The discovery, analysis and comparison of the patient discharge process – A case study

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Contents

1 Introduction

The quality of business processes is highly dependent on the suitability and efficiency of their execution. Healthcare emphasizes this dependency as the processes within the domain are concerned with activities that aim to diagnose, treat and prevent diseases in order to improve the quality of life for its patients [1]. These processes consist of clinical and non-clinical activities, which are executed by different types of resources, ranging from physicians, nurses and technical specialists to managers, data analysists and other support staff. Hospital processes are characterized by being highly dynamic, multidisciplinary, flexible and can, depending on the urgency, have an ad-hoc nature [2]. Improving these processes is a challenging task, it is shown that healthcare costs continue to rise [3] and waiting times are increasing as a result of an imbalance between the supply and demand of healthcare services [4]. There is a need to reduce waiting times, costs and increase the efficiency and transparency of healthcare processes. The analysis of clinical and non-clinical (organizational) processes can be of aid in the fulfilment of these needs.

Traditionally, process improvement could be achieved using techniques such as interviews [5] and process audits. Even though these techniques have showed promising results in the past they have one apparent disadvantage, they rely mostly on subjective process data. Process mining is relatively young research discipline that uses event log data to extract knowledge about the processes at hand [6]. These event logs can be acquired from Process-Aware Information Systems (PAIS) that are able to collect information about activities performed within complex business processes [1]. Event logs can be viewed as a set of traces, also called cases. Each trace contains all the activities that were executed inside a process instance [7]. Process mining consists of three main aspects: discovery, conformance and enhancement. Discovery techniques use an event log to produce a model that represents the process execution sequences of the activities present in the event log. Conformance is a checking process where an existing process model is compared to the event log that concerns the same process. Enhancement focuses on extending and improving the existing process model with the information that was gathered from analysing the actual process recorded in an event log.

A common trend among process mining studies is the application of process mining techniques on a single dataset that concern a single hospital department. As a result, process models that were obtained in these studies are challenging to compare, as they do not include datasets from

other departments that are concerned with the same process. Therefore, there is a need to fill this research gap. In this study, we conducted a systematic evaluation using process mining to compare a set of different hospital departments which are concerned with the same patient discharge process.

1.1 Research Statement

The research objective of this thesis is to discover and analyse the patient discharge process for the purpose of comparing three different hospital departments that each have their own unique dataset containing event logs. This leads to the following main research question.

RQ: How can we systematically compare the patient discharge process across different hospital departments?

To explore how process mining techniques can be used to gain insights into the patient discharge process across different departments. We make use of event data (i.e. the recorded events of process instances that occurred over time in the healthcare process) to analyse these processes and make an systematic comparison. Therefore, the first research sub-question focuses on process discovery:

SQ1: What activities does the patient discharge process consists of and how do they relate to each other?

SQ2: What actors are involved in the patient discharge process and how do they collaborate?

Once we have discovered the activities and actors that are present in the current patient discharge process. We need to determine on what grounds we are going to compare them, this leads to the third research sub-question:

SQ3: What process indicators and metrics can we define to gain valuable insight from comparing the same discharge process across different departments?

1.2 Expected contributions

Provide a systematic comparison of different hospital departments concerned with the same process by means of:

- Discovering the hospital discharge process based on process mining techniques.
- Discovering relationships of the actors within the discharge process.
- A comparison of the involved departments by a series of metrics and process indicators.

2 Preliminaries

2.1 Process Mining fundamentals

Today's Information system log an enormous amount of data regarding the activities inside business processes. *Process Mining* is a process modelling and analysis technique that aims to discover, monitor, and improve real processes by extracting knowledge from these information systems. We can define Process Mining as follows [8]:

"The method of distilling a structured process description from a set of real executions."

Real executions, refer to the set of sequential activities that were captured by the information system. This sequential set of executions shows the history of what activities were executed and at what time they were performed. This set can also be called an *Event Log.*

The event log consists of several process instances or *cases*. A case includes a number of attributes that characterize an event log record (Table 2.1). The record shows that George performed activity *Register request* for case 1 on 28-03-2022 at 11:02.

1	Register request	George	28-03-2022.11:02

Table 2.1: An example event log record.

Case ID	**Activity**	**Actor**	**Timestamp**
1	Register request	George	28-03-2022.11:02
1	Examine request	Anna	28-03-2022.12:43
1	Check ticket	Mike	29-03-2022.09:06
1	Reject request	Pete	29-03-2022.12:03
2	Register request	George	28-03-2022.11:05
2	Examine request	Anna	28-03-2022.14:00

2	Check ticket	Mike	29-03-2022.10:08
2	Accept request	Pete	29-03-2022.14:11
2	Initiate reimbursement	Thomas	31-03-2022.08:29

Table 2.2 Example Event Log.

An example of an event log can be viewed in Table 2.2. A new case starts with registering the request for an insurance reimbursement. The activities that were executed are recorded in column 2 and the actor that executed this activity is shown in column 3. Additionally, the timestamp for when each activity was recorded in the system is included in column 4.
With the use of Process Mining, these event logs allow for the extraction of valuable information about how a process was carried out, as recorded by the information system supporting the process.

In the next section we show a collection of applications of Process Mining across the literature, with the focus on how PM can be viewed from multiple perspectives and how these perspectives can be used to extract a variety of valuable information from the output of PM techniques.

3 Related works

3.1 Process Mining

Process mining (PM) is applicable to a wide range of systems [6]. Information systems such as Enterprise Resource Planning (ERP) systems are a prime example of systems that are suitable for PM as they collect massive amounts of data about the activities conducted inside an organization. Systems where the software is more tightly entangled with the hardware e.g. embedded systems can also be used for this purpose. The most prominent requirement for process mining is that the system can produce a sequential log of the activities performed that are recorded inside the system. The event logs describe the actual behaviour of the actors within the system. Systems that we are concerned with are Hospital Information Systems (HIS). Similarly to ERPs, hospital information systems can generate an abundance of data that relates to the healthcare processes that are executed throughout the hospital. Van der Aalst [7] categorized process mining into discovery, conformance and enhancement. Discovery techniques use an event log to produce a model that represents the process execution sequence of the activities present in the event log. The discovery of valid healthcare processes is one of the most challenging aspects of applying PM in the complex healthcare setting [9].

3.2 Healthcare processes

To clarify which type of healthcare processes (HCP) we are concerned with; it is important to make a distinction between medical treatment processes (MTP) and (generic) organizational processes[10] . Medical treatment or clinical processes are closely related to individual patients and are executed according to a diagnostic-therapeutic cycle (DTC), collecting observations, reasoning and action. The DTC relies on medical knowledge to deal with *case-specific* decisions based on patient-specific information. Furthermore, we have organizational processes. Their purpose is to support the medical treatment processes. In general, these processes are not tailored to specific cases, however they aim to support and coordinate medical treatment processes among different people and their organizational units. Patient scheduling and consult requests are two examples of organizational processes [10].

Besides the two types of healthcare processes, it is important to characterize what makes HPC distinct from business processes in other domains. First, they are highly dynamic as process changes can occur due to a variety of reasons including the introduction of new administrative procedures, technological developments or the discovery of new drugs [1,10]. Additionally, the discovery of new diseases and financial incentives may also require hospitals to implement new processes. Second, the complexity is high. Complexity can arise from many different factors including complex medical decisions, (large) data exchanges and unpredictability of patient care paths [9,11,12]. Medical decisions are based on interpreting patient-specific data and acting accordingly with the help of medical knowledge or guidelines and the personal expertise of physicians. Moreover, large amounts of data including lab results, anamneses and daily observations of patients need to be exchanged between physicians, nurses and other supporting medical staff for the process to be as efficient as possible. This brings us to the third point; healthcare processes are increasingly multi-disciplinary. Healthcare organizations are mostly structured in multiple specialized departments each concerned with their own medical disciplines and services for care. This means that HCP span across a wide range of distributed activities performed in a collaborative effort by healthcare professionals with different skills, knowledge and organizational culture. Fourth, HCPs have an *ad hoc* nature [1,10,11]. Autonomous actors such as physicians decide, their own working procedures as they have the knowledge and experience to deviate from medical guidelines to deal with patient-specific situations. This results in processes with a high degree of variability whose order of execution can be non-deterministic.

3.3 The application of process mining in healthcare

The application of process mining in healthcare was first tested in 2008 by researchers at the University of Amsterdam. They concluded that it was possible to derive meaningful and understandable models from the inherently complex hospital processes containing large groups of patients with variable lines of care [2]. Since then, several case studies have been published to give insight into various processes. For instance, Mannhardt & Blinde (2017) applied PM to model the patient flow of sepsis patients from their admission to the ER until their discharge [14]. Alvarez et al. (2018) constructed role interaction models of healthcare professionals in the emergency room to give insight in how they operate and most importantly collaborate [15]. Furthermore, Kim et al. (2013) discovered the outpatient care process model to find the most frequent clinical pathways and compared them to the model that was obtained by consulting domain experts to check the rate of conformance between the two processes[16].

3.3.1 Three perspectives

One of the key pillars of this thesis is the discovery of process models. Mans et al. applied [2] PM mining techniques on healthcare processes from three different perspectives: (1) the control-flow perspective, (2) the organizational perspective and (3) the performance perspective. In the discovery of process models, the control-flow perspective gives significant insights in how the process is handled based on the extracted event logs. In this case, Mans et al. made use of the heuristics miner [17] to shape the process model in the control-flow perspective giving insight into the care paths for patients. The organizational perspective was formed using the social network miner which showed what actors were involved in the process and how they related to each other in terms of (in)frequent interaction and missing or misleading connections. At last, the performance perspective used dotted chart analysis to show how the process was performing. Metrics such as the number of events in an activity instance, case durations and the time of the first and last events were used to represent its performance. This work showed the applicability of using PM techniques to give insight into the healthcare process from three perspectives.

The focus on the control flow perspective has led the research on process mining in healthcare the past years. A broad literature review by Rojas et al. showed that around 60% of all case studies focused on this area. On the contrary, the organizational perspective only accounted for 12% of all case

studies. This thesis will focus upon a combination of the control flow and organizational perspectives.

Organizational perspective

The organizational perspective aims to discover the relationships and connections of collaborations between resources involved in the healthcare process. For example, Alvarez et al. [15] , have implemented a method for the discovery of role interaction models that aims to use process mining techniques, in this case the disco miner [18], to describe and match the collaboration of ER professionals who treat patient in an ER episode. Their proposed method included the extraction of the ER episodes data, building the event log, discovering the role interaction models using the disco miner and finally validating their results with an ER expert. This has shown how several resources work together within a single department. The hierarchy among these different actors is analyzed by Krutanard et al. [19] , who discovered what doctors oversaw particular treatment processes and to what doctors they responded to. In turn this could help the hospital management to restructure and improve the treatment process efficiency by exposing the hierarchy with the use of the role hierarchy miner.

Other approaches have analyzed the organizational perspective and collaboration by employing social network analysis. The work by Rattanavayakorn [20] employed the social network miner to generate a social network of all the roles involved in the treatment process, this helped them neglect the causal dependencies and count the frequency of interaction between two physicians working on the same treatment process but working in different departments. Showing which doctors performed better in groups and devoted the most time and responsibility to the treatment process of patients. To optimize the usage of process mining techniques such as the role and social network miner other data mining techniques might be needed. For example, Ferreira & Alvez [21] developed a plug-in for a hierarchical clustering technique to divide the actors of the healthcare process into communities. This makes it possible to look at how different clusters of actors work together within the process.

Frameworks that inspire and streamline new approaches for analysing the organizational perspective have also been defined in recent years. A guide by Lismont et al. [22] describes a six-step methodology for applying process analysis in the healthcare setting. The framework tackles the main challenges defined by Ferreira [12] and complements these with their own set of identified challenges. It provides a good path to follow in conducting process analytics in the healthcare domain and among other relevant work will form an inspiration for this thesis.

Title	**Main (PM) Techniques**	**Dataset**	**Scope**
A collaborative method for simultaneous operations: case of an eye clinic [23]	Lean six sigma in combination with process mining algorithms in DISCO (miner not specified).	The activities of eye surgeries of 1 month. 325 surgeries in total.	Single department
A data-driven methodology for supporting resource planning of health services [24]	Application of the Heurstics miner and Inductive miner in ProM in combination with Time-Driven Activity-Based Costing (TDABC).	470 patient cases, 14 types of activities and more than 9,800 events in total.	Hospital wide
A guide for the application of analytics on healthcare processes: A dynamic view on patient pathways [22]	Usage of the dotted chart analysis, Fuzzy Miner, Role-hierarchy miner and Social network miner.	10 clusters of Diabetus Mellitus patients with a total of 571 traces containing the activities of each patient.	Singe patient group

A Hybrid Process Mining Framework for Automated Simulation Modelling for Healthcare [25]	Auto-Simulation Model Builder framework consisting of a custom process mining algorithm called BupaR and a data analyzer.	An event log containing 19.000 executed events for 1438 unique actors.	Hospital wide
Analysis of the Social Network Miner (Working Together) of Physicians [20]	Social Network miner (ProM).	An event log containing 9691 patient cases, 10 activities– 40 actors and 16599 events in total.	Hospital wide
Application of Process Mining in Healthcare - A Case Study in a Dutch Hospital [2]	Fuzzy miner, Heuristics miner, Social network miner and dotted chart analysis.	An event log containing 627 oncology patients with a total of 376 events.	Single patient group
Discovering Organizational Process Models of Resources in a Hospital using Role Hierarchy Miner [19]	Role-hierarchy miner in ProM and Fuzzy miner (DISCO).	An event log containing a total of 192,419 events from 10 activities.	Hospital wide
Discovering role interaction models in the Emergency Room using Process Mining [15]	DISCO miner (based on fuzzy miner).	An event log containing 5175 traces, with 69 variants – 10 different activities – 149 different actors.	Hospital wide
Discovering User Communities in Large Event Logs [21]	Hierarchical-clustering plug-in (ProM) with the use of modularity for social clustering.	An event log spanning 6 months containing 507 actors – 78623 traces – 536735 events and 21 activities.	Single department
Improving Organizational Process of a Hospital through Petri-Net Based Repair Models [26]	Fuzzy miner, Genetic miner, Heuristic miner and Repair model plug-in (ProM).	An event log containing 40,815 traces – 482,446 events and 12 activities.	Hospital wide
Monitoring care processes in the gynaecologic oncology department [27]	Heuristics miner, LTL-checker, Trace alignment and Social-network miner.	An event log containing a total of 150,291 events from 677 activities.	Single department
Process mining approach for efficient utilization of resources in a hospital [28]	Alpha-algorithm and replay-fitness plug-in (ProM).	An event log containing 1000 traces with a total of 14854 events.	Hospital wide
Process mining as support to simulation modelling: A hospital-based case study [29]	Infrequent-Inductive miner and Simul8 plug-in (ProM).	An event log containing 790 traces – 2789 events and 18 activities.	Single department
Service Reconfiguration in Healthcare Systems: The Case of a New Focused Hospital Unit [30]	Heuristics miner, Inductive miner and Fuzzy miner.	An event log containing 470 traces from 61 different events`.	Single patient group

Supporting Governance in Healthcare Through Process Mining: A Case Study [31]	Inductive miner, Transition system miner, Social-network miner and dotted chart analysis.	Three main event logs extracted from three departments containing 299,685 and 22,043 and 10,843 traces respectively.	Multi department
Tethered to the EHR: primary care physician workload assessment using EHR event log data and time-motion observations [32]	Descriptive statistics	Not specified	Single department

Table 3.1: Comparison of the literature regarding PM research datasets and scope.

