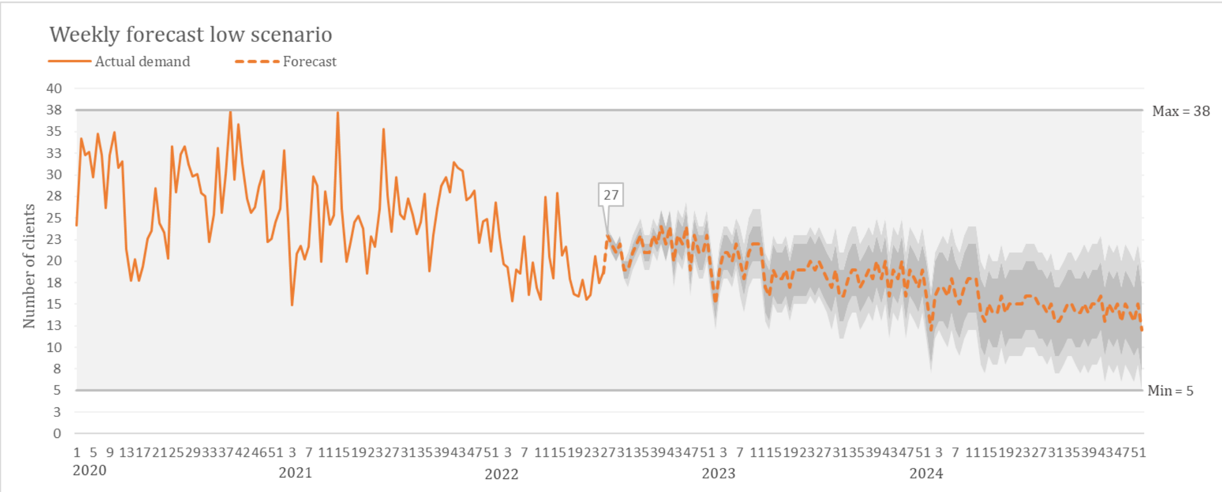
L. Forecasting figures



Appendix L-1 Projection of refusals from the Slingeland hospital to the home care environment of Sensire



Appendix L-2 Monthly forecast LowD



Appendix L-3 Weekly forecast LowD

M. Outlier removal

First off, identifying outliers is necessary to remove the trend from the Outpatient Clinic, Clinic, Outpatient Clinic & Clinic and Refusals. Consequently, Table 0-2 shows the identified outliers. The only true outliers are the 2018-1, 2021-40 observation, and the 2020-40 observation. Therefore, they are removed using the mean of previous and consequent observations. Interesting to observe is that the Corona crisis did not result in significant outliers.

Table 0-2 Outlier identification for the demand

Aggregation level	Demand element	IQR	Z-score
Weekly	Outpatient Clinic	2021-40, 2022-5	2021-40, 2022-5
	Clinic	2018-1, 2021-23	2018-1, 2021-23
	Outpatient Clinic & Clinic	-	-
	Refusals	2020-40	2020-40
Monthly	Outpatient Clinic	-	-
	Clinic	2021-June	-
	Outpatient Clinic & Clinic	-	-
`	Refusals	2020-Sept	-

N. Experimental design forecast

Method	Vertical aggregation	Horizontal aggregation
Classical Decomposition: Additive	Weekly	Outpatient clinic
Classical Decomposition: Additive	Weekly	Clinic
Classical Decomposition: Additive	Weekly	Outpatient clinic & Clinic
Classical Decomposition: Additive	Monthly	Outpatient clinic
Classical Decomposition: Additive	Monthly	Clinic
Classical Decomposition: Additive	Monthly	Outpatient clinic & Clinic
Classical Decomposition: Multiplicative	Weekly	Outpatient clinic
Classical Decomposition: Multiplicative	Weekly	Clinic
Classical Decomposition: Multiplicative	Weekly	Outpatient clinic & Clinic
Classical Decomposition: Multiplicative	Monthly	Outpatient clinic
Classical Decomposition: Multiplicative	Monthly	Clinic
Classical Decomposition: Multiplicative	Monthly	Outpatient clinic & Clinic
Holt-Winters: Additive	Weekly	Outpatient clinic
Holt-Winters: Additive	Weekly	Clinic
Holt-Winters: Additive	Weekly	Outpatient clinic & Clinic
Holt-Winters: Additive	Monthly	Outpatient clinic
Holt-Winters: Additive	Monthly	Clinic
Holt-Winters: Additive	Monthly	Outpatient clinic & Clinic
Holt-Winters: Mixed	Weekly	Outpatient clinic
Holt-Winters: Mixed	Weekly	Clinic
Holt-Winters: Mixed	Weekly	Outpatient clinic & Clinic
Holt-Winters: Mixed	Monthly	Outpatient clinic
Holt-Winters: Mixed	Monthly	Clinic
Holt-Winters: Mixed	Monthly	Outpatient clinic & Clinic
Linear Holt	Weekly	Outpatient clinic
Linear Holt	Weekly	Clinic
Linear Holt	Weekly	Outpatient clinic & Clinic

Linear Holt	Monthly	Outpatient clinic
Linear Holt	Monthly	Clinic
Linear Holt	Monthly	Outpatient clinic & Clinic
Linear	Weekly	Outpatient clinic
Linear	Weekly	Clinic
Linear	Weekly	Outpatient clinic & Clinic
Linear	Monthly	Outpatient clinic
Linear	Monthly	Clinic
Linear	Monthly	Outpatient clinic & Clinic

O. *Experiment Results forecast*

Classical Decomposition

			Accuracy training set					**Accuracy test set**					**Decomposition validity**	
Decomposition	**Vertical aggregation**	**Horizontal aggregation**	**ME**	**MAE**	**MSE**	**MPE**	**MAPE**	**ME2**	**MAE3**	**MSE4**	**MPE5**	**MAPE6**	**Expected value**	**Autocorrelation**
Multiplicative	Weekly	Poli	-0.02	2.03	6.99	-4.38%	16.90%	-0.26097	1.89975	5.186161	-15.73%	32.82%	H1: mu errors <> 1	H1: R1 <> 0 (correlation)
Multiplicative	Weekly	Clinic	-0.01	2.60	11.25	-4.90%	18.01%	1.13	2.83	5.50	-11.36%	25.73%	H0: mu errors = 1	H1: R1 <> 0 (correlation)
Multiplicative	Weekly	Poli&Clinic	0.07	3.79	23.45	-2.64%	13.68%	-0.89	3.79	17.85	-9.39%	21.23%	H0: mu errors = 1	H1: R1 <> 0 (correlation)
Additive	Weekly	Poli	-1.02	2.24	7.78	-13.29%	42.86%	-1.31	2.34	7.87	-31.83%	42.86%	H1: mu errors <> 0	H1: R1 <> 0 (correlation)
Additive	Weekly	Clinic	-0.01	2.61	11.33	-4.98%	18.26%	-0.62	3.01	12.49	-11.83%	27.43%	H0: mu errors = 0	H1: R1 <> 0 (correlation)
Additive	Weekly	Poli&Clinic	0.07	3.85	23.45	-2.69%	14.04%	-1.00	3.92	20.15	-10%	22%	H0: mu errors = 0	H1: R1 <> 0 (correlation)

Holt-Winters: Optimize MAPE test set

Optimized MAPE test set								
			Training set		**Test set**		**Training & Test set**	
Decomposition	**Vertical aggregation**	**Horizontal aggregation**	**MPE**	**MAPE**	**MPE**	**MAPE**	**MPE**	**MAPE**
Multiplicative	Weekly	Poli	-9.40%	26.82%	-40.76%	53.76%	-17.70%	33.96%
Multiplicative	Weekly	Clinic	-11.45%	27.55%	-43.63%	54.90%	-19.98%	34.80%
Multiplicative	Weekly	Poli&Clinic	-7.30%	20.63%	-10.55%	25.08%	-8.16%	21.81%
Multiplicative	Monthly	Poli	-7.62%	19.54%	-3%	17%	-6.48%	18.83%
Multiplicative	Monthly	Clinic	-4.26%	18.89%	4.57%	14.67%	-1.80%	17.71%
Multiplicative	Monthly	Poli&Clinic	-6.97%	16.85%	4.22%	11.54%	-3.84%	15.37%
Additive	Weekly	Poli	-6.33%	28.72%	-30.94%	51.46%	-12.85%	34.75%
Additive	Weekly	Clinic	-3.57%	25.90%	-72.53%	77.05%	-21.84%	39.45%
Additive	Weekly	Poli&Clinic	-4.77%	20.79%	-7%	24%	-5.33%	21.72%
Additive	Monthly	Poli	-7.84%	19.99%	-9.53%	19.57%	-8.31%	19.87%
Additive	Monthly	Clinic	-1.32%	18.40%	-13.30%	25.70%	-4.66%	20.43%
Additive	Monthly	Poli&Clinic	-5.36%	16.54%	-5.50%	17.97%	-5.40%	16.94%

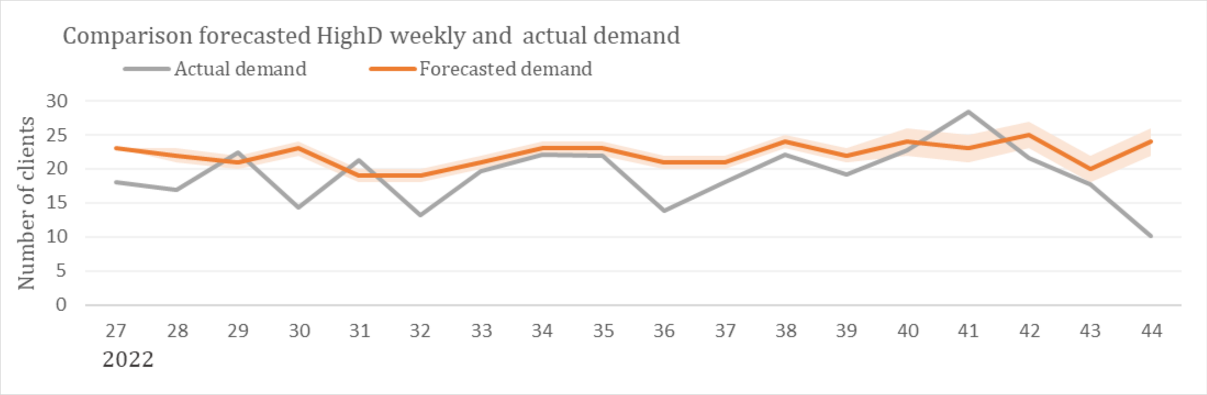
Holt-Winters: Optimize MAPE test & validation set

Optimized MAPE Test & Validation set								
			Training set		**Test set**		**Training & Test set**	
Decomposition	**Vertical aggregation**	**Horizontal aggregation**	**MPE**	**MAPE**	**MPE**	**MAPE**	**MPE**	**MAPE**
Multiplicative	Weekly	Poli	-10.62%	27.98%	4.99%	30.78%	-6.48%	28.72%
Multiplicative	Weekly	Clinic	-14.92%	30.93%	-0.52%	31.41%	-11.10%	31.06%
Multiplicative	Weekly	Poli&Clinic	-9.00%	21.54%	-1.56%	20.50%	-7.03%	21.26%
Multiplicative	Monthly	Poli	-8.55%	19.66%	-4%	16%	-7.24%	18.77%
Multiplicative	Monthly	Clinic	-7.02%	19.37%	5.42%	10.98%	-3.55%	17.03%
Multiplicative	Monthly	Poli&Clinic	-6.73%	16.83%	4.54%	11.50%	-3.59%	15.34%
Additive	Weekly	Poli	-7.20%	29.95%	3.25%	34.36%	-4.43%	31.12%
Additive	Weekly	Clinic	-8.93%	29.20%	3.08%	30.63%	-5.75%	29.58%
Additive	Weekly	Poli&Clinic	-6.65%	21.33%	0%	22%	-4.96%	21.48%
Additive	Monthly	Poli	-8.48%	20.32%	-2.58%	17.34%	-6.83%	19.49%
Additive	Monthly	Clinic	-5.03%	19.92%	3.88%	9.26%	-2.54%	16.95%
Additive	Monthly	Poli&Clinic	-4.89%	16.65%	-2.55%	17.18%	-4.23%	16.80%

