OPTIMIZING NURSING HOME PLACEMENT: THE EFFECT OF PATIENT PREFERENCES ON ADMISSION STRATEGIES

Joost van den Nieuwenhof

Dissertation Committee:
Supervisor: Dr. René Bekker
Second Reader: Prof. Dr. Rob van der Mei
Daily Supervisor: Msc. Tim de Boer

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Abstract

With increasing pressure on elderly care facilities, optimizing nursing home admission policies is essential to balance costs, crisis prevention, and patient well-being. This study examines the impact of incorporating individual patient preferences into a cost-optimal admission policy under imperfect information.

The proposed Markov Decision Process (MDP) models the gradual deterioration of an individual's health, determining both the optimal timing for nursing home admission and the scheduling of medical check-ups, which serve as an information-gathering mechanism to reduce uncertainty in decision-making. We first determine the cost-optimal admission policy and subsequently evaluate the impact of incorporating patient preferences regarding their preferred care situation.

The model can be used to assess the impact of incorporating personal preferences into the admission policy, allowing for a structured evaluation of its effects. The healthcare office responsible for these admissions can use these insights to make well-informed decisions on whether and how to account for personal preferences in the admission process, specifically by evaluating their impact on both costs and crisis risk. The results indicate that even a small shift in preference toward earlier nursing home admissions can lead to a significant reduction in crisis situations with minimal financial impact. For instance, adjusting the policy slightly reduces the crisis fraction from 47% to 22.5%, while increasing total costs by only 1.42%. This demonstrates that a carefully adjusted policy can achieve substantial improvements in crisis prevention while maintaining cost efficiency.

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Contents

1 Introduction

The global population is undergoing an unprecedented demographic shift. Societies around the world are aging rapidly, increasing the demand for elderly care services. By 2030, there will be 72 million adults in the United States who are 65 years of age or older, accounting for 20% of the population [45]. China is experiencing an even steeper aging trend, with the proportion of older adults projected to grow from 6.8% to 23.6% over the first half of the twenty-first century [12]. The UK and the Netherlands face similar patterns, with individuals aged 65 and over expected to make up 26% of the Dutch population by 2060 [19].

This demographic shift places an increasing strain on healthcare systems, especially nursing homes. Many facilities struggle to keep up with demand due to staffing

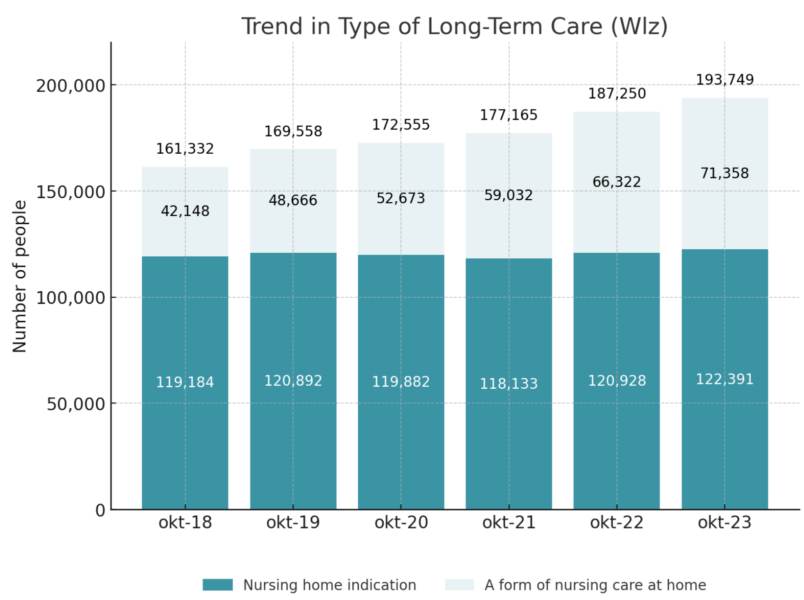

FIGURE 1.1: Increasing pressure on healthcare for older adults [2]

shortages and limited capacity, resulting in long waiting lists. In the Netherlands, 22,218 individuals are currently on the waiting list for a nursing home, with an additional 10,820 waiting as a precautionary measure [2]. These waiting lists are a widespread issue across multiple countries [5]. Figure 1.1 illustrates the growing demand for long-term elderly care in the Netherlands. The green section represents older adults currently residing in nursing homes, while the white section represents those receiving home care.

Long waiting times for nursing homes pose serious risks for older adults, affecting both their health and well-being. Delayed admission increases the likelihood of frailty, confusion, distress, and anxiety [4]. Beyond mental health consequences, prolonged waiting periods elevate the risk of acute hospitalizations, often forcing individuals into nursing homes under emergency conditions. A lack of adequate supervision and unsafe home environments—such as steep stairs and high doorsteps—can lead to falls and accidents [15]. According to Bär [8], each month of delay increases urgent hospitalization risk by 2.6 percentage points (15% of the baseline probability), particularly among individuals with dementia living alone.

Not only does delayed access to nursing homes impact older adults' well-being, but it also imposes a significant financial burden on healthcare systems. When timely admission is unavailable, frail individuals require additional home care and emergency interventions, leading to rising healthcare expenditures. Many remain at home longer, relying on formal home care services that strain public long-term care insurance and government subsidies [8].

Crises further complicate nursing home admissions, as emergency placements disrupt the queue. Nearly half of all nursing home admissions result from such crises [1], exacerbating delays for those who are not yet in immediate need. Next to that, crises lead to high costs that could have been avoided through timely interventions and better monitoring of patient health. To prevent crisis situations, it is crucial to ensure timely admissions by prioritizing patients at the highest risk. By determining the optimal timing for an individual to transition to a nursing home, emergencies can be prevented, resource allocation can be improved, and long-term care efficiency can be enhanced.

However, identifying individuals most at risk based on health status is challenging due to the lack of accurate and up-to-date health information on older adults. The decision to transition someone to a nursing home depends on multiple factors, including financial costs [46]. Predicting and preventing crises requires continuous monitoring, yet health status is often inferred indirectly. Research by Smeekes et al. highlights the use of proxies such as home care service intensity to estimate health deterioration [38]. While these proxies provide insights into frailty levels, they do not offer real-time health assessments, further complicating timely decision-making. Next to that, it is challenging to model health due to personal variability and the many factors influencing deterioration rates.

Another key consideration is that not all older adults have the same preferences regarding nursing home admission. Many individuals prefer to remain in their own homes as long as possible, as it promotes independence and improves quality of life. Research by Pedlar and Walker [33] found that 90% of patients preferred increased home care over nursing home admission. This suggests that developing an optimal admission policy requires balancing both cost efficiency and individual preferences to create a sustainable and patient-centered approach.

1.1 Problem Statement

The decision to transition an individual to a nursing home depends on multiple factors, including financial considerations, individual preferences, and health risks associated with remaining at home. The challenge is to develop a decision framework that identifies individuals most at risk and optimally determines when to admit them to a nursing home or schedule check-ups, balancing these competing objectives.

This study models the progression of elderly individuals' health states and analyzes how uncertainty in health deterioration affects decision-making. Based on these insights, we develop a Markov Decision Process (MDP) that incorporates all relevant costs, including home care, check-ups, crisis events, and nursing home admissions. This results in an optimal policy for admissions and check-ups, ensuring that high-risk patients are prioritized before their health deteriorates to a crisis.

However, to be practically effective, the model must also account for patient preferences. Some individuals prefer to stay at home as long as possible due to strong family support and a comfortable living environment, while others experience loneliness or inadequate home care, making earlier nursing home admission more desirable. Incorporating these preferences allows for a more patient-centered decision-making approach, balancing individual well-being and crisis prevention.

Additionally, it is important to explore different check-up strategies, as the choice of monitoring frequency directly impacts decision outcomes. Fixed-interval check-ups, commonly used in practice, may lead to inefficiencies; some patients are monitored too frequently, while others deteriorate before their next scheduled check-up. Exploring alternative strategies, such as state-based check-ups that adapt to individual risk levels, could improve early detection of health decline while minimizing unnecessary costs.

Therefore, this study investigates how the cost-optimal admission strategy is impacted by:

- Patient preferences (utility rewards for staying at home longer).
- Different check-up strategies (state-based vs. time-based scheduling).

The results provide quantitative insights into how nursing home admission decisions can be optimized, ensuring that limited spots are allocated to those at the highest risk. This helps reduce crisis-driven admissions and control healthcare costs while respecting patient preferences. This study is guided by the following research question:

> **Research Question**
>
> How does the incorporation of patient preferences impact the cost-optimal timing of nursing home admissions and health check-ups?

To answer these questions, the following sub questions are formulated:

1. How do older people progress through different health states?
2. How can the optimal timing for nursing home admissions and health check-ups be determined to minimize healthcare costs?

3. How do different check-up strategies affect the crisis risk and health expenditures?

4. How does incorporating patient preference impact crisis risk and health expenditures?

The output of this research is an analysis of how incorporating patient preferences affects crisis risk and total healthcare costs, providing valuable insights that can aid in determining the optimal timing for admitting patients to nursing homes.

1.2 Organizational Context

This research is conducted in cooperation with Centrum Wiskunde & Informatica (CWI). CWI, located in Amsterdam Science Park, is the national research institute and was founded in 1946. It is run by NWO-I, the Institutes Organization of NWO. CWI, which is well-known for its creative research, combines computer science and mathematics to solve basic and real-world problems, advancing fields including smart energy systems, internet security and healthcare problems. As an internationally renowned organization, CWI actively engages in European research initiatives and works closely with academia and industry to convert theoretical understandings into practical implementations [16].

This research is part of the "Data-Driven Optimization for a Vital Elderly Care System in the Netherlands" or DOLCE VITA project, a collaborative initiative involving Amsterdam UMC, CWI, and Vrije Universiteit Amsterdam. DOLCE VITA is an initiative that combines medical and mathematical knowledge to tackle problems in elderly care.

1.3 Thesis Outline

This thesis is organized into several chapters. Chapter 2 introduces the foundational concepts and mathematical techniques relevant to this research. Chapter 3 reviews existing studies, identifying gaps that this study addresses. Chapter 4 outlines the methodological approach and conceptual model. Chapter 5 examines how sensitive the model is to key parameters, while Chapter 6 details the estimation of probability and cost parameters. Chapter 7 presents the key findings and derived policies, which are analyzed in Chapter 8. This chapter also discusses the research's limitations and practical implications. Finally, Chapter 9 summarizes the main insights of this study.

2 Background

This chapter provides the theoretical background necessary to understand the techniques and context underlying this research. Section 2.1 discusses the current elderly care system, while mathematical concepts used in this research will be discussed in Section 2.2.

2.1 Care system in the Netherlands

The Dutch healthcare system is a complex structure comprising various legal frameworks and care services, each with distinct responsibilities and financial arrangements. This section provides an overview of elderly care in the Netherlands, detailing the key legislative frameworks that govern care provision. Additionally, this section examines crisis situations in elderly care, the process of Nursing Home (NH) placement, and the concept of health profiles.

2.1.1 Framework Elderly Care in the Netherlands

Figure 2.1 shows an overview of the different components involved in the Dutch healthcare system. The green arrows indicate smooth cooperation and transfer without major issues. In contrast, the red dotted arrows highlight potential risks or concerns, while the red arrows signify significant obstacles in coordination and transfer. As the figure illustrates, the Dutch healthcare system is complex, with numerous connections and challenges. This research focuses specifically on the pathway leading to NH admissions.

The system provides financial coverage for elderly care through various legal frameworks. Each framework addresses specific types of care and involves distinct

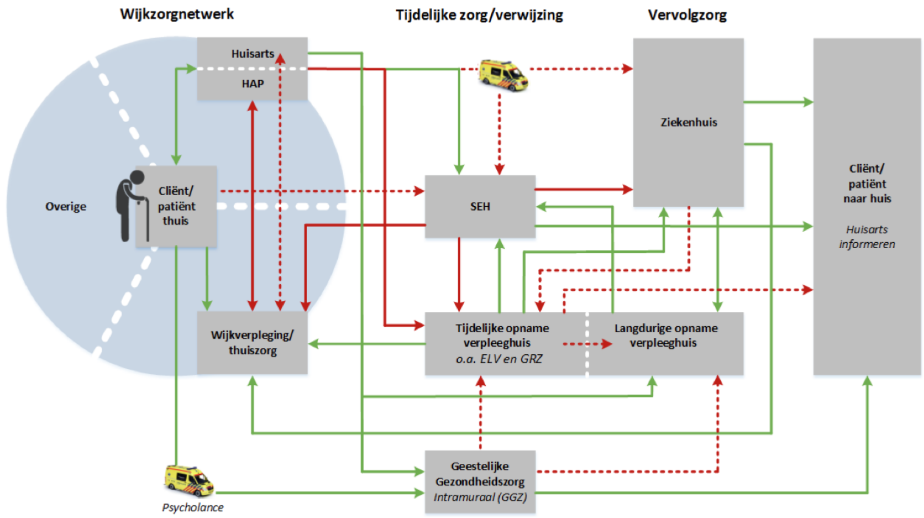

FIGURE 2.1: Dutch healthcare system [37]

responsibilities for reimbursement and implementation. In the following, we detail the different types of elderly care systems together with the financial arrangements [42] [18] [28].

Zorgverzekeringswet (ZVW)

The *Zorgverzekeringswet* (Health Insurance Act) covers medical care, including several forms of elderly care, through basic health insurance. Services included under ZVW are:

- **District Nursing (Wijkverpleging)**: Care provided at home for individuals requiring nursing support.
- **Terminal Care**: For individuals with a life expectancy of fewer than three months, provided at home or in a hospice through district nursing (wijkverpleging).
- **Short-term residential care (Eerstelijnsverblijf)**: Temporary stays in an NH or specialized care center, including geriatric rehabilitation and terminal care.

The services provided under ZVW are reimbursed from the basic health insurance, though they are subject to the insured person's deductible (*eigen risico*).

Wet Maatschappelijke Ondersteuning (WMO)

The *Wet Maatschappelijke Ondersteuning* (Social Support Act) ensures support for individuals with limitations in daily functioning, administered and financed by municipalities. Key services under WMO include:

- **Personal Care**: Assistance with personal hygiene and basic daily activities.
- **Guidance for Independent Living**: Support for those with psychosocial limitations to function autonomously.
- **Home support**: Assistance with household tasks for individuals unable to perform these themselves.

WMO services are implemented by municipalities, ensuring localized and tailored support for residents.

Wet Langdurige Zorg (WLZ)

The *Wet Langdurige Zorg* (Long-Term Care Act) covers intensive, round-the-clock care for individuals with severe health conditions, including:

- **24-Hour Care and Night Care**: Necessary for individuals unable to live independently.
- **WLZ-zorg thuis**: Long-term care provided at home instead of in an NH, available through arrangements like Volledig Pakket Thuis (VPT) or Modulair Pakket Thuis (MPT), depending on the individual's needs and feasibility.

Clients contribute an income-dependent personal fee, while the remainder of the costs are funded by the *AWBZ-premie*, a tax-based premium. WLZ care is specifically for those requiring heavy, intensive care, including elderly individuals, people with disabilities, and those with chronic psychiatric conditions. Eligibility is determined by the *Centrum Indicatiestelling Zorg* (CIZ). Care can be provided in institutions or, where possible, at home, following the client's preferences and circumstances. WLZ often represents the final stage of care received by older adults, typically preceding the end of life.

Relevance to this Research

In the context of this research, two key components of the Dutch healthcare framework are particularly relevant: ZVW and WLZ. The ZVW plays a crucial role in the model, as individuals are assumed to receive home care before being considered for placement in an NH, which is financed and administered under this framework. As individuals' health deteriorates over time, they may transition toward more intensive care needs. The final stage of our system is NH admission, which falls under the WLZ, since WLZ provides long-term institutional care for those who cannot live independently.

2.1.2 Crisis Definition

Preventing crisis situations is one of the primary objectives in developing an optimal policy for NH admissions. To provide clarity, we first define what constitutes a crisis:

> **Definition of a crisis:** "An acute situation in which the current living arrangement of a patient becomes untenable due to medical, social, or interactional factors, and immediate intervention is required."

From a medical perspective, crises often arise due to the unexpected deterioration of chronic conditions or acute episodes that do not warrant hospital or psychiatric admission but cannot be managed effectively with existing home care services. Socially, crises may result from abrupt changes in a patient's support network, such as the loss or burnout of caregivers. Interactional crises involve breakdowns within the care environment, such as conflicts between caregivers and patients, leading to unsafe or unmanageable situations. These scenarios require rapid evaluation and action to ensure the patient's safety and well-being, often necessitating either temporary hospitalization or permanent NH admission [41].

2.1.3 Current practice for placement in Nursing Homes

The placement of older adults in NHs in the Netherlands involves a structured process managed by regional healthcare offices. This process aims to ensure timely and appropriate care for those with a valid indication under the WLZ. However, due to limited availability and high demand for certain NHs, waiting lists are a significant component of this system.

The regional healthcare office ("zorgkantoor") oversees the waiting lists and is responsible for ensuring timely care provision, even when a preferred placement is unavailable. There are 31 healthcare offices in the Netherlands, each managing the placement of older individuals in NHs within their designated region. If immediate placement is not possible, the waiting list management process begins. This also applies if a care provider can no longer meet a client's care needs due to changes in their condition. The major consideration when placing a client, is the client's preferred NH, which they can specify at the moment that they receive a WLZ-indication. In order to foster familiarity and limit interruption to the client's social network, care is offered as close as possible to the client's present or preferred location. Currently, only one preferred provider can be registered due to restrictions in the administrative system, which significantly limits placement options and reduces flexibility in accommodating individual preferences.