A common trend among the work in Table 3.1 is that the basis of its analysis is an event log that is concerned with hospital-wide patient process that spans multiple departments or only a single department/patient group.

The research gap that this thesis tried to address was the comparison of multiple departments involving a wide variety of patients. A subset of hospital departments representing a hospital-wide process was analysed using event logs that each corresponds to a specific department. However, each department is concerned with the same process, namely the patient discharge process (PDP). This allows for a comparison of how each unit handles the same process and enables us to gain valuable insight in potential process improvements.

4 Research methods

4.1 Process Mining methodology

The literature (table 3.1) has shown that no one-size-fits-all technique exists for process mining projects. Rojas et al. [9] showed that no predominant methodology is used for the unstructured processes in the healthcare domain. Depending on the context of study, availability of the data, goals of the study and other factors one might need to design an ad hoc methodology to achieve the desired results. In this thesis, the desired results were achieved with the help of the generalized PM methodology described in [33]. This methodology consists of a six-phase process that includes (1) Defining research questions (2) Data collection (3) Data preprocessing (4) Mining and analysis (5) Stakeholder evaluation and (6) Implementation.

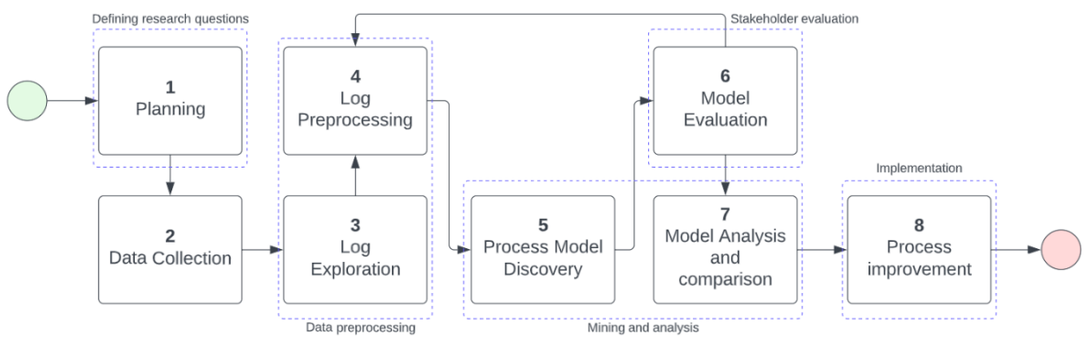

*Figure 4.1: **Stages** of the PM approach for the ETZ hospital case-study in relation to the phases of the generalized PM methodology.*

The methodology aims to answer the research questions and produce results that will lead to the improvement of the patient discharge process. For this thesis, the six main phases of the generalized PM methodology have been divided into several *stages* (figure 4.1) to better fit the structure of the project. The main stages give an indication of the main tasks performed within each stage. The blue dotted boxes around the stages in figure 4.1 indicate how the main phases of the generalized PM methodology relate to the stages that form the foundation of this thesis.

Moreover, the objective, input and output for each stage have been defined in table 4.1.

	Stage	Definition
1	Planning	**Objective.** Setting up the project in the context of the analysis and determining what output we want based on the research questions and project goals. **Input.** Healthcare processes, project goals and research questions. **Output.** Selection of organizational units for analysis, refined research questions and project goals.
2	Data collection	**Objective.** Extraction of event data and manually designed process models. **Input.** Parameters of the healthcare process, Hospital information system databases. **Output.** Raw dataset with event data and process models
3	Log exploration	**Objective.** Get an initial impression of the data regarding noise, irregularities and variance. **Input.** Raw dataset of event data. **Output.** The state of the data and ideas on what needs to be done in pre-processing.
4	Log pre-processing	**Objective.** Conversion of the event data into event logs while minimizing noise and irregularities. **Input.** Raw event data, manually designed healthcare processes, *Feedback from domain experts **Output.** Event log(s)
5	Process model discovery	**Objective.** Gain insight into the healthcare processes based on the pre-processed event logs. **Input.** Pre-processed event log. **Output.** Process models
6	Model evaluation	**Objective.** Verification and validation of the obtained process models with the help of domain experts. **Input.** Process models **Output.** Refined process models
7	Model analysis and comparison	**Objective.** Compare the process models on a series of process mining related metrics to gain insight in their differences and commonalities. **Input.** Process models **Output.** Process model comparison
8	Process improvement	**Objective**. Use the insights from the analysis to give recommendations on possible process improvement strategies. **Input.** Results from the process models discovery and comparison, Improvement ideas. **Output.** Process recommendations

Table 4.1: The stages of our PM approach and their definitions.

4.2 Planning

Case study context

The research was conducted in the Elisabeth – TweeSteden hospital (ETZ) in Tilburg the Netherlands. The hospital has a total of 789 beds and had around 32.000 hospital admissions in 2020. The motivation for this research originates from an internal investigation on the supply and demand of bed availability done by the Tactical Planning department of the ETZ. The investigation concluded three main points with regards to improving this availability. For the scope of this study, the most important conclusion was improving the patient discharge process. With the main goal of streamlining the process so that patients who were ready for discharge would be discharged as soon as possible to improve availability of hospital beds.

Initially, getting insight into the hospital-wide patient discharge process was the main goal. However, after consulting with the healthcare professionals and looking at the vast amount of data this would encompass, the decision was made to focus this thesis on a subset of departments.

The final selection resulted in the internal medicine, neurology and neurosurgery. Two contemplative specialisms (beschouwende) and one surgical department (snijdende). Moreover, neurology was a special case, as the PDP was already altered there once with the purpose of streamlining the process. This gave us essentially two highly related processes on the same department. Together with two un-altered PDP processes gave us a sufficient sample of how the PDP is carried out across the hospital.

4.3 Data collection

The collection for the PDP starts at the hospital departments that are involved in the interdepartmental analysis (Fig. 3). Healthcare professionals on the involved departments (neurology, internal medicine and neurosurgery) record diagnostic and administrative data inside of the core information system for patient data, a Hospital Information System called *Epic.* This data is taken from the information systems to the staging area. Inside the staging area a data lake holds all the structured and unstructured data until it is needed for analytic purposes. The ETZ hospital uses an in-house datawarehouse (DWH) solution to manage all the data they collect through their core information systems namely their Human Resource Management system (HRM) called AFAS, Epic and other

specialized HIS which are used from some departments. The DWH functions as a central repository and makes analysis and reporting possible without interfering with the core systems. A SQL-client then fires a SQL-query (Appendix A) to the DWH and extracts only the necessary information needed to construct the event log.

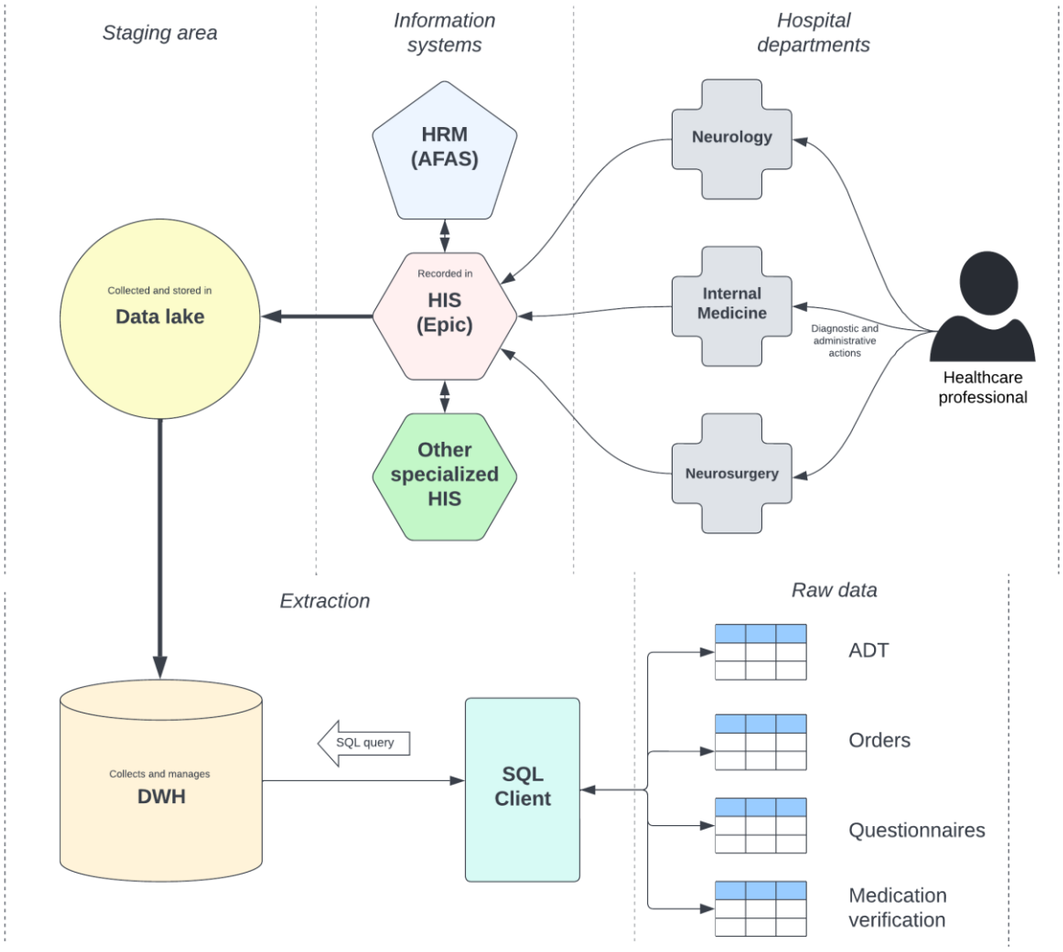

Figure 4.2: ETZ data collection pipeline

The extraction process results in four tables of raw data needed to construct the base version of the event log. These include:

I. *Admission Discharge Transfer (ADT)* data. This table holds all the timestamps for which patient were either admitted, discharged or transferred.
II. *Orders*. An order can be a multitude of actions. In our case, orders are predominantly consultations for specialized healthcare professionals such as physiotherapists.
III. *Questionnaires*. These involve (mostly) standardized questions to keep track of patient status throughout the PDP.

IV. *Medication verification*. This dataset contains the timestamps for the status of the medication verification process. It is executed at the start and end of each admission and therefore is a vital component of the PDP.

4.4 Log pre-processing

The event log is the basis for the generation of process models. An event log with low quality data (missing, erroneous and noisy values) can lead to complex and unstructured (spaghetti-type) models that are difficult to interpret (Fig. 4). These models are not only hard to interpret, but they may also not even reflect the true behaviour of the business process. Therefore, data pre-processing is a vital step in ensuring that the process mining techniques can generate models that are understandable [34].

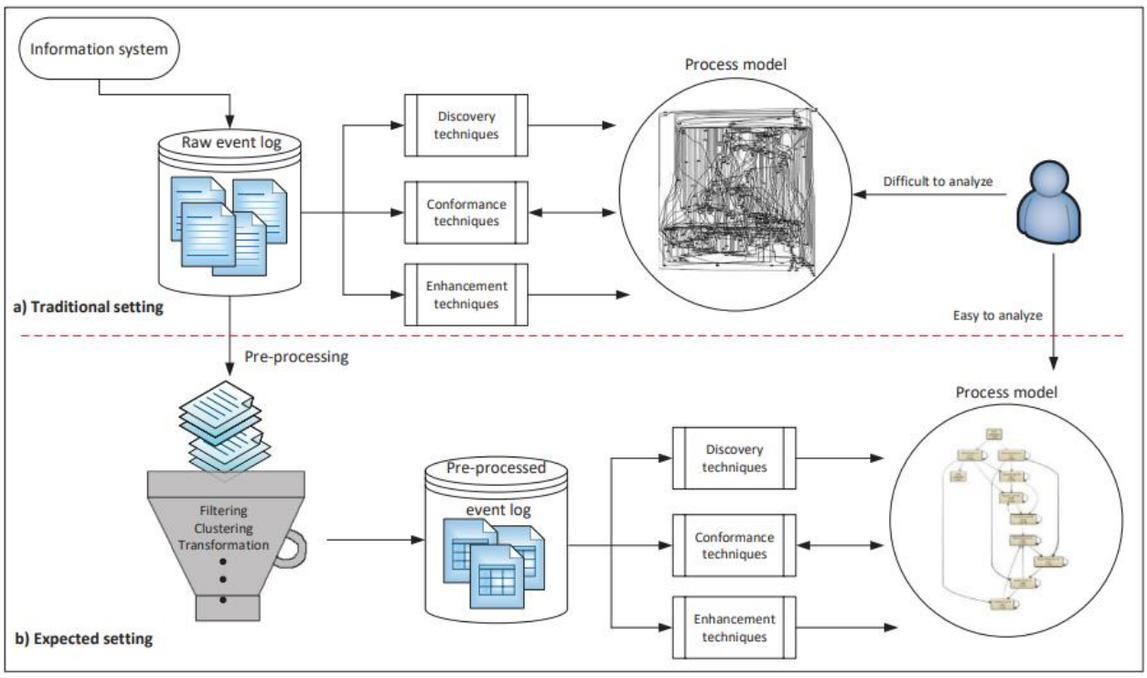

Figure 4.3: The application of process mining techniques on raw data (traditional) versus pre-processed event logs. (expected) [33].

4.4.1 Log exploration

The initial raw dataset contained all the records for patients regarding their discharge process. This included the departments neurology, internal medicine and neurosurgery respectively.