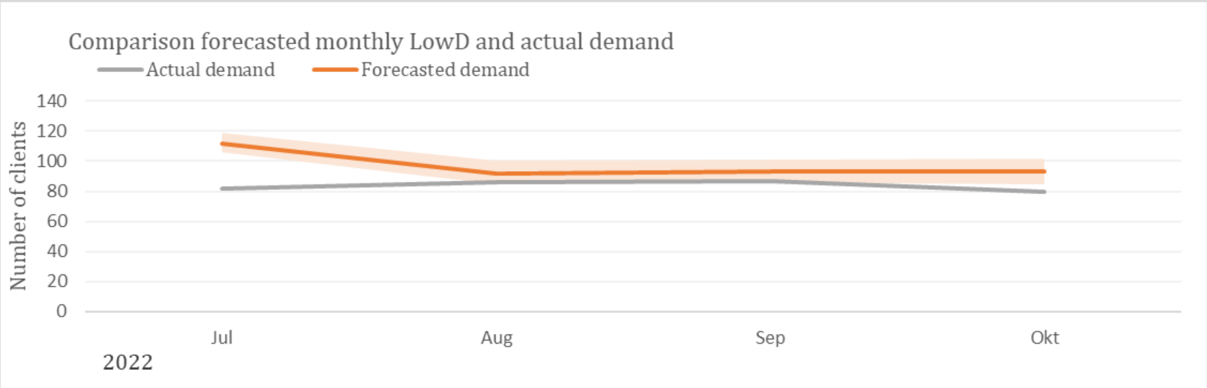
Holt-Winters: Validation of decomposition

			Decomposition validity	
Decomposition	**Vertical aggregation**	**Horizontal aggregation**	**Expected Value**	**Autocorrelation**
Multiplicative	Weekly	Poli	H0: mu errors = 1	H1: R1 <> 0 (No significant correlation)
Multiplicative	Weekly	Clinic	H0: mu errors = 1	H1: R1 <> 0 (No significant correlation)
Multiplicative	Weekly	Poli&Clinic	H0: mu errors = 1	H1: R1 <> 0 (No significant correlation)
Multiplicative	Monthly	Poli	H0: mu errors = 1	H1: R1 <> 0 (No significant correlation)
Multiplicative	Monthly	Clinic	H0: mu errors = 1	H1: R1 <> 0 (No significant correlation)
Multiplicative	Monthly	Poli&Clinic	H0: mu errors = 1	H1: R1 <> 0 (No significant correlation)
Additive	Weekly	Poli	H0: mu errors = 0	H1: R1 <> 0 (No significant correlation)
Additive	Weekly	Clinic	H0: mu errors = 0	H1: R1 <> 0 (No significant correlation)
Additive	Weekly	Poli&Clinic	H0: mu errors = 0	H1: R1 <> 0 (No significant correlation)
Additive	Monthly	Poli	H0: mu errors = 0	H1: R1 <> 0 (No significant correlation)
Additive	Monthly	Clinic	H0: mu errors = 0	H1: R1 <> 0 (No significant correlation)
Additive	Monthly	Poli&Clinic	H0: mu errors = 0	H1: R1 <> 0 (No significant correlation)

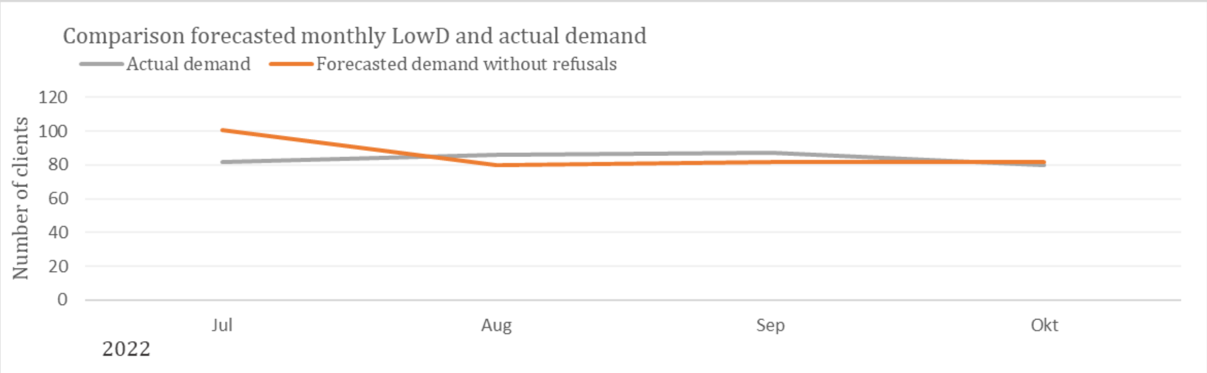
P. Additional validation forecast



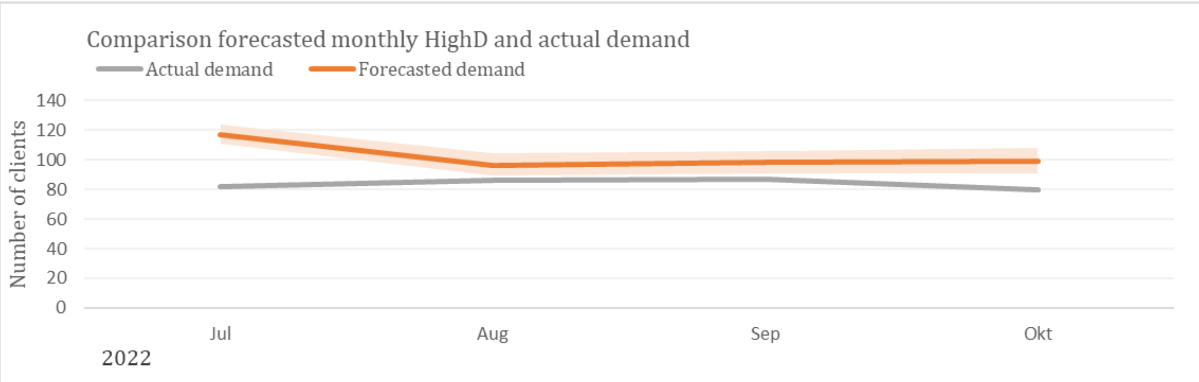
Appendix P-1 Comparison of forecasted demand HighD weekly and actual demand



Appendix P-2 Comparison forecasted monthly LowD and actual demand

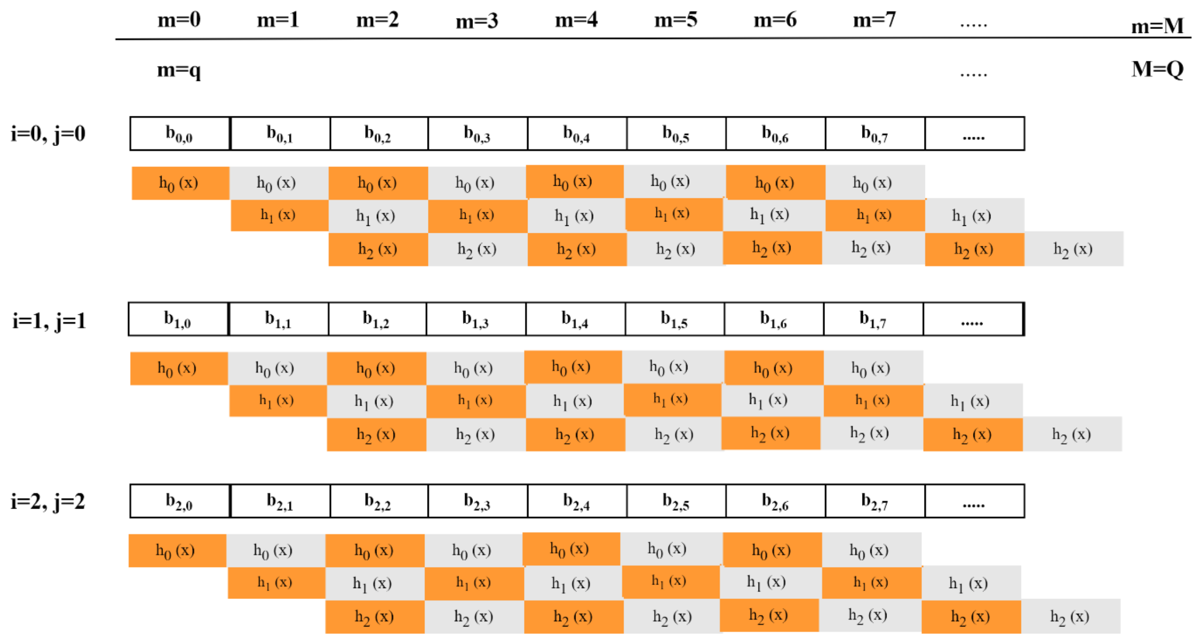


Appendix P-3 Comparison forecasted monthly LowD and Actual demand

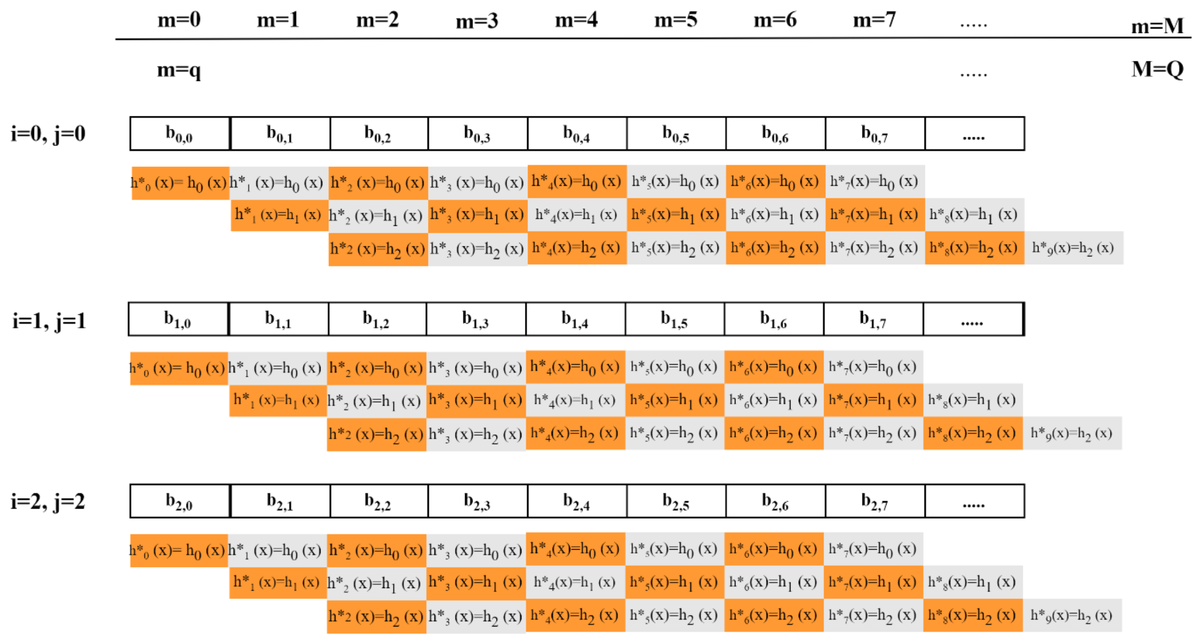


Appendix P-4 Comparison forecasted monthly HighD and actual demand

Q. Adjusted convolution model

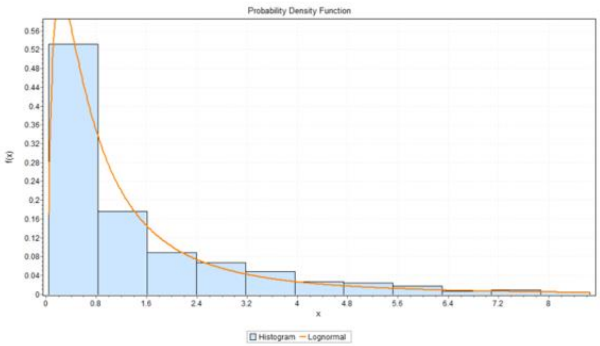


Appendix Q-1 Non-cyclic demand cycle adjusted convolution model



Appendix Q-2 h to h in the non-cyclic demand cycle of the adjusted convolution model*

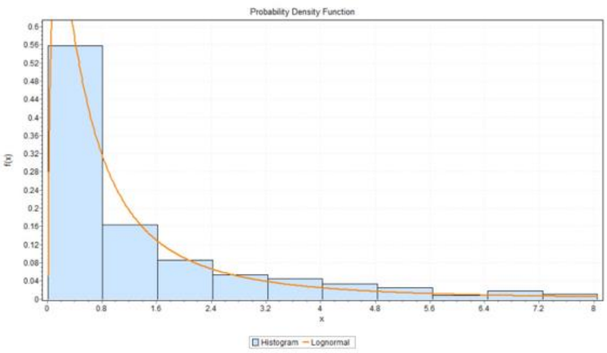
R. Derivation probability distributions for f



Lognormal	σ=1.1252 μ=-0.19739

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	1372 0.04039 0.0221 4				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.02897	0.03302	0.03666	0.04098	0.04398
Reject?	Yes	Yes	Yes	No	No