Classification of waiting statuses

To streamline the process and prioritize care effectively, clients are currently categorized into different waiting statuses at the time they are placed on the waiting list for NHs [43]. The waiting time varies significantly based on the urgency of the situation and bed availability at the preferred nursing home. Additionally, the assigned VV profile influences the selection of the waiting status. Clients with urgent needs are prioritized and placed as quickly as possible. For others, waiting times can span several weeks to months. The indicated urgency level is dynamic and can be changed when the situation changes. For every urgency level, there is a targeted waiting time; however, due to the increasing pressure on health care, these targets are not always met. The percentage of placements that met their target ranges from 74% to 84% [2]. Figure 2.2 shows the number of older adults that are classified in each urgency level. The bars are divided into two parts, indicating the fraction of people receiving care. As shown in the right part of the picture, the majority of the waiting people are currently being provided with some kind of care, usually this indicates home care.

- **Urgent Placement**: Clients in unsafe or unlivable home situations are given priority for placement. Temporary measures, such as bridging care at home, may be arranged if feasible. For this urgency level, a waiting period of 0–4 weeks is indicated.

- **Active Placement**: Clients actively waiting for placement while receiving necessary care at home. The targeted waiting times for active placement is 0-6 months.

- **Waiting for Preference**: Clients who are willing to wait for a placement in their preferred NH. The targeted waiting time is 0-12 months

- **Preventive Waiting**: Individuals who do not require immediate care but anticipate needing NH placement in the future. There is no target for the waiting time.

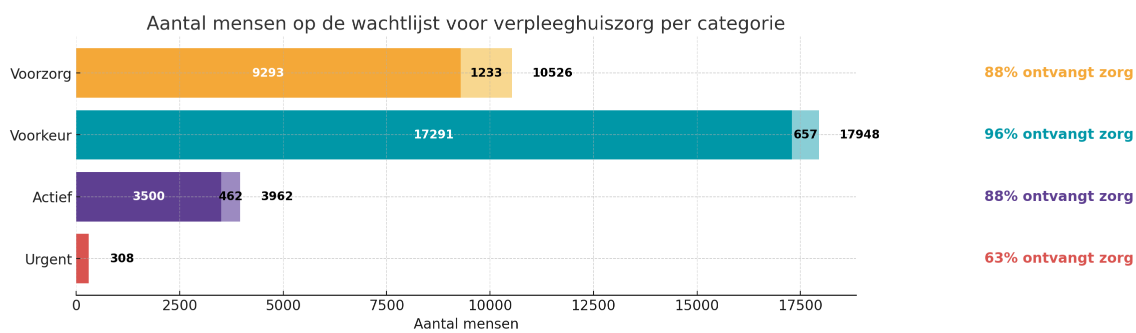

FIGURE 2.2: Number of patients per urgency level. Source: [2]

Handling placement

Once an NH is identified, the regional healthcare office coordinates the transition. Providers are expected to contact the client within 10 working days of receiving the allocation to discuss the care arrangement. If necessary, temporary measures such as bridging care are arranged to ensure continuity of care until the client's placement is finalized.

2.1.4 Health profiles

A health profile called a "VV profiel" (*Verpleegzorg Verblijfszorg* profile) is given to older people in the Netherlands who meet the requirements for a WLZ indication. These profiles, which range from VV1 to VV10, categorize people according to the degree of care they need; higher numbers denote more intense care requirements [30]. When a person receives a WLZ indication, a VV profile is assigned. This classification helps to determine the kind and degree of care that the person needs. A nursing facility is often recommended for older adults with VV profiles of VV4 and above, but this threshold may shift to later profiles as pressure on nursing homes increases. These characteristics usually relate to people who need constant supervision or significant help with daily tasks. Therefore, the VV profile system is essential for maximizing the provision of care and directing choices for a person's transfer to an NH when required. The different VV-profiles together with an explanation are given in Table 1 in the Appendix.

2.2 Mathematical models

Mathematical models are used to represent the health dynamics of elderly individuals and to optimize the decision-making process. This section introduces the key methods employed in this research.

2.2.1 Markov model

The aim of this research is to create optimal schedules for NH admission based on the health condition of older adults. For this purpose, health is expressed using a discrete set of states, referred to as 'health states'. Since these states are dynamic, meaning they change over time, a stochastic model is well-suited for this situation. A well-known mathematical model used for modeling states in a stochastic setting, is a Markov chain. As shown in Figure 2.3, a Markov chain is a mathematical system that undergoes transitions from one state to another within a finite or countably infinite set of states, where each transition depends only on the current state. These transitions are governed by probabilities that depend only on the current state ("the

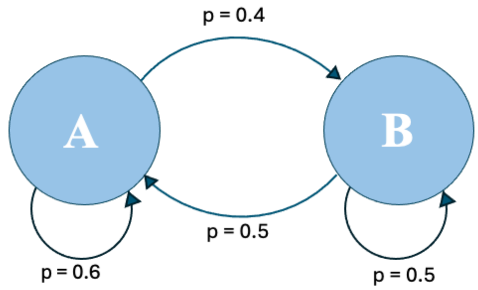

FIGURE 2.3: Simple example of a Markov chain

Markov property"). Markov chains can be categorized into Discrete-Time (DTMC) and Continuous-Time (CTMC) models. Figure 2.3 illustrates a simple example of a Markov Chain, demonstrating how the system transitions between states at each time step with probability p. In a continuous setting, the system evolves in continuous time, meaning that transitions occur at random time intervals rather than at fixed steps [39]. In this research, we adopt the discrete setting, as check-ups and placements are scheduled on a weekly basis. While the exact timing within the week is not strictly fixed, the model remains flexible enough to accommodate decisions at designated weekly time points. A special type of state within a Markov chain is an absorbing state, a state that once entered cannot be left. When this state is entered, the system remains there indefinitely.

2.2.2 Markov Decision Processes

A Markov Decision Process (MDP) models state transitions influenced by actions and provides a framework for identifying the optimal policy. This model can be used when there are certain rewards associated with taking action a in state s. An MDP models sequential decision-making scenarios where outcomes are influenced by both transition probabilities and the actions of a decision-maker. Solving an MDP yields a policy that minimizes expected future costs, considering long-term average, discounted, or horizon-based costs, depending on the objective.

To formalize decision-making within an MDP, key functions are defined to evaluate and optimize choices. One such function is the value function, which quantifies the total expected reward (or minimized cost) for being in a particular state while accounting for future transitions and actions. It is expressed as:

$$V(s) = \max_{a \in A} \left(R(s,a) + \gamma \sum_{s'} P(s' \mid s,a) V(s') \right)$$

From this value function, the optimal policy π^* can be derived, which specifies the best action to take in each state:

$$\pi^*(s) = \arg\max_{a \in A} \left(R(s,a) + \gamma \sum_{s'} P(s' \mid s,a) V(s') \right)$$

Where:

- s: Current state.
- a: Action taken.
- s': Next state.
- A: Set of all possible actions.
- $R(s,a)$: Immediate reward received after taking action a in state s.
- $P(s' \mid s,a)$: Probability of transitioning to state s' from state s after taking action a.
- γ: Discount factor ($0 \leq \gamma < 1$), representing the present value of future rewards.

These equations are fundamental in Markov Decision Processes and can be found in [36].

An MDP can be solved using various approaches, including policy iteration, value iteration, and linear programming. Although all methods ultimately converge to the same optimal policy, they differ in computational efficiency and numerical stability. Value Iteration is often preferred for medium to large MDPs as it avoids the computational overhead of matrix inversions required in policy iteration [34]. Given these advantages, this research adopts Value Iteration as the solution method.

In this research, a key challenge arises from the uncertainty caused by the lack of up-to-date information about the health of elderly individuals. Models such as

Partially Observable Markov Decision Processes (POMDPs) are specifically designed to handle such uncertainty. However, instead of adopting a POMDP framework, we take a different approach by creating a custom version of an MDP that incorporates mechanisms to deal with imperfect information. We chose this method because in a POMDP, uncertainty is handled by using belief states, which indicate the probability of being in a certain state. However, this is challenging to interpret, particularly for those who will be using the model—namely, the individuals responsible for assigning clients to nursing homes. To ensure that the model remains accessible and user-friendly, we design a state space that is intuitive and easily understandable, even for those without a mathematical background. This MDP framework accounts for the limited observations of an individual's health state by introducing additional states that reflect the time elapsed since the last health check. The decision-making process in this modified MDP revolves around actions taken without having full information about the current health state of an older adult.

3 Related work

This chapter reviews the literature relevant to this research, structured into four main sections. Section 3.1 explores studies on patient flow and allocation models in healthcare, with a particular emphasis on elderly care and nursing home admissions. Section 3.2 delves into mathematical approaches to health modeling, which are applied in this research to optimize health care strategies for elderly populations. After that, Section 3.3 discusses research on preventive maintenance strategies of similar systems in a different application domain. Finally, the contribution of this research will be outlined in Section 3.4.

3.1 Patient Flow and Allocation Models in Elderly Care

Since optimizing patient flow is central to reducing crises and waiting times in elderly care, this section first reviews existing models for patient allocation and nursing home admissions. As outlined in the introduction, crises have a detrimental impact on the mental and physical well-being of older adults and are associated with significant financial costs. Bom et al. [7] demonstrate that being admitted to a nursing home can significantly reduce the risk of acute hospitalizations. Their study highlights that timely access to nursing home facilities prevents critical health deterioration that would otherwise lead to costly and urgent medical interventions . This finding emphasizes the importance of timely admissions. However, due to a shortage of healthcare workers, expanding capacity is currently not feasible [9]. This limitation requires research on waiting list management, focusing on alternative prioritization strategies to prevent crises.

Several researchers have explored methods to reduce waiting times using advanced allocation techniques. Burkell et al. [10] examined the impact of transitioning from a first-come, first-served admission policy to a needs-based approach in a chronic care hospital in London, Ontario. Their study used a computer modeling technique to analyze waiting list dynamics under both policies. The results highlighted substantial variability in patients' care requirements, demonstrating that implementing a needs-based criterion would significantly alter individual placement priorities and overall admission decisions. As this research also aims to develop a needs-based prioritization policy, the findings demonstrate the potential impact such an approach can have on admission decisions.

Meiland et al. [27] focused on urgency-based prioritization as well. According to their research, non-urgent patients had to wait longer, but their health status did not change during that time. Additionally, waiting at home had no effect on the satisfaction levels of non-urgent patients. These results show that it is possible to prioritize urgent patients without having a significant detrimental impact on non-urgent patients.

Arntzen et al. [5] propose a preference-based allocation model for nursing home admissions that balances waiting time reduction with patients' individual preferences. Their approach, validated through simulations in the Amsterdam area, demonstrates a significant reduction in abandonment rates from 32.2% to 7.4% while simultaneously lowering waiting times and maintaining patient-centered care. This research shows that effective allocation strategies can significantly reduce waiting times, improve patient satisfaction, and optimize resource utilization.

Hallal [21] utilized a Markov chain model to analyze and optimize patient flow within Nova Scotia's long-term care system. The model represented key stages, such as home care, acute hospitalization, LTC placement, and system departure, with transitions between these states determined by historical data. By simulating patient flow and testing interventions like increased LTC capacity or enhanced home care, the model identified strategies to reduce waiting times and improve resource allocation, showcasing the effectiveness of Markov chains in addressing bottlenecks in healthcare systems.

The patient flow models discussed in this section primarily focus on managing queues and optimizing system-wide allocation strategies. These models determine the best way to reduce waiting times and improve resource distribution at a macro level. However, this research shifts the focus to individual-level decision-making, where patient health states are explicitly modeled as a Markov process. The next section explores how health modeling techniques can capture individual patient transitions and guide optimal decision-making.

3.2 Modeling Health Dynamics

In this research, health condition is a key factor influencing decision making. Health is conceptualized as a dynamic process with multiple discrete states, transitioning over time due to aging and external factors. Previous research on health modeling has utilized dynamic state-based approaches. Stochastic processes are frequently employed to model individual health trajectories, whereas System Dynamics (SD) is typically utilized for modeling health dynamics at the population level.

Health can be expressed using health states. Walsh et al. [44] defines health status using the *Frailty Index (FI)*, a widely used measure for quantifying frailty in elderly individuals. The FI classifies health along a spectrum from "fit" to "severe frailty" based on the accumulation of health deficits, allowing for the tracking of frailty progression.

Similarly, the Clinical Frailty Scale (CFS) provides a structured approach to assessing frailty by classifying individuals on a nine-point scale ranging from "very fit" to "terminally ill" [14]. The CFS evaluates a combination of comorbidities, functional ability, and cognitive impairment, making it a widely used tool in geriatric care. A scoping review of its applications highlights its strong association with key health outcomes, including mortality, hospitalization, and functional decline. The CFS is frequently used across various healthcare settings, such as acute care, intensive care, and long-term care facilities, to support clinical decision-making and prioritize healthcare interventions. Given its predictive power and practical applicability, the CFS could serve as a valuable framework for mapping individuals to discrete health states in dynamic health models.

System dynamics (SD) is a commonly used approach for modeling healthcare systems, particularly when a broad, strategic perspective is needed ([11] [22]). In its quantitative stock-flow representation, SD effectively models disease progression within a population by capturing transitions between health states, which can be influenced by both natural disease dynamics and healthcare interventions ([20] [17]).

England et al. [20] integrates the Frailty Index (FI), into a system dynamics simulation model, using routine healthcare data from over 2.2 million primary care patients in England. Their model projects frailty prevalence over time, estimating that by 2027, nearly 50% of individuals aged 50 and older will exhibit some degree of frailty. The study highlights the importance of early detection and targeted interventions to prevent crisis situations and optimize healthcare resource allocation. However, it does not account for the possibility of frailty decreasing, meaning that an individual's health may improve over time due to recovery, medical interventions, or lifestyle changes, highlighting areas for improvement.

SD is particularly useful for studying large populations where individual variations are less relevant. However, when the focus shifts to smaller subgroups or individual patient trajectories, the aggregated nature of SD may not be sufficient. In such cases, stochastic models, including Markov processes, provide a more suitable framework for capturing uncertainty in individual health transitions over time.

Beyond static frailty indices, mathematical models such as Markov chains have been employed to capture health dynamics in a probabilistic manner. Chiang [13] introduced a health index derived from a Continuous-Time Markov process, conceptualizing individual health as a dynamic continuum ranging from optimal well-being to severe illness. This continuum is segmented into ordered health states, with transition probabilities between states defined by intensity functions. The index quantifies the expected proportion of time an individual spends in each health state over a year, offering a numerical measure of population health that ranges from zero to one.

Kaushik et al. [23] developed a Markov-based methodology to monitor the health status of elderly individuals living at home. Their model represents daily activity patterns as discrete states and employs transition probabilities derived from sensor data (e.g., infrared or magnetic switches). By comparing a "profile" Markov chain, representing typical behavior, with a "test" Markov chain based on recent observations, deviations in health status can be detected using statistical tests such as chi-square goodness-of-fit. This methodology offers an unobtrusive, real-time approach to monitoring elderly individuals, making it valuable for early intervention.

3.3 Preventive Maintenance

As a person's health gradually deteriorates, timely interventions are crucial to prevent escalation into a crisis situation. This process is analogous to the field of preventive maintenance in engineering, where machines undergo progressive deterioration and require maintenance to prevent failure. In both cases, the goal is to determine the optimal timing for interventions to minimize long-term costs and adverse outcomes. Various methods have been developed to optimize intervention strategies in such processes. This field is called preventive maintenance. This section explores these approaches and their relevance to healthcare decision-making.

Systems often transition through various states over time, each associated with different risks. In maintenance optimization, an optimal schedule for interventions is determined to prevent costly failures, which is called Preventive Maintenance (PM). There are 2 types of PM: Condition-Based Maintenance (CBM) schedules interventions based on observed conditions, while Time-Based Maintenance (TBM) schedules interventions at fixed intervals, regardless of the system's actual condition.

Recent research has focused on optimizing CBM and TBM policies using Markov decision processes (MDPs) to model deterioration and determine cost-effective maintenance strategies. Andersen [3] highlights that CBM reduces unnecessary maintenance by performing interventions only when the system's monitored condition indicates a need for action, whereas TBM follows a rigid schedule that does not account for actual wear and tear.

Liao et al. [25] propose a reliability-centered sequential preventive maintenance model for repairable deteriorating systems. Unlike traditional preventive maintenance strategies with fixed intervals, this model schedules maintenance actions based on continuously monitored system reliability. When reliability reaches a predefined threshold, an imperfect repair is performed, and after a set number of cycles, the system is replaced. The model optimizes maintenance scheduling by considering failure rates, operational costs, and breakdown costs, aiming to minimize long-term total cost. Their approach demonstrates improved cost efficiency and practicality compared to conventional methods. This method is well suited for situations where real-time information is available. However, this research proposes a model capable of handling uncertainty regarding the system's current state.

Assis and Marques [6] introduced a dynamic methodology for inspection scheduling, addressing uncertainty with safe and unsafe time windows (STW and UTW). STWs allow detection and management of potential failures, while UTWs pose higher risks of undetected failures. By dynamically adjusting inspection intervals based on real-time observations, the methodology reduces costs and mitigates risks. Noori et al. [32] propose an integrated inspection and preventive maintenance planning model for a Markov deteriorating system under scenario-based demand uncertainty. The study employs a two-stage stochastic programming approach to optimize inspection and maintenance decisions over a finite time horizon. In the first stage, inspections are scheduled based on the machine's state, while in the second stage, maintenance actions are determined based on inspection outcomes.

This research builds on these principles by modeling health transitions, aiming to minimize crisis risks and associated costs. It further enhances this approach by comparing benchmark strategies, such as periodic health checks or fixed schedules, with dynamic and optimal strategies introduced in previous research. For example, periodic strategies might involve routine inspections at set intervals regardless of individual health conditions, while dynamic strategies adjust based on real-time observations or estimated probabilities of health deterioration. By incorporating these comparisons, this research investigates the effect of implementing optimal policies created by the MDP, on costs and the well-being of older adults, while dealing with imperfect information.