Timeframe

The chosen dataset timeframe was mainly affected by the inclusion of the

D	E	F	G	H	I	J	K	L	M	N
Specialisme	Patient_nummer	Patient_CSN	Opname_datum_tijd	Ontslag_datum_tijd	Onderdeel	Datum_sort	Onderdeel_ID	Omschrijving	Order_datum	Flowsheet_opgenomen
Neurologie	6933479	87698746	2021-12-31 23:48:00,000	2022-01-03 18:00:00,000	Stap_2_3_5_Flowsheet	2021-12-31 00:01:00,000	20470	Verwachte ontslagdatum		2021-12-31 00:01:00,000
Neurologie	6933479	87698746	2021-12-31 23:48:00,000	2022-01-03 18:00:00,000	ADT-acties	2021-12-31 23:48:00,000		Opname	2021-12-31 23:48:00,000	
Neurologie	6933479	87698746	2021-12-31 23:48:00,000	2022-01-03 18:00:00,000	ADT-acties	2022-01-01 00:33:00,000		Overpl in	2022-01-01 00:33:00,000	
Neurologie	6933479	87698746	2021-12-31 23:48:00,000	2022-01-03 18:00:00,000	ADT-acties	2022-01-01 00:52:00,000		Overpl in	2022-01-01 00:52:00,000	
Neurologie	6933479	87698746	2021-12-31 23:48:00,000	2022-01-03 18:00:00,000	ADT-acties	2022-01-01 14:39:00,000		Overpl in	2022-01-01 14:39:00,000	
Neurologie	6933479	87698746	2021-12-31 23:48:00,000	2022-01-03 18:00:00,000	Stap_1_Order	2022-01-01 14:41:50,000	94206218	Consult fysiotherapie	2022-01-01 14:41:50,000	
Neurologie	6933479	87698746	2021-12-31 23:48:00,000	2022-01-03 18:00:00,000	Stap_4_Order	2022-01-01 15:18:00,000	94206220	ICC revalidatie geneeskunde	2022-01-01 15:18:00,000	
Neurologie	6933479	87698746	2021-12-31 23:48:00,000	2022-01-03 18:00:00,000	Stap_1_Order	2022-01-01 15:18:31,000	94214585	Consult ergotherapie	2022-01-01 15:18:31,000	
Neurologie	6933479	87698746	2021-12-31 23:48:00,000	2022-01-03 18:00:00,000	ADT-acties	2022-01-01 23:20:00,000		Patiëntupdate	2022-01-01 23:20:00,000	
Neurologie	6933479	87698746	2021-12-31 23:48:00,000	2022-01-03 18:00:00,000	Stap_2_3_5_Flowsheet	2022-01-03 13:28:00,000	3041300143	Advies ontslag - fysiotherapie		2022-01-03 13:28:00,000
Neurologie	6933479	87698746	2021-12-31 23:48:00,000	2022-01-03 18:00:00,000	ADT-acties	2022-01-03 18:00:00,000		Ontslag	2022-01-03 18:00:00,000	
Neurologie	5805558	87698626	2021-12-31 20:19:00,000	2022-01-01 16:00:00,000	ADT-acties	2021-12-31 20:19:00,000		Opname	2021-12-31 20:19:00,000	
Neurologie	5805558	87698626	2021-12-31 20:19:00,000	2022-01-01 16:00:00,000	ADT-acties	2022-01-01 01:07:00,000		Overpl in	2022-01-01 01:07:00,000	
Neurologie	5805558	87698626	2021-12-31 20:19:00,000	2022-01-01 16:00:00,000	ADT-acties	2022-01-01 01:14:00,000		Overpl in	2022-01-01 01:14:00,000	
Neurologie	5805558	87698626	2021-12-31 20:19:00,000	2022-01-01 16:00:00,000	ADT-acties	2022-01-01 16:00:00,000		Ontslag	2022-01-01 16:00:00,000	
Interne geneeskunde	2037196	87698620	2021-12-31 19:19:00,000	2022-01-05 15:12:00,000	Stap_2_3_5_Flowsheet	2021-12-31 00:03:00,000	20470	Verwachte ontslagdatum		2021-12-31 00:03:00,000
Interne geneeskunde	2037196	87698620	2021-12-31 19:19:00,000	2022-01-05 15:12:00,000	ADT-acties	2021-12-31 19:19:00,000		Opname	2021-12-31 19:19:00,000	
Interne geneeskunde	2037196	87698620	2021-12-31 19:19:00,000	2022-01-05 15:12:00,000	ADT-acties	2021-12-31 23:57:00,000		Overpl in	2021-12-31 23:57:00,000	
Interne geneeskunde	2037196	87698620	2021-12-31 19:19:00,000	2022-01-05 15:12:00,000	ADT-acties	2022-01-01 00:17:00,000		Overpl in	2022-01-01 00:17:00,000	
Interne geneeskunde	2037196	87698620	2021-12-31 19:19:00,000	2022-01-05 15:12:00,000	ADT-acties	2022-01-05 15:12:00,000		Ontslag	2022-01-05 15:12:00,000	
Neurologie	4070040	87698408	2021-12-31 17:05:00,000	2021-12-31 20:09:00,000	ADT-acties	2021-12-31 17:05:00,000		Opname	2021-12-31 17:05:00,000	
Neurologie	4070040	87698408	2021-12-31 17:05:00,000	2021-12-31 20:09:00,000	ADT-acties	2021-12-31 17:40:00,000		Overpl in	2021-12-31 17:40:00,000	
Neurologie	4070040	87698408	2021-12-31 17:05:00,000	2021-12-31 20:09:00,000	ADT-acties	2021-12-31 20:09:00,000		Ontslag	2021-12-31 20:09:00,000	
Neurochirurgie	2176048	87697318	2021-12-31 16:05:00,000	2022-01-14 12:00:00,000	ADT-acties	2021-12-31 16:05:00,000		Opname	2021-12-31 16:05:00,000	
Neurochirurgie	2176048	87697318	2021-12-31 16:05:00,000	2022-01-14 12:00:00,000	ADT-acties	2021-12-31 16:06:00,000		Overpl in	2021-12-31 16:06:00,000	
Neurochirurgie	2176048	87697318	2021-12-31 16:05:00,000	2022-01-14 12:00:00,000	ADT-acties	2021-12-31 17:00:00,000		Overpl in	2021-12-31 17:00:00,000	
Neurochirurgie	2176048	87697318	2021-12-31 16:05:00,000	2022-01-14 12:00:00,000	ADT-acties	2021-12-31 17:19:00,000		Overpl in	2021-12-31 17:19:00,000	
Neurochirurgie	2176048	87697318	2021-12-31 16:05:00,000	2022-01-14 12:00:00,000	ADT-acties	2022-01-01 00:26:00,000		Overpl in	2022-01-01 00:26:00,000	
Neurochirurgie	2176048	87697318	2021-12-31 16:05:00,000	2022-01-14 12:00:00,000	ADT-acties	2022-01-01 02:19:00,000		Overpl in	2022-01-01 02:19:00,000	
Neurochirurgie	2176048	87697318	2021-12-31 16:05:00,000	2022-01-14 12:00:00,000	ADT-acties	2022-01-01 17:05:00,000		Overpl in	2022-01-01 17:05:00,000	
Neurochirurgie	2176048	87697318	2021-12-31 16:05:00,000	2022-01-14 12:00:00,000	Stap_1_Order	2022-01-01 22:28:33,000	94216177	Consult fysiotherapie - contractuurpreventie	2022-01-01 22:28:33,000	
Neurochirurgie	2176048	87697318	2021-12-31 16:05:00,000	2022-01-14 12:00:00,000	Stap_1_Order	2022-01-01 22:28:33,000	94216178	Consult fysiotherapie - mobiliseren	2022-01-01 22:28:33,000	

Figure 4.4: Snippet of the raw data in XLSX format

neurology department. The neurology was a special case, as the patient discharge process for this department was altered around January 2021, therefore we chose a timeframe that included data from a year before and a year after the implementation. This made it possible to not only compare the neurology with the internal medicine and neurosurgery, but also compare the old and new patient discharge protocols. This resulted in the final timeframe being set from January 2020 until January 2022.

Event log components

The first step was to explore the raw data (figure 4.4) to see what data components we need to construct an event log.

The raw data was delivered by the ETZ DWH in the XLSX format. It contained a total of 25 columns and 360.520 rows of data.

To construct an event log, the following attributes are needed:

- Unique case identifier.
- Description of the performed activity.
- Date and time of that activity.
- Resource that executed the activity.

The raw data included two identifiers, patient number and patient CSN (Contact Serial Number). Patient numbers are not necessarily unique so

to avoid duplicates, we used the patient CSN. The CSN functions as a unique patient case identifier that is generated each time a patient enters the hospital. For the activity description we used the "Omschrijving" column that gives a description of the performed activity within a particular case.

The core of the event log is the date/time of when activities are performed inside a case. The data originally had multiple date/time columns, depending on what type of subsystem it came from.

For instance, activities that were recorded in information sheets for the questionnaires data were registered under the column "flowsheet_opgenomen". Moreover, orders and ADT-actions were registered under "Order_datum" (figure 4.4). For the event log, these date/time columns were combined under the "datum_sort" column. This gave us a singular column of all the timestamps that activities were performed at, independent of what subsystem they were originally recorded in.

The final piece of the event log are the resources that performed the activities. We had access to both the name and role of each resource. However, for privacy reasons and the generalizability of the results we only included the role of each resource for the event log.

Figure 4.5 gives an overview of what columns were included for the final event log.

#	Event log component	Column(s) included
1	Unique ID	Patient_CSN
2	Description	Omschrijving
3	Date/Time	Datum_sort
4	Resource	Actor_functie

Figure 4.5: Final selection of event log columns from the raw event log.

Dataset exploration

After collection of the main data sources, the next step was to explore the type of patient cases that extracted. To give an impression of what the data looked like, we used ProM Lite 1.3.1 and its event log visualization plug-in. ProM does not natively support the XLSX format for analysis. Therefore, it was converted into the XES (eXtensible Event Stream) format [35] using the Convert CSV to XES plug-in.

A total of 48.613 cases (trace) were converted consisting of 360.520 events, 9.078 case variants and 126 total activities. A visualization including a subsample of process instances is shown in figure 4.6.

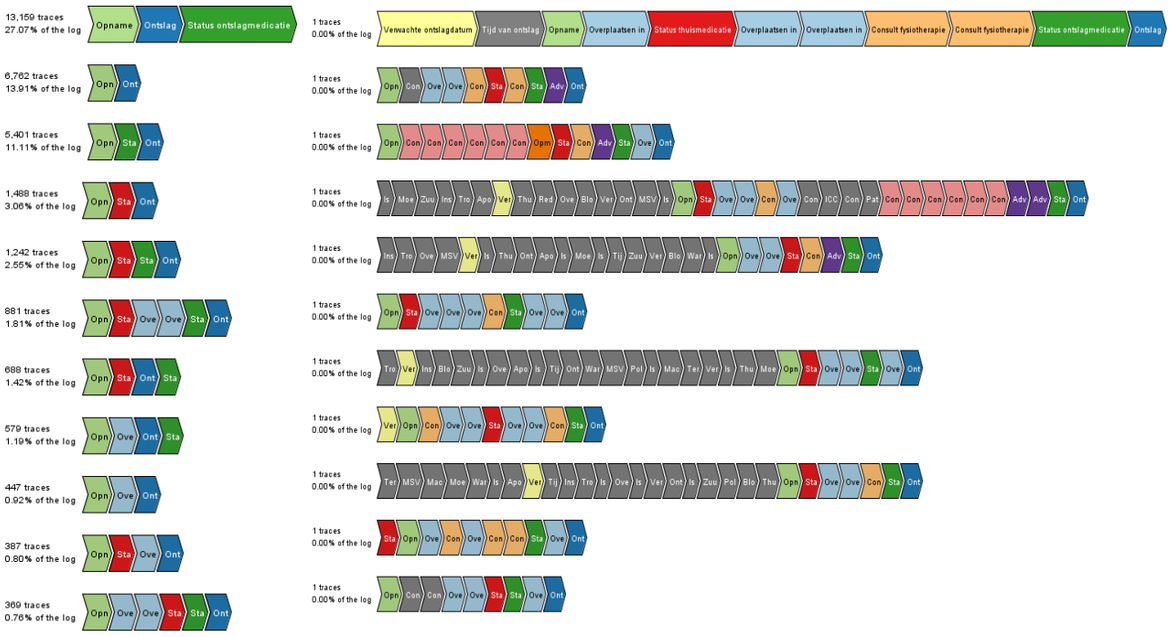

Figure 4.5: A visualization of a subset of the raw event log. (Appendix E for more detail.)

The visualization tells us that there is a very high rate of variability inside the event log. From the 48.613 traces, the amount of case variants is 18.7% of the total amount of cases in the event log. The high variability originates from the characteristics of the healthcare domain. Due to patient journeys being non-structured processes and each patient undergoes their own (unique) path from admission to discharge.

For instance, the trace below includes activities that are part of the PDP however, they are not part of the designed PDP process, therefore they fall outside the scope of our research.

Figure 4.6: Example of trace with irrelevant activities.

The first six activities of this trace (figure 4.6) are listed in table 4.2.

#	Activity (Dutch)	Activity (English)
1	Tijd (gepland)	Time (planned)
2	Moet er voor de patient na ontslag vervoer geregeld worden?	Do we need to plan vehicle transport after discharge?
3	Overige informatie m.b.t. ontslag	Other information w.r.t. discharge
4	Is vervoer na ontslag geregeld?	Was there vehicle transport planned?
5	Type vervoer	Type of transport
6	Datum (gepland)	Date (planned)

Table 4.2: First six activities of example trace (figure 4.6).

The next section describes how we will handle such activities across the entirety of the raw event log.

4.4.2 Filtering steps

Transformation

The first step in our cleaning process was dividing the raw event log into three separate event logs based (Fig. 6) on the involved departments. This allows us to find department-dependent inconsistencies across the data more efficiently. The advantages of this approach are threefold: 1) it gives us a better overview of the data, 2) makes sure that any department specific cleaning does not affect the event logs of the other departments and 3) it allows for easier generation of process models inside the process mining tools.

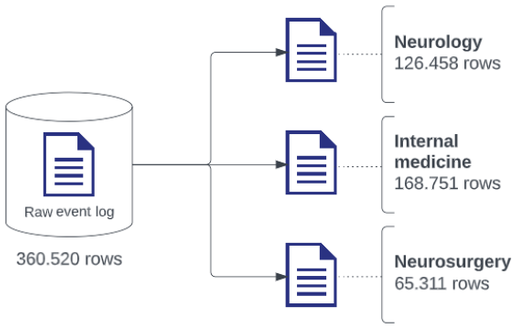

Figure 4.7: The separation of the raw event logs based on the involved departments.

After the separation of the event logs, we needed to get the timeframe for the event log in order. The timeframe spans around two years of data. The SQL-query used for the data extraction removed all ongoing cases from the dataset, making sure that the model could not be contaminated by cases that were not yet finished. This resulted in a timeframe from January 1st 2020 until January 25th 2022. Neurology had an additional separation in its timeframe as the PDP was altered around January 2021. Therefore, we divided the event log for neurology into two separate event logs, one spanning from Jan 2020-Jan 2021 and the other spanning from Feb 2021-Jan 2022. How this alteration in the PDP affected the process will be discussed in chapter 5.

The data exploration concluded that there was a high degree of variability inside the event logs. Disco gives us an overview of how the variants are distributed. The histogram shows the number of cases in relation to the case variability.

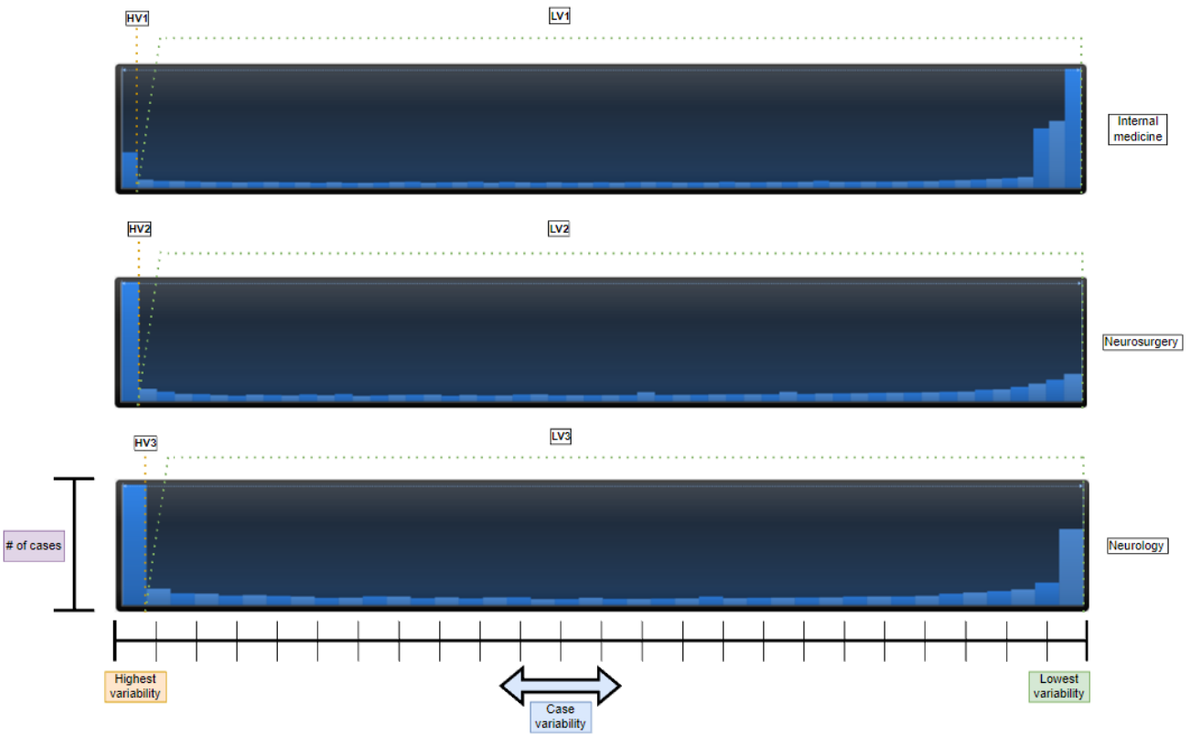

Figure 4.8: Case variability distribution for the included departments.