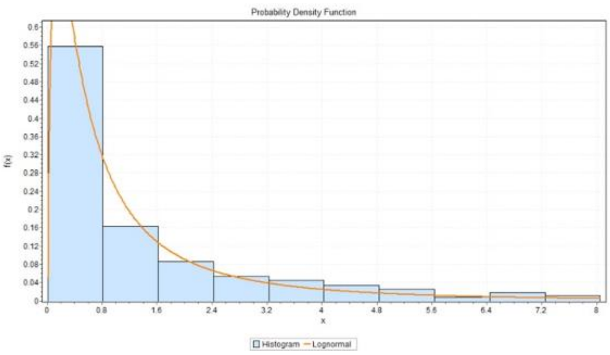
Appendix R-1 monthly aggregation probability distribution f: j=0, n=0



Lognormal	σ=1.2537 μ=-0.34673

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	575 0.03486 0.47621 1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.04475	0.051	0.05663	0.0633	0.06793
Reject?	No	No	No	No	No

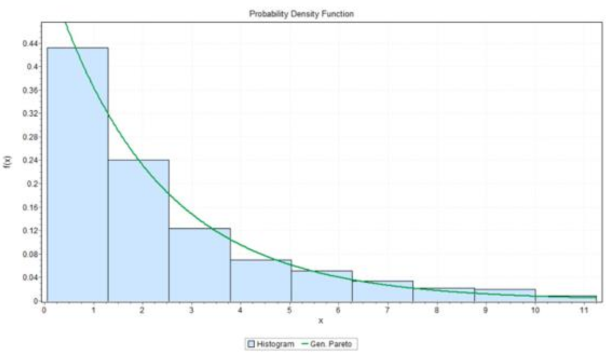
Appendix R-2 monthly aggregation probability distribution f: j=0, n=1



Lognormal	σ=1.2537 μ=-0.34673

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	575 0.03486 0.47621 1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.04475	0.051	0.05663	0.0633	0.06793
Reject?	No	No	No	No	No

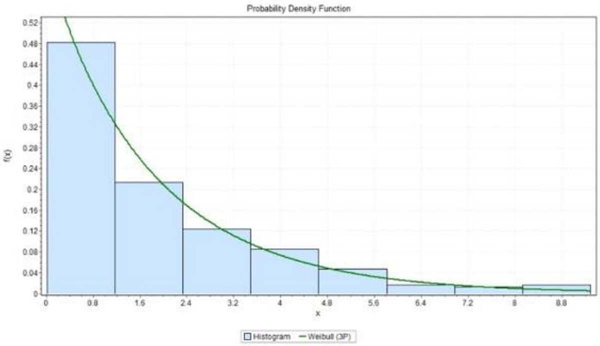
Appendix R-3 monthly aggregation probability distribution f: j=0, n=2



k=0.03095 σ=2.2291 μ=0.06775

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	504 0.0427 0.30828 3				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.0478	0.05448	0.06049	0.06762	0.07256
Reject?	No	No	No	No	No

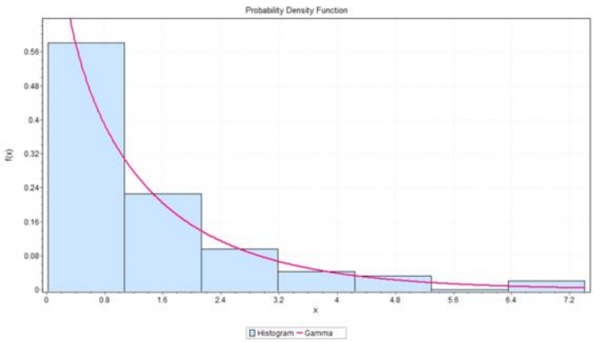
Appendix R-4monthly aggregation probability distribution f: j=1, n=0



α=0.97673 β=1.8744 γ=0.01006

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	234 0.03591 0.91272 6				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.07014	0.07995	0.08878	0.09923	0.10649
Reject?	No	No	No	No	No

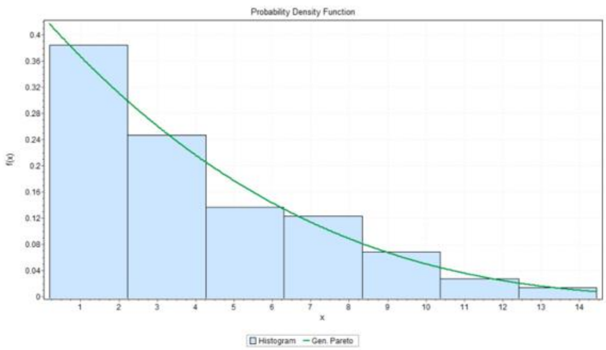
Appendix R-5 monthly aggregation probability distribution f: j=1, n=1



α=0.77 β=1.6535

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	93 0.04921 0.96973 1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.10947	0.12506	0.13891	0.15533	0.16666
Reject?	No	No	No	No	No

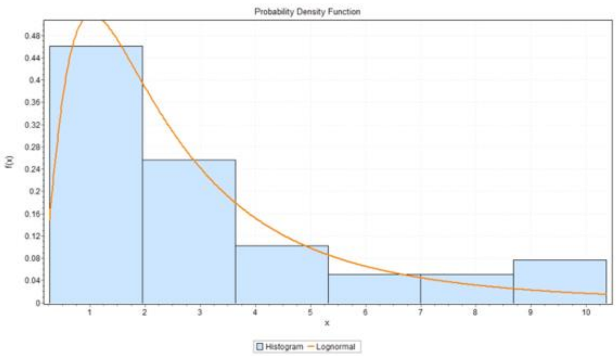
Appendix R-6 monthly aggregation probability distribution f: j=1, n=2



k=-0.25226 σ=4.8533 μ=0.13934

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	73 0.03638 0.99992 1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.12329	0.14087	0.15649	0.17498	0.18776
Reject?	No	No	No	No	No

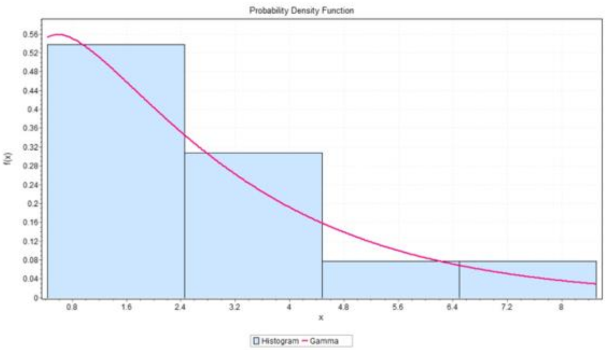
Appendix R-7 monthly aggregation probability distribution f: j=2, n=0



σ=0.86317 μ=0.78031

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	39 0.0721 0.97842 7				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.16753	0.19148	0.21273	0.23786	0.25518
Reject?	No	No	No	No	No

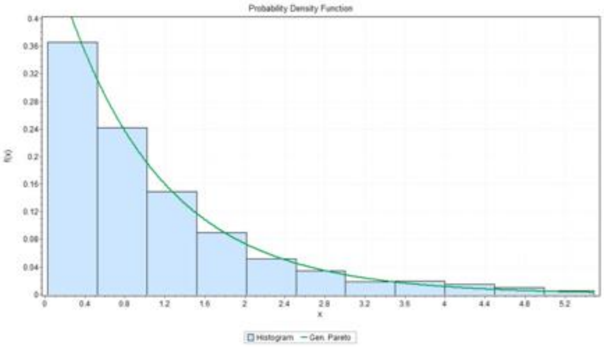
Appendix R-8 monthly aggregation probability distribution f: j=2, n=1



α=1.2736 β=2.1398

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	13 0.10124 0.99729 2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.2847	0.32549	0.36143	0.40362	0.43247
Reject?	No	No	No	No	No

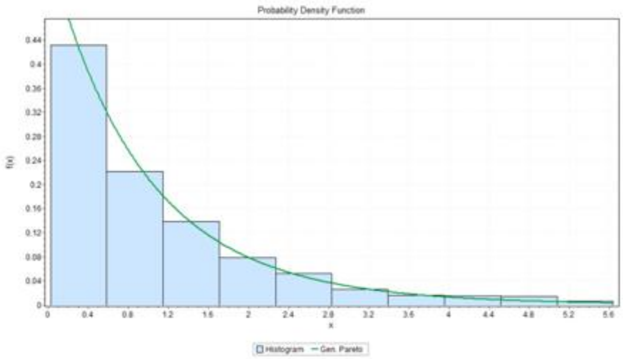
Appendix R-9 monthly aggregation probability distribution f: j=2, n=2



k=0.01977 σ=1.0201 μ=0.07377

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	1368 0.03591 0.05732 5				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.02901	0.03307	0.03672	0.04104	0.04404
Reject?	Yes	Yes	No	No	No

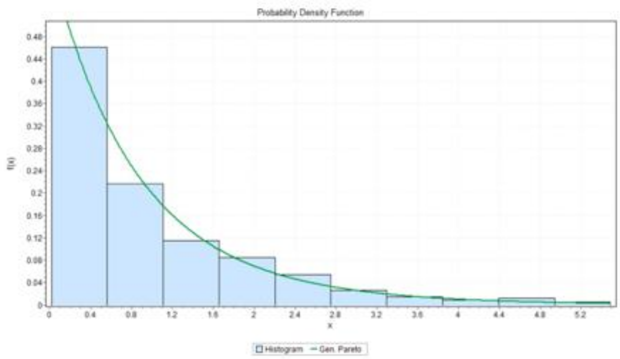
Appendix R-10 weekly aggregation probability distribution f: j=0, n=0



k=0.0521 σ=0.99512 μ=0.04227

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	953 0.0326 0.25758 2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.03476	0.03962	0.04399	0.04917	0.05277
Reject?	No	No	No	No	No

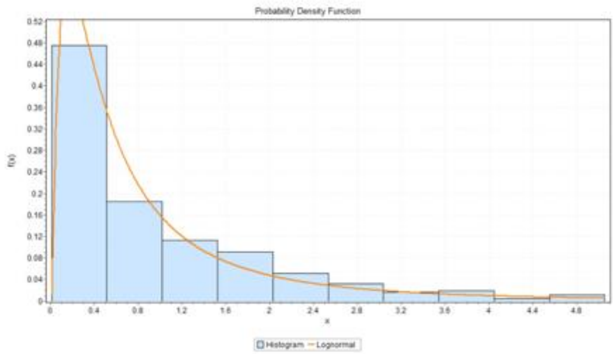
Appendix R-11 weekly aggregation probability distribution f: j=0, n=1



k=0.06777 σ=0.91371 μ=0.02523

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	830 0.04148 0.11185 3				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.03724	0.04245	0.04714	0.05269	0.05654
Reject?	Yes	No	No	No	No

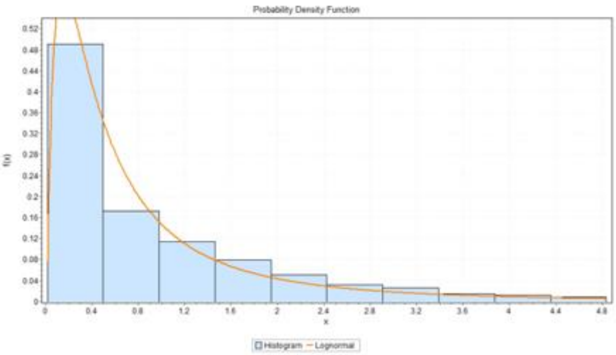
Appendix R-12 weekly aggregation probability distribution f: j=0, n=2



σ=1.1097 μ=-0.57199

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	681 0.05072 0.05808 3				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.04112	0.04687	0.05204	0.05817	0.06242
Reject?	Yes	Yes	No	No	No

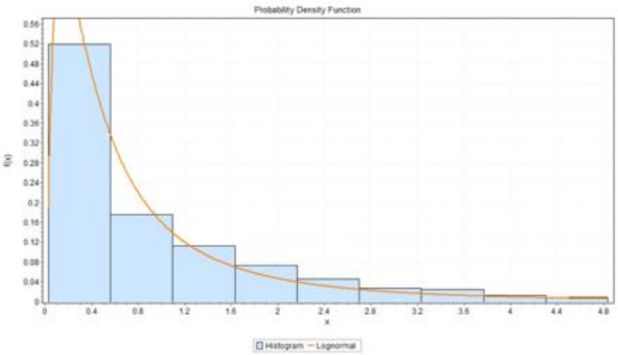
Appendix R-13 weekly aggregation probability distribution f: j=0, n=3



σ=1.1195 μ=-0.62412

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	570 0.0539 0.07024 5				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.04494	0.05123	0.05688	0.06358	0.06823
Reject?	Yes	Yes	No	No	No

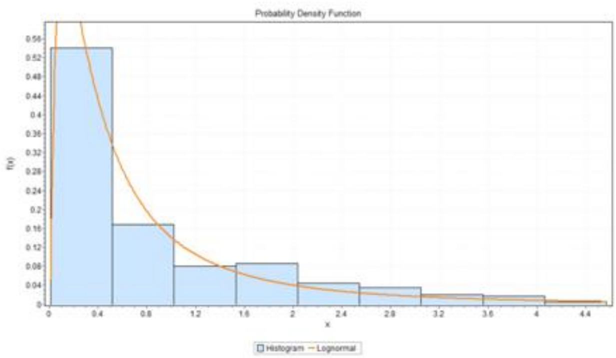
Appendix R-14 weekly aggregation probability distribution f: j=0, n=4