3.4 Contribution

The reviewed studies illustrate a variety of approaches for patient allocation, modeling health dynamics, and preventive maintenance. Despite extensive research in patient flow optimization and health modeling, there is a significant research gap in integrating dynamic policies for real-time decision making in nursing home admissions, while taking into account uncertainty about health state. Previous studies often assume static parameters or overlook the uncertainty in health state observations. This research addresses these gaps by developing a model to dynamically manage health state transitions in elderly care, while incorporating uncertainty into decision making using probabilistic tools.

4 Modeling

This section offers a step-by-step explanation of how the final model was developed to determine the optimal policy for assigning patients to Nursing Homes (NHs) and performing check-ups. First, Section 4.1 discusses the underlying health model that reflects the dynamics of an individual's health. Secondly, Section 4.2 builds on this concept by adding the possibility to take actions in each state, that is, NH placements will be included. This model assumes perfect information, which means it always has access to the current health state of an individual. Uncertainty about this information will be incorporated in the final model discussed in Section 4.3.

4.1 Health-model

To effectively capture the dynamics of patient health states and transitions, our model incorporates an underlying structure, referred to here as the Health Model. The Health Model represents the process of an individual's changing health over time, where the states correspond to different health conditions, and the transition probabilities define the likelihood of health progression or deterioration. The Health Model $\mathcal{M}$ consists of $N+1$ states, representing N health states, and a single absorbing state, named the *crisis state*. The health states reflect the various stages of a patient's condition, while the crisis state denotes a point at which intervention becomes mandatory. As time progresses, health deteriorates, meaning a patient's condition worsens until they ultimately reach a crisis state. It is important to note that, due to this progression, without intervention, everyone will eventually experience a crisis, which is a fundamental assumption of this model. The first state in the model represents the point at which a person's health begins to be at risk, marked by the

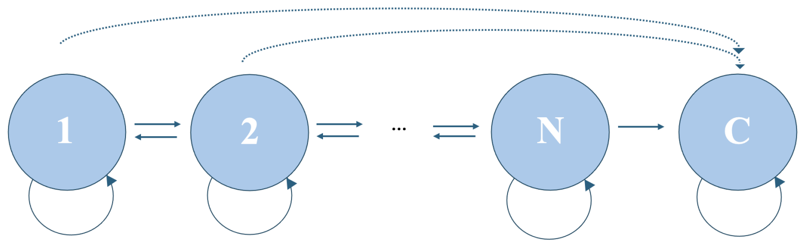

FIGURE 4.1: Health Model $\mathcal{M}$

initiation of home care, or "wijkverpleging". This stage indicates the first signs of frailty or an increased risk of health deterioration, where minimal support is required to maintain daily activities. As such, it serves as the natural starting point for modeling health progression, capturing the shift from independence to increasing levels of care dependency. The next states represent gradual health deterioration until a person has a crisis.

The state space of the Health Model $\mathcal{M}$ is given by:

$$S_{\mathcal{M}} = \{1, \ldots, N, C\}$$

where $1, \ldots, N$ represent the health states, and C denotes the absorbing crisis state. The structure of the model is shown in Figure 4.1.

4.1.1 Initial Distribution

To account for the differences in health conditions among individuals entering the system, not all patients start in the first health state. Instead, an initial distribution μ is introduced to model the probability of an individual beginning in each possible health state. This distribution allows flexibility in representing different population characteristics at the point of entry. The initial distribution is represented as a probability vector:

$$\mu = (\mu_1, \mu_2, \ldots, \mu_N)$$

where μ_i denotes the probability of starting in health state i, satisfying:

$$\sum_{i=1}^{N} \mu_i = 1, \quad \mu_i \geq 0 \quad \forall i \in \{1, \dots, N\}.$$

Different assumptions can be made about the health distribution of new patients, such as a uniform, linear, or exponential distribution over the discrete states with finite support. By selecting an appropriate initial distribution, the model can better reflect real-world patient characteristics upon entry.

4.1.2 Transition Probabilities

Figure 4.1 displays the structure of the Health Model. In every state, there is a probability of staying in the same state, transitioning to the next state, or to the absorbing crisis state. Although Figure 4.1 does not show the possibility of skipping a state and moving two states forward, the model is flexible, and this can be included. The transition probability matrix of the general Health Model is denoted by $\mathbf{P}_{\mathcal{M}}$, which is defined as follows:

$$\mathbf{P}_{\mathcal{M}} = \begin{bmatrix} p_{11} & p_{12} & p_{13} & \cdots & p_{1N} & p_{1C} \\ p_{21} & p_{22} & p_{23} & \cdots & p_{2N} & p_{2C} \\ p_{31} & p_{32} & p_{33} & \cdots & p_{3N} & p_{3C} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ p_{N1} & p_{N2} & p_{N3} & \cdots & p_{NN} & p_{NC} \\ 0 & 0 & 0 & \cdots & 0 & 1 \end{bmatrix}$$

The probability parameters used to calculate the transitions within $\mathcal{M}$ are given in Table 4.1. These probabilities are based on the assumptions made about the structure of the model. Given these assumptions, the transition probabilities for each state i are computed as follows:

Parameter	Description
N	The number of health states
μ	Initial distribution
$p_{\text{same state}}$	The probability of remaining in the same health state
p_{crisis}	The base probability of transitioning to the crisis state
$p_{\text{crisis growth}}$	A scaling factor that increases the crisis probability as health deteriorates
p_{back}	The probability of improving in health by moving back to a previous state

TABLE 4.1: Parameters of the Health Model

- Probability of staying in the same state:

$$p_{i,i} = p_{\text{same state}}$$

- Probability of transitioning to crisis:

  The probability of a crisis increases linearly as health deteriorates, starting at p_{crisis} and growing with $p_{\text{crisis growth}}$ over time:

$$p_{i,C} = p_{\text{crisis}} + \left(p_{\text{crisis growth}} \times \frac{i}{N}\right)$$

- Probability of improving in health (moving to a better state, only if $i > 1$):

$$p_{i,i-1} = p_{\text{back}}, \quad i > 1$$

- Probability of health deterioration (moving to a worse state):

$$p_{i,i+1} = 1 - p_{i,C} - p_{i,i} - p_{i,i-1} \quad i < N$$

- Boundary conditions for the last pre-crisis state:

$$\begin{aligned} p_{N-1,C} &= 1 - p_{\text{same state}} - p_{\text{back}}, \\ p_{N-1,N-1} &= p_{\text{same state}}, \\ p_{N-1,N-2} &= p_{\text{back}} \end{aligned}$$

- Absorbing crisis state:

$$p_{C,C} = 1$$

To calculate the expected time until absorption in the Markov chain, we consider the transition probability matrix $\mathbf{P}_{\mathcal{M}}$, which can be partitioned as:

$$\mathbf{P}_{\mathcal{M}} = \begin{bmatrix} Q & R \\ 0 & I \end{bmatrix}$$

where:

- Q is the transition matrix for transient states.
- R is a vector representing the transition probabilities from transient to absorbing states.
- I represents the identity matrix associated with the absorbing states. Since there is only one absorbing state, I reduces to the scalar value 1.

The fundamental matrix L is defined in Equation 4.1, where each entry L_{ij} represents the expected number of times the process visits transient state j given that it started in transient state i. The expected time until absorption for each transient state is then given in Equation 4.2, where $\mathbf{1}$ is a column vector of ones. The vector t contains the expected number of steps before absorption for each transient state [36].

$$L = (I - Q)^{-1} \tag{4.1}$$

$$t = N\mathbf{1} \tag{4.2}$$

4.1.3 Example model

To illustrate the model's intuition, this section presents an example. The health states from England et al. [20] are used, which has 4 health states, so we define $N = 4$. This results in a total of 5 states, including the crisis state. The states are defined as follows:

$$S_{\mathcal{M}} = \{Fit, Mild, Moderate, Severe, Crisis\}$$

Next, we define the transition probabilities for the health states, and the initial distribution. The transition matrix of the Markov Chain is shown in the matrix below.

$$\begin{aligned} p_{\text{same state}} &= 0.8 \\ p_{\text{crisis}} &= 0.1 \\ p_{\text{crisis growth}} &= 0 \\ p_{\text{back}} &= 0 \\ \mu &= [1, 0, 0, 0, 0] \end{aligned}$$

$$\mathbf{P}_{\mathcal{M}} = \begin{bmatrix} 0.8 & 0.1 & 0 & 0 & 0.1 \\ 0 & 0.8 & 0.1 & 0 & 0.1 \\ 0 & 0 & 0.8 & 0.1 & 0.1 \\ 0 & 0 & 0 & 0.8 & 0.2 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Implementing these transition probabilities result in the example model shown in Figure 4.2. Using Equations 4.2 and 4.1, the expected time until absorption can be calculated, which means the expected time it takes to transition from any of the four predefined health states to the crisis state. Figure 4.3 shows the expected values resulting from the calculation. As shown in the figure, using this transition structure, the expected time until absorption decreases as the condition of the patient worsens. This aligns with the intuitive expectation that individuals in worse health states have a higher probability of transitioning to a crisis sooner. The findings validate the transition structure used in the model and highlight the importance of timely

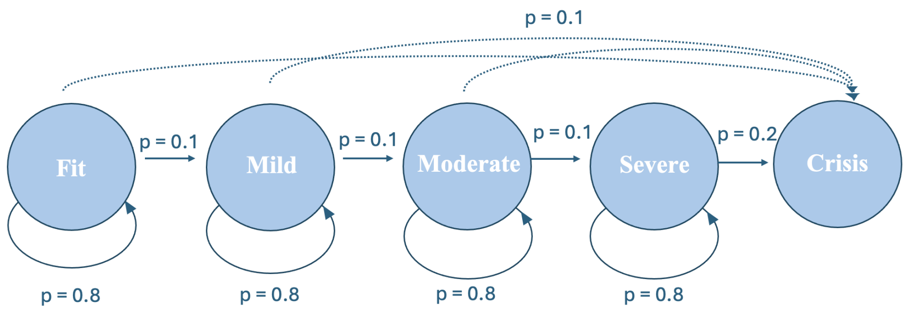

FIGURE 4.2: Example of the Health Model

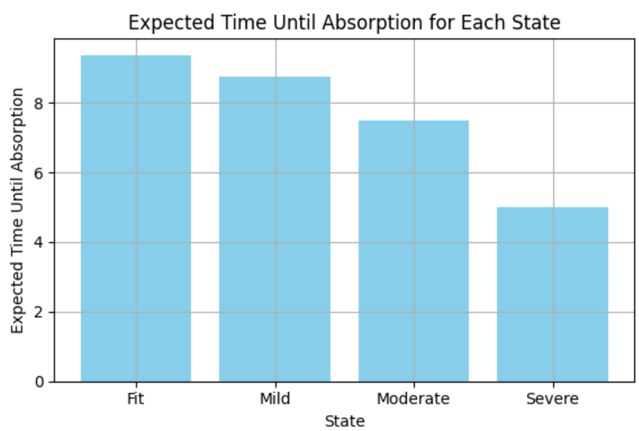

FIGURE 4.3: Time until absorption per state

interventions to delay or prevent crisis situations.

4.1.4 Interpretation

To apply this Markov model in practice, healthcare professionals need a structured approach to assign patients to one of the N discrete health states based on observable characteristics. In the following, several possible approaches to assess patient health and determine their corresponding state in the model will be proposed.

One option is to use the Frailty Index (FI) [44] as a basis for defining health states, where a connection is established between FI scores and the discrete states in the model. Lower FI scores represent better health conditions, while higher scores indicate increasing frailty, providing a structured way to classify individuals. Alternatively, the Clinical Frailty Scale (CFS) [14], which assess functional independence, could be used to categorize patients. These tools provide well-established thresholds that can be aligned with health states, ensuring a clinically interpretable classification. Lastly, a possible approach is to leverage activity-based monitoring [23], where deviations in mobility or daily activity patterns help determine a patient's state. In this case, real-time movement data from wearables or caregiver reports could refine the state assignment. In the next sections, we will build on this concept by adding actions to every state.

4.2 Optimization Model with Perfect Information

The optimization model with perfect information, denoted by $\mathcal{G}$, operates under the assumption of perfect information, maintaining complete and accurate knowledge of an individual's health state at all times. It provides a simplified version of the complete framework, serving as a foundational step before introducing the final model. $\mathcal{G}$ includes the same health states as in $\mathcal{M}$, and is designed to make a decision on the optimal timing to admit a person to an NH, accounting for all associated costs. This section will give an overview of all the key elements used to create this model.

The model is formulated as a Discrete-Time Markov Decision Process (MDP). As explained in Chapter 2, a discrete-time approach is chosen to allow for structured decision-making at fixed intervals, such as the option to examine patients on a weekly basis. This simplifies the implementation of scheduled check-ups without requiring a continuous-time framework. The MDP used in this study is designed to optimize decisions regarding patient admission to a NH within the healthcare system. Figure 4.4 shows the structure of this model. The key elements of the MDP are described below.

4.2.1 States

The state space of $\mathcal{G}$ expands upon the health states defined in the health model $\mathcal{M}$ by introducing an additional state: the nursing home state (NH). In $\mathcal{M}$, the crisis state is modeled as an absorbing state, representing the final state of the system. However, in $\mathcal{G}$, the crisis state is no longer absorbing, as individuals in a crisis state always transition to the newly introduced nursing home state. The nursing home

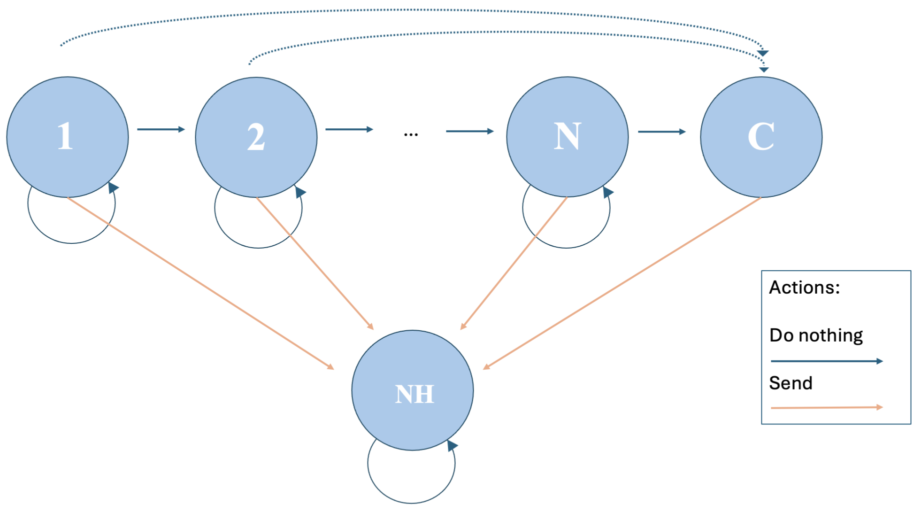

FIGURE 4.4: Optimization model with perfect information $\mathcal{G}$

state serves as the final and absorbing state of the model, representing the ultimate destination for all individuals. This gives us the following states:

- The first N states represent different health conditions while the patient is living at home and receives home care.
- The $(N + 1)$-th state represents a crisis.
- The last state $N + 2$ is the absorbing NH state.

4.2.2 Actions

An essential component of an MDP is the set of actions available to the decision-maker. These actions determine possible transitions between states and ultimately shape the optimal policy by identifying the best course of action for each state. In $\mathcal{G}$, there are two actions available:

- **Action 0: Do Nothing**: This action allows the client to naturally transition within the health states of the model. Over time, the client will ultimately reach the crisis state, which subsequently leads to a transition to the nursing home.

- **Action 1: Send**: The patient is directly transferred to the absorbing nursing home state. This action can be chosen in any health state, including the crisis state.

This results in the following action space:

$$A_{\mathcal{G}} = \{0, 1\}$$

4.2.3 Transition probabilities

In an MDP, the transition probabilities depend on both the current state and the chosen action. In $\mathcal{G}$, two different probabilities are used: $p_{i,j}$ indicates the probability of transitioning to one of the health states, specifically, transitioning from state i to state j. Probability p_i^{NH} indicates the probability of transitioning from state i to the NH state. The probabilities are defined as follows:

$$\begin{aligned}
p_{i,j} &= P(X_{t+1} = j \mid X_t = i, a = 0) = \mathbf{P}_{\mathcal{M}}[i, j], \qquad i, j \in \{1, \ldots, N, C\} \\
p_i^{\text{NH}} &= P(X_{t+1} = \text{NH} \mid X_t = i, a = 1) = 1 \\
p_{\text{NH}}^{\text{NH}} &= P(X_{t+1} = \text{NH} \mid X_t = \text{NH}, a = 0) = 1 \\
p_C^{\text{NH}} &= P(X_{t+1} = \text{NH} \mid X_t = C, a = 1) = 1 \qquad i \in \{1, \ldots, N, C\}
\end{aligned}$$

4.2.4 Reward function

Each (state, action)-pair in the model is associated with specific costs, some of which vary based on the individual's health condition. There are 3 types of costs involved in $\mathcal{G}$, and 1 utility component. The utility component represents the client's personal preference within the system. Specifically, if a client prefers to remain at home for as long as possible, a positive utility is added to the home rewards. Conversely, if a client prefers early admission to a nursing home, a negative utility is incorporated into the home rewards, reflecting their preference for transition. The *home cost* depends on the current health state, as individuals with deteriorating health require more intensive home care, leading to higher expenses. Similarly, the *nursing home cost* also varies with the individual's health state at the time of admission. A healthier person who is placed in a nursing home is expected to stay there longer, accumulating more costs, whereas a frail person is likely to have a shorter stay due to a higher mortality risk. The *crisis cost* is fixed and not dependent on the state prior to the crisis state. To capture this dependency, we define:

- $C_{\text{home}}(s)$ as the home cost for an individual in state s.
- $C_{\text{NH}}(s)$ as the expected nursing home cost for an individual admitted from state s.
- C_{crisis} as the fixed cost associated with a crisis.
- U_{home} is a utility term that captures the personal preferences to stay at home.