For instance, section HV1 (figure 4.8) contains a high degree of variability. It accounts for 86% of all process variants (figure 4.9), but accounts only for 10% of the total cases that have this high degree of variability. Moreover, it contains 43% of all the activities executed in the PDP carried out at the internal medicine. LV1 contains the remainder of the distribution, the variability is relatively low, as only 13% of all process variants are included in this section. On the contrary, LV1 includes 90% of all cases and 57% of all activities.

Department	%Process variants		%Cases		%Activities	
	HV1	LV1	HV1	LV1	HV1	LV1
Internal medicine	86	14	10	90	43	57
	HV2	LV2	HV2	LV2	HV2	LV2
Neurosurgery	87	13	33	67	64	36
	HV3	LV3	HV3	LV3	HV3	LV3
Neurology	92	8	39	61	79	21

Figure 4.9: Comparison of case variant distributions with regards to their process variants, number of cases and activities.

The process variance distribution looked similar for the neurology and neurosurgery. The internal medicine stood out with a low percentage of cases included in the high variance section of the distribution. This is an unexpected observation, because in healthcare processes we expect that most cases are of high variability. High degrees of variance across the distribution accounted for 10-39% of all cases and low variance between 61-90% of cases (table 4.2). We want to find out the main PDP process, but we do not want to dismiss a large portion of the cases just because there is high variance. Thus, we included both high and low variance sections of the event log into the next steps of the filtering process.

Deletion

The next step of the filtering process is analysing the three event logs we created and finding inconsistencies and illogical sequences of activities that will not contribute to a better process model. Finding large illogical sequences was proven to be difficult in a high variance process. However, our analysis of the process variance distribution showed that the internal medicine (IM) unexpectedly deviated from the other departments. After analyzing the frequencies of the case lengths, we found 6027 cases or 40% of the IM dataset that consisted of only 1 or 2 activities. Moreover, neurology had 3% and neurosurgery 4.2% of these case types. The cases found showed only admission, admission → discharge, admission → transfer or transfer → discharge. All cases with these characteristics are outside our scope and were deleted from all departmental event logs. Even though these cases might not influence the process model in its sequence of events. More performance-oriented measures such as average time between events can be greatly influenced by a high influx of these type of cases.

In addition to the deletion of cases with a specific length, the number of activities inside the process was reduced significantly. To limit the complexity of the process model we only wanted to include core activities. In a series of consults with domain experts (table 4.5) we selected core activities that were deemed the most significant in the PDP process. We first focused on the scope of the patient discharge process. A total of 126 initial activities were extracted from the raw dataset. Together we with the domain experts we analysed these activities and concluded if they fell inside the scope of the PDP. If activities were inside the scope, the next step was to position their importance inside the entire patient discharge process. As we only wanted to include core activities. The hospital had already designed a new concept patient discharge process protocol. This

protocol already had a subset of all the activities present in the PDP. Therefore, we compared the activities that were present in concepts for a new potential PDP protocol and compared if, out the 126 activities in the raw dataset, there was a corresponding activity. If the activity was present in the raw dataset, we considered it essential, and it was included in the final list of activities.

Besides this, we looked at missing activities. These were activities that were present in the designed PDP concepts but were not yet present in dataset. After comparing the raw dataset with the concepts for a new PDP we concluded that the medication verification data and consult data for dieticians was missing from the raw dataset. With the help of the business analysts at the hospital we managed to include the activities related to the medication verification and dietician orders as well.

The frequencies of the activities were also considered. However, there were cases present where the frequency of the activity was not in line with other included activities and in the end, it was still included in the model as the domain experts expressed its importance in the process.

Summarizing, a total of 126 activities was extracted from the raw dataset. For each activity the answer to the following two questions determined their inclusion:

Q1. Does the activity fall inside the scope of the PDP?
Q2. Is the activity present in the (concept) designs of the PDP process?

Appendix B gives an overview of how each activity answers these criteria.

Re-labelling and re-clustering

In addition to the selection of core activities, several activities needed to be relabeled or re-clustered to clarify their role in the process. These activities included: (appendix B) *Soort aanvraag, indicatie intramuraal, indicatie extramuraal* and *status thuismedicatie*.

The raw dataset contained a column that included the corresponding input by healthcare professionals for the *Soort aanvraag, indicatie intramuraal, indicatie extramuraal* activities. Based on that we renamed the activities in the following way (table 4.3):

Old	New
Soort aanvraag	Beslissing zorg type (intra/extra murale zorg)
Indicatie intramuraal	Beslissing type zorg intramuraal
Indicatie extramuraal	Beslissing type zorg intramuraal

Table 4.3: Renamed core activities.

In addition, we relabelled the *status thuismedicatie* to give a more meaningful indication of what type of status it indicated. Using the medication verification data, we renamed the statusmedicatie to include the statuscode. This resulted in 9 different codes indicating the status. After generating the process models using these codes, we concluded that using all 9 codes would increase the complexity of the model and decided we would cluster the least frequent status codes under one activity. This became *Status thuismedicatie overig.* The most frequent codes were still included in the model. After the re-labelling and re-clustering of these activities, we constructed the final list of core activities that would be used for generation of the process models.

Moreover, the activity of a physiotherapy consult order included in the data was divided into seven type (table 4.4) To limit the complexity of the model we only included only the main *consult fysiotherapie* activity. We found that each patient that had one of the specifications of the physiotherapy consult also included the main consult order, therefore there was no need to include the specifications of a physiotherapy consult order.

Activity
Consult fysiotherapie - mobiliseren
Consult fysiotherapie - ademhalingsoefeningen
Consult fysiotherapie - contractuurpreventie
Consult fysiotherapie - mobiliseren
Consult fysiotherapie - overig
Consult fysiotherapie- ademhalingsoefeningen
Consult fysiotherapie- contractuurpreventie

Table 4.4: The specifications of the physiotherapy consult order activity.

An overview of all included activities can be found in table 4.5.

#	Activity (Dutch)	Activity (English)
1	Verwachte ontslagdatum	Preliminary discharge date
2	Reden waarom VOD niet gehaald is?	Reason why preliminary discharge date was not achieved (VOD)
3	Is de oorspronkelijke VOD gehaald?	Was the preliminary discharge data achieved? (VOD)
4	Opname	Admission
5	Overplaatsing in	Internal transfer
6	Status thuismedicatie code: 1	Status home medication code: 1
7	Status thuismedicatie code: 3A	Status home medication code: 3A
8	Status thuismedicatie overig	Status home medication other
9	Status ontslagmedicatie	Status discharge medicine
10	Consult fysiotherapie	Consult physiotherapy
11	Consult diëtetiek	Consult dietician
12	Consult ergotherapie	Consult ergotherapy
13	Consult logopedie	Consult Logopaedic
14	Advies ontslag – fysiotherapie	Discharge advice – physiotherapy
15	Advies ontslag – ergotherapie	Discharge advice – ergotherapy
16	Advies ontslag – logopedie	Discharge advice – logopaedic
17	Gezamelijk advise ETZ	Collective advice ETZ
18	ICC SO (specialist ouderengeneeskunde)	ICC geriatric specialist (SO)
19	ICC revalidatie geneeskunde/arts	ICC rehabilitation specialist (RA)
20	Advies SO	Advice SO
21	Advies RA	Advice RA
22	Beslissing type zorg (intra/extra murale zorg)	Decision care type (intra/extra mural care)
23	Beslissing type zorg intramuraal	Decision type of intramural care
24	Beslssing type zorg extramuraal	Decision type of extramural care
25	Datum medisch gereed (MGD) bevestigd door afdeling	Date medically ready confirmed by department
26	Ontslag	Discharge

Table 4.5: Final selection of core activities including their translation.

In addition to the collection of quantitative data, semi-structured interviews with domain experts and observation sessions on the involved departments were conducted to further enhance the patient discharge process as discovered by the data analysis. Process mining is a proven tool in process discovery however, to get a complete picture of reality it is vital [32,33] to include information extracted directly from the process actors. This qualitative data was collected using traditional process discovery techniques.

4.5 Process model discovery

To answer our main research question, we first to need address the building blocks that are represented by our research sub-questions. SQ1 and SQ2 bring forth the questions of how we can discover the activities in the patient discharge process and who executes these activities in the ETZ hospital. To achieve this, we need to analyse the collected quantitative and qualitative data and use this to discover an objective process model that represents reality as closely as possible. Process mining algorithms will be the main tools for discovering the process models from the quantitative data collected.

Quantitative data analysis

We want to use PM discovery techniques that have a history of generating robust and understandable models. They need to be capable of handling the complex processes in healthcare without resulting in spaghetti-like models that are impossible to understand. Previous research has indicated that the **Heuristics miner** and **Fuzzy miner** are the most promising process mining techniques to produce such models [6]. The Heuristics Miner is a discovery algorithm that focuses on the *control-flow perspective* of process mining and has shown to be robust in dealing with noisy data [17]. The Fuzzy Miner is a configurable discovery algorithm that makes it possible to alter its parameters and extract models and different levels of abstraction, this is useful in dealing with mostly unstructured (healthcare) processes [37]. Even though these two approaches have proven themselves in a variety of use cases (table 3.1), early experimentation with the Fuzzy miner in ProM lite 1.3.1 resulted in models with spaghetti-like properties.

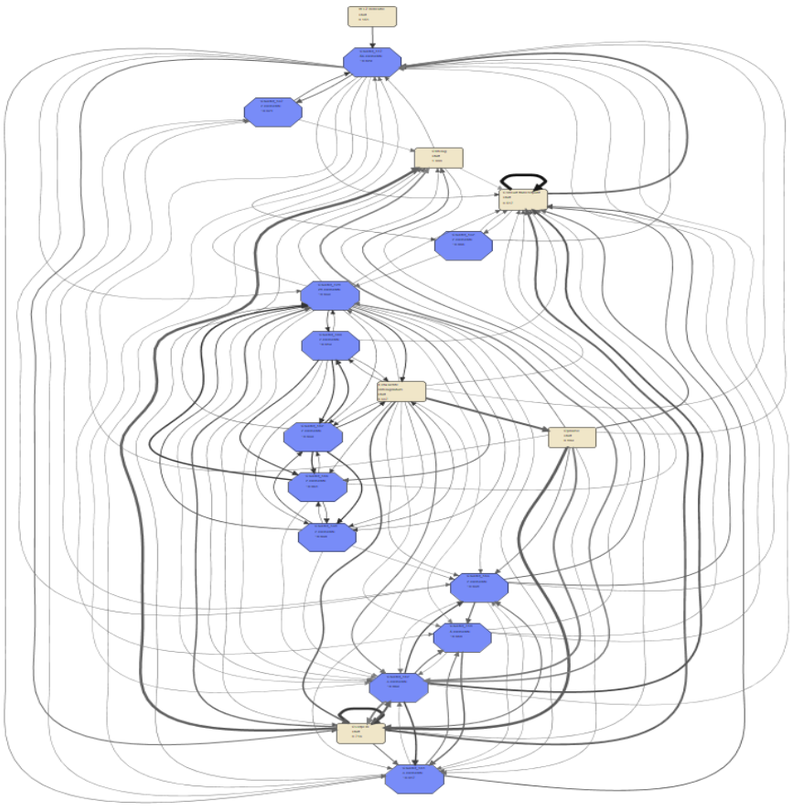

Figure 4.10: Early Fuzzy model in ProM (Node cut-off 0.151, Edge cut-off 0.56, Utility rt 0.75)

We wanted to use a process mining solution that could handle all our data without limiting the dataset to only include mainstream cases, severely limiting the cases included. After consulting domain experts (business information data analyst, policy advisor) the main arguments to move away from ProM were threefold: 1) tuning the parameters of ProM to get understandable and readable models would be too time consuming in the available timeframe 2), the resulting models are difficult to understand for domain experts and would need constant simplification to gather feedback, 3) The software suite for ProM is poorly optimised in terms of performance (especially on local hospital hardware), making the process slow and cumbersome.

Disco miner [17, 25, 21], a solution build by Dutch researchers and their company Fluxicon showed the best usability in the context of our project. Disco's mining algorithm is based on the proven Fuzzy miner and expands upon its functionality. Disco was designed with three core principles in mind [38]:

1) *Usability*, the models produced by Disco can be understood more easily by process mining researchers and domain experts by minimizing visual overload.

2) *Fidelity*, disco uses an intelligent information extraction method that makes it possible to include large complex datasets while maintaining a good balance of complexity and comprehensibility of the generated models.
3) *Performance*, Disco is designed to be fast. Tuning of parameters, importing datasets and process model generation can be done in the span of seconds. Process mining is an interactive task where back and forth communication between domain experts and researchers is vital. The fast execution of tasks inside Disco makes this a suitable tool for our use case.

Qualitative data

Informal interviews with domain experts served as the main tool for qualitative data collection. The main purpose of these interviews was twofold:

(1) Extraction and refinement of representative event data.
(2) Refine and validate the process models that were discovered using process mining. (SQ1)

A series of domain experts were consulted during this thesis. Table 4.5 gives an overview of what the main topic of conversation was during each meeting and when they were consulted.

Domain expert	Main goal(s)	Interview date(s)
Nurse	Neurology observation session, observing the patient discharge process in practice to get a better understanding of the data.	28th of October 21'
Business data analyst	• Extracting the data from the HIS, refining to data into a format that was suitable for process mining. • Discussing the data collection pipeline. • Data pre-processing. • Discussing and adding missing activities.	Nov 11th, February 18th, March 1st, April 18th and May 30th
Two nursing team leaders	Getting a broader understanding of the process and looking for missing activities.	16th of March 22'
Two Physician assistants	Developing a more detailed understanding of the activity definitions and their logical flow.	25th of April 22'

Two policy advisors	Refinement of the generated process models. Areas of interest were logical flow of activities, missing activities and clustering of activities.	9 & 16th of May 22'

Table 4.6: Consulted domain experts during the project.

4.6 Threats to validity

Threats to validity can be considered from both the internal and external perspectives. Internal validity refers to the cause-and-effect relationship that is established with the results of the experiment. External validity refers the generalization of the results and to what degree these results can be applied to broader context. In this case study, process mining techniques will be the main source of the results. Therefore, the execution of these techniques plays a major role in the validity of this study.