σ=1.1313 μ=-0.65087

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	479 0.0609 0.05493 8				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.04903	0.05588	0.06205	0.06936	0.07443
Reject?	Yes	Yes	No	No	No

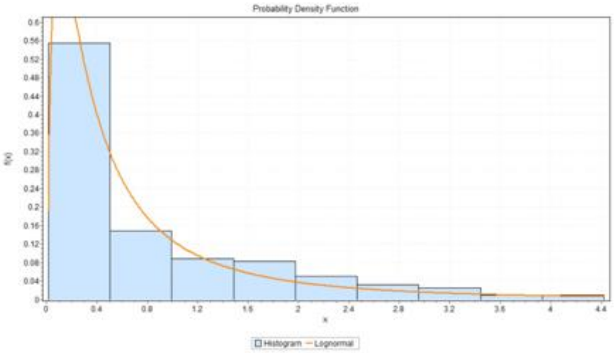
Appendix R-15 weekly aggregation probability distribution f: j=0, n=5



σ=1.159 μ=-0.75186

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	397 0.06013 0.10878 5				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.05385	0.06138	0.06816	0.07619	0.08176
Reject?	Yes	No	No	No	No

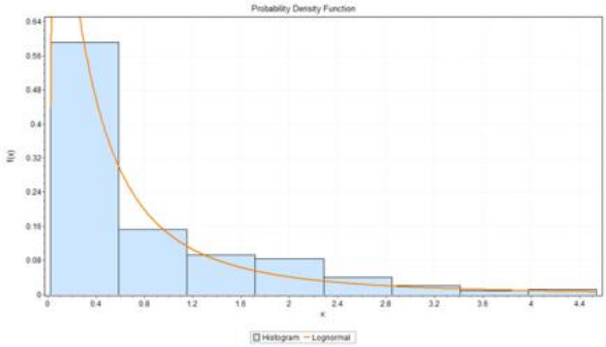
Appendix R-16 weekly aggregation probability distribution f: j=0, n=6



σ=1.2155 μ=-0.83055

Kolmogorov-Smirnov					
Sample Size	317				
Statistic	0.07332				
P-Value	0.06294				
Rank	6				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.06027	0.06869	0.07627	0.08526	0.09149
Reject?	Yes	Yes	No	No	No

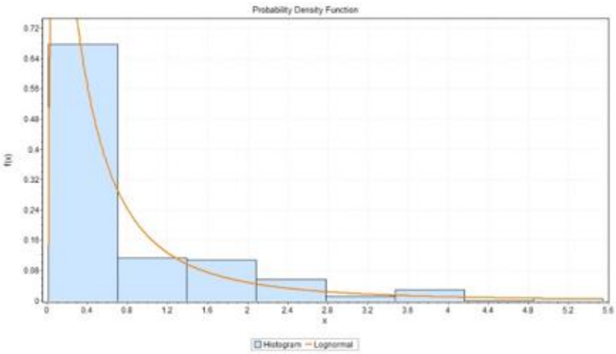
Appendix R-17 weekly aggregation probability distribution f: j=0, n=7



σ=1.2282 μ=-0.88072

Kolmogorov-Smirnov					
Sample Size	250				
Statistic	0.07076				
P-Value	0.15591				
Rank	7				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.06786	0.07735	0.08589	0.09601	0.10303
Reject?	Yes	No	No	No	No

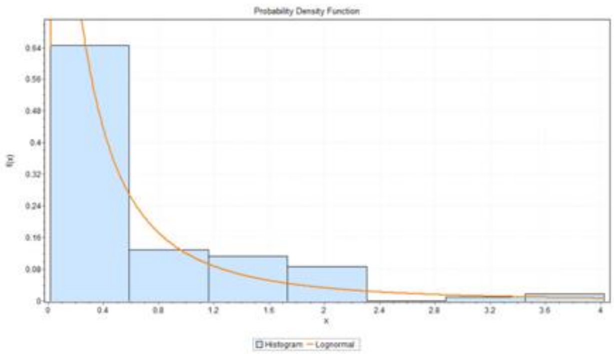
Appendix R-18 weekly aggregation probability distribution f: j=0, n=8



σ=1.2165 μ=-0.91301

Kolmogorov-Smirnov					
Sample Size	177				
Statistic	0.06713				
P-Value	0.38531				
Rank	2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.08065	0.09193	0.10207	0.1141	0.12244
Reject?	No	No	No	No	No

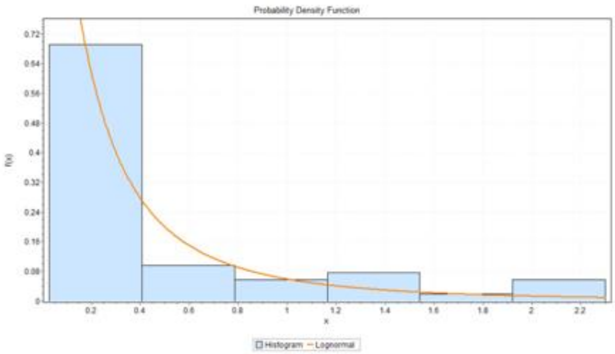
Appendix R-19 weekly aggregation probability distribution f: j=0, n=9



σ=1.2974 μ=-1.1416

Kolmogorov-Smirnov					
Sample Size	116				
Statistic	0.08358				
P-Value	0.37195				
Rank	8				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.09963	0.11355	0.12609	0.14094	0.15125
Reject?	No	No	No	No	No

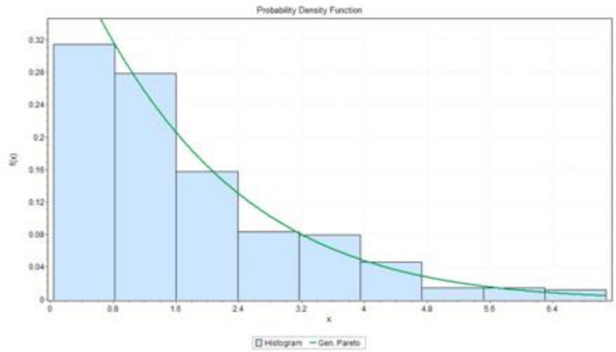
Appendix R-20 weekly aggregation probability distribution f: j=0, n=10



σ=1.2197 μ=-1.4921

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	52 0.13039 0.31198 22				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.14558	0.16637	0.18482	0.20667	0.22174
Reject?	No	No	No	No	No

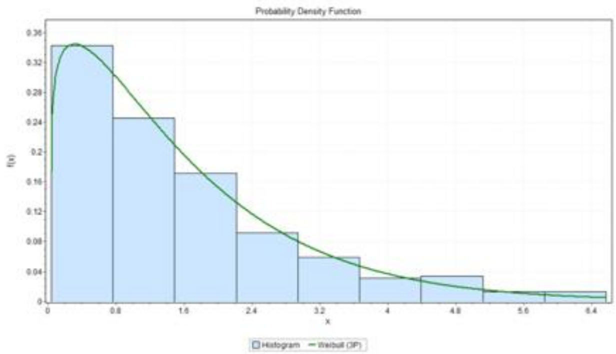
Appendix R-21 weekly aggregation probability distribution f: j=0, n=11



k=-0.11239 σ=1.7558 μ=0.14305

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	502 0.03051 0.72637 4				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.04789	0.05459	0.06061	0.06775	0.07271
Reject?	No	No	No	No	No

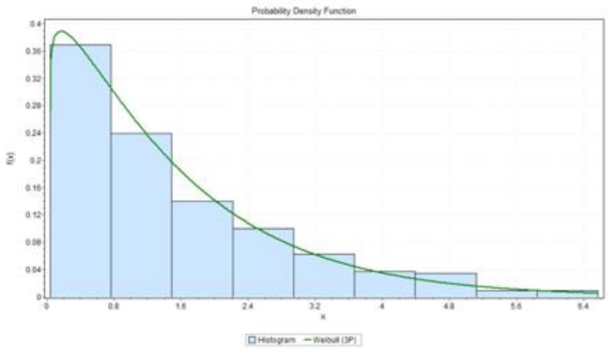
Appendix R-22 weekly aggregation probability distribution f: j=1, n=0



α=1.1495 β=1.6336 γ=0.03337

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	391 0.02495 0.96301 2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.05426	0.06185	0.06868	0.07677	0.08238
Reject?	No	No	No	No	No

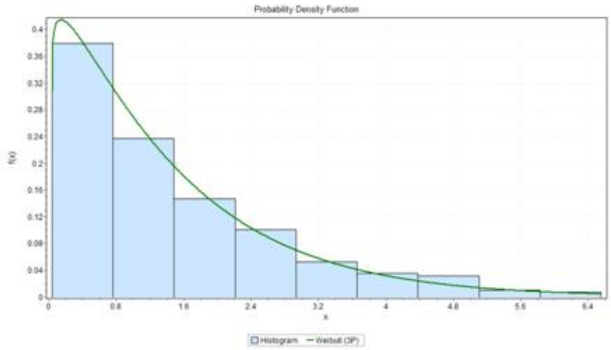
Appendix R-23 weekly aggregation probability distribution f: j=1, n=1



α=1.0767 β=1.5508 γ=0.03402

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	322 0.02872 0.94623 5				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.0598	0.06816	0.07568	0.08459	0.09078
Reject?	No	No	No	No	No

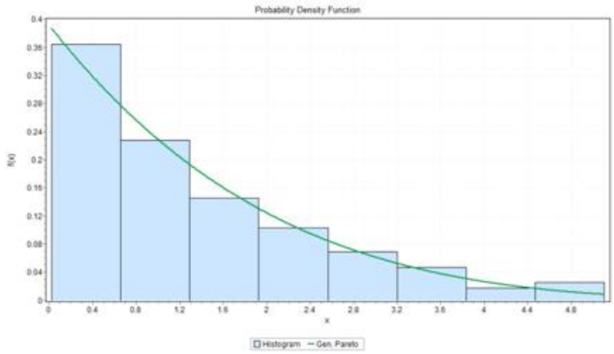
Appendix R-24 weekly aggregation probability distribution f: j=1, n=2



α=1.0658 β=1.4733 γ=0.03408

Kolmogorov-Smirnov					
Sample Size	287				
Statistic	0.02301				
P-Value	0.99728				
Rank	3				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.06334	0.07219	0.08016	0.0896	0.09616
Reject?	No	No	No	No	No

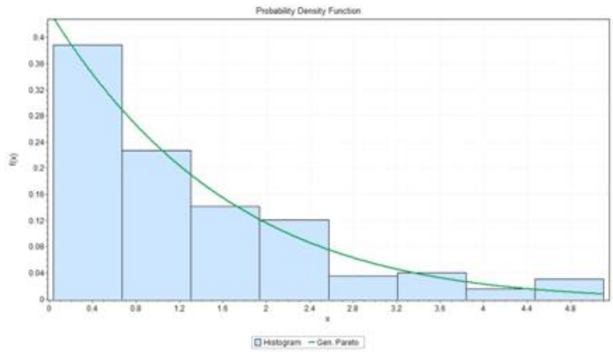
Appendix R-25 weekly aggregation probability distribution f: j=1, n=3



k=-0.18451 σ=1.6162 μ=-0.00743

Kolmogorov-Smirnov					
Sample Size	233				
Statistic	0.0306				
P-Value	0.97657				
Rank	2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.07029	0.08012	0.08897	0.09945	0.10672
Reject?	No	No	No	No	No

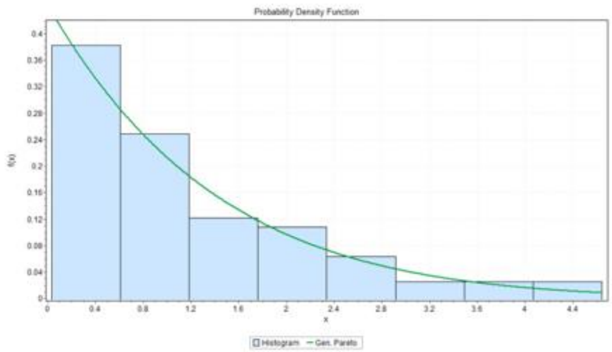
Appendix R-26 weekly aggregation probability distribution f: j=1, n=4



k=-0.1235 σ=1.4419 μ=9.1126E-4

Kolmogorov-Smirnov					
Sample Size	198				
Statistic	0.04072				
P-Value	0.88433				
Rank	2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.07625	0.08691	0.09651	0.10788	0.11577
Reject?	No	No	No	No	No