The costs are mapped to a reward function, which is defined as follows:

$$R_{\mathcal{G}}(a, s, s') = \begin{cases} C_{\text{home}}(s') + U_{\text{home}} & \text{if } s' \in \{1, \dots, N\} \\ C_{\text{NH}}(s) & \text{if } s' = \text{NH},\ s \in \{1, \dots, N\} \\ C_{\text{crisis}} & \text{if } s' = C \end{cases}$$

4.3 Model with Imperfect Information

The final model, which incorporates imperfect information, includes a critical extension to better capture the lack of real-time information about health statuses. In this model, check-ups are used to establish the current health state of a client in the model. This section will delve into all the components of this model.

4.3.1 States

The model with imperfect information, denoted by $\mathcal{F}$, represents an expansion of the model without uncertainty $\mathcal{G}$ and incorporates additional states to account for the passage of time. In this model, each health state $1, \dots, N$ is represented as a combination of two variables, (i, j), where i denotes the health state and j represents the time since the last check. To limit uncertainty, j is capped at T, which means that there is a maximum allowed time between health checks. Once T time steps have elapsed without a check, a health check is required to observe the current health state. This structure results in a total of $(N \times (T+1)) + 2$ states within $\mathcal{F}$. The state space of the model $\mathcal{F}$ is given by:

$$S_{\mathcal{F}} = \{(1,0), (1,1), \ldots, (1,T), \ldots, (N,0), \ldots, (N,T), C, \mathrm{NH}\}$$

where C represents the crisis state, and NH denotes the absorbing NH state.

4.3.2 Actions

Model $\mathcal{F}$ includes one additional action within the MDP framework of $\mathcal{G}$: the action "check". This action represents a health check performed by a specialist to determine the current health status of a client. Chapter 6 will elaborate further on the specifications of this check. This action complements the actions of model $\mathcal{G}$, that is, "do nothing" and "send to nursing home". Combining these action spaces creates a set of three distinct actions available at each decision point. However, not every action is available in every state. The next section will specify in which states each action can be taken.

- **Action 0: Do nothing**: Doing nothing results in an increasing uncertainty of the current health state of the client.
- **Action 1: Send to nursing home**: Directly move the client to the nursing home state, used to avoid a crisis.
- **Action 2: Check**: Perform a health check to observe the current health state of the patient. This action reduces the uncertainty about the client's condition, enabling more informed decisions regarding subsequent actions.

This results in the following action space:

$$A_{\mathcal{F}} = \{0, 1, 2\}$$

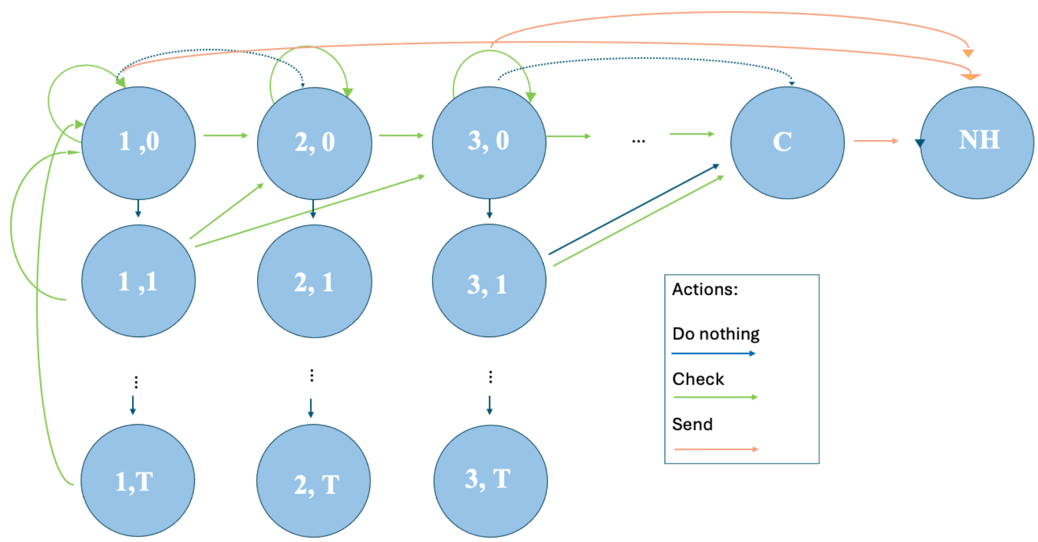

FIGURE 4.5: Transitions of model with imperfect information $\mathcal{F}$

Figure 4.5 illustrates the structure of this model, with colored arrows depicting possible transitions and the corresponding actions. For clarity purposes, not all transitions are indicated with arrows. The different actions and their associated transitions will be explained in detail below.

Action 0: Do Nothing

The action *do nothing* can be taken in all states except for:

- States (i, T) for $i \in \{1, \ldots, N\}$, where T represents the maximum time since the last check. In these states, the model is forced to perform a check to ensure the patient's current health state.
- The *crisis state* C, as a patient in this state must be sent to the nursing home.

There are two possible outcomes when taking action *do nothing* in state (i, j):

- The patient transitions to the *crisis state* C with probability $p_{i,j}^C$. This transition occurs independently of the chosen action and reflects a critical health deterioration. When a crisis occurs, the model is immediately informed without requiring a check.

- If the patient does not transition to the crisis state, the uncertainty regarding their health state increases, resulting in a transition from state (i, j) to $(i, j+1)$ with probability $1 - p^C_{i,j}$.

Action 1: Send

The action *send* can be taken from the states $(i, 0)$ for $i \in \{1, \ldots, N\}$ and state C. This condition ensures that patients are only sent to the nursing home after their health status has been verified through a check. The *send* action guarantees that a patient avoids entering the crisis state by transitioning directly to the NH state. Furthermore, if a patient enters the *crisis state* C, they are always sent to the nursing home in the next step.

Action 2: Check

The *check* action can be performed in every state except for:

- The *crisis state* C.
- The *nursing home state* NH.

When choosing the *check* action in state (i, j) , there are 2 types of subsequent states:

- C: the probability of transitioning to C remains the same as it is for *do nothing*.
- $(k, 0)$: the system transitions from state (i, j) to $(k, 0)$ with probability $p^k_{i,j}$, where $k \in \{i, \ldots, N\}$. The index j resets to 0, indicating that the time since the last check is zero.

4.3.3 Transition probabilities

To calculate the transition probabilities for $\mathcal{F}$, we rely on those derived from the health model $\mathcal{M}$. However, because we are dealing with imperfect information, we need the n-step transition matrix of $\mathcal{M}$, denoted by $\mathbf{P}^{(n)}_{\mathcal{M}}$, which represents the likelihood of moving from one state to another in n steps.

We denote the current state of the model by X_t, therefore, a transition in 1 time step from state i to state j is denoted as

$$P(X_{t+1} = i \mid X_t = j) = \mathbf{P}_{\mathcal{M}}[i, j] \tag{4.3}$$

The n-step transition probabilities are defined as follows:

$$P(X_{t+n} = j \mid X_t = i) = \mathbf{P}_{\mathcal{M}}^{(n)}[i, j] = \mathbf{P}_{\mathcal{M}}^{n}[i, j] \tag{4.4}$$

When the last check was performed j time steps ago, the transition probabilities between states must account for the dynamics over j time steps. For example, to determine the probability of transitioning from state i to state k after not checking for 4 time steps, we use the 4-step transition probabilities from $\mathbf{P}_{\mathcal{M}}^{(4)}$. An important aspect to consider is the fact that model $\mathcal{M}$ is an absorbing Markov chain. This means that when we calculate the n-step transition probability from state i to a crisis, denoted by $\mathbf{P}_{\mathcal{M}}^{(n)}[i, C]$, we have the probability that the chain transitioned to the crisis state within n steps, so n steps or less. However, when calculating the probability of transitioning from state (i, j) to a crisis, we want to know the probability of transitioning to a crisis in exactly j time steps, as we know that the client was not in a crisis until time step $j - 1$. To account for this, conditional probabilities are used in the transition probability calculations, which are discussed below.

Probability of a crisis

The client can transition to the crisis state from any state in the state space except the NH state. The probability of a crisis is calculated for every state in the state space, and depends on the health state as well as the uncertainty. The probability of a crisis in state (i, j) is denoted by $p_{i,j}^{C}$.

When the last check was 0 time steps ago, that is, $j = 0$, the exact health state of the patient is known. Therefore, the probability of a crisis is easy to calculate, as it directly represents the transition from a health state to the crisis state in $\mathcal{M}$.

$$p_{i,0}^{c} = P(X_{t+1} = C \mid X_t = i) = \mathbf{P}_{\mathcal{M}}^{(1)}[i, C] \qquad i \in \{1, \dots, N\}$$

Difficulty arises when the last check was not performed in the current time step, that is, $j > 0$. The probability of transitioning to the crisis state from state i when the last check was j time steps ago can be calculated using the fact that there was no crisis up until the current time step. In other words, when the model is in state (i, j), it is known that until time $j - 1$, there was no crisis situation. Therefore, the probability of a crisis can be calculated as follows.

$$
\begin{aligned}
p_{i,j}^{C} = P(X_{t+j+1} = C \mid X_t = i, X_{t+j} \neq C) &= \frac{P(X_{t+j+1} = C \cap X_{t+j} \neq C \mid X_t = i)}{P(X_{t+j} \neq C \mid X_t = i)} \\
&= \frac{\mathbf{P}_{\mathcal{M}}^{(j+1)}[i, C] - \mathbf{P}_{\mathcal{M}}^{(j)}[i, C]}{1 - \mathbf{P}_{\mathcal{M}}^{(j)}[i, C]} \\
& i \in \{1, \ldots, N\}, j \in \{1, \ldots, T\}
\end{aligned}
$$

By incorporating the case where $j = 0$, the resulting function for the transition probabilities to the crisis state is given as follows:

$$
p_{i,j}^{C} = \begin{cases} \mathbf{P}_{\mathcal{M}}^{(1)}[i, C] & i \in \{1, \ldots, N\}, j = 0 \\ \frac{\mathbf{P}_{\mathcal{M}}^{(j+1)}[i,C] - \mathbf{P}_{\mathcal{M}}^{(j)}[i,C]}{1 - \mathbf{P}_{\mathcal{M}}^{(j)}[i,C]} & i \in \{1, \ldots, N\}, j \in \{1, \ldots, T\} \end{cases}
$$

Probability of transitioning to a different state

When a check is performed in state (i, j), three outcomes are possible: the system may remain in the current state, move to another health state, or transition to the crisis state. The probability to transition from state i to state k, when the last check is j time steps ago, is denoted by $p_{i,j}^{k}$. When a check is performed with $j = 0$, the transition probabilities are straightforward to compute, as they correspond to the transition from state i to state j in the health model, and are defined as follows:

$$
p_{i,0}^{k} = P(X_{t+1} = k \mid X_t = i) = \mathbf{P}_{\mathcal{M}}^{(1)}[i, k] \qquad i, k \in \{1, \ldots, N\}
$$

The probabilities become more complex to calculate when $j > 0$, due to the increased uncertainty. Similar to the crisis probability calculation, we must again account for the absence of a crisis up to time $j-1$, leading to the following computations:

$$
\begin{aligned}
p_{i,j}^{k} &= P(X_{t+j+1} = k \mid X_t = i, X_{t+j} \neq C) \\
&= \frac{P(X_{t+j+1} = k \cap X_{t+j} \neq C \mid X_t = i)}{P(X_{t+j} \neq C \mid X_t = i)} \\
&= \frac{\mathbf{P}_{\mathcal{M}}^{(j+1)}[i,k]}{1-\mathbf{P}_{\mathcal{M}}^{(j)}[i,C]} \text{ for } i \in \{1,\dots,N\}, j \in \{1,\dots,T\}, k \in \{i,\dots,N\}
\end{aligned}
$$

By incorporating the case where $j=0$, the resulting function for the transition probabilities to any health state is given as follows:

$$
p_{i,j}^{k} = \begin{cases} \mathbf{P}_{\mathcal{M}}^{(1)}[i,k] & i, \in \{1,\dots,N\}, k \in \{i,\dots,N\}, j = 0 \\ \frac{\mathbf{P}_{\mathcal{M}}^{(j+1)}[i,k]}{1-\mathbf{P}_{\mathcal{M}}^{(j)}[i,C]} & i \in \{1,\dots,N\}, k \in \{i,\dots,N\}, j \in \{1,\dots,T\} \end{cases}
$$

Transition probability matrices

Using the probabilities calculated above, the transitions of $\mathcal{F}$ can be formulated. For clarity purposes, the initial distribution μ is not shown in the matrices.

Action 0: Do Nothing

For the "Do Nothing" action, the transition probabilities depend on the current state (i,j). There are three possible cases:

- If the system is in state (i,j), there is a probability $p_{i,j}^{c}$ of transitioning to the crisis state C.
- With probability $1-p_{i,j}^{c}$, the system transitions to state $(i,j+1)$, increasing the time since the last check.
- If the system is in the nursing home state NH, it remains there, as this state is absorbing.

Formally, the transition probabilities are given by:

$$\mathbf{P}(s'|s,a=0) = \begin{cases} p^C_{i,j} & \text{if } s=(i,j); s'=C, \\ 1-p^C_{i,j} & \text{if } s=(i,j); s'=(i,j+1), \\ 1 & \text{if } s=\text{NH and } s'=\text{NH}, \\ 0 & \text{otherwise.} \end{cases}$$

$$\mathbf{P}(s'|s,a=0) = \begin{array}{c|ccccccccc} & (1,0) & (1,1) & (1,2) & \cdots & (1,T) & \cdots & (N,T) & C & NH \\ \hline (1,0) & 0 & 1-p^C_{1,0} & 0 & \cdots & 0 & \cdots & 0 & p^C_{1,0} & 0 \\ (1,1) & 0 & 0 & 1-p^C_{1,1} & \cdots & 0 & \cdots & 0 & p^C_{1,1} & 0 \\ (1,2) & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & p^C_{1,2} & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \vdots \\ (1,T) & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & p^C_{1,T} & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ (N,T) & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & p^C_{N,T} & 0 \\ C & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & 0 \\ NH & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & 1 \end{array}$$

Action 1: Send For the "Send" action, the transition probability is either 0 or 1. This action can solely be chosen when the health state of the person is known, i.e. $j = 0$.

$$\mathbf{P}(s'|s,a=1) = \begin{cases} 1 & \text{if } s'=\text{NH} \\ 0 & \text{otherwise} \end{cases}$$

Action 2: Check For the "Check" action, the transition probabilities are determined by the following cases:

- If the system is in state (i,j), it transitions to a new observed state $(k,0)$ with probability $p^k_{i,j}$.
- The probability of transitioning to C remains $p^C_{i,j}$, as similar in the "Do Nothing" action.

Formally, the transition probabilities are given by:

$$\mathbf{P}(s'|s,a=2)=\begin{cases}p_{i,j}^{k} & \text{if } s=(i,j);s'=(k,0) \text{ for } k\in\{1,\dots,N\},\\ p_{i,j}^{C} & \text{if } s=(i,j);s'=C,\\ 0 & \text{otherwise.}\end{cases}$$

$$\mathbf{P}(s'|s,a=2)=\begin{array}{c|ccccccccc} & (1,0) & (1,1) & (1,2) & \cdots & (N,0) & \cdots & (N,T) & C & NH\\ \hline (1,0) & p_{1,0}^{1} & 0 & 0 & \cdots & p_{1,0}^{N} & \cdots & 0 & p_{1,0}^{C} & 0\\ (1,1) & p_{1,1}^{1} & 0 & 0 & \cdots & p_{1,1}^{N} & \cdots & 0 & p_{1,1}^{C} & 0\\ (1,2) & p_{1,2}^{1} & 0 & 0 & \cdots & p_{1,2}^{N} & \cdots & 0 & p_{1,2}^{C} & 0\\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \vdots\\ (N,0) & p_{N,0}^{1} & 0 & 0 & \cdots & p_{N,0}^{N} & \cdots & 0 & p_{N,0}^{C} & 0\\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots\\ (N,T) & p_{N,T}^{1} & 0 & 0 & \cdots & p_{N,T}^{N} & \cdots & 0 & p_{N,T}^{C} & 0\\ C & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & 0\\ NH & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & 0\end{array}$$

4.3.4 Reward Function

The reward function $R_{\mathcal{F}}(a,s,s')$ of $\mathcal{F}$ is defined for every action a, state s, and next state s' and is based on four different cost components: *nursing home cost*, *home cost*, *check cost*, and *crisis cost*, and one utility component: *utility home.* Since the cost of home care depends on an individual's health condition and the expected cost of nursing home care depends on the state at admission, these costs are modeled as functions of the health state.

We define:

- $C_{\text{home}}(s)$ as the cost of home care when the individual is in state s, which depends only on the last observed health state i (the first component of s'), since the level of care needed is based on the most recent check.
- $C_{\text{NH}}(s)$ as the total expected nursing home cost for an individual admitted from state s, reflecting longer stays for healthier individuals.

The reward function can be formally expressed as follows:

$$R_{\mathcal{F}}(a,s,s') = \begin{cases} C_{\text{crisis}} & \text{if } a \in \{0{,}1\} \text{ and } s' = C \\ C_{\text{check}} + C_{\text{crisis}} & \text{if } a = 2 \text{ and } s' = C \\ C_{\text{check}} + C_{\text{home}}(s) + U_{\text{home}} & \text{if } a = 2 \text{ and } s' \neq C \\ C_{\text{home}}(s) + U_{\text{home}} & \text{if } a = 0 \text{ and } s' \neq C \\ C_{\text{NH}}(s) & \text{if } a = 1 \text{ and } s' = NH \end{cases}$$

The home cost, $C_{\text{home}}(s)$, accounts for the fact that individuals in worse health states require more intensive home care, leading to higher costs. If a health check is performed, an additional check cost C_{check} is incurred. When a patient is sent to a nursing home, the total cost $C_{\text{NH}}(s)$ depends on their initial state s, as healthier individuals are expected to stay in the nursing home longer, accumulating higher expenses. More details on these cost functions will be provided in Chapter 6.