Threat 1 Using the wrong evaluation data.

Mitigation strategy The event data that was gathered during this study was directly extracted from the hospital information system Epic. This system is the technological foundation of many healthcare processes inside the ETZ. By using the data directly registered in this system we believe we established an event log that is representative of the process to be evaluated.

Threat 2 Not recognizing applied technique limitations.

Mitigation strategy Process mining is a proven tool in discovering potential process improvement, however the results of applying process mining algorithms to real-life event data are not airtight. Therefore, we have explicitly stated the limitations and implications of any findings resulting from this study.

Threat 3 Absence of domain experts.

Mitigation In most studies the researcher applying the chosen methods are unaware of the inner workings of the investigated process, especially in the healthcare domain it is difficult to fully understand what activities truly entail. Therefore, we closely worked together with the domain experts to ensure that the activities chosen for the main process flows were representative of the patient discharge process.

5 Results

This section presents the results obtained from the application of the Disco miner on the constructed event logs. Section 5.1 presents the discovered patient discharge process models for internal medicine, neurology and neurosurgery. Moreover, section 5.2 includes the discovery of the actors present and the relations among them. Finally, a comparison of the three departments based on a series of metrics is included in section 5.3.

5.1 Discovered process models

This subsection presents the process models that were discovered by applying process mining tools. Each department will have a separate description of the process flow. Potential differences between the models will be discussed later in section 5.1.5.

Parameters

Disco gives us the possibility to generate models at different levels of abstraction. The parameters can be altered for the amount of detail desired in the activities and paths included in the model. To make a fair comparison between the models possible we used the same parameter settings in the generation of all the models.

The parameters for the process models could be altered in two ways: 1) a slider that could be used to alter the frequency cut-off point for included activities and 2) a slider for the frequency cut-off point for included paths. The selection of core activities made parameter tuning more limited, as using a low cut-off point, including the most frequent activities, would exclude infrequent core activities. For this reason, we chose to set the activity slider on its highest setting, including 100% of all (core) activities. The paths slider was on the opposite side of the spectrum. We wanted to include as much detail without the model turning into spaghetti. Unfortunately, using a cut-off point > 1% would quickly result in an unreadable process model due to the nature of the data. Therefore, we kept it at 1%, including only the most frequent paths found between the activities.

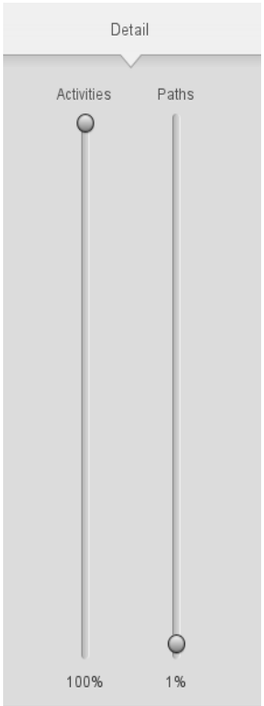

Figure 5.1: Disco miner sliders for altering activity and path detail.

Reading the model

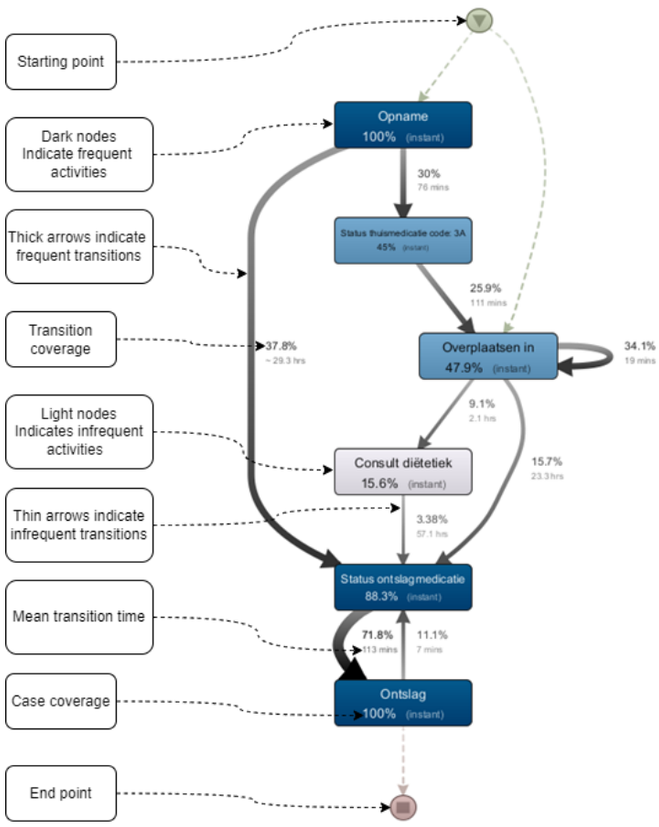

Figure 5.2: Overview of all the attributes needed to read the discovered process models. The values of this model are for illustrative purposes only.

Figure 5.2 gives us an overview of what elements the discovered process models consist of. The process models can be read in the following way:

- The start of the process is indicated by a green circle.
- Dotted arrows that originate from the starting point, point towards the starting activities.
- Activities or nodes are represented by rectangles, where the darkness of the node indicates its relative frequency among all other activities included in the process model.
- Percentages inside a node represent its case coverage (section 5.3).
- Arrows indicate transitions/paths between activities, where the thickness of the arrow indicates its relatively frequency and is also indicated by the transition rate alongside the arrows.
- The second number alongside the arrows is the mean transition time (section 5.3).
- A red circle indicates the end of the process and is always connected to the ending activities of the process.

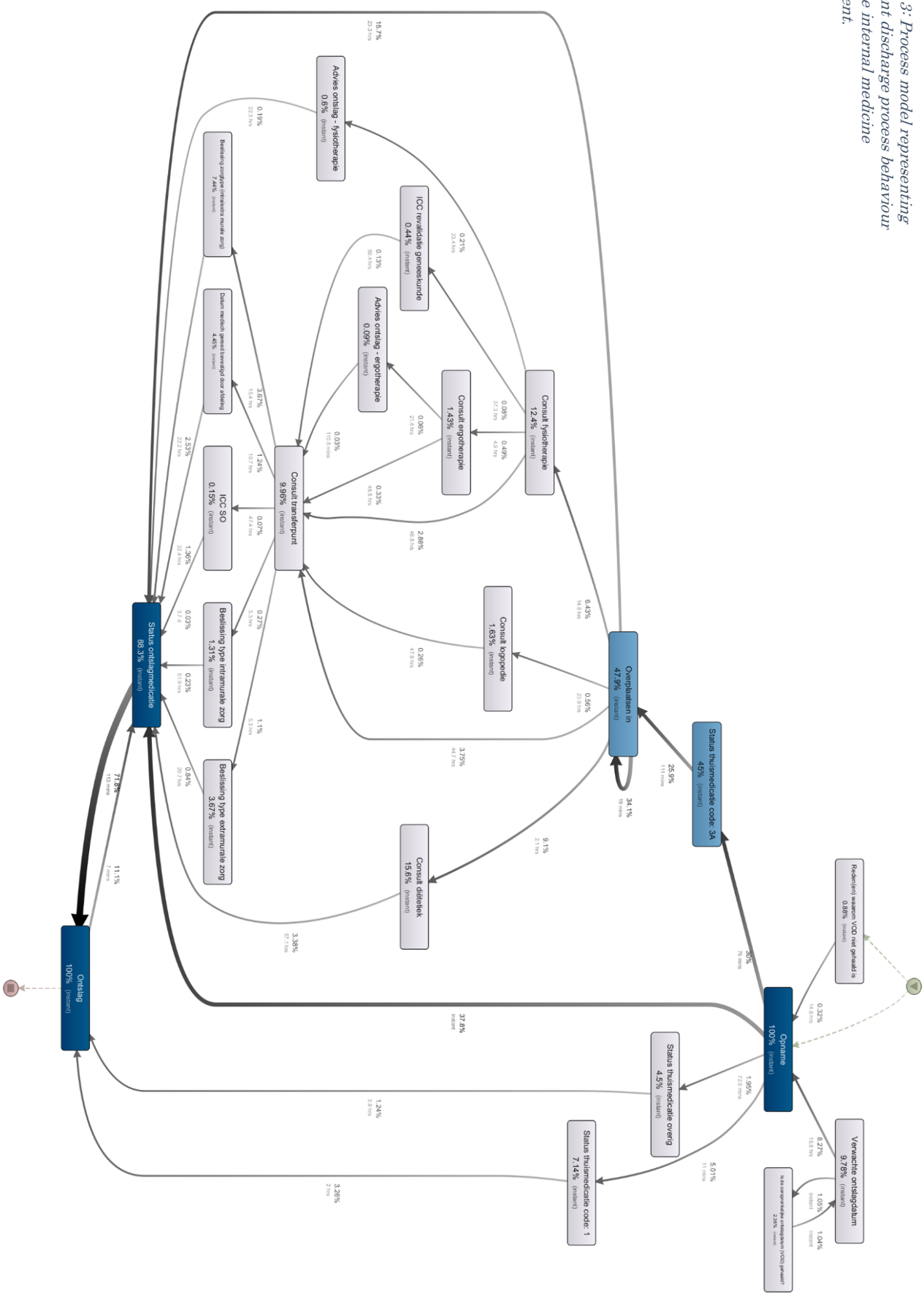

Figure 5.3: Process model representing the patient discharge process behaviour inside the internal medicine department.

Section 5.1.1 - 5.1.4 gives a textual description of the discovered process models. Starting from admission, a number of paths can be followed leading to several activities. For all these activities the most frequent subsequent transitions are described. The strength of the transitions between activities can be described in terms of the Transition Coverage. This is calculated by the case frequency of the transition and dividing this by the total amount of cases. Transitions that have a very low TC are deemed as weak and can be considered inconclusive in describing the actual behaviour inside the department. This will be discussed further in section 7.

5.1.1 Internal medicine

The starting activity is linked to the green circle in the model (figure 5.1). This means that the process starts with *Admission* or *Reason preliminary discharge date was not achieved.* In addition, two other pre-admission activities were found. The registration of the *Preliminary discharge date* and a check, *was the preliminary date achieved?*

After *Admission,* four paths are most frequently taken (Table 5.1).

	Activity	Transition coverage (%)
Admission →	1. Status discharge medication	37.8
	2. Status home medication code: 3A	30.0
	3. Status home medication code: 1	5.01
	4. Status home medication other	1.95

Table 5.1: Most frequent paths after Admission

After *Status discharge medication*, *Status home medication code: 1* and *Status home medication other* the next activity is *Discharge*. This is where the process ends for most patients (red circle is linked to discharge).

The remaining patients originate from the *Status home medication code: 3A,* meaning that their medication was verified and approved. The next most frequent activity for these patients is the internal transfer, this means that the patient is still part of the internal medicine department, however they have been transferred to another department for logistical reasons.

After the internal transfer, five paths are most frequently taken:

Internal transfer →	1. Status discharge medication	15.7
	2. Consult dietician	9.1
	3. Consult Physiotherapy	6.43
	4. Consult transfer point	3.75
	5. Consult Logopaedic	0.56

Table 5.2: Most frequent paths after internal transfer

After the *internal transfer* or *dietician consult order*, a patient's discharge medication was checked, and they were discharged after.

Patients that received a consult from the physiotherapist had four paths that they most frequently took:

Note

Activities that refer to healthcare professionals such as *Consult Physiotherapy* indicate when the order for such a healthcare professional was placed. We have no data on when the actual consult was performed.

Consult physiotherapy →	1. Discharge advice - Physiotherapy	0.21
	2. ICC rehabilitation specialist (RA)	0.08
	3. Consult ergotherapy	0.49
	4. Consult transfer point	2.88

Table 5.3: Most frequent paths after consult with physiotherapist.

Patients that got a *Discharge advice (Physiotherapy)* were followed up by the verification of their discharge medicine (status discharge medication) and discharged after.

1. Consult physiotherapy →	2.88	
2. Consult ergotherapy → Discharge advice – ergotherapy	0.33	Consult transfer point
3. ICC rehabilitation specialist (RA) →	0.13	
4. Consult logopaedic →	0.26	
5. Internal transfer →	3.77	

Table 5.4: Activities followed by a consult with the transfer point.

Table 5.4 gives an overview of all the activities that are followed up by a consult with the transfer point. Paths originating from multiple points in the process come together at the transfer point and the process continues from there onwards.

After a consult with the transfer point five paths are most frequently taken:

	1. Decision care type (intra/extra mural care)	3.67
Consult transfer point →	2. Date medically ready confirmed by department	1.24
	3. ICC geriatric specialist (SO)	0.07
	4. Decision type of intramural care	0.27
	5. Decision type of extramural care	1.1

Table 5.5: Most frequent paths after Consult transfer point.

The numbered activities shown in table 5.5 are followed up by the verification of the discharge medication. This is followed by the Discharge activity, where the process ends for all patients.

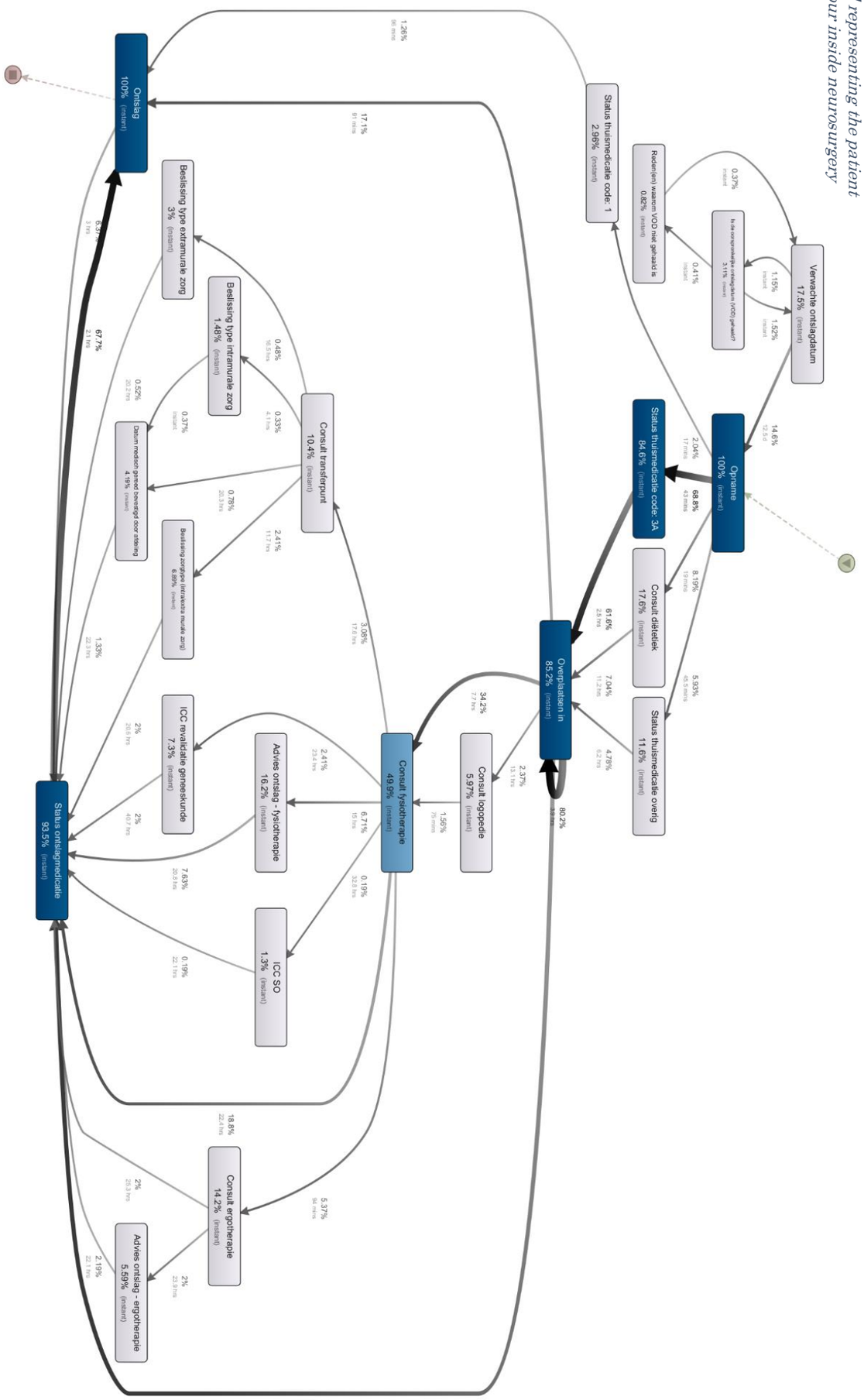

Figure 5.4: Process model representing the patient discharge process behaviour inside neurosurgery department.