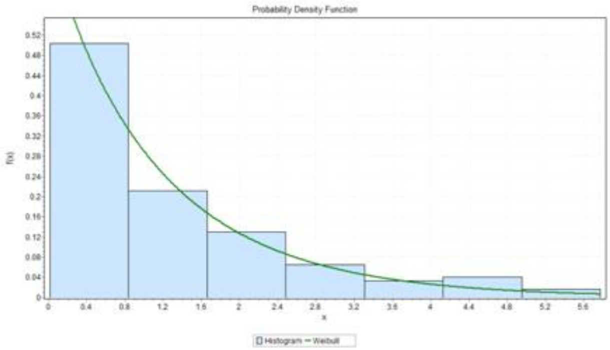
Appendix R-27 weekly aggregation probability distribution f: j=1, n=5



k=-0.08838 σ=1.291 μ=-0.01399

Kolmogorov-Smirnov					
Sample Size	157				
Statistic	0.03759				
P-Value	0.97356				
Rank	1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.08563	0.09761	0.10838	0.12115	0.13001
Reject?	No	No	No	No	No

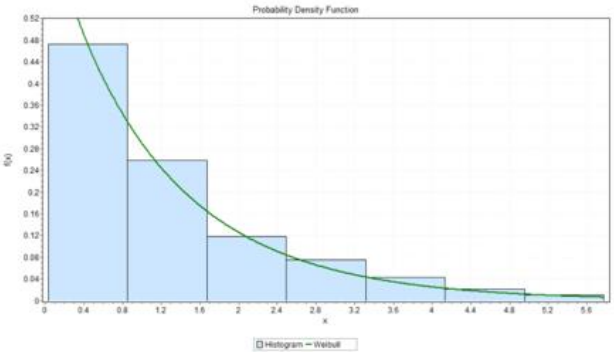
Appendix R-28 weekly aggregation probability distribution f: j=1, n=6



α=0.96981 β=1.1984

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	123 0.05601 0.81412 6				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.09675	0.11027	0.12245	0.13687	0.14688
Reject?	No	No	No	No	No

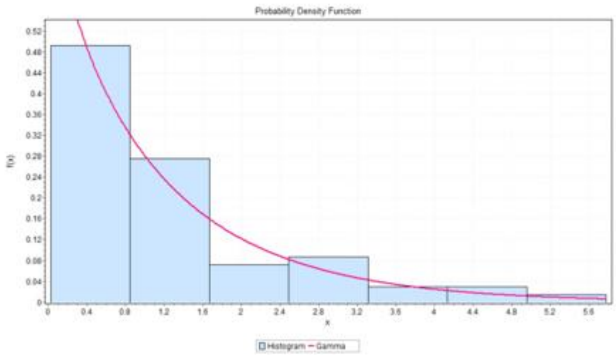
Appendix R-29 weekly aggregation probability distribution f: j=1, n=7



α=0.97153 β=1.1845

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	93 0.05794 0.89568 3				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.10947	0.12506	0.13891	0.15533	0.16666
Reject?	No	No	No	No	No

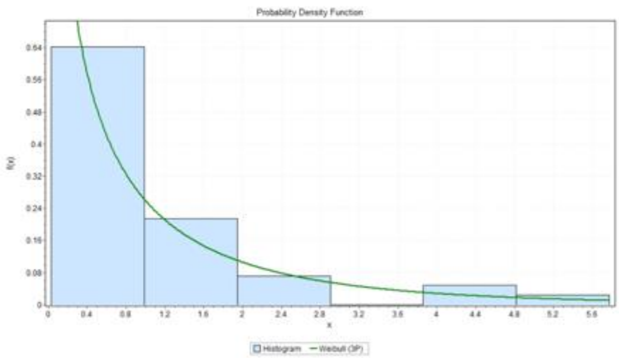
Appendix R-30 weekly aggregation probability distribution f: j=1, n=8



α=0.89587 β=1.3095

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	69 0.06358 0.92628 8				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.12675	0.14483	0.16088	0.1799	0.19303
Reject?	No	No	No	No	No

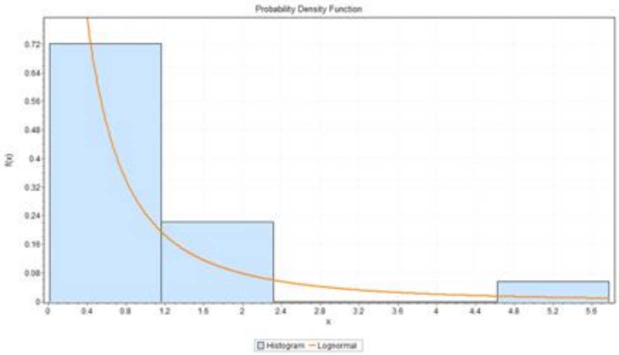
Appendix R-31 weekly aggregation probability distribution f: j=1, n=9



α=0.71705 β=0.89598 γ=0.02568

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	42 0.0641 0.99085 4				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.16158	0.18468	0.20517	0.22941	0.24613
Reject?	No	No	No	No	No

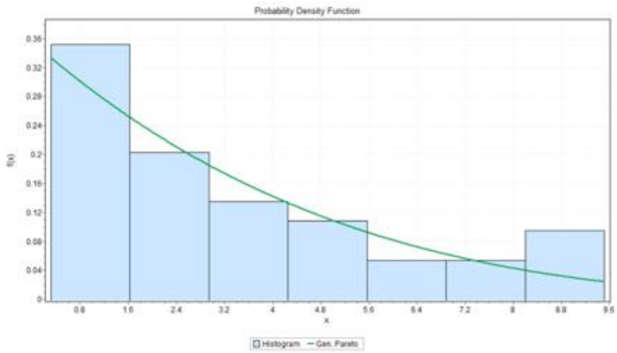
Appendix R-32 weekly aggregation probability distribution f: j=1, n=10



σ=1.4511 μ=-1.0381

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	18 0.14225 0.81092 6				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.2436	0.27851	0.30936	0.34569	0.37062
Reject?	No	No	No	No	No

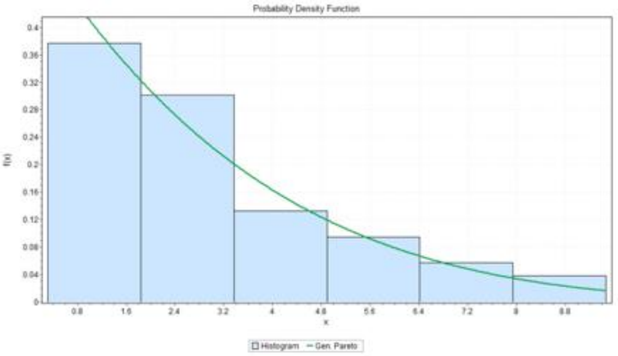
Appendix R-33 weekly aggregation probability distribution f: j=1, n=11



k=-0.20384 σ=3.8519 μ=0.19635

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	74 0.04573 0.99595 1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.12247	0.13993	0.15544	0.17382	0.1865
Reject?	No	No	No	No	No

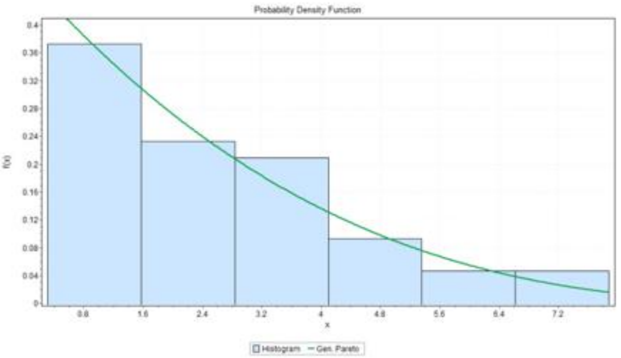
Appendix R-34 weekly aggregation probability distribution f: j=2, n=0



k=-0.16898 σ=3.0726 μ=0.30756

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	53 0.05436 0.99521 2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.14423	0.16483	0.18311	0.20475	0.21968
Reject?	No	No	No	No	No

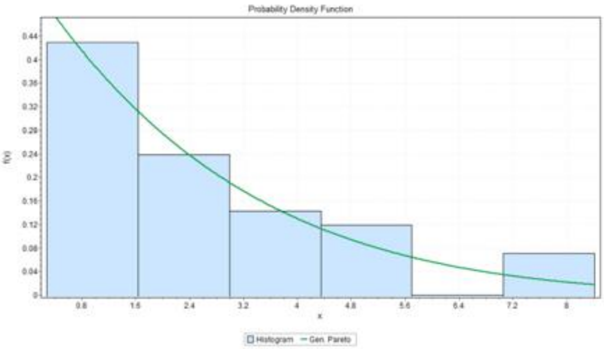
Appendix R-35 weekly aggregation probability distribution f: j=2, n=1



k=-0.25893 σ=2.8578 μ=0.2768

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	43 0.0521 0.99941 1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.15974	0.18257	0.20283	0.22679	0.24332
Reject?	No	No	No	No	No

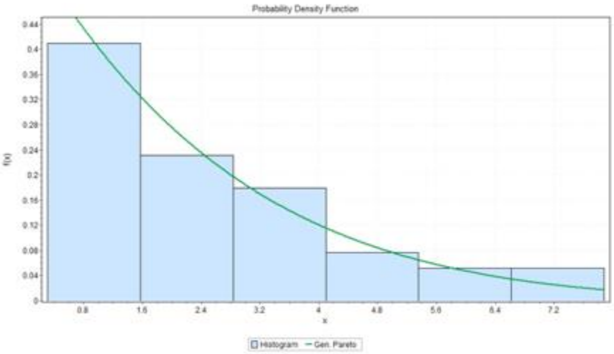
Appendix R-36 weekly aggregation probability distribution f: j=2, n=2



$k=-0.12261 \quad \sigma=2.691 \quad \mu=0.20781$

Kolmogorov-Smirnov					
Sample Size	42				
Statistic	0.0471				
P-Value	0.99993				
Rank	1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.16158	0.18468	0.20517	0.22941	0.24613
Reject?	No	No	No	No	No

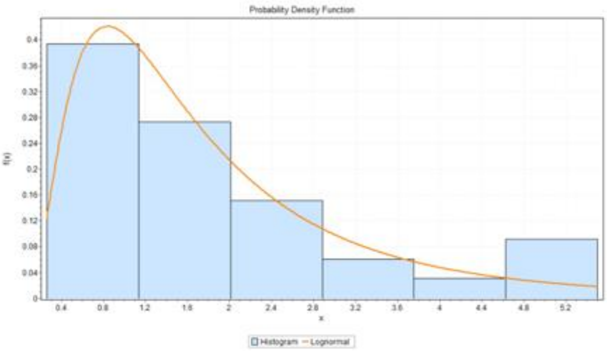
Appendix R-37 weekly aggregation probability distribution f: j=2, n=3



$k=-0.12881 \quad \sigma=2.4492 \quad \mu=0.32229$

Kolmogorov-Smirnov					
Sample Size	39				
Statistic	0.05061				
P-Value	0.99985				
Rank	2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.16753	0.19148	0.21273	0.23786	0.25518
Reject?	No	No	No	No	No

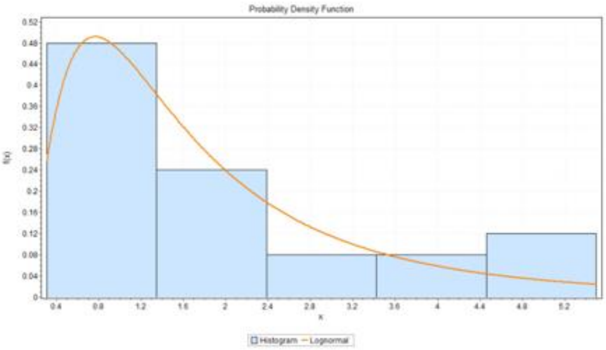
Appendix R-38 weekly aggregation probability distribution f: j=2, n=4



$\sigma=0.74785 \quad \mu=0.3825$

Kolmogorov-Smirnov					
Sample Size	33				
Statistic	0.07487				
P-Value	0.98583				
Rank	5				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.18171	0.20771	0.23076	0.25801	0.27677
Reject?	No	No	No	No	No

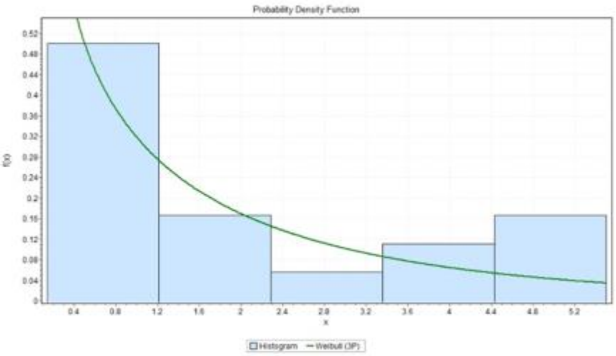
Appendix R-39 weekly aggregation probability distribution f: j=2, n=5