Optimal Policy Calculation

Having defined the critical components of the MDP, the optimal policy for every state in $S_{\mathcal{F}}$ can be calculated using value iteration [36], which iteratively updates the value function until convergence. Since the costs are defined as negative values, the optimization process maximizes the value function, which is expressed as follows:

$$V(s,t) = \max_{a\in\{0,1,2\}} \left(R_{\mathcal{F}}(a,s,s') + \gamma \cdot \sum_{s'} P(s' \mid s,a) \cdot V(s',t+1) \right) \tag{4.5}$$

where:

- $V(s,t)$ represents the value of being in state s at time t
- $R_{\mathcal{F}}(a,s,s')$ is the reward function
- $P(s' \mid s,a)$ is the transition probability of moving to state s' given action a, given in the transition probability matrices.
- γ is the discount factor, which determines the weight of future rewards relative to immediate rewards. In this model, we set $\gamma = 1$, as future rewards are considered equally important as immediate rewards.

Value iteration proceeds by iteratively updating $V(s,t)$ for all states until the change in values across iterations is smaller than a predefined threshold ϵ, ensuring convergence. In this research, $\epsilon = 0.001$ is chosen through trial and error as a sufficiently small value to achieve convergence to optimality. Once the value function has stabilized, the optimal policy $\pi^*(s)$ can be derived by selecting the action that minimizes the value function:

$$\pi^*(s) = \arg\max_{a\in\{0,1,2\}} \left(R_{\mathcal{F}}(a,s,s') + \gamma \sum_{s'} P(s' \mid s,a) V(s',t+1) \right). \tag{4.6}$$

The algorithm is given by:

Algorithm 1 Value Iteration Algorithm

1: **Initialize:** Set $V(s,t) = 0$ for all $s \in S_{\mathcal{F}}$
2: **repeat**
3: $\quad V' \leftarrow V$
4: $\quad$ **for** each state $s \in S_{\mathcal{F}}$ **do**
5: $\quad\quad V(s,t) \leftarrow \max_{a\in\{0,1,2\}} \left(R_{\mathcal{F}}(a,s,s') + \gamma \sum_{s'} P(s' \mid s,a) V(s',t+1) \right)$
6: $\quad$ **end for**
7: **until** $\max_s |V(s,t) - V'(s,t)| < \epsilon$
8: **Return** optimal policy:
9: $\pi^*(s) = \arg\max_{a\in\{0,1,2\}} \left(R_{\mathcal{F}}(a,s,s') + \gamma \sum_{s'} P(s' \mid s,a) V(s',t+1) \right)$

The optimal policy determines the best action to take in each state, ensuring that decisions are made in a way that maximizes long-term rewards. For instance, it identifies the point at which uncertainty about a client's health has increased to a level where a check-up becomes necessary. Additionally, it specifies the state when a client's health has deteriorated to a degree that justifies transitioning them to a nursing home, balancing timely interventions with resource efficiency. Some example policies will be shown in the next chapter, where we introduce a toy model and analyze the impact of varying parameter values on the output.

5 Sensitivity Analysis

In this chapter, we analyze the model introduced in Chapter 4. The objective of this chapter is twofold: first, to create a policy using toy values, second, to demonstrate how the policy adapts when certain model parameters are adjusted. This process serves to verify the correctness and robustness of the model.

5.1 Example: Toy Model

To analyze the sensitivity of the model, we first define an example model that follows the same structure as the model $\mathcal{F}$, introduced in Section 4.3. This model serves as a baseline for further analysis, allowing us to investigate how changes in key parameters affect the outcome.

5.1.1 Defining the Model

The example model uses the Health Model $\mathcal{M}$, which includes the parameters described in Section 4.1, which serves as the underlying structure of the model. Next to that, example cost parameters are introduced to create a full toy model $\mathcal{F}$. Table 5.1 displays all the parameter values chosen to create this toy model. The home and nursing costs are represented as intervals, within which they increase or decrease linearly over time. Chapter 6 will provide a detailed explanation of the behavior of these parameters. Once the model is fully specified, we compute the optimal policy by iteratively solving the value function defined in Equation 4.6 in Section 4.3. This is done by using value iteration until convergence.

The heat map in Figure 5.1 illustrates the optimal policy created by solving this function. The figure shows the optimal action that should be taken in state (i, j)

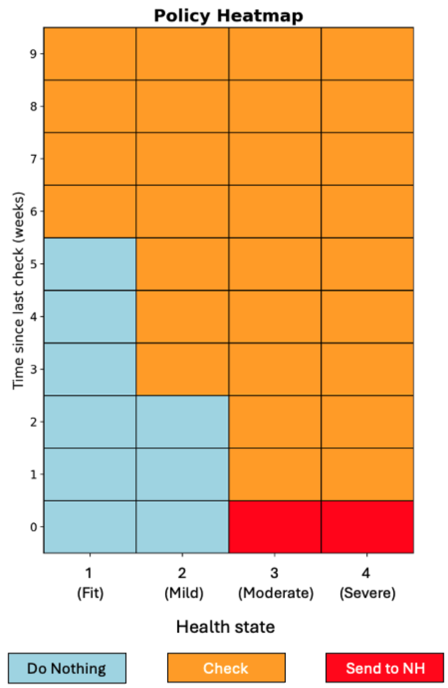

FIGURE 5.1: Heat map of the optimal policy of the toy model

Parameter	**Value**
μ	[1,0,0,0,0]
$p_{\text{same state}}$	0.8
p_{crisis}	0.1
$p_{\text{crisis growth}}$	0
p_{back}	0
Crisis cost	-150
Home cost	[-35,-35]
Nursing cost	[-1.000,-2.000]
Check cost	-5
Utility	0

TABLE 5.1: Parameters of the baseline model

to minimize the total expected cost. As shown in the heat map, the threshold for sending a patient to a nursing home is reached when their health status is classified as 'moderate,' indicating that home care is no longer optimal. In the mild health state, the model suggests performing a health check if three weeks have passed since the last check-up, while the model recommends waiting for 6 weeks when the state is "fit".

5.2 Impact of Parameter Variations

With the model defined, we now conduct a sensitivity analysis to examine the impact of key parameter changes on the optimal policy. The optimal policy, calculated in Section 5.1, serves as a reference for comparison.

5.2.1 Effect of Cost Variations

First, the effect of varying the cost parameters will be examined.

Varying Home Care Cost

The home care cost consists of two components: low cost for healthier individuals and high cost for individuals in later stages of deterioration. As discussed in Chapter 4, home care costs increase linearly with declining health, as individuals in poorer health require more intensive care. In this analysis, we vary the high cost of home care while keeping the low cost fixed, which results in a steeper ascent of the costs. As shown in Figure 5.2, increasing the high cost of home care provides the model with a stronger incentive to send individuals to a nursing home earlier to avoid accumulating high home care expenses.

Varying Nursing Home Cost

The nursing home cost also consists of high and low components, where sending a healthier individual to a nursing home results in a longer stay and thus higher cumulative costs. In this analysis, we vary the high cost of nursing homes while keeping the low cost fixed. As shown in Figure 5.3, reducing the high cost of nursing

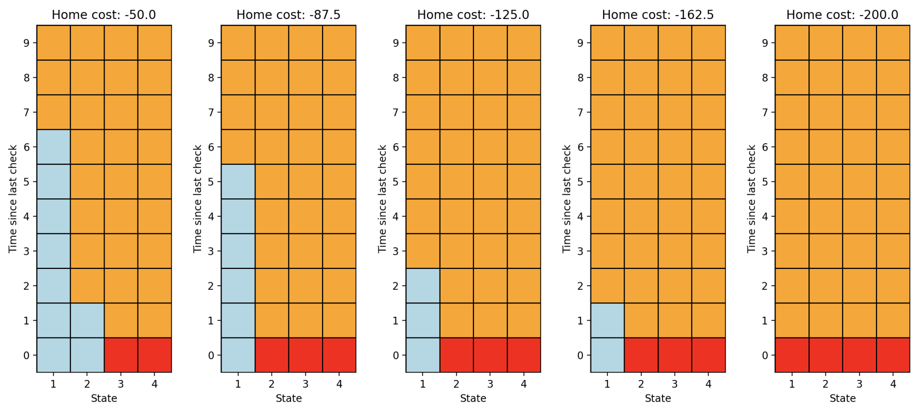

FIGURE 5.2: Effect of varying home care costs on the optimal policy

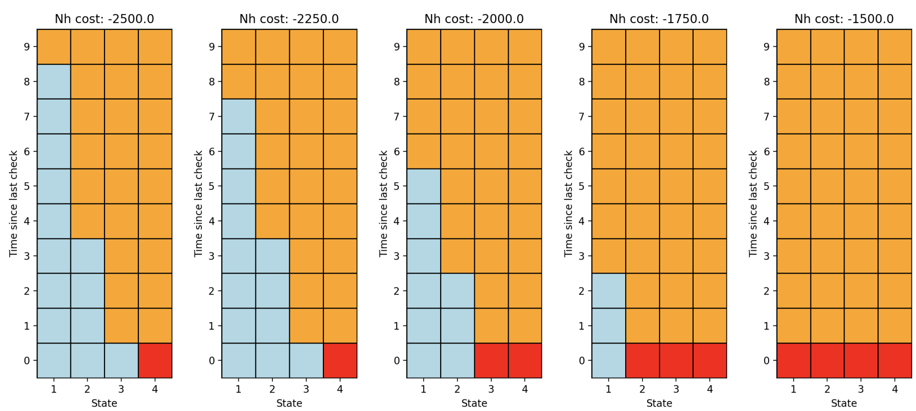

FIGURE 5.3: Effect of varying nursing home costs on the optimal policy

home reduces the incentive to keep individuals at home, leading to earlier nursing home admissions.

Varying Crisis Cost

Figure 5.4 illustrates the effect of changing the crisis cost. As expected, when the cost of the crisis is high, the model prefers earlier admission to the nursing home to avoid the financial burden of a crisis. In contrast, if the cost of the crisis is low, the model no longer prioritizes avoiding a crisis and instead focuses on delaying nursing home admission.

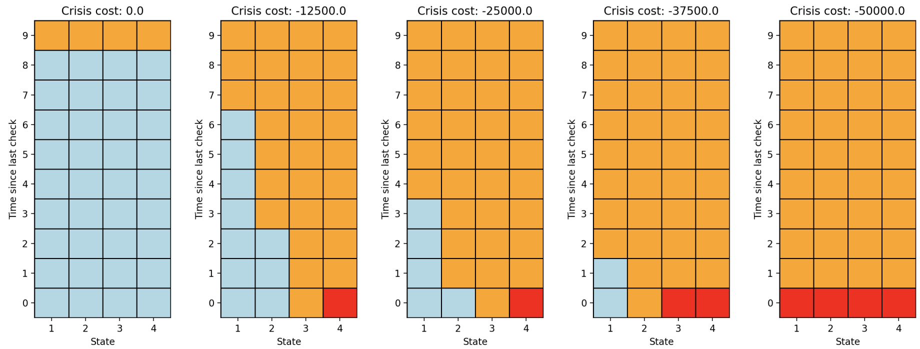

FIGURE 5.4: Effect of varying crisis costs on the optimal policy

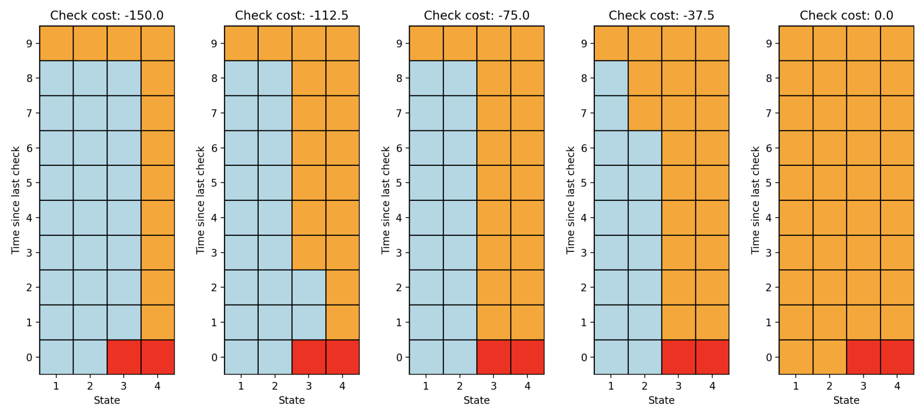

FIGURE 5.5: Effect of varying checking costs on the optimal policy

Varying Checking Cost

The check cost affects how frequently the model chooses to monitor the individual's health status. As shown in Figure 5.5, when the checking cost is low, the model checks more frequently to reduce uncertainty and prevent crises. In the extreme case where the check cost is zero, the model always checks, ensuring maximum information. Since it checks at every time step, it has full access to the current health state, making it behave identically to the model with perfect information. In contrast, when checking is expensive, the model reduces the frequency of health assessments. As shown in the figure, varying these costs only affects the checking policy while the sending threshold remains constant. However, this is not a strict rule, if the cost values become extreme, they could also influence the sending policy, potentially lowering or increasing the threshold for sending individuals to a nursing home.

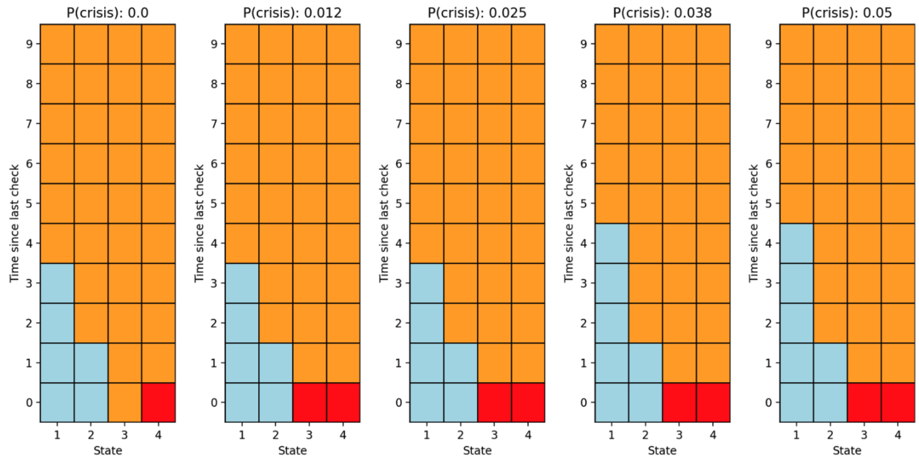

FIGURE 5.6: Effect of varying crisis probability on the optimal policy

5.2.2 Effect of Probability Variations

Varying Crisis Probability

As shown in Figure 5.6, increasing the probability of a crisis primarily leads to earlier nursing home admissions in the leftmost figure, while the other figures remain largely unchanged. This suggests that the impact of crisis probability on the optimal policy is limited, possibly due to the relatively small probability values used in the analysis. Additionally, if the crisis probability is uniform across all health states, its effect may be less pronounced in later stages, as the decision to admit a patient is already strongly influenced by other cost factors.

Varying Self-Transition Probability

Increasing the self-transition probability results in individuals spending more time in each state before transitioning to the next health stage. This slows down the progression through the system while accumulating home care costs. As shown in Figure 5.7, this effect causes the model to favor earlier nursing home admission to reduce prolonged home care expenses.

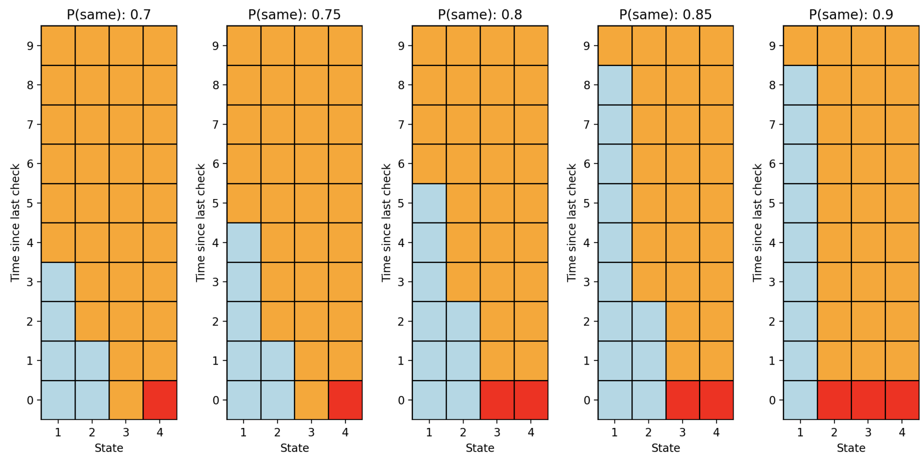

FIGURE 5.7: Effect of varying self-transition probability on the optimal policy

Conclusion

The sensitivity analysis confirms that the model behaves as expected, with parameter changes producing logically consistent adjustments in the optimal policy. Increasing home care costs encourages earlier nursing home admission, while higher crisis costs reinforce preventive measures. Similarly, adjustments in transition probabilities influence the timing of interventions in a predictable manner. These findings validate the model's robustness and correctness, allowing us to proceed with refining it based on real-world data. In the next chapters, we will focus on identifying and integrating realistic cost and probability parameters to enhance the applicability of the model.

6 Parameter Estimation

This chapter presents the parameter estimation process required to operationalize the conceptual model introduced in Chapter 4. Using real-world data, it establishes both probability and cost parameters crucial for accurately representing the dynamics of elderly patient flow and optimizing policies for nursing home admissions. This chapter is structured into two main sections. Section 6.1 on the estimation of transition probabilities between health states, while Section 6.2 on the estimation of associated costs and rewards.

6.1 Probability Parameter Estimation

This section details the analysis used to estimate the transition probability parameters of the Health Model. The data originates from the non-public micro data provided by Statistics Netherlands (CBS), and from "Zorginstituut Nederland" [31]. The analysis focuses on estimating the time required for a patient to transition from the initial health state to the crisis state, offering key insights into the model's transition dynamics and informing the probability estimates that drive the simulation.