5.1.2 Neurosurgery

On the neurosurgery department (figure 5.2) we see similar behaviour at the start of the process. The order of activities does deviate, but this will be discussed in section 5.3. Therefore, we continue the textual description of the process model after the pre-admission activities.

After *Admission* four paths were most frequently taken:

	Activity	Transition coverage (%)
Admission →	1. Status home medication code: 3A	68.9
	2. Consult dietician	8.19
	3. Status home medication other	5.93
	4. Status home medication code: 1	2.04

Table 5.6: Most frequent paths after admission

After *Status home medication code: 1*, *Discharge* follows and the process ends for these patients.

From activities *Status home medication code:3A*, *Consult dietician* and *Status home medication other,* a separate path connects them to the *Internal transfer*. After the internal transfer four paths are most frequently taken:

Internal transfer →	1. Status discharge medication	35.8
	2. Consult physiotherapy	34.2
	3. Discharge	17.1
	4. Consult logopaedic	2.37

Table 5.7: Most frequent paths after internal transfer

Patients that received a verification of their discharge medication (1) were discharged after.

Moreover, patients that a logopaedic consult was ordered for, were followed up by the physiotherapy consult order.

After a physiotherapy consult order six paths were most frequently taken:

Consult physiotherapy →	1. Status discharge medication	18.8
	2. Discharge advice – physiotherapy	6.71
	3. Consult ergotherapy → Discharge advice – ergotherapy	5.37, 2
	4. Consult transfer point	3.08

	5. ICC rehabilitation specialist (RA)	2.41
	6. ICC geriatric specialist (SO)	0.19

Table 5.8: Most frequent paths after a physiotherapy consult order.

Activities 1-3, 5 and 6 all were followed up by a verification of the discharge medicine and patient were discharged after, ending their process.

After a consult transfer point (4) four paths were most frequently taken:

	1. Decision care type (intra/extra mural care)	2.41
Consult transfer point →	2. Date medically ready confirmed by department	0.78
	3. Decision type of intramural care → Date medically ready confirmed by department	0.33
	4. Decision type of extramural care	0.48

Table 5.9: Most frequents paths after a consult transfer point order.

All paths in table 5.9 were followed up by a verification of the discharge medication and were discharged after, ending the process for all patients.

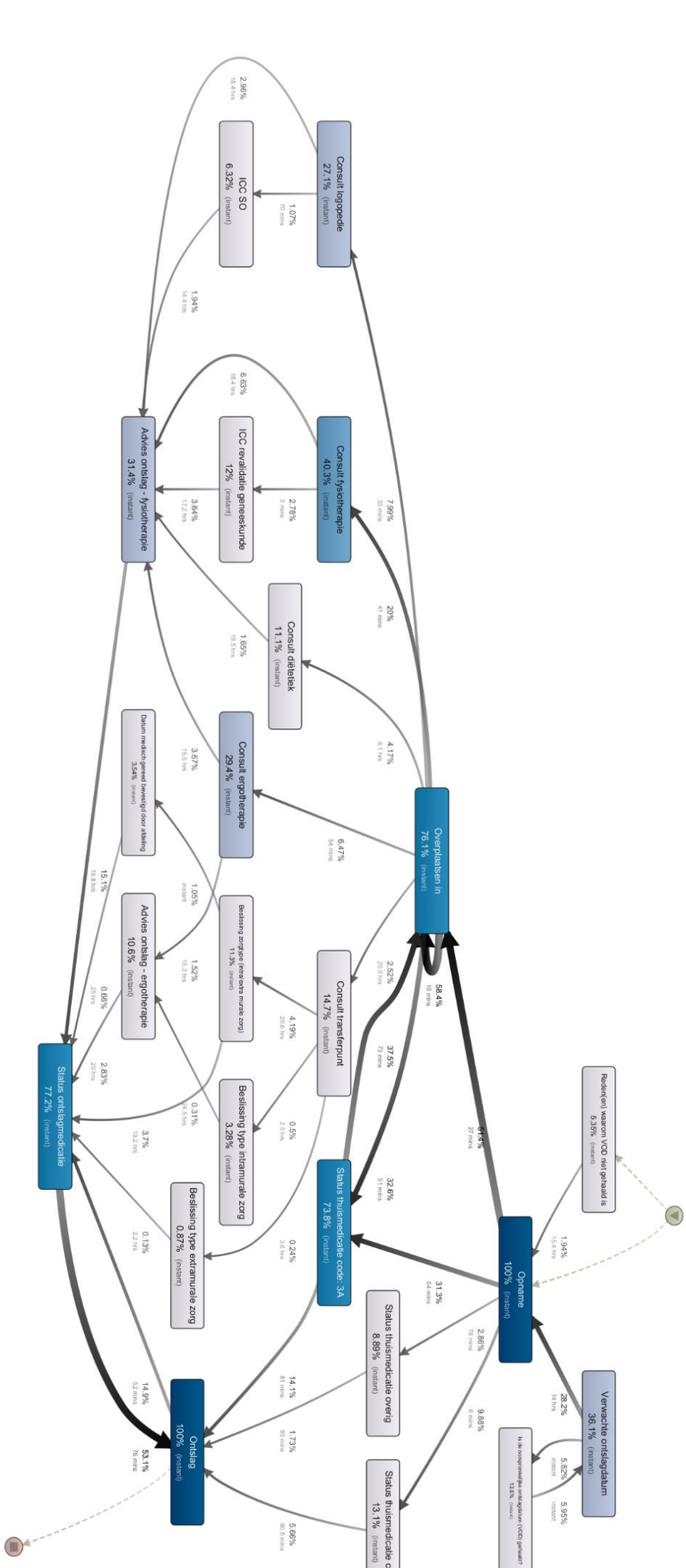

Figure 5.5: Process model representing the patient discharge process behaviour inside neurology department Jan 2020-Jan2021 (old).

5.1.3 Neurology old

This section describes the process model (figure 5.3) for the neurology department (old) which entails the same implementation of the patient discharge process as on the internal medicine and neurosurgery departments.

Similarly, to other the previously described departments, after *Admission* four paths are most frequently taken (table 5.10):

	Activity	Transition coverage (%)
Admission →	1. Internal transfer	51.4
	2. Status home medication code: 3A	31.3
	3. Status home medication code: 1	9.88
	4. Status home medication other	2.86

Table 5.10: Most frequent paths after admission on the neurology (old) department.

After *Status discharge medication 3A*, *Status home medication code: 1* and *Status home medication other* the next activity is *Discharge*. This is where the process ends for these patients.

The status home medication 3A activity also has an additional transition to the internal transfer. After the *internal transfer* five paths are most frequently taken:

Internal transfer →	1. Consult physiotherapy	20
	2. Consult logopaedic	7.99
	3. Consult ergotherapy	6.47
	4. Consult dietician	4.17
	5. Consult transfer point	2.52

Table 5.11: Most frequent paths after internal transfer (Neurology old)

Each activity in table 5.11 had their own path to the *Status Discharge medication* activity, the transitions are as follows:

Consult physiotherapy →	1. Discharge advice – physiotherapy	6.63
	2. ICC rehabilitation specialist (RA) → Discharge advice – physiotherapy	2.78, 3.64

Table 5.12: Most frequent paths after a physiotherapy consult order (Neurology old)

Consult logopaedic →	1. Discharge advice – physiotherapy	2.96
	2. ICC geriatric specialist → Discharge advice – physiotherapy	1.07, 1.94

Table 5.13: Most frequent paths after a logopaedic consult order (Neurology old)

Consult dietician →	1. Discharge advice – physiotherapy	1.65

Table 5.14: Most frequent paths after a dietician consult order (Neurology old)

Consult Ergotherapy →	1. Discharge advice – physiotherapy	3.67
	2. Discharge advice – ergotherapy	1.52

Table 5.15: Most frequent paths after an ergotherapy consult order (Neurology old)

Consult transfer point→	1. Decision care type (intra/extra mural care) → Date medically confirmed by department	4.19, 1.05
	2. Decision type of intramural care → Discharge advice – ergotherapy	0.5, 0.31
	3. Decision type of extramural care	0.24

Table 5.16: Most frequent paths after consult transfer point (Neurology old)

All transitions from tables 5.12-15.16 lead to the verification of the discharge medication and are followed by the end activity *Discharge* ending the process for all patients.

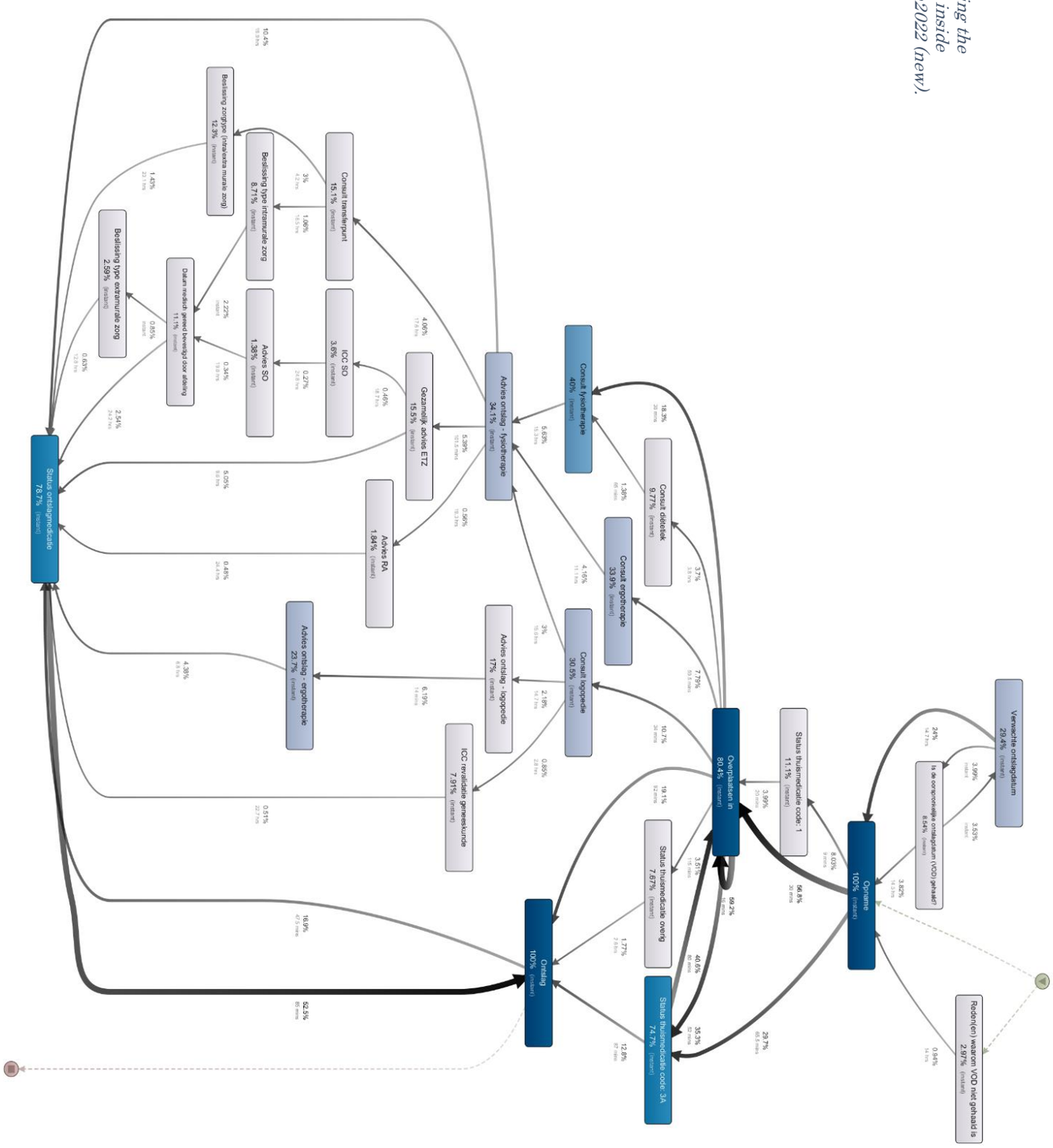

Figure 5.6: Process model representing the patient discharge process behaviour inside neurology department Feb 2021-Jan2022 (new).

5.1.4 Neurology new

This section describes the process model (figure 5.4) for the neurology department (new) which entails a more structured protocol for the patient discharge process.

After *Admission* three paths are most frequently taken (table 5.17):

	Activity	Transition coverage (%)
Admission →	1. Internal transfer	56.8
	2. Status home medication code: 3A	29.7
	3. Status home medication code: 1 → Internal transfer	8.03, 3.99

Table 5.17: Most frequent paths after admission on the neurology (new) department.

Some patients that received a verification of their home medication immediately after admission were either discharged, ending the process for these patients, or were followed up by an internal transfer.

After the internal transfer seven paths were most frequently taken:

Internal transfer →	1. Status home medication code: 3A → Discharge	35.3
	2. Discharge	19.1
	3. Consult physiotherapy	18.3
	4. Consult logopaedic	10.7
	5. Consult ergotherapy	7.79
	6. Consult dietician → consult physiotherapy	3.7, 1.38
	7. Status home medication code: 1	3.51

Table 5.18: Most frequent paths after internal transfer on the neurology (new) department.

After the ordering of a logopaedic consult (4, table 5.19) three paths were most frequently taken:

Consult Logopaedic →	1. Discharge advice – physiotherapy	3
	2. Discharge advice – logopaedic → Discharge advice – ergotherapy	2.18, 6.19
	3. ICC rehabilitation specialist (RA)	0.85

Table 5.19: Most frequent paths after a logopaedic consult order on the neurology (new) department.

Patients that followed path 2 and 3 (table 5.18) were most frequently followed by a verification of their discharge medication and discharged after, ending the process for these patients.

The most frequent subsequent activity after a consult order for the physiotherapy, logopaedic and ergotherapy was *Discharge advice – physiotherapy*. After this activity followed several paths that all resulted in a check of the discharge medication (*status discharge medication*) followed by *discharge*, ending the process for all patients.