$\sigma=0.80064 \quad \mu=0.37223$

Kolmogorov-Smirnov					
Sample Size	25				
Statistic	0.07697				
P-Value	0.99572				
Rank	3				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.2079	0.23768	0.26404	0.29516	0.31657
Reject?	No	No	No	No	No

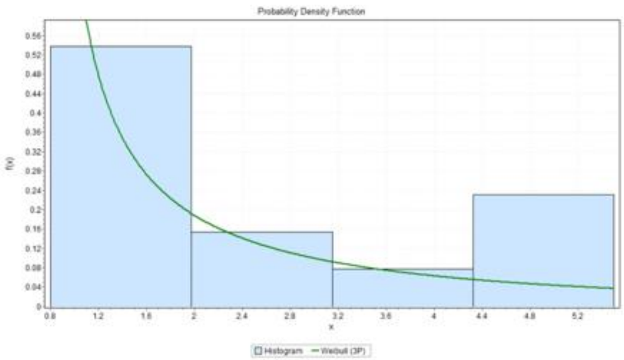
Appendix R-40 weekly aggregation probability distribution f: j=2, n=6



α=0.7991 β=1.7883 γ=0.14083

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	18 0.09152 0.99467 1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.2436	0.27851	0.30936	0.34569	0.37062
Reject?	No	No	No	No	No

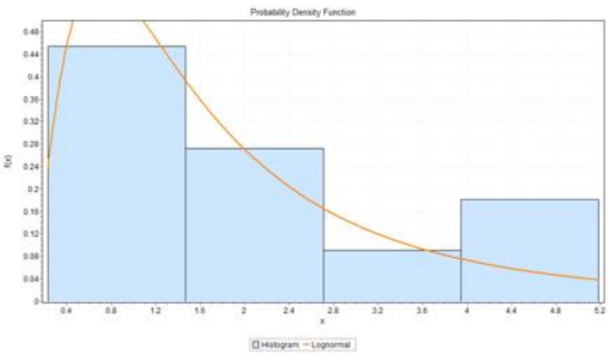
Appendix R-41 weekly aggregation probability distribution f: j=2, n=7



α=0.52384 β=1.3475 γ=0.79872

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	13 0.14595 0.90741 7				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.2847	0.32549	0.36143	0.40362	0.43247
Reject?	No	No	No	No	No

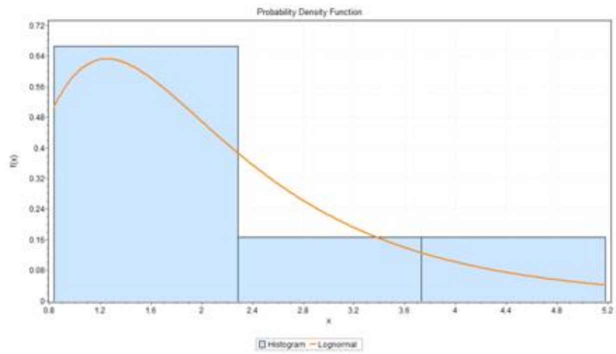
Appendix R-42 weekly aggregation probability distribution f: j=2, n=8



σ=0.85623 μ=0.38385

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	11 0.14351 0.95361 12				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.30829	0.35242	0.39122	0.4367	0.4677
Reject?	No	No	No	No	No

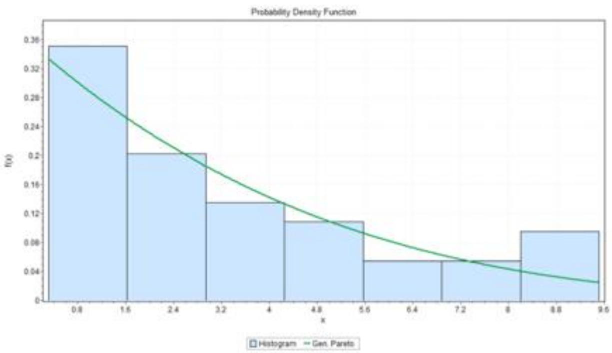
Appendix R-43 weekly aggregation probability distribution f: j=2, n=9



σ=0.60824 μ=0.59275

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	6 0.18692 0.95817 8				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.41037	0.46799	0.51926	0.57741	0.61661
Reject?	No	No	No	No	No

Appendix R-44 weekly aggregation probability distribution f: j=2, n=10



k=-0.20384 σ=3.8519 μ=0.19635

Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	74 0.04573 0.99595 1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.12247	0.13993	0.15544	0.17382	0.1865
Reject?	No	No	No	No	No

Appendix R-45 weekly aggregation probability distribution f: j=2, n=11

S. Determination of care needs per week/month

Option 1

When	How to determine
Care Period =< 28	Care per month = Total Care
Care Period > 28	Care per month = (Total Care/ Care Period)*28

Option 2

When	How to determine
Care Period =< 28	Care per month = Total Care
Care Period > 28	Care per Day = Total Care/Care Period
	Split Care Period of a client in days in month 1, days in month 2, and when necessary, days in month 3
	Calculate monthly care needs based on the days a client receives that month. Care Need Month x = Days in Month x * Care per Day

Example: An observation x=1 has a Length Period of 80 days. So, this client receives three months of care of 28 days in the first month, 28 days in the second month and 24 days in the third month. Total care is 800, so Care per Day = 800/80 = 10. The care need of month one = 28*10 = 280 minutes. The care needed for the second month = 28*10 = 280 minutes. Last, the care needed for the third month = 24*10 = 240 minutes. Therefore, this option splits one observation into three observations making it group and number of months/week and group dependent.

Option 3

When	How to determine
Care Period =< 28	Care per month = Total Care
Care Period >28 and =< 56	Care per month = Total Care/ 2
Care Period > 56	Care per Month = Total Care/3

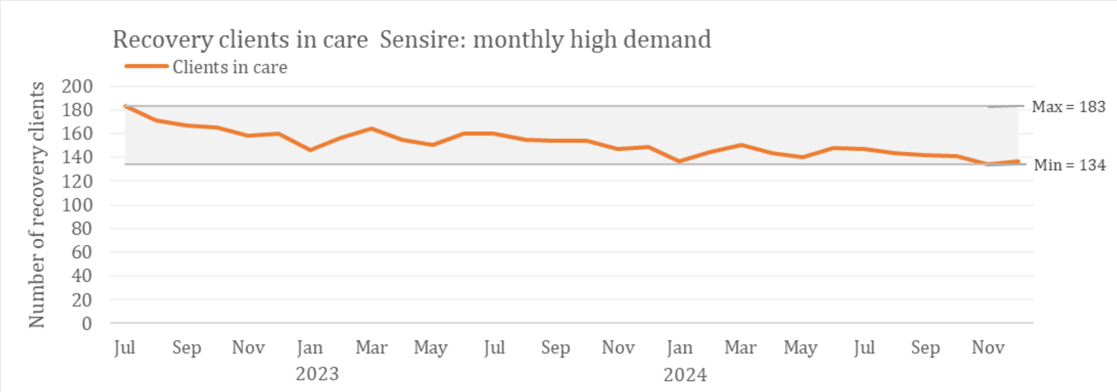
Option 4

Take averages for every client group for client group and the month/week receiving care.

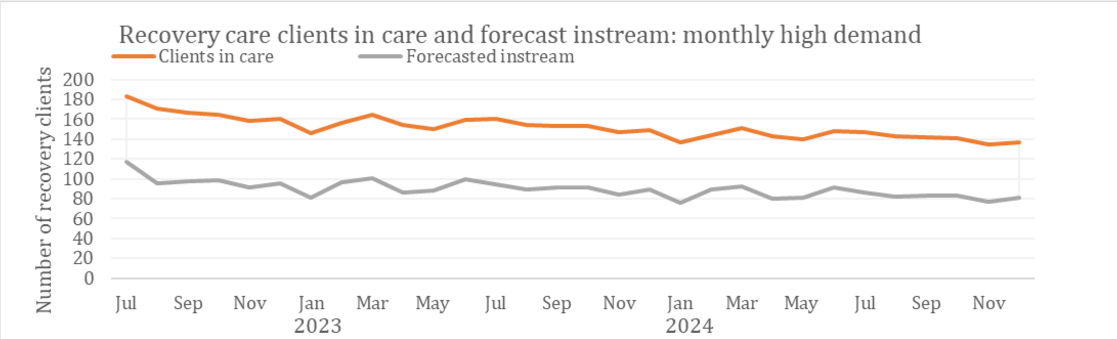
	Monthly average care need (minutes)		
	1st-month care	2nd-month care	3rd-month care
Client Group 1	420	382	264
Client Group 2	646	541	404
Client Group 3	1123	789	654

When choosing option 2, option 1 would unrealistically increase the care needed for the third month. Option 3 would unrealistically decrease care needs for the first and second months. Option 4 takes the averages for every client group and month/week receiving care and could function as a means of comparison to the outcomes of option 2. Option two and option four are included as experimental parameters, referred to as care needs determined via probability density function (pdf) and averages (avg).

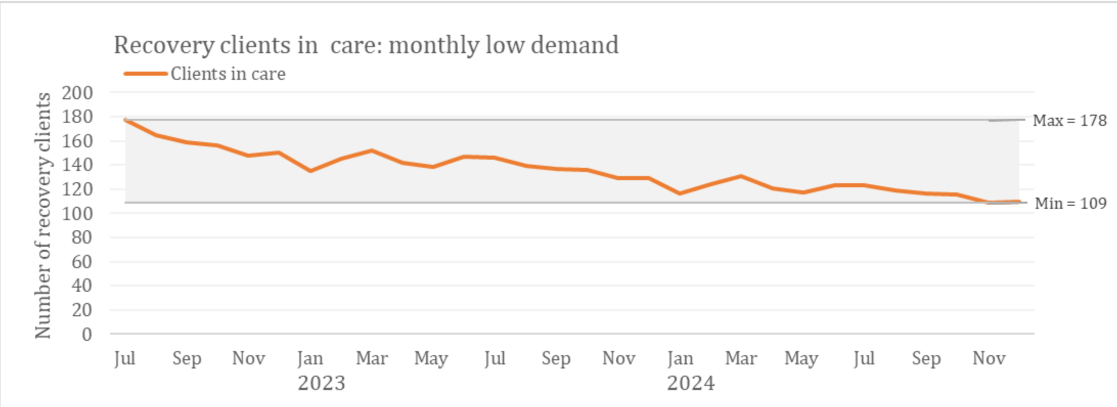
T. Images result from the number of clients, care needs, FTEs and contracts



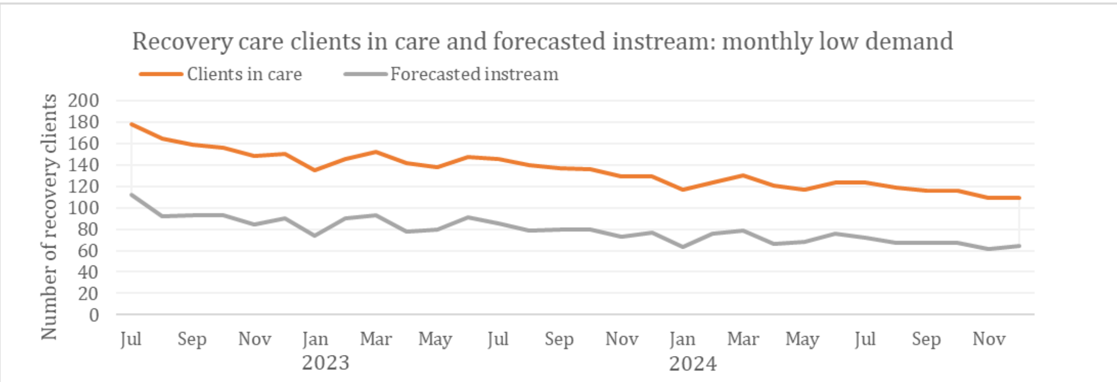
Appendix T-1 Number of recovery clients in home care environment Sensire: monthly high



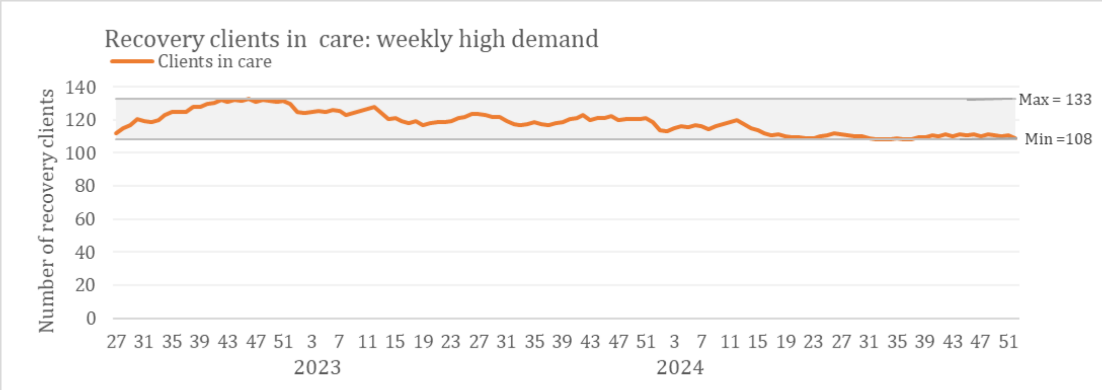
Appendix T-2 Number of recovery clients with forecasted demand: monthly high