6.1.1 Estimating Transition Probability Parameters

In this section, we describe the process of estimating the transition probabilities of the model introduced in Chapter 4 based on real-life data. For this purpose, we used non-public micro data from Statistics Netherlands (CBS) covering the years 2017–2019. The dataset includes individuals aged 65 and older and was filtered to focus on those who progressed to a nursing home, ensuring that the analysis captures the full transition from home care to institutionalized care. The dataset encompasses the entire

Dutch population, providing a comprehensive view of elderly care transitions. Additionally, experts were consulted to gain insights into health deterioration, the role of home care, the onset of crises, and the overall process leading up to a crisis state.

The transitions of the model with imperfect information ($\mathcal{F}$) can be calculated based on the transitions of the Health Model ($\mathcal{M}$). To achieve this, we will first connect the states to the data. Subsequently, an appropriate number of states along with the transitions will be determined by fitting a data distribution to the model.

Connecting the States to the Data

The health decline process of an older adult is captured by $\mathcal{M}$. This model comprises N health states, with the final absorbing state representing a crisis. The initial entry point into the system reflects a state in which health is expected to deteriorate. Therefore, the first state is defined as the moment an older adult begins to receive home care. Furthermore, expert opinions corroborated that this serves as an appropriate starting point for modeling the onset of declining health. As discussed in Chapter 2, most older adults with a WLZ indication receive some level of home care, which means that most clients waiting for a place in a nursing home, are included in our data analysis.

As mentioned before, it is assumed that every individual receiving home care would eventually experience a crisis if no action is taken. This assumption is essential for applying a consistent model to all individuals. Therefore, to capture the dynamics of $\mathcal{M}$, the expected period between the initial home care registration and the start of a crisis must be estimated.

Estimating the Time Distribution from Home Care to Crisis

To estimate the distribution of the time it takes for individuals receiving home care (*wijkverpleging*) to experience a crisis, we began by extracting data from the CBS data. This data includes individuals registered for home care and records of emergency department visits (*SEH bezoek*), which we consider indicative of a crisis. The time in between these two events is considered to be the time it takes to progress through $\mathcal{M}$. The data shows that, in most cases, clients transition into a nursing home after an emergency department visit, which aligns with the progression of the model.

Additionally, we observed that a significant number of clients transitioned to a nursing home within three weeks. As we believe that these individuals were already too frail and that no intervention could have prevented their transition, we excluded them from our analysis.

Unfortunately, the dataset is limited to the years 2017–2019. This short time frame results in censored data when estimating the time until crisis, as not all individuals who receive home care experience a crisis within the observation period. To address this, we filtered the dataset to include only individuals who eventually experienced a crisis, based on the assumption that, in the absence of intervention, every individual will ultimately reach a crisis state. We then applied a Kaplan-Meier curve, a non-parametric method widely used in survival analysis to estimate the survival function from censored data [35]. This ensures that the analysis properly accounts for the truncated nature of the dataset. The Kaplan-Meier estimator [35] is defined as:

$$\hat{S}(t) = \prod_{t_i \leq t} \left(1 - \frac{d_i}{n_i}\right) \tag{6.1}$$

where:

- t_i represents the distinct observed event times, meaning the moments when at least one individual transitions to SEH.
- d_i is the number of individuals who transition to SEH at time t_i.
- n_i is the number of individuals who were still receiving home care before t_i.

This method estimates the survival probability $S(t)$, which represents the proportion of individuals who remain in home care at time t, without having transitioned to SEH.

To determine the transition probability parameters of the Markov chain, we fit its simulated survival curve to the Kaplan-Meier curve. This ensures that the model accurately reflects the observed duration distribution of individuals in home care before experiencing a crisis. Below we will further detail the methodology used for this fitting process.

Fitting the Markov Chain to the Distribution

To ensure that the Markov chain accurately reflects the real-life distribution of time from home care to crisis, we fit the transition probabilities of the model to the survival function obtained from the Kaplan-Meier estimator. This is achieved by performing a grid search over a parameter space, while minimizing the distance between the survival function derived from Markov chain simulations and the empirical Kaplan-Meier survival curve. The survival function of the Markov chain is determined by simulating the time until absorption and subsequently estimating the survival function using Equation 6.2.

$$S_{\mathcal{M}}(t) = \frac{\sum_{i=1}^{n} \mathbb{1}(x_i > t + \Delta t)}{n} \tag{6.2}$$

In this function, $S_{\mathcal{M}}(t)$ represents the probability of not reaching the absorbing state by time t, based on simulated absorption times. It depends on transition probabilities the initial state distribution and the time step size (Δt), which shape the expected duration before absorption.

The parameter space is given by Table 4.1 shown in Chapter 4.1. This space includes the probability parameters, the number of states, and the initial distribution. For each combination of parameters, the Markov chain is simulated one thousand times to generate an empirical distribution of transition times. From this empirical distribution, we compute the corresponding survival function.

The next step involves calculating the distance between the simulated survival function and the empirical Kaplan-Meier survival function. By minimizing this distance, we identify the optimal set of transition probability parameters that best fit the observed duration distribution. This approach aims to capture the real-life progression from home care to crisis as accurately as possible within the Markov chain framework. The following section details the methodology used to quantify the distance between survival functions and optimize the model parameters.

Parameter	**Parameter space**
N	$\in \{10, 20\}$
P_same	$\in [0, 1]$
P_crisis	$\in [0, 1]$
P_back	$\in [0, 1]$
Crisis growth	$\in [0, 1]$
Distribution type	$\in \{Uniform, Exponential, Linear\}$
Distribution steepness	$\in [1, 15]$

Table 6.1: Parameters grid search

Minimization Problem Formulation

To accurately fit the Markov chain to the Kaplan-Meier survival curve, several transition probability parameters and model configurations are considered. These parameters influence the behavior of the Markov chain and are adjusted during the optimization process. A grid search was performed to find the optimal set of parameters. Since the grid search operates on discrete values, the parameter ranges have been discretized accordingly using a step size of 0.001. One of these parameters, distribution steepness, controls the steepness of the initial distribution and is only applicable when the exponential distribution is used, determining how sharply probabilities increase. Table 6.1 summarizes the parameter ranges included in the grid search.

Formally, the optimization problem is defined as follows:

$$\min_{\theta,\mu} \sum_{t} \left(S_{\mathcal{M}}(t;\theta) - S_{\text{KM}}(t)\right)^2 \tag{6.3}$$

$$\text{s.t.} \quad \sum_{j} P_{\mathcal{M}}[i,j] = 1, \quad \forall i, \tag{6.4}$$

$$P_{\mathcal{M}}[i,j] \geq 0, \quad \forall i,j, \tag{6.5}$$

$$p_{\text{back}} < p_{\text{forward}}, \tag{6.6}$$

$$\sum_{i} \mu_i = 1, \quad \mu_i \geq 0, \quad \forall i, \tag{6.7}$$

$$\mu_i = \begin{cases} \frac{1}{N}, & \text{if uniform distribution,} \\ \frac{e^{-\lambda i}}{\sum_j e^{-\lambda j}}, & \text{if exponential distribution,} \quad \lambda > 0, \\ \frac{N-i}{\sum_j (N-j)}, & \text{if linear distribution.} \end{cases} \tag{6.8}$$

The objective function in Equation (6.3) minimizes the mean squared error (MSE) between the survival function obtained from Markov chain simulations, $S_{\mathcal{M}}(t;\theta)$, and the empirical Kaplan-Meier survival function, $S_{\text{KM}}(t)$. Here, θ represents the set of probability parameters that influence the survival function of the Markov chain. The goal is to find the optimal parameter set θ^* that best aligns the simulated survival function with the real-world data.

The constraints in Equations (6.4), (6.5), and (6.6) ensure that the transition probabilities of the Markov chain remain valid and adhere to reasonable assumptions about health transitions. Equation (6.4) ensures that the sum of transition probabilities for each state equals 1, maintaining a well-defined probability distribution. Equation (6.5) enforces non-negativity, ensuring that no probability values are negative. Equation (6.6) introduces an additional structural constraint, ensuring that the probability of transitioning to a worse state (p_{forward}) is always greater than the probability of transitioning to a better health state (p_{back}). This reflects the assumption that health deterioration is more likely than recovery in the modeled population. Equations (6.7) and (6.8) ensure that the initial distribution μ is a valid probability distribution, with non-negative values summing to 1. Additionally, Equation (6.8) enforces a predefined structure for μ, assuming either a uniform, exponential, or linear distribution, each reflecting different assumptions about patient entry into the

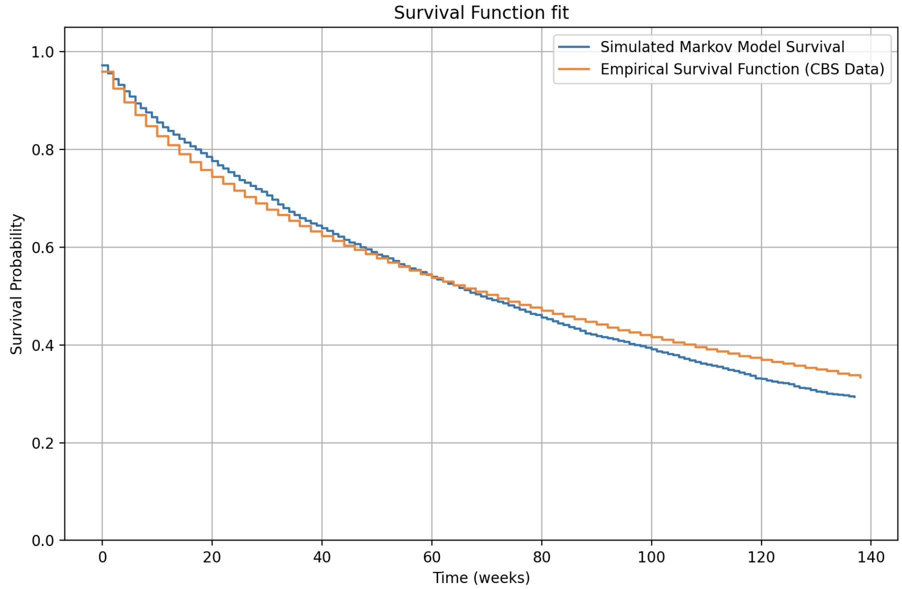

FIGURE 6.1: Simulated survival function vs Empirical survival function

system.

Results

The results of the optimization process are summarized in Table 6.2, which presents the parameter set that minimizes the mean squared error (MSE) between the two survival functions. These optimized parameters define the transition probabilities, the number of states, and the shape of the initial distribution.

Figure 6.1 shows the fitted survival function of the Markov chain, together with the Kaplan-Meier survival function. While the two curves do not align perfectly, this was the best achievable fit given the constraints and parameter space explored during the optimization process. The remaining discrepancy suggests that additional refinements to the model, such as adjusting the structure of transition probabilities or incorporating a more flexible initial distribution, may further improve the alignment. Next to that, using other datasets could be helpful to better understand the progression of declining health.

Overall, the optimization successfully identified a parameter set that closely approximates the empirical survival function, while maintaining interpretability and

Table 6.2: Optimized Parameter Set

Parameter	Value
p_{same}	0.86
p_{crisis}	0.0
p_{back}	0.06
Crisis growth	0.01
Distribution type	Exponential
Distribution steepness	2
N	20
Objective function value	0.000236

adherence to the underlying Markov model constraints.

6.2 Cost Parameter Estimation

This section outlines the estimation of cost and reward parameters to ensure the model accurately reflects real-life scenarios. It first describes how the theoretical health states from the conceptual model were translated into a practical analytical framework. This includes analyzing the expected length of stay in nursing homes, specifically how a client's health condition at the time of admission influences their duration of stay. Using these insights, along with the transition probabilities estimated in the previous section, realistic reward values are assigned to different states and actions within the model. Finally, several assumptions are made to align the model with the current healthcare environment in the Netherlands.

6.2.1 Cost Structure and Reward Function

The economic aspects of healthcare interventions and transitions are represented by the model parameters, which are based on a variety of cost estimations. Zorginstituut Nederland's "Kostenhandleiding voor economische evaluaties in de gezondheidszorg: Methodologie en Referentieprijzen" [40] contains useful information about current pricing in health care. These are used to calculate the expenditures for the model parameters.

It is crucial to remember that calculating the exact prices for each parameter is not feasible. All costs in the model are approximates due to the complexity and variety of healthcare expenses, which are affected by regional variations, individual situations, and data restrictions. Although these values give the model a useful foundation, it is important to recognize the uncertainty in their interpretation.

Overview of Cost Categories

Four primary categories of costs are considered in the model:

- **Home care cost:** The cost associated with providing care to people in their own homes.
- **Nursing home cost:** The cost incurred when an individual transitions to a nursing home.
- **Crisis cost:** The cost of managing an individual in a crisis state.
- **Checking cost**: The cost of evaluating the health of an older adult in a consultation.

This section provides a detailed examination of each cost category, outlining the specific costs involved. However, before delving into these details, the expected length of stay in nursing homes will first be determined, as this is a crucial factor in accurately calculating nursing home costs.

6.2.2 Length of Stay Analysis

In Model $\mathcal{F}$, explained in Chapter 4, the final absorbing state represents a nursing home. Within this system, individuals can be sent to this state from any health state, provided their health state is known. To calculate the costs associated with taking the action "send to nursing home" from a given health state, it is essential to understand the expected length of stay in the nursing home, which depends on the current health situation of the individual. This section aims to analyze the relationship between health state at the moment of sending and the associated length of stay. To do this, we need to first find a connection between real life and the model states.

Identifying Relevant Health Profiles

Zorginstituut Nederland [31] conducted an analysis that examined the length of stay in nursing homes. This expectation is based on their VV profile at the time of admission, which is a concept introduced in Chapter 2. The description of every VV profile can be found in Table 1 in the Appendix. A link between the states in our model and the VV profiles must be established to use these data for the model parameters. However, health profiles typically lack the dynamic nature of the health states in the model, making a one-to-one mapping between health profiles and states infeasible.

To simplify the model's parametrization while allowing flexibility in the number of states, we assume that the expected length of stay decreases linearly from the first to the last state. Therefore, the expected length of stay in a nursing home must be determined at the time of admission for both the first and last health states. The expected length of stay for the intermediate health states will be estimated through interpolation.

The first state corresponds to individuals with minimal care needs who are capable of living at home with support. Among the available health profiles, we identify the profile with the lowest care requirements to represent this state. Therefore, VV profile 1 serves as a reasonable approximation of the health condition for individuals in state 1.

The state N represents the stage immediately preceding a crisis and is therefore associated with intensive care needs that can only be adequately provided within a nursing home setting. Given the characteristics of individuals in this state, VV profile 6 is the most appropriate match. According to Zorginsitiuut [29], VV profile 6 includes individuals with significant variations in care needs. Although some may still receive care at home or in a sheltered living environment, others may already require intensive nursing and personal care, necessitating nursing home-level support. Therefore, VV profile 6 aligns well with state N in the model, as it captures the care needs among individuals approaching a crisis state. It reflects increasing dependency of individuals in this stage and supports timely interventions to prevent a crisis. While some patients may initially be managed with home care, the progressive nature of their condition often requires a transition to a nursing home setting, where specialized medical supervision, intensive care, and personal care are readily available.

Estimating Length of Stay

The expected duration of stay in an NH was determined using data from Zorginstituut Nederland [31]. This data set provides information on the distribution of the length of stay for older adults in NHs based on their health status at the time of admission. Since the dataset includes such distributions for every VV profile, it enables the estimation of the duration for each specific VV profile. Generally, individuals admitted while still relatively healthy tend to remain in the nursing home longer than those admitted in a more deteriorated state, as the latter group has a higher mortality risk.

Figure 6.2 illustrates the distribution with flexible number of states. The expected length of stay was calculated using the weighted average of the provided data. Specifically, as described before, the expected length of stay for the healthiest (State 1) and most deteriorated (State N) individuals was derived from the weighted average values of VV1 and VV6, respectively. This resulted in an expected stay of 166.49 weeks for VV1 and 94.77 weeks for VV6. The expected stay duration for intermediate health states was then estimated using linear interpolation between these two values, producing the results shown in Figure 6.2. Mathematically, the expected length of stay in weeks for a client admitted to a nursing home when in state s is calculated as:

$$LOS_{NH}(s) = 166.49 - \frac{s-1}{N-1}71.72 \tag{6.9}$$

where N is the total number of states, and s ranges from 1 (home care) to N (crisis).

Nursing home cost

The Nursing Home (NH) state in the model represents the final and absorbing state. Once this state is reached, no further actions are taken, and no additional rewards are received. Therefore, the reward associated with the transition to an NH must account for the total cost of the entire stay, including all expenses until the end of life. These costs are calculated based on the expected duration of stay and the daily cost of NH care, taking into account the state in which the person is admitted to an NH. The data from Zorginstituut Nederland indicate an average cost of €290 per day. By integrating this with the length of stay equation introduced in Section 6.2.2,

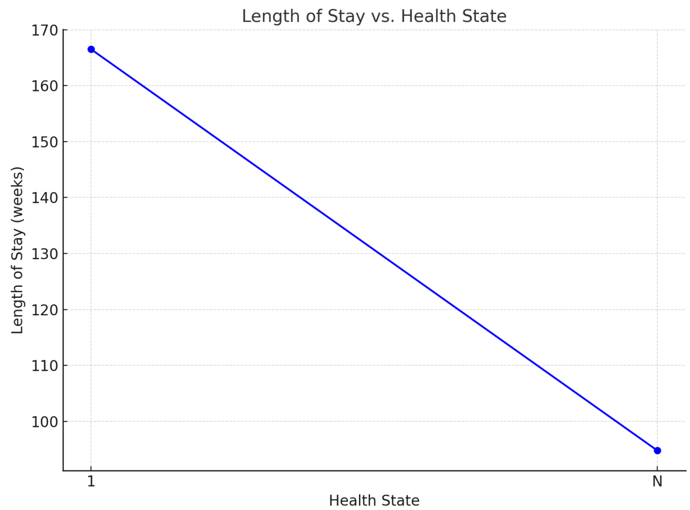

FIGURE 6.2: Length of stay approximation by interpolation

we derive the following calculation for the NH cost in each state where the patient is sent.

$$C_{\mathrm{NH}}(s) = LOS_{NH}(s) \times (290 \times 7)$$
$$C_{\mathrm{NH}}(s) = LOS_{NH}(s) \times 2030$$
$$LOS_{\mathrm{NH}}(s) = 166.49 - \frac{s-1}{N-1} \times 71.72$$

Substituting $LOS_{\mathrm{NH}}(s)$ into the first equation gives:

$$C_{\mathrm{NH}}(s) = (166.49 - \frac{s-1}{N-1} \times 71.72) \times 2030$$

Home cost

The weekly costs for home care are estimated using a method similar to the estimation of the length of stay per health state. Reference points are established for the first and last health states, and a linear interpolation is applied to estimate the states in between.