Table 5.20 gives an overview of all paths between a consult order for physiotherapy and status discharge medication.

Starting activity	Follow-up path(s)	Transition coverage (%)
Discharge advice – physiotherapy →	1. Status discharge medication	10.4
	2. Collective advice ETZ	5.39
	3. Collective advice ETZ → ICC geriatric specialist (SO) → Advice SO → date medically ready confirmed by department	5.39, 0.46, 0.27, 0.34
	4. Collective advice ETZ → ICC geriatric specialist (SO) → Advice SO → date medically ready confirmed by department → decision type of extramural care	5.39, 0.46, 0.27, 0.34, 0.85
	Consult transfer point → Decision care type (intra/extramural care)	4.06, 3
	Consult transfer point → Decision type intramural care → date medically ready confirmed by department	4.06, 1.06, 2.22
	Consult transfer point → Decision type intramural care → date medically ready confirmed by department → decision type extramural care	4.06, 1.06, 2.22, 0.85
	Advice rehabilitation specialist	0.56

Table 5.20: Most frequent paths after Discharge advice - physiotherapy on the neurology (new) department.

5.1.5 Deviations

This section discusses activity sequences that deviate from the expected behaviour of the patient discharge process. We will only focus on the transitions between certain activities and their position inside the process. The percentages shown in the model will be discussed in section 5.3.

Pre-admission

Before patients are admitted in their respective departments, we see all process models (figure 5.1-4) include three pre-admission activities related to the preliminary discharge date (VOD). These include the activities *Reason why VOD was not achieved*, *preliminary discharge date* and *was the initial discharge date achieved?* The first notable observation here is the fact that the *Reason why VOD was not achieved* activity is a starting point of the process besides admission. Meaning that this activity is more often the starting point in a patient's case when compared to the preliminary discharge date itself. The reasons that this is peculiar are twofold: 1) The VOD is registered at the beginning of the process and is expected to be registered *before* the activity *Reason why VOD was not achieved*. 2) The reason the VOD was not achieved is only known at a later stage in the patient discharge process, thus we expected this activity only until later in the process and not as a starting point. In addition, the activity *was the initial discharge date achieved?* is also an activity we expect only until later in the patient discharge process. Ideally, the activities *was the initial discharge date achieved?* and *Reason why VOD was not achieved are* expected before or just after discharge.

Moreover, the VOD can be altered during the patient discharge process and in the process models, we see the initial registration of the VOD (as expected) in the beginning of the case for most patients. However, we also expect that the VOD changes during the case of a patient and is changed accordingly. Unfortunately, we do no not see the activity *"Preliminary discharge date"* reoccurring later in the process. This could imply that the VOD after its initial registration is not altered at all, or its mutation is not properly reflected in the information registration inside the hospital information system.

5.2 Organizational perspective

This subsection presents a series of actor interaction models giving insight into the degree of participation of each actor in the patient discharge process. Each activity in the patient discharge process was executed by an actor. The participation rate is the total amount of activities the actor executed as a percentage of the total amount of activities. A high participation rate means that the actor executed many activities in the patient discharge process and thus plays a significant role in its execution.

In addition, the model will show the degree of interaction between the actors giving insight into how the different actors collaborate. The significance of the collaboration is expressed by the transition coverage.

Parameters

The amount of detail in the actor interaction models could be altered in the same way as in the generation of the process models (section 5.1). After experimentation with a multitude of cut-off points for the actor interaction models, we chose a cut-off point of 30% for the activity slider and a cut-off point 1% paths slider inside in the Disco software. This gave us a good balance between the complexity and completeness of the model.

Internal medicine

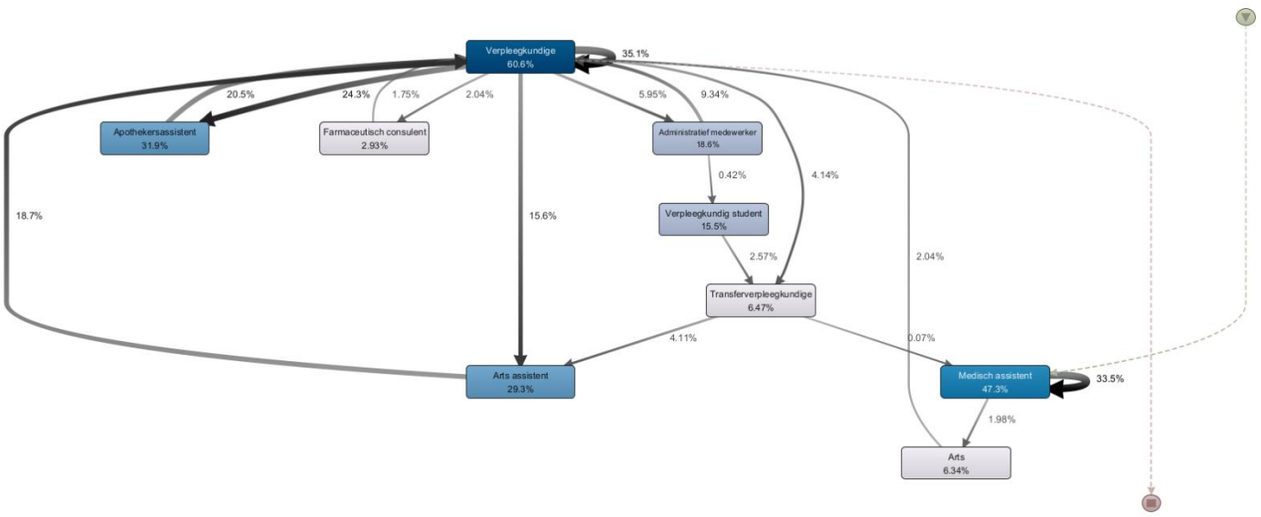

Figure 5.7: Actor interaction model for the internal medicine department.

Actor	Participation rate (%)
Nurse	60.6
Medical assistant	47.3
Pharmacist assistant	31.9
Physician assistant	29.3

Administrative employee	18.6
Nurse student	15.5
Transfer nurse	6.47
Physician	6.34
Pharmacist	2.93

Table 5.21: Participation rate for each actor in the patient discharge process at the internal medicine department.

Actor interaction	**Transition coverage (%)**
Nurse → Nurse	35.1
Medical assistant → Medical assistant	33.5
Nurse → Pharmacist assistant	24.3
Pharmacist assistant → Nurse	20.5
Physician assistant → Nurse	18.7
Nurse → Physician assistant	15.6

Table 5.22: Most common (TC > 15%) actor interactions at the internal medicine department.

Neurosurgery

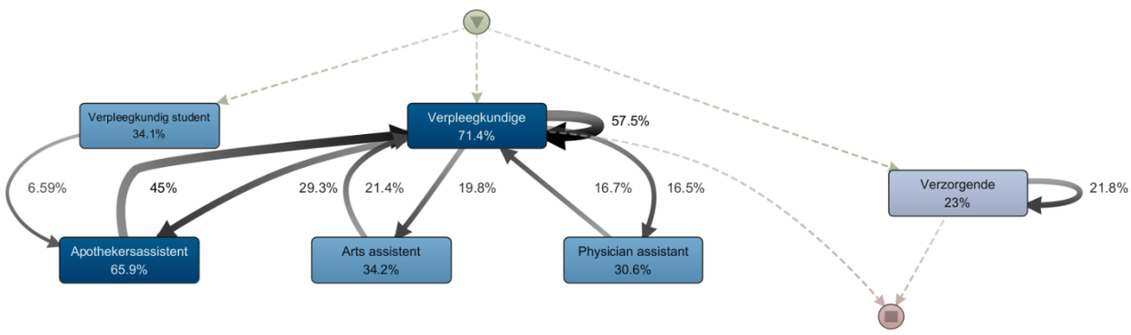

Figure 5.8: Actor interaction model for the neurosurgery department.

Actor	**Participation rate (%)**
Nurse	71.4
Pharmacist assistant	65.9
Physician assistant*	64.8
Nurse student	34.1
Caretaker	23

Table 5.23: Overview of the participation rate for each actor in the patient discharge process at the neurosurgery department.

*Note The hospital information system seems to have the English translation of the actor “Arts” as a separate actor even though they are equal.

Actor interaction	Transition coverage (%)
Nurse → Nurse	57.5
Pharmacist assistant → Nurse	45
Physician assistant → Nurse	38.1
Nurse → Physician assistant	36.3
Nurse → Pharmacist assistant	29.5
Caretaker → Caretaker	21.8

Table 5.24: Most common (TC > 15%) actor interactions at neurosurgery department.

Neurology (old + new)

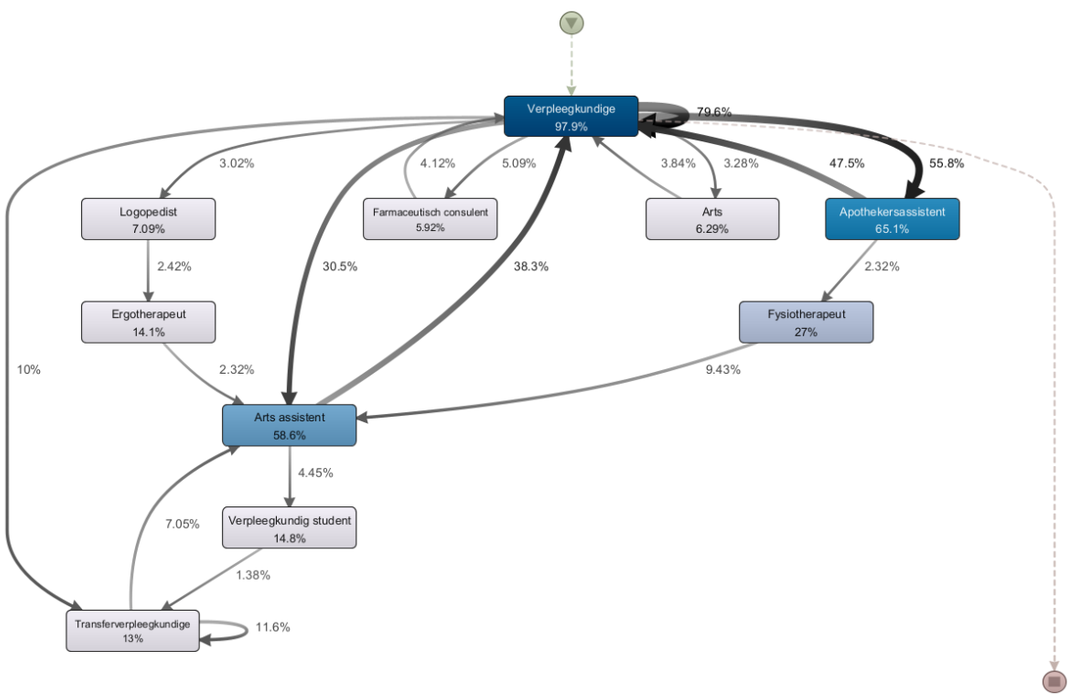

Figure 5.9: Actor interaction model for the neurology department (old + new)

Actor	Participation rate (%)
Nurse	97.9
Pharmacist assistant	65.1
Physician assistant	58.6
Physiotherapist	27
Nurse student	14.8
Ergo therapist	14.1
Transfer nurse	13

Logopaedic	7.09
Physician	6.29
Pharmacist	5.92

Table 5.25: Overview of the participation rate for each actor in the patient discharge process at the neurology (old + new) department.

Actor interaction	**Transition coverage (%)**
Nurse → Nurse	79.6
Nurse → Pharmacist assistant	55.8
Pharmacist assistant → Nurse	47.5
Physician assistant → Nurse	38.3
Nurse → Physician assistant	30.5

Table 5.26: Most common (TC > 15%) actor interactions at the neurology department.

Significant actors

Overall, we can observe that nurses play the most significant role in thein the execution of activities inside the patient discharge process showing the highest participation rates across all the involved departments. Furthermore, the pharmacist and physician assistants also show relatively high transition coverage, showing their significant involvement inside the PDP between all the departments. The internal medicine has an additional actor that is not present on the neurology and neurosurgery, namely the medical assistant. This actor has the second highest transition coverage at the internal medicine at therefore can also be considered as significant inside the patient discharge process at the internal medicine. The reason for the absence of this actor on the other two departments is currently unknown.

Significant interactions

Overall, we can observe that nurses and the collaboration between nurses have the highest transition rates for the patient discharge process across all the departments. This implies that they collaborate the most between each other. Next, the collaboration of pharmacist ↔ nurse and physician assistant ↔ nurse are observed as the most prominent interactions across the departments.

5.3 Interdepartmental comparison

This section presents a comparison of the internal medicine, neurology and neurosurgery departments. We selected two metrics and one process indicator for the interdepartmental comparison. The first metric is case coverage which in essence is the occurrence of an activity as a percentage of the total amount of cases. This can help us quantify the differences between the frequencies of several activities related to the patient discharge process across departments. The second metrics is the mean transition time between activities. This shows us how much time that certain activity transitions take and by comparing the same activity transitions we can identify the differences in performance between departments. In addition, we listed the most frequent paths that are taken on each department.

Case coverage

Table 5.27 gives an overview of the case coverage percentages found inside the discovered process models of section 5.1.

#	Activity	Case coverage (%)			
		IM	NS	NR OLD	NR NEW
1	Preliminary discharge date	9.78	17.7	36.1	29.4
2	Reason why preliminary discharge date was not achieved (VOD)	0.88	0.82	5.35	2.97
3	Was the preliminary discharge data achieved? (VOD)	2.26	3.1	13.6	8.54
4	Admission	100	100	100	100
5	Internal transfer	47.9	85.2	76.1	80.4
6	Status home medication code: 1	7.14	2.96	13.1	11.1
7	Status home medication code: 3A	45	84.6	73.8	74.7
8	Status home medication other	4.5	11.6	8.89	7.67
9	Status discharge medicine	88.3	93.5	77.2	78.7
10	Consult physiotherapy	12.4	49.9	40.3	40

11	Consult dietician	15.6	17.6	11.1	9.77
12	Consult ergotherapy	1.43	14.2	29.4	33.9
13	Consult Logopaedic	1.63	5.97	27.1	30.5
14	Discharge advice – physiotherapy	0.6	16.2	31.4	34.1
15	Discharge advice – ergotherapy	0.09	5.59	10.6	23.7
16	Discharge advice – logopaedic	NA	NA	NA	17
17	Collective advice ETZ	NA	NA	NA	15.5
18	ICC geriatric specialist (SO)	0.15	1.3	6.32	3.6
19	ICC rehabilitation specialist (RA)	0.44	7.3	12	7.91
20	Advice SO	NA	NA	NA	1.38
21	Advice RA	NA	NA	NA	1.84
22	Decision care type (intra/extra mural care)	7.44	6.89	11.3	12.3
23	Decision type of intramural care	1.31	1.48	3.28	8.71
24	Decision type of extramural care	3.67	3	0.87	2.59
25	Date medically ready confirmed (MGD) by department	4.45	4.19	3.54	11.1
26	Discharge	100	100	100	100

Table 5.27: Comparison of case coverage per activity between internal medicine (IM), Neurosurgery (NS), Neurology (old) and Neurology (new)

By analysing the case coverages percentages found in table 5.21 we discovered several activities that show notable discrepancies between the departments.