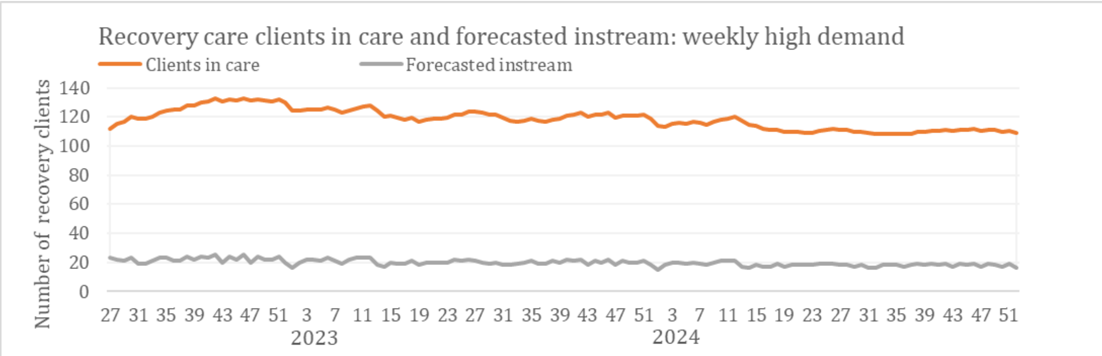
Appendix T-3 Number of recovery clients in home care environment Sensire: monthly low



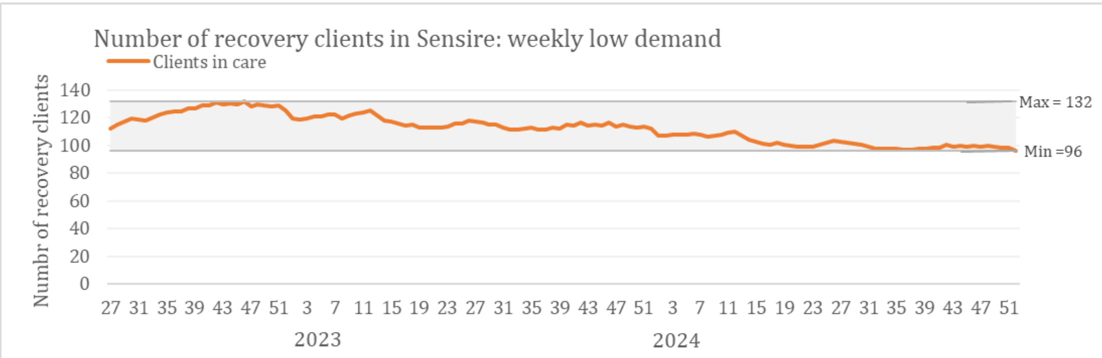
Appendix T-4 Number of recovery clients with forecasted demand: monthly low



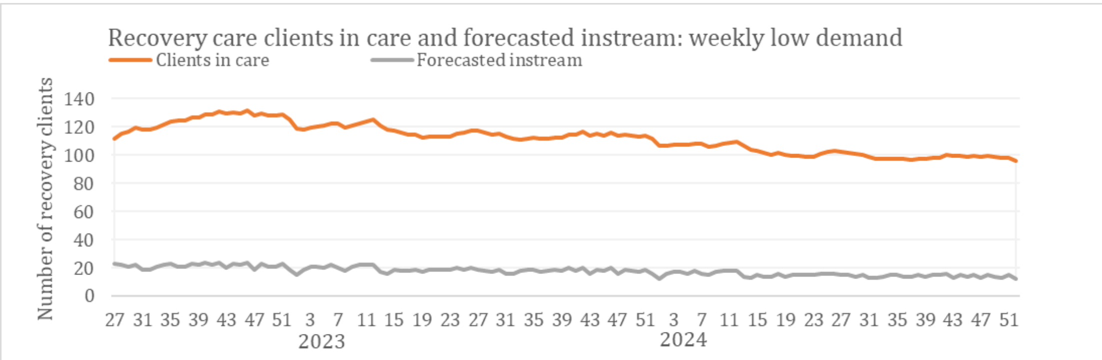
Appendix T-5 Number of recovery clients in home care environment Sensire: weekly high



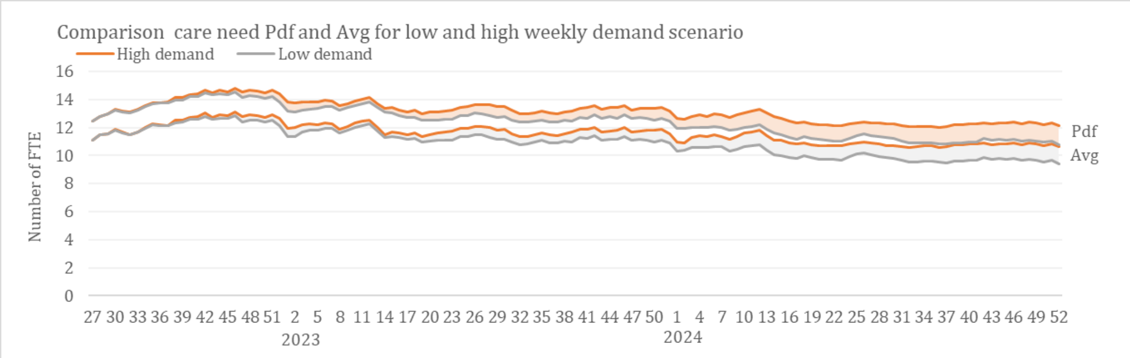
Appendix T-6 Number of recovery clients with forecasted demand: weekly high



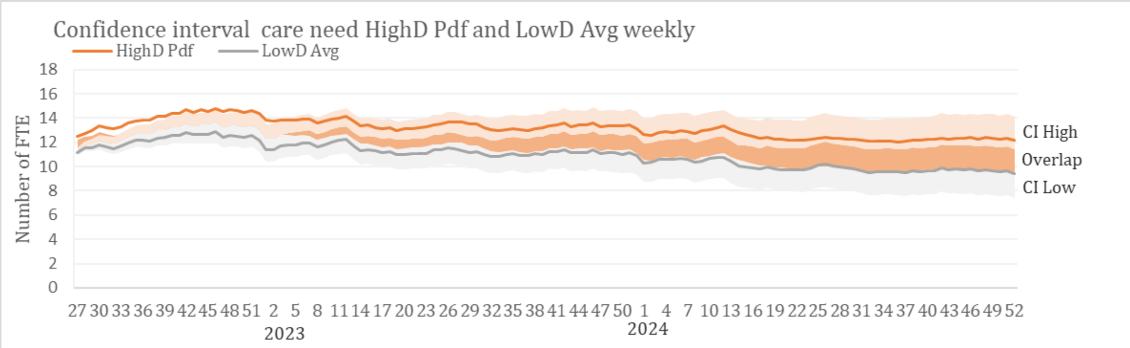
Appendix T-7 Number of recovery clients in home care environment Sensire: weekly low



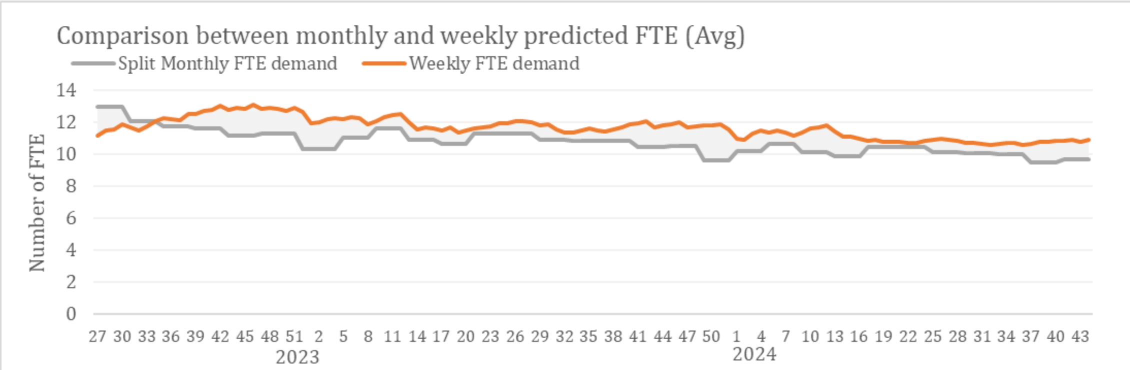
Appendix T-8 Number of recovery clients with forecasted demand: weekly low



Appendix T-9 Comparison care needs Pdf and Av for the weekly high-demand scenario

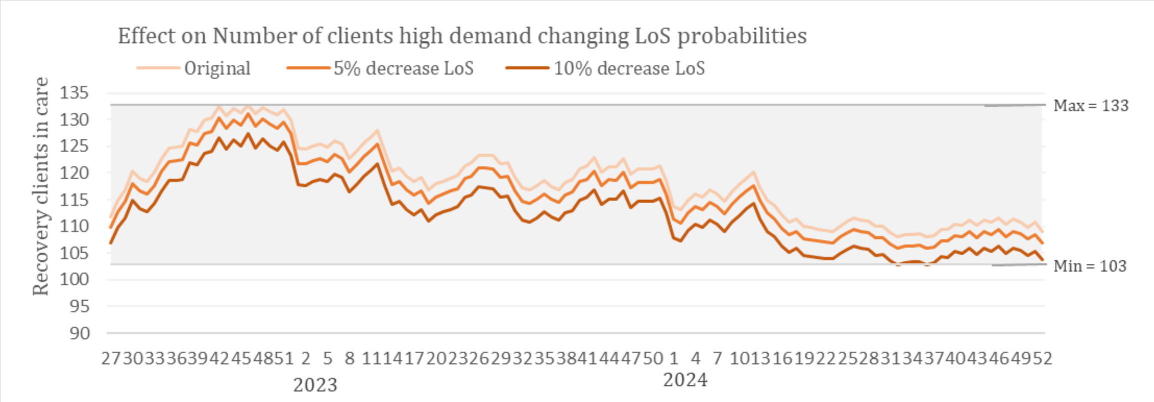


Appendix T-10 Confidence interval care needs HighD Pdf and LowD Avg weekly

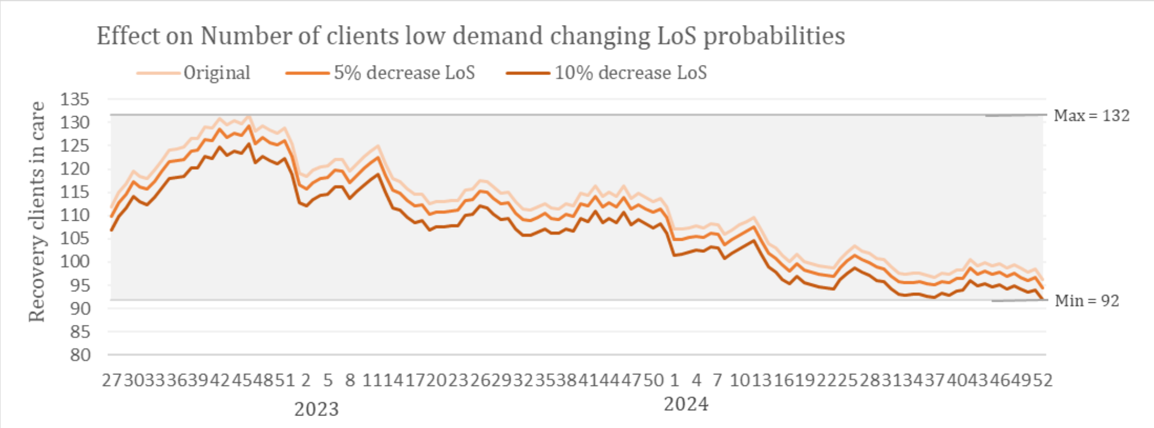


Appendix T-11 Comparison between monthly and weekly predicted FTE (Avg)