A report by Nederlandse Zorgautoriteit (NZa) [24] provides data on the average hours of home care needed for various groups of people having different kinds of care need. Two groups are chosen to be a good match for the first and last health state of the model. The analysis by NZa shows that the minimal home care category, referred to as “Prevention for vulnerable older adults who do not yet have a care demand (PREV)”. PREV receives an average of 5 hours of home care per month, which translates to 1.17 hours per week. This group consists of individuals who are still largely independent but receive preventive home care support to maintain their well-being and delay further health deterioration. Given that State 1 in the model represents individuals at the beginning of home care needs, it is reasonable to equate their care requirements with those of the PREV group. Thus, we estimate that individuals in State 1 receive approximately 1.17 hours of home care per week, aligning with the data provided by NZa.

For the last state, the Long-Term Care Somatic Problems (LT-SOM) category is selected as the best match. The NZa analysis indicates that this group consists of individuals with severe physical health conditions who require intensive home care but have not yet transitioned to an NH. Given that the final health state in the model represents individuals on the verge of a physical health crisis, LT-SOM aligns well with the care needs of this group. This group has an average need of 17 hours of home care per month, which equals approximately 3.97 hours of weekly home care.

The estimated weekly hours of home care for each profile are multiplied by the average hourly cost of home care. This is calculated by taking the average of different kinds of home care costs [40], which results in an average hourly cost of €73.47. Multiplying this by the number of hours of home care per week and adding the travel cost per visit (€30.64) gives us the the following equation for the home cost:

$$C_{home}(s) = 73.47 \times \left(1.17 + \frac{s-1}{N-1} \times 2.8\right) + 30.64 \tag{6.10}$$

Crisis cost

Determining the cost of a crisis is challenging due to the wide range of scenarios a crisis can encompass. A crisis could involve various levels of medical intervention, ranging from mild to severe, and the associated costs can vary significantly based on the services required. Costs possibly associated with a crisis are given below [40].

- Ambulance Ride: The cost of transportation to a medical facility by ambulance is €528.
- Emergency Department Visit: A visit to the emergency department (spoedeisende hulp) incurs a cost of €258.
- Hospitalization: A standard hospital stay costs €644 per day.
- Intensive Care Unit Stay: For more severe cases requiring intensive care, the cost is €2727 per day.

As reported by Medisch Contact [26], the average cost of a crisis for individuals aged 65 and older is €8,400, while for those aged 85 and older, it is €15,000. Since the exact cost of a crisis varies depending on individual circumstances, we use the average of these two amounts (€11,700) as the crisis cost in the model. This provides a reasonable estimate based on available data while keeping the model clear and practical.

Checking cost

The cost of performing a health check on an older adult was defined based on the nature and duration of the check. A check involves a healthcare specialist conducting a comprehensive review of the individual's health, ensuring all relevant factors are evaluated. According to expert input, such a check typically takes approximately one hour to complete. With an estimated cost of €50 per hour for the specialist's time, the cost of a single health check was set at €50 [40]. This value serves as a reasonable approximation for inclusion in the model parameters. A limitation is that crises not only lead to immediate costs but also increase healthcare expenses in the long term. Patients who experience a crisis often require more intensive care afterward, resulting in higher overall costs that are not fully accounted for in the model.

Summary of Parameterization

The model parameters, including the number of states, transition probabilities, and cost structure, have been defined based on empirical data and expert insights. The home cost and checking cost are incurred per time unit, where one time unit corresponds to a week, while the crisis cost and nursing home cost are one-time costs incurred at the moment of transition. A summary of the cost parameters is given below:

Parameter	**Value**
`Home cost`	`Varying from €115.96 to €322.32`
`Nursing home cost`	`Varying from €192,383.10 to €337,974.70`
`Crisis cost`	`€11,700`
`Checking cost`	`€50`

Table 6.3: Cost Parameters

In the next chapter, the cost and probability parameters will be incorporated into model $\mathcal{F}$, and the results will be generated accordingly.

7 Results

This chapter presents the results that provide insights into the research question, as formulated in Chapter 1. The analysis focuses on addressing the sub questions outlined in the introduction, examining the progression of older individuals through different health states, determining the cost-optimal timing for nursing home admissions and health check-ups, and evaluating the impact of different check-up strategies and patient preferences on crisis risk and health expenditures.

Each section in this chapter presents the results that contribute to answering these questions. In Section 7.1, we analyze how older adults transition between health states. Section 7.2 examines how the cost-optimal admission strategy was determined, and how different check-up strategies impact the crisis risk and total expected costs. Finally, Section 7.3 investigates how patient preference affects the results of the model.

7.1 Analyzing Health Dynamics

In Chapter 6, we established the transition probability parameters of the Markov Model based on real-world data, reflecting the expected time from the start of home care until a crisis occurs. These parameters define how individuals transition between different health states over time and allow for a realistic simulation of elderly care dynamics. In this section, we analyze and interpret the transition probability matrix, the initial distribution of health states, and the expected time until absorption.

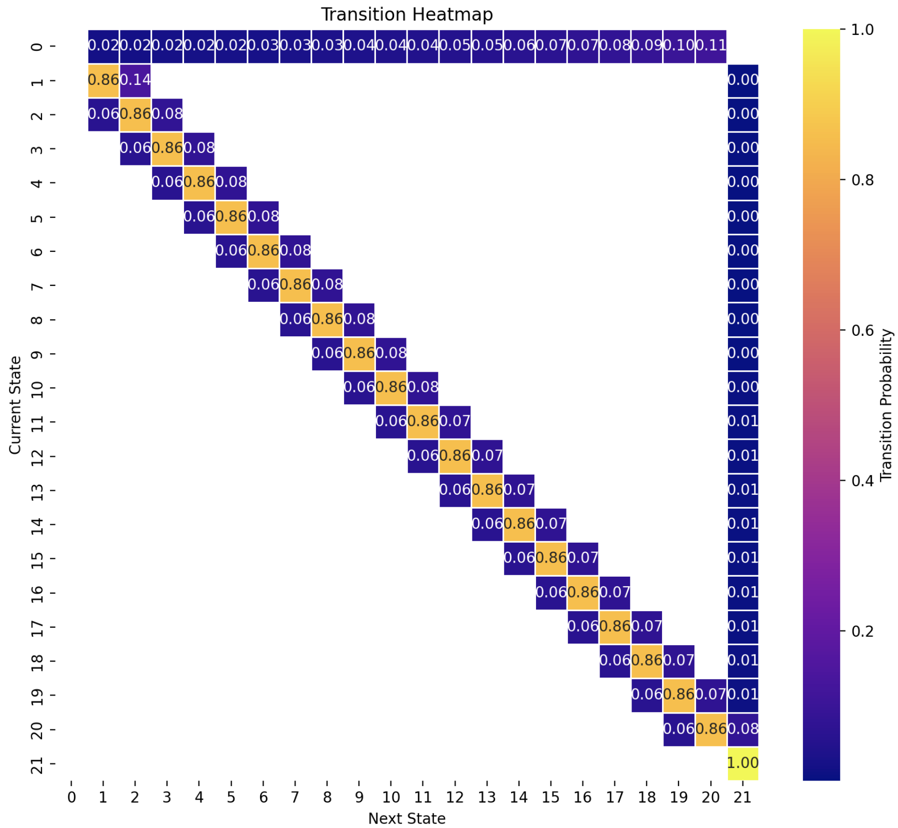

FIGURE 7.1: Heat map of transition probabilities

7.1.1 Health State Transitions

The transition probability matrix, visualized in Figure 7.1, displays the estimated transition probability parameters, based on the matching of the Markov chain with the CBS micro data. In this heat map, the first row represents the initial distribution, and the values in the matrix are rounded to two decimals, which makes them appear constant, but they do increase very slightly. One of the most notable patterns in this heat map is that the probability of moving forward, that is, transitioning to a more frail state, is consistently slightly higher than the probability of improving and moving back to a healthier state. This suggests that deterioration is the dominant trend, which is in line with the fact that people in this system already require home care and are generally in a frail condition. However, since they receive care, the probability of rapid deterioration remains limited, indicating that home care helps slow down the decline.

Another important observation is that the probability of transitioning into a crisis state gradually increases as individuals become more frail. While the probability of a crisis is negligible in the early health states, it steadily rises in more advanced frailty stages, reaching approximately 1%. This increase is expected, as individuals in worse health conditions inherently have a higher risk of experiencing a sudden crisis event. Finally, we note that the probability of entering a crisis in the last state before crisis (state 20) is 8%. This is significantly higher than in previous states, which is expected since this state represents the final stage before a crisis. Patients in this state have already undergone a significant deterioration, which increases the likelihood of a crisis event.

7.1.2 Initial Health State Distribution

Figure 7.2 presents the initial distribution of individuals across health states upon entering the system. The distribution follows an exponentially increasing pattern, indicating that the probability that individuals start in a frail state is greater than in a healthy one. The probability of entering the system in the most healthy state is less than 2% while the probability of entering the system in the most frail state is more than 10%. This big difference suggests that frailty is often recognized too late, potentially due to delayed registration for home care. As a result, many individuals enter the system only after their health has already deteriorated significantly, increasing their risk of experiencing a crisis.

7.1.3 Expected Time Until Absorption

Figure 7.3 illustrates the expected time until absorption (that is, reaching the crisis state) for individuals starting in each health state. The red dotted line shows that the mean expected time until absorption is approximately 132 weeks, which is more than 2.5 years. The values shown in the figure are calculated using Equation 4.2. As shown in the figure, there is a clear linear decrease in the expected time until absorption as individuals start in worse health states. Individuals who enter the system at the earliest health state take more than 300 weeks (more than 6 years) to reach a

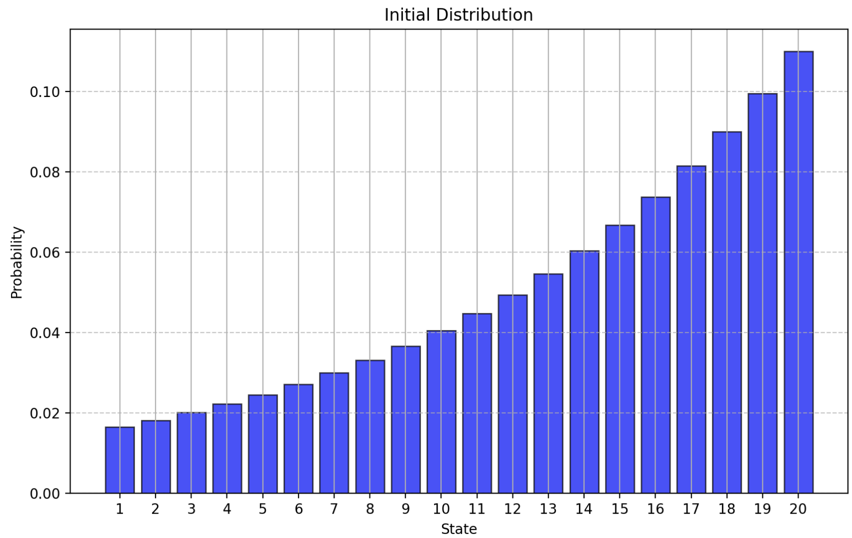

FIGURE 7.2: Initial distribution

crisis, whereas those who enter at the most deteriorated state progress to a crisis in approximately 25 weeks (half a year). This big contrast shows that early recognition of frailty could potentially prevent crisis situations, as it provides significantly more time for interventions and regular health checks. Table 2 in the Appendix provides additional information on crisis risks, calculated using similar methods as the time until absorption estimates. These insights allow for a more practical interpretation of health states, helping specialists make informed assessments.

7.2 Effect of Different Check-Up Strategies on Decision-Making

To answer the second and third sub-questions, we analyze how the optimal policy for NH admission and check-ups can be determined, and how different check-up strategies perform compared to the optimal policy.

7.2.1 Optimal Policy

Figure 7.4 presents the optimal policy derived by incorporating the estimated cost and probability parameters from Chapter 6. The figure visualizes the recommended

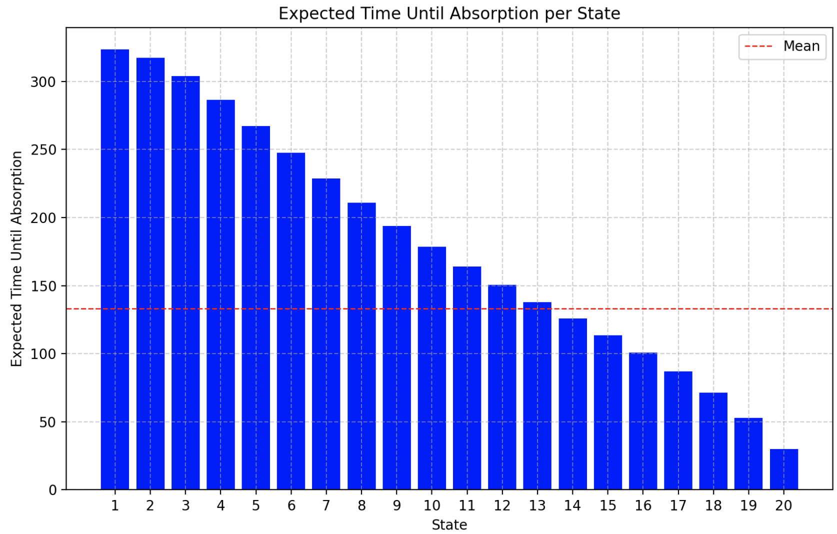

FIGURE 7.3: Expected time until absorption

decisions across different health states, illustrating when a patient should be checked, and when a transition to an NH becomes the cost-optimal choice. The figure shows that the optimal state for admission is at health state 18. Additionally, check-ups become necessary earlier than the predefined threshold, starting at health state 15, where the recommended check interval is 14 weeks. Beyond this point, the interval between check-ups decreases progressively, ensuring closer monitoring as the patient's condition deteriorates. Notably, the policy recommends sending patients to a nursing home relatively late, as the likelihood of a crisis remains low, particularly in the early stages of deterioration. Additionally, early admissions to NHs are relatively costly, providing further incentive to delay placement until it becomes more necessary.

7.2.2 Impact on Crisis Risk and Costs

Figure 7.6 presents examples of fixed-interval checking rules, to illustrate how the time-based check-up policies were constructed. To assess the impact of these strategies relative to the optimal policy, a simulation was conducted. The simulation results provide key insights into the effect of different check-up strategies on two indicators, the total expected costs and the crisis risk. Figure 7.5 presents the results of this simulation, featuring a dual-axis representation: one for total cost and another for the crisis fraction, both derived from the simulation. The dotted lines indicate the

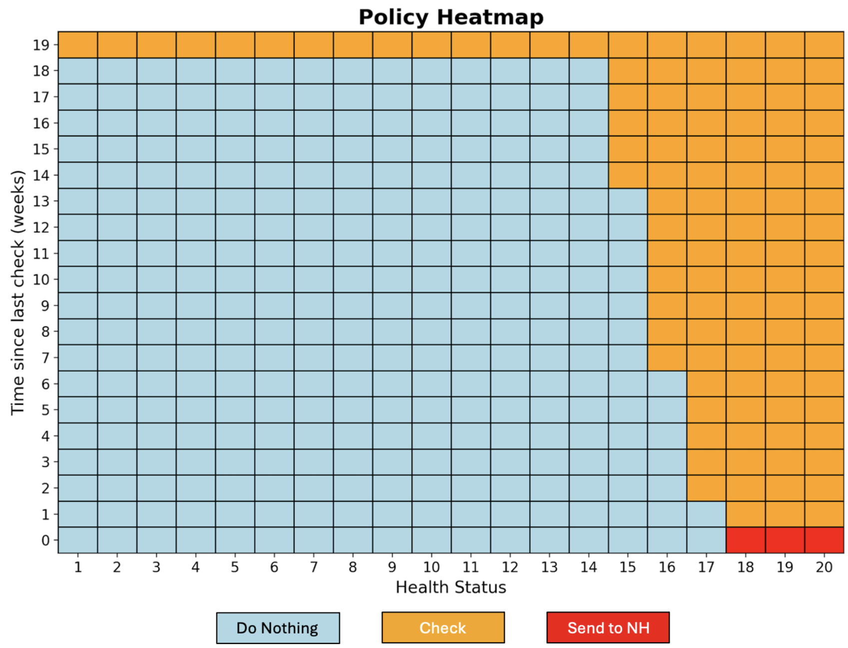

FIGURE 7.4: Heat map of the optimal policy

corresponding values under the optimal policy, providing a clear comparison between the simulated outcomes of the optimized decision strategy versus the time-based checking strategies. The figure highlights three key takeaways. First, the MDP-optimized schedule outperforms all time-based schedules in terms of cost efficiency, as it has an expected cost of €228500. Secondly, the only scenario where time-based check-ups result in a lower crisis risk than the MDP-optimized schedule is when checks occur at every time step (t=0). This indicates that the MDP approach can maintain an almost equally low crisis risk while significantly reducing unnecessary check-ups, improving overall efficiency. Lastly, the red axis shows a narrow range in the crisis risk fraction, as it varies from just under 46% to 55.5%. This occurs because only the checking policy is modified, while the threshold for NH admission remains constant, which has the biggest impact on the risk on a crisis. Since patients are still sent to the nursing home at the same health state, the impact on the overall crisis fraction remains minimal.

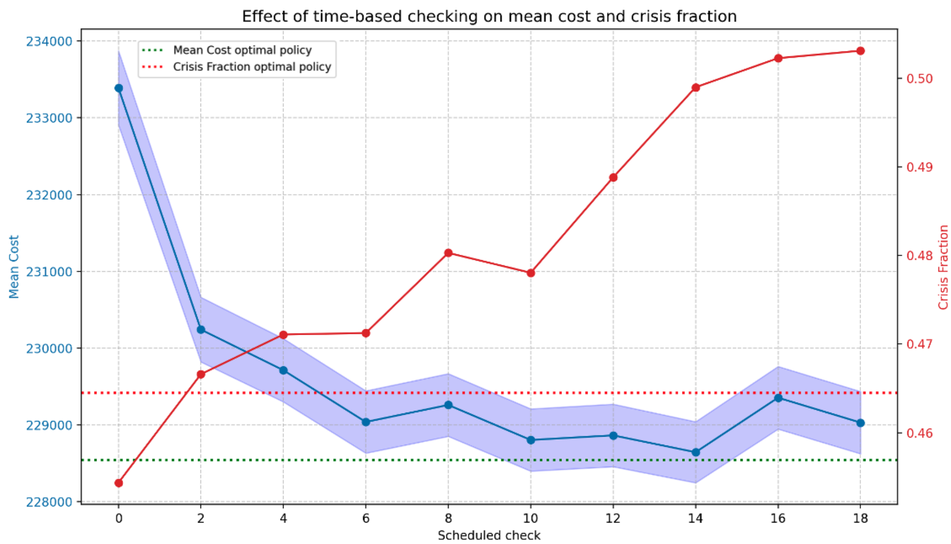

FIGURE 7.5: Time-based checking

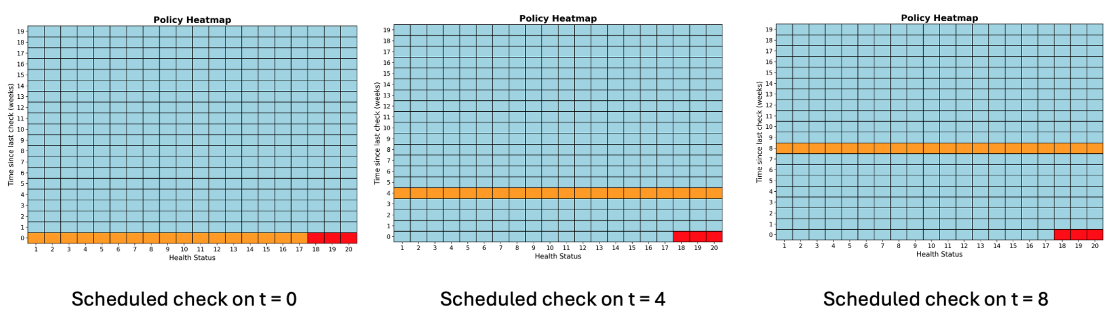

FIGURE 7.6: Time-based checking schedules

7.3 Impact of Patient Preference on the Optimal Policy

The last sub-question is answered by investigating how incorporating patient preference influences decision making. As discussed in Chapter 4, the model includes a utility reward that accounts for patient preferences. Some patients prefer to stay at home as long as possible, while others may prefer earlier NH admission. By adjusting the utility parameter, we can analyze how these preferences shift the optimal policy for admission and check-ups and influence the cost and crisis risk.

7.3.1 Effect on Admission Timing

A utility reward is received at each time step the individual remains at home. Therefore, a positive utility leads to a delayed NH admission, while a negative utility encourages an earlier admission. The check-up policy also adapts to these shifts; when home care becomes more favorable, the model relies more on check-ups and earlier admission to minimize uncertainty. To analyze the effect of patient preference, we first adjust the policy by incorporating a utility reward into the cost function, and after we evaluate their effectiveness by simulating the environment using the original cost function. This allows for a fair comparison by assessing both total costs and crisis fractions under different preference scenarios. The impact of these adaptations on the policy can be found in Chapter 5, which examines how changes in the cost function influence policy schemes.

The results of the simulation are visualized in Figure 7.7. The figure shows that the crisis fraction (red line) ranges from 0 to 1, illustrating the two extreme scenarios: either all individuals are immediately admitted to an NH, or everyone remains at home until a crisis occurs. As expected, the lowest cost is observed at utility = 0, which aligns with the cost-optimal policy. Furthermore, a stronger preference for NH admission results in higher costs compared to a preference for staying at home. However, this cost difference comes at the expense of crisis risk. When preference shifts toward staying home, costs remain lower than in the case of early NH admissions, but the likelihood of crises increases.

As mentioned in the introduction, approximately 50% of nursing home admissions in the Netherlands currently occur through a crisis [1]. The figure shows that while this approach is close to minimizing total costs, it has a big impact on crisis risk, affecting the physical and mental health of patients. To address this, it is essential to examine the cost implications of reducing the crisis fraction by shifting the preference toward earlier NH admissions.

The results indicate that without significantly increasing costs, a substantial reduction in the crisis fraction can be achieved. When the utility is set to 0 (neutral preference), the crisis fraction is 47%, and the total cost is €228,548. However, when the utility is adjusted to -250, shifting the preference slightly toward earlier nursing home admissions, the crisis fraction drops to 22.5% while total costs increase only

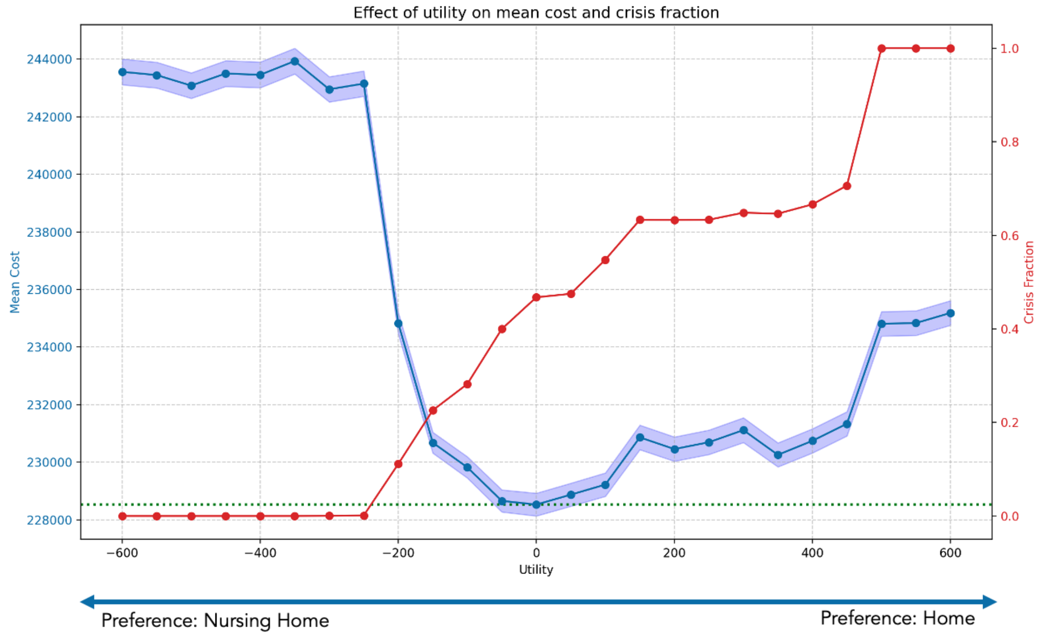

FIGURE 7.7: Effect of Patient Preference

slightly to €231,786. This represents a cost increase of just 1.42%, while the crisis fraction is reduced by 24.5 percentage points. These results highlight that by making a relatively small adjustment in preference, a significant reduction in crisis situations can be achieved without a major financial impact. This demonstrates the potential for optimizing policy to balance crisis prevention and cost efficiency effectively.

8 Discussion

This chapter interprets and evaluates the results presented in this research. Section 8.1 summarizes the main findings. Section 8.2 discusses potential limitations that may affect the interpretation or generalization of these results. Finally, Section 8.3 suggests areas for future research, considering both academic advancements and practical implications.

8.1 Main Findings

This study aims to address the following research question: "How can patient preferences be incorporated into cost-optimal nursing home admission timing and check-up scheduling?"

To address this, we developed a priority-based admission policy that evaluates clients' health states to determine who should be prioritized for nursing home placement. Burkell et al. [10] demonstrated that implementing such a needs-based approach can lead to significant shifts in individual placement priorities and overall admission decisions. We modeled the health of older adults as a dynamic process using a Markov model, a widely applied approach in healthcare settings [23, 13]. We further investigated the associated costs in the process of health deterioration, including home care expenses, nursing home costs, and costs arising from crisis situations. The optimum can be determined using an MDP, a well-established framework for decision-making under uncertainty that has been widely applied in healthcare allocation models [21] and preventive maintenance scheduling [25]. The model incorporates uncertainty due to the lack of real-time health information. The optimal strategy will be used as a benchmark to test the effect of patient preference and time-based checking schedules. The resulting policy provides valuable insights that can be used to effectively prioritize clients waiting for nursing home placement, by minimizing health care expenditures, and incorporating patient preference.

The main findings are structured around four key areas, based on the sub-questions of this research. First, the progression of health states is examined. According to probability estimates from the Kaplan-Meier model applied to CBS data, many patients enter home care in an already deteriorated state, limiting opportunities for preventive measures. Earlier screening could help delay or prevent crisis-driven admissions.

Second, the optimal timing for NH admissions and health check-ups was determined by minimizing healthcare costs using an MDP. The results indicate that older adults are admitted to nursing homes relatively late in the progression of health states to avoid the high costs associated with early admissions. Additionally, as health deteriorates, the intervals between check-ups become shorter, ensuring more frequent monitoring. This adaptive approach helps mitigate the risk of undetected deterioration and enables timely interventions.

Third, the research evaluated the efficacy of different check-up scheduling strategies in relation to crisis risk and costs. The results indicate that the optimal policy, which dynamically adjusts check-up timing based on the patient's health state, outperforms time-based schedules. This aligns with findings from Andersen [3], who highlights that Condition-Based Maintenance reduces unnecessary interventions by scheduling actions only when needed, whereas Time-Based Maintenance follows a rigid schedule that does not account for actual wear and tear. Similarly, in the healthcare context, state-based checks allow for earlier detection of declining health while preventing unnecessary medical examinations, leading to improved cost efficiency and patient outcomes. Specifically, delaying check-ups increases the likelihood of a crisis, as later detection of health deterioration reduces opportunities for timely intervention. In contrast, a state-based check-up strategy allows for earlier detection of declining health, effectively lowering crisis risk while preventing unnecessary healthcare expenditures. These findings highlight the importance of adaptive check-up policies in improving both cost efficiency and patient outcomes.

Lastly, introducing a utility score to capture patient preferences has a significant effect on both healthcare expenditures and crisis risk. The analysis shows that even a modest increase in spending can lead to a substantial reduction in crisis situations, highlighting the trade-off between cost and patient well-being. By using these insights, policymakers can make more informed decisions on nursing home admissions, ensuring that resources are allocated effectively while minimizing crisis risks.

8.2 Limitations

Several limitations must be acknowledged in this research. First, the data used for estimating the time from home care until crisis was modified by cutting off the first three weeks due to an excessively steep descent, which may have influenced the estimated survival probabilities. Although we assume that this steep descent was caused by incorrect data related to the billing of home care services, further research is needed to confirm this. Additionally, the fit of the transition probabilities to the Kaplan-Meier curve is not perfect and could be further refined to improve model accuracy. The Markov Chain was simulated to estimate the survival curve, but due to computational constraints, the simulation was limited to 1,000 runs, which may not fully capture the underlying randomness. Increasing the number of runs could enhance the accuracy of the fitted probability parameters. Next to that, the data used for this estimate was censored. Another way to improve the fit is by incorporating more data, providing deeper insights into how health deteriorates over time and refining the transition estimates accordingly.

Furthermore, the model applies the same transition dynamics and cost structures to all patients, assuming a uniform progression through health states. However, in reality, each patient follows a unique health trajectory and incurs different healthcare costs, which this simplification does not fully capture. The homogeneous patient trajectory assumption presents several challenges. Firstly, it implies that all individuals will inevitably experience a crisis if no intervention is made, which is not always the case. In addition, the model assumes that all individuals transition to a nursing home after experiencing a crisis, overlooking the possibility that some may recover and return home instead. Incorporating patient-specific factors into the model could improve its accuracy and lead to more personalized and effective decision-making.

Next to that, the model does not account for patient mortality while waiting for nursing home placement, which may impact the practical applicability of the policy recommendations. Ignoring mortality could lead to overestimation of long-term care costs and suboptimal admission strategies.

Lastly, estimating crisis-related costs is complex, as crises vary in severity, and not all result in emergency department visits. This introduces uncertainty in the cost estimation process. However, this limitation can be partially addressed by conducting a sensitivity analysis on these parameters, allowing for an evaluation of how different assumptions regarding crisis costs impact the overall model outcomes. Similarly, the interpolation of costs for intermediate health states between home care and NH care may not accurately reflect real-world expenditures. A more precise approach would involve defining exact costs for each specific health state, improving the model's overall accuracy.

8.3 Future Work

Future research could explore further enhancements to the model, including integrating more detailed patient-specific health trajectories. Additionally, collaboration with healthcare experts is essential to accurately define the health states, ensuring that the model aligns with real-world medical assessments and care needs. Another important extension would be to incorporate mortality into the model, allowing for a more realistic representation of patient transitions over time. Finally, simulating the nursing home queue including the capacity could provide valuable insights into the broader system dynamics, helping to assess the practical implications of the proposed decision policies on waiting times and crisis risk.

8.3.1 Practical Implications

In the Netherlands, NH placements are managed by the "zorgkantoor" (regional healthcare office), which assigns individuals a waiting status based on the urgency of their need for care. This urgency is primarily determined by the VV-profile, assigned by the CIZ, which reflects the required intensity of home care. The zorgkantoor then evaluates the VV-profile and other factors to determine when a patient should be admitted to an NH. However, these assigned statuses are largely static, relying on predefined urgency levels rather than real-time health dynamics. Instead of static prioritization, the proposed dynamic approach can be integrated into existing systems to optimize admission timing and check-ups based on real-time health assessments. This enables more responsive and cost-effective decision-making while considering crisis risk and patient preferences.

9 Conclusion

This research investigated how patient preferences can be incorporated into cost-optimal nursing home admission timing and check-up scheduling. By integrating a utility score into a Markov Decision Process (MDP) model, patient preferences - either favoring early nursing home admission or extended home care - can be explicitly accounted for in the decision-making process.

The findings reveal that while adjusting for patient preference allows for more personalized care decisions, it also influences crisis risk and healthcare expenditures. A slight shift in preference toward earlier nursing home admission can have a substantial positive impact by significantly reducing crisis risk, while only marginally increasing total costs. Conversely, prioritizing home care lowers expenditures but leads to a higher likelihood of crises, emphasizing the need for a balanced approach in admission policies.

This study contributes to the field by introducing a quantitative framework that integrates patient preferences into optimal elderly care decisions. By providing a structured, data-driven approach, it helps policymakers make informed decisions about nursing home admissions, ensuring that the right individuals are prioritized. Future research can refine this model by incorporating more detailed patient health trajectories and real-world healthcare constraints, further enhancing its practical relevance.

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Appendix

This appendix contains additional figures and tables used in this research.

Profile	Description
VV1	Basic care needs, including support with simple daily activities and light supervision.
VV2	Moderate care needs, requiring assistance with several daily activities and occasional supervision.
VV3	Significant care needs, including help with most daily activities and regular supervision.
VV4	Extensive care needs, involving frequent assistance with daily activities and supervision, often for individuals with moderate cognitive impairments.
VV5	High care needs, requiring intensive assistance with daily activities, continuous supervision, and potential medical care, typically associated with severe cognitive or physical impairments.
VV6	Specialized care needs for individuals with advanced cognitive disorders, such as dementia, requiring tailored care and constant supervision.
VV7	Intensive care needs for individuals with severe physical disabilities, requiring constant assistance and medical care.
VV8	Complex care needs involving severe physical and cognitive impairments, often necessitating specialized medical interventions and 24/7 care.
VV9	Critical care needs, typically for individuals in end-of-life care, requiring specialized palliative care and support.
VV10	Exceptional care needs for highly complex cases involving intensive medical and psychosocial care, requiring a multidisciplinary approach in an NH or specialized facility.

Table 1: Description of care needs per health profile

State	**Crisis within a week (%)**	**Crisis within 4 weeks (%)**	**Crisis within half a year (%)**	**Crisis within a year (%)**
0	0.05	0.23	2.43	6.14
1	0.10	0.39	2.99	6.96
2	0.14	0.58	3.99	8.58
3	0.19	0.76	5.11	10.55
4	0.24	0.95	6.26	12.62
5	0.29	1.14	7.41	14.71
6	0.33	1.33	8.54	16.77
7	0.38	1.52	9.67	18.78
8	0.43	1.71	10.78	20.76
9	0.48	1.90	11.87	22.69
10	0.52	2.08	12.96	24.60
11	0.57	2.27	14.03	26.53
12	0.62	2.46	15.10	28.60
13	0.67	2.64	16.20	31.03
14	0.71	2.83	17.47	34.27
15	0.76	3.02	19.40	39.03
16	0.81	3.20	23.24	46.14
17	0.86	3.52	31.47	56.31
18	0.90	6.03	47.19	69.53
19	8.00	26.29	71.45	84.76

TABLE 2: Probability of experiencing a crisis within different timeframes for each state.