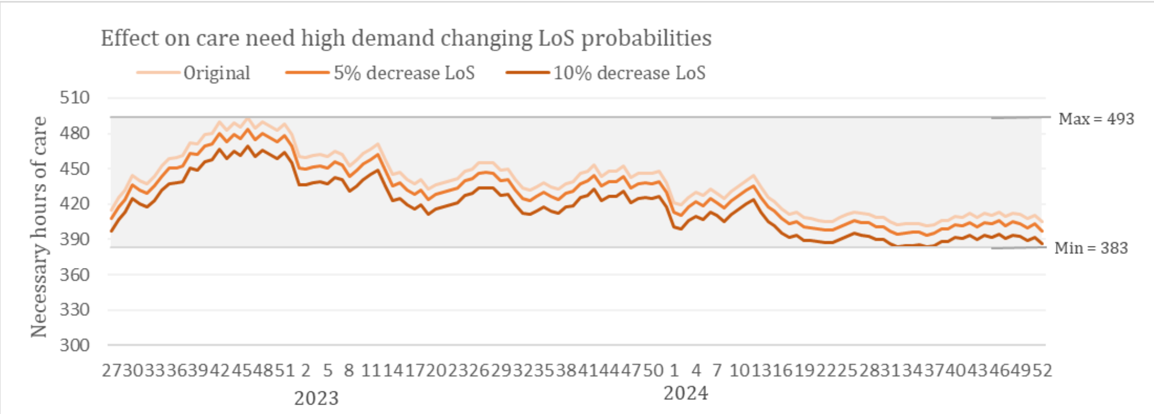
U. Sensitivity analyses



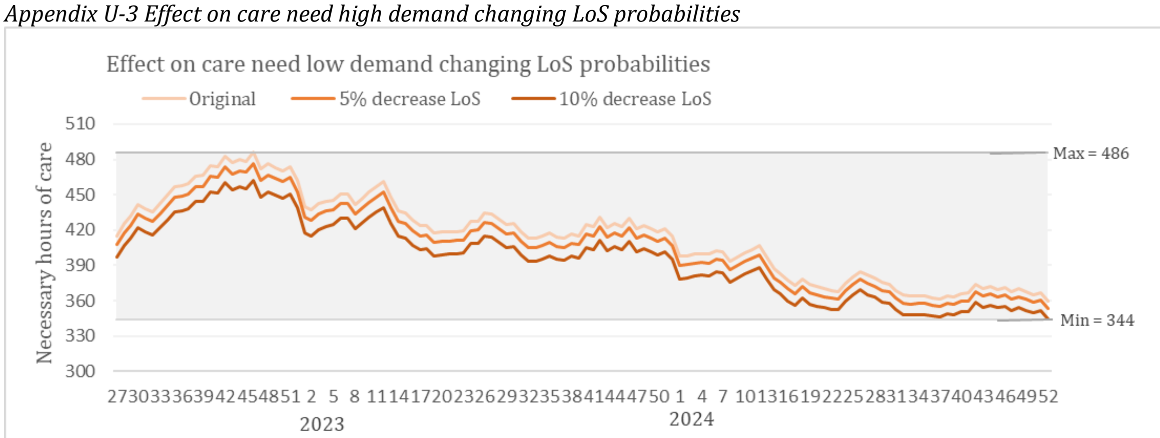
Appendix U-1 Effect on number of clients HighD changing LoS probabilities



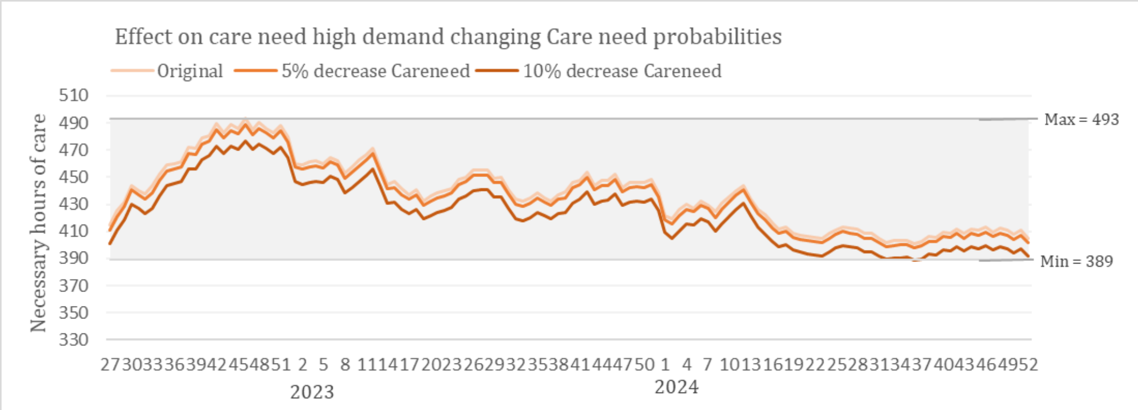
Appendix U-2 Effect on number of clients LowD changing LoS probabilities



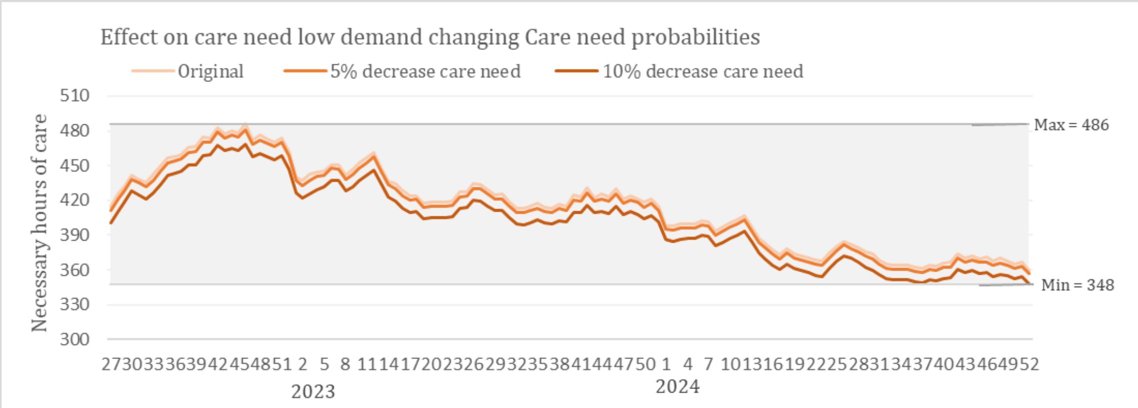
Appendix U-3 Effect on care need high demand changing LoS probabilities



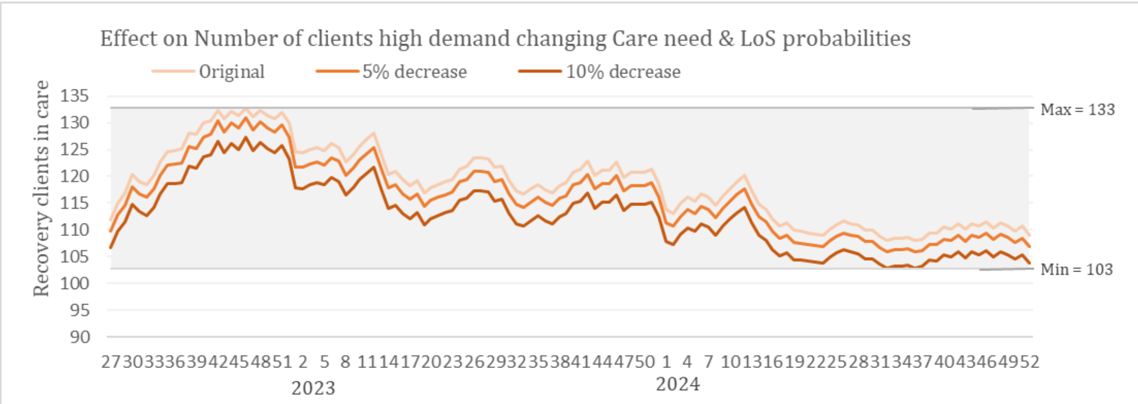
Appendix U-4 Effect on care need low demand changing LoS probabilities



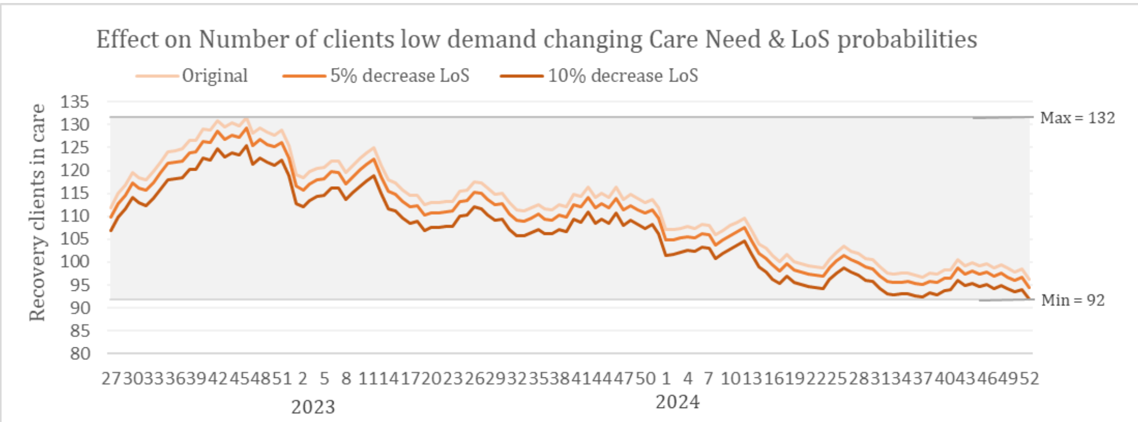
Appendix U-5 Effect on care need high demand changing care need probabilities



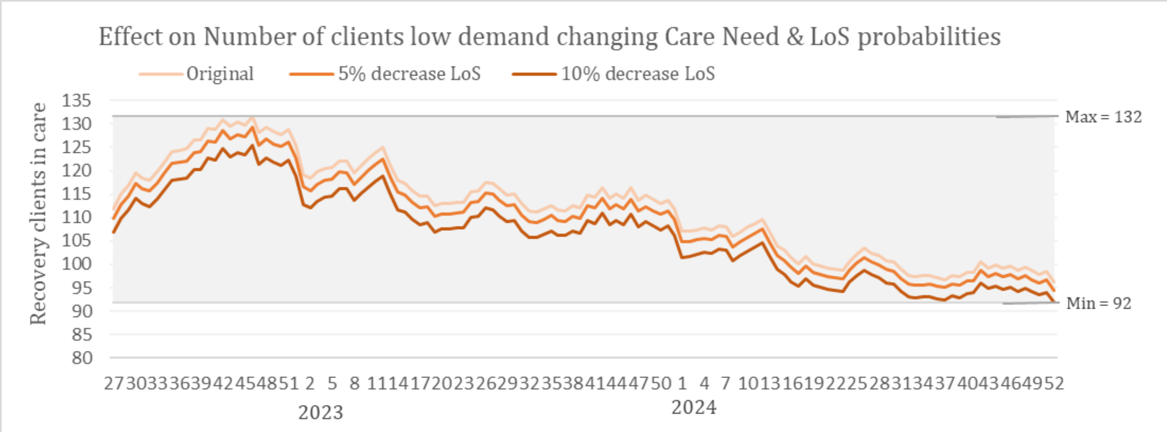
Appendix U-6 Effect on care need low demand changing care need probabilities



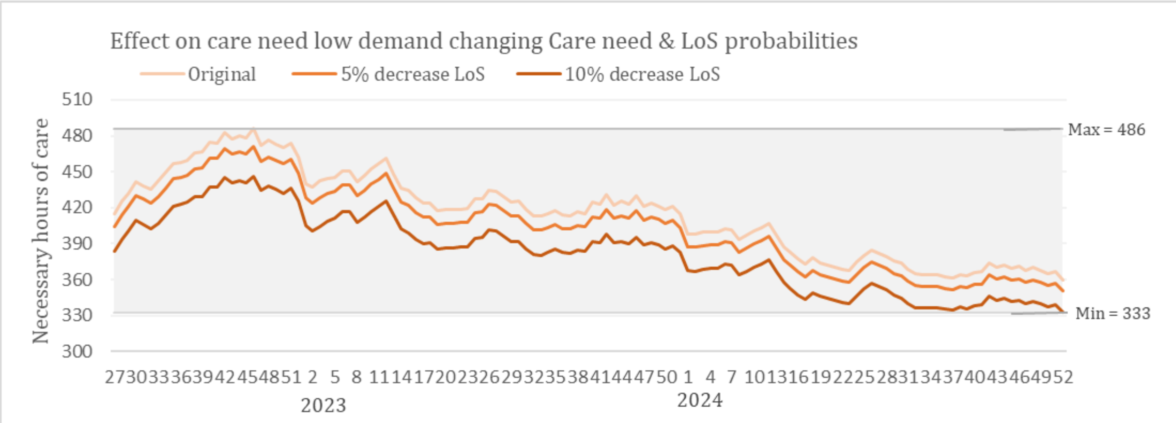
Appendix U-7 Effect on number of clients high demand changing Care need & LoS probabilities



Appendix U-8 Effect on number of clients low demand changing Care Need & LoS probabilities



Appendix U-9 Effect on number of clients low demand changing care need & LoS probabilities



Appendix U-10 Effect on care need low demand changing Care need & LoS probabilities