Preliminary discharge date

Starting with the activity *Preliminary discharge date* or "Voorlopige ontslagdatum" (VOD). The VOD is a date that is registered at the beginning of an admission and can be altered during admission. An overview of the case coverage rate regarding the activity *preliminary discharge date* can be found in table 5.28.

Preliminary discharge date (VOD)		
Rank	Department	Case coverage (%)
1	Neurology (new)	36.1
2	Neurology (old)	29.4
3	Neurosurgery	17.7
4	Internal medicine	9.78

Table 5.28: Ranking of the case coverage regarding the activity Preliminary Discharge Date across the involved departments.

According to the domain experts, ideally the VOD needs to be registered for all patients that are admitted to the hospital (occasionally even before they are admitted). However, considering the case coverage rates for the VOD, the highest case coverage rate can be observed at the neurology (old) department at 36.1%. The neurology (new) department follows with 29.4%, neurosurgery and internal medicine departments follow with 17.7 and 9.78% respectively. This means that at most around 1 in 3 patient's VOD is registered in their respective field inside the HIS. Due to the importance of the VOD, it is highly likely that the VOD is still registered for the remaining patients, however the data suggests that it is poorly registered in its respective place in the hospital information system. Moreover, the relatively low case coverage of the preliminary discharge date is also reflected by other VOD related activities.

VOD related activities	
Activity	Average Case coverage (%)
Was the preliminary discharge data achieved?	6.9
Reason why preliminary discharge date was not achieved	2.5

Table 5.29: The average case coverage of VOD related activities across the internal medicine, neurology and neurosurgery.

These VOD related activities (table 5.29) both show relatively low average case coverages across the departments. In essence, these two activities

reflect moments in the patient discharge process where the healthcare professionals reflect upon the preliminary discharge date that was set at the beginning of the patient discharge process. This reflection is done by stating in the HIS if the preliminary discharge date was achieved and if not, why it was not achieved. By calculating these activities, denoting a reflection point in time, as a percentage of the average amount of preliminary discharge dates that were set across all the departments, we found that on average 24% of cases that registered a VOD, also registered if the VOD was achieved. If the VOD was not achieved, the reason why it was not achieved was only registered on average in 9% of cases.

Medication verification

In essence, medication verification (MV) is the process of checking the current medication of a patient for adverse-drug interactions. Therefore, it is an essential step in the patient discharge process. A division can be made between a check of the home medication and discharge medication. With regards to our data, the status of the home medication verification during the patient discharge process is represented by three activities and the discharge medication status by one activity (table 5.30).

Medication verification activities

Activity	Department			
	IM	NS	NR OLD	NR NEW
Status home medication code: 1	7.14	2.96	13.1	11.1
Status home medication code: 3A	45	84.6	73.8	74.7
Status home medication other	4.5	11.6	8.89	7.67
Status discharge medicine	88.3	93.5	77.2	78.7

Table 5.30: The case coverage of activities representing the medication verification process for the internal medicine, neurology and neurosurgery.

The first MV-related activity is the *Status home medication code: 1,* code 1 means that the verification process was either not executed or unfinished. Table 5.30 shows that for around 1 in 10 cases, the home medication verification process was not executed or unfinished at the neurology department followed by the internal medicine department (7.14%). The neurosurgery shows the lowest rate 2.96% of medication verification processes ending not executed or unfinished.

The second activity with regards to the medication verification process is the *Status home medication code: 3A*, code 3A means that the home

medication was verified and approved by the hospital pharmacist. The difference in case coverage between the neurology (≈74%) and neurosurgery (≈84%) is around 10%. A possible explanation for this can be found by also considering the non-executed or unfinished medication verification processes. The neurology department has around 9.1% more MV-processes that end in a non-execution or remain unfished when compared to the neurosurgery. Note that this close to the 10% difference found in case coverage when comparing cases that resulted in the verification and approvement of the medication (code: 3A) between the neurology and neurosurgery. As the total amount of cases does not change, when more MV-processes end up incomplete, naturally resulting in a similar decrease (around 10%) for the *Status home medication code: 3A* activity between the neurology and neurosurgery, as there a simply less cases left to be verified.

However, the difference in case coverage of the *Status home medication code: 3A* activity between the internal medicine, neurology and neurosurgery departments is very notable. With a discrepancy of around 40% between the neurosurgery and internal medicine, the difference is much more significant than when we compared the neurosurgery to neurology department.

The further clarify this difference we need to consider the medication verification as whole. Ideally, the home medication verification process should be executed for each patient that is admitted at the neurology, internal medicine, or neurosurgery departments. This implies that if we aggregate the case coverages of all the activities that represent the home medication verification process, we should get close to 100%.

Variable	Department			
	IM	NS	NR OLD	NR NEW
Sum of home medication activities	56.6	99.2	95.8	93.5

Table 5.31: The aggregation of the case coverages for three stratus codes related to the medication verification process.

The results of this aggregation (table 5.31) show that for the neurosurgery and neurology departments this is the case. However, the internal medicine shows that only 56.6% of cases result in one of three status codes after the home medication verification process. This means that approximately 54% of cases the medication verification process was absent.

Acknowledging this, the most likely explanation is that 53.4% of cases at the internal medicine are concerned with patients who do not have any home medication that needs to be verified. However, with the importance of the medication verification in mind, further analysis is needed to further clarify this.

Healthcare professional consults and advice

The next group of activities where we observed notable differences between the departments are the activities related to consult orders for the healthcare professionals. Discrepancies in case coverage between the consult orders for the healthcare professionals does not necessarily indicate any real difference in behaviour. As differences in the case coverage are most likely due to certain departments needing different paramedics more than others.

Healthcare professional consult orders + matching discharge advice

Activity		Department							
		IM		NS		NR OLD		NR NEW	
Consult physiotherapy	Advice physiotherapy	12.4	0.6	49.9	16.2	40.3	31.4	40	34.1
Consult ergotherapy	Advice ergotherapy	1.43	0.09	14.2	5.59	29.4	10.6	33.9	23.7
Consult logopaedic	Advice logopaedic	1.63	NA	5.97	NA	27.1	NA	30.5	17

Table 5.32: Overview showing the case coverages of the (paramedic) consult orders that have a matching discharge advice activity (Cell shading is for readability purposes only).

However, there are three (paramedic) consult orders (table 5.32) that have a matching discharge advice activity. After such a consult is executed, it should ideally result in an advice that is registered with regards to the patient's discharge. By comparing the case coverage of the consult orders with the case coverage of its matching discharge advice activity we can more conclusive observations as opposed to only analysing the case coverage of the orders.

Physiotherapy and ergotherapy

The consult physiotherapy case coverage is on average around 40% for the neurology, the matching discharge advice case is similar with around 33%. Observing the internal medicine and neurosurgery, we see different behaviour. If a consult physiotherapy is ordered around 1 in 3 neurosurgery cases also get an advice registered. Moreover, on the internal medicine department less than 1% off these patients gets that advice registered in its respective place in the HIS.

Similar behaviour can be observed for the ergotherapy consult for the neurosurgery and internal medicine departments, here the old implementation of the patient discharge process at the neurology (old) department also only has a matching advice in around one third of the cases that an ergotherapy consult was ordered. Fortunately, the current implementation of the patient discharge process at the neurology (new) department improves this by having 2 in 3 cases that also get an ergotherapy advice registered.

Logopaedic

Unfortunately, the matching discharge advice for this consult is not present in the data for the IM, NS and NR (old). The neurology does show that in 55% of logopaedic consult orders a matching advice was also registered later in the patient discharge process.

Specialists

Furthermore, advice after a inter collegial consult with a geriatric (SO) and rehabilitation specialist (RA) are also only registered in the new patient discharge protocol at the neurology (new) department. For the geriatric specialists, in 13% of cases a consult was ordered, advice was also registered. In cases where an order for the RA was placed, this was 24%.

Overall, is there still a possibility that advice is noted somewhere else in the HIS. However, the data suggests that in many consult orders, the registration of advice after a consult order is relatively low.

Date medically ready (MGD)

The final activity that shows a difference in behaviour between the departments is the *Date medically ready confirmed (MGD) by department.* The MGD is a date that determines if the patient is ready for discharge. Domain experts expressed the importance of the MGD and concluded that it ideally should be registered for all patients. According to the data, the confirmation of this date by their respective department happens only in 4-11% of cases. Unfortunately, we have no data on when the MGD was initially registered, however we do see that the case coverage overall indicates that at most around 1 in 10 patient's MGD is confirmed by the department.

Process performance – time between activities

The data has provided us with the start times of all activities. Completion time of activities are not provided, meaning we cannot look at the exact waiting time between activities. We can, however, look at the time between activities to get an indication of the time between certain activities. Due to the nature of the data, not all transitions are suitable to evaluate. If a transition is very infrequent, a median transition time does not say much. Also, a cut-off point is difficult to determine. However, after discussion with the domain experts and looking at the times between certain activities we chose an arbitrary cut-off point. We determined that transitions had to have a case coverage > 3% before it would be evaluated. Appendix C contains all qualified median transition times.

To minimize the influence of outlying cases, we use the median transition time instead of the mean transition time. Using the mean transition might result in very long cases influencing the mean too much.

Table 5.33 gives an overview of the median transition times (MTT) between the departments. Transitions 1-12 occurred on at least two departments, transitions 13-16 are exclusive to the neurology department but occurred in both the new and old implementations of the patient discharge process.

#	Transition	Median transition duration (hours)			
		IM	NS	NR OLD	NR NEW
1	Preliminary discharge date → Admission (VOD)	15.8	297.6	14	14.7
2	Admission → Status homeMed 3A	1.27	0.71	1.06	1.09
3	Admission → Status homeMed 1	0.18	0.75	0.13	0.15
4	Status homeMed 3A → IT	1.85	2.5	2.6	1.33
5	Status dischargeMed → Discharge	3.7	2.1	5.3	4.9
6	IT → Status dischargeMed	23.3	18.2	NA	NA
7	IT → Consult physiotherapist	14.8	7.7	0.68	0.63
8	IT → Consult dietician	2.1	NA	6.1	3.8
9	IT → Consult transfer point	44.7	25.3	NA	NA

10	Consult physiotherapist → Discharge advice physiotherapist	NA	15	18.4	15.3
11	Consult transfer point → Decision care type (intra/extramural care)	15.4	NA	20.6	4.2
12	Discharge advice physiotherapist → Status DischargeMed	NA	20.8	19.8	19.9
	Neurology exclusive transitions				
13	IT → Consult physiotherapist	NA	NA	0.68	0.63
14	IT → Consult dietician	NA	NA	6.1	3.8
15	IT → Consult logopaedic	NA	NA	0.55	0.56
16	IT → Consult ergotherapy	NA	NA	0.9	1

Table 5.33: Overview of the median transition time between departments.

VOD registration

The median transition time between admission and registration of the VOD is similar across the internal medicine and neurology. The neurosurgery shows a significantly higher mean transition time of 297.6 hours or around 12 days. Transitions 2 – 6 see small differences between mean transition times and will not be discussed.

Steps after an internal transfer

Next, we observe the set of transitions that occur after an internal transfer. When patients are internally transferred it takes the neurosurgery department around 5 hours longer than the internal medicine to check the discharge medication (#6). In addition, the physiotherapy consults ordered after an internal transfer (#7) also take longer on the neurosurgery. The neurology is very fast (avg. 0.65 MTT) to order the consult, however it takes the neurosurgery around 7 hours before the consult is ordered and internal medicine around 15 hours. Both could be caused by numerous factors; a possible explanation could be that patients on the neurosurgery and internal medicine departments on average need more diagnostics after transfer before they know what the next step is going to be. However further analysis will have to determine where these differences originate from.

At the neurology we see similar performance in most transitions between the old and new protocol for the patient discharge process. We see the

biggest improvement in transition 11. It takes the current protocol around 15 hours less to determine what type of care a patient will need after discharge. This is most likely due to the streamlining of the process inside the HIS, where the healthcare professionals are forced to enter this information before they can continue with the process.

Summarizing, the mean transition time between the departments are similar enough that there is no reason for concern. However, several outliers have been discovered that might need additional attention and clarification in further research to investigate the found differences.

Frequent paths

Table 5.11 gives an overview, comparing the four most frequent sequences of activities that were discovered by applying the disco miner. The most frequent paths are at the top of the list for each department.

Legend:

- Code 3A: Home medication verified and approved by pharmacist
- IT abbreviation for Internal Transfer

#	**Internal medicine**
1	**Admission** → Status HomeMed 3A → IT → Status DischargeM → **Discharge**
2	**Admission** → Status HomeMed 3A → IT → Consult dietician → Status DischargeMed → **Discharge**
3	**Admission** → Status HomeMed 3A → IT → Consult physiotherapy → Consult transfer point → Decision care type (intra/extra mural care) → Status DischargeMed → **Discharge**
4	**Admission** → Status HomeMed 3A → IT → Consult transfer point → Decision care type (intra/extra mural care) → Status DischargeMed → **Discharge**
	Neurosurgery
5	**Admission** → Status HomeMed 3A → IT → Status DischargeMed → **Discharge**
6	**Admission** → Status HomeMed 3A → IT → Consult physiotherapy → Status DischargeMed → **Discharge**

Most frequent

7	**Admission** → Status HomeMed 3A → IT → **Discharge**
8	**Admission** → Status HomeMed 3A → Consult dietician→ IT → Status DischargeMed → **Discharge**

Neurology (old)

9	**Admission** → IT → Status HomeMed 3A → IT → Consult physiotherapy → Discharge advice – physiotherapy → Status dischargeMed → **Discharge**
10	**Admission** → IT → Status HomeMed 3A → **Discharge**
11	**Admission** → IT → Status HomeMed 3A → Consult logopaedic → discharge advice – physiotherapy → Status dischargeMed → Discharge
12	**Admission** → IT → Status HomeMed 3A → Consult dietician → Discharge advice – physiotherapy → Status dischargeMed → **Discharge**

Neurology (new)

13	**Admission** → IT → Status HomeMed 3A → IT → **Discharge**
14	**Admission** → IT → Status HomeMed 3A → IT → Consult physiotherapy → Discharge advice – physiotherapy → Status DischargeMed → **Discharge**
15	**Admission** → IT → Status HomeMed 3A → IT → Consult logopaedic → Discharge advice – physiotherapy → Status DischargeMed → **Discharge**
16	**Admission** → IT → Status HomeMed 3A → IT → Consult ergotherapy → Discharge advice – physiotherapy → Status DischargeMed → **Discharge**

Table 5.34: Overview showing the most frequent paths discovered at the internal medicine, neurosurgery and neurology (old and new) departments.

6 Conclusion

The aim of this study was to systematically compare the patient discharge process of three hospital departments from a local Dutch hospital. Our goal differentiated itself by encapsulating the scope of the research out of line with the reviewed body of research related to the application of process mining techniques (table 3.1). We achieved this by steering away from event log data that represented multi-departmental processes from hospital wide data [15,19,24] or focused on a single patient group [14,30] or department [27, 29]. The comparison of the departments was achieved by applying process mining techniques to the event log data from several departments that executed the same process independent from each other. The techniques applied are commonly used [14,16,38] amongst process mining projects in the healthcare domain.

Discovery techniques such as the Disco miner [38] were applied to generate process models of three hospital departments in a local Dutch hospital (SQ1). In the comparison and analysis of these models, we have shown that the sequences of activities vary between the different departments, and we can observe where in the process these variations take place.

Moreover, from the organisational perspective we have identified which actors have contributed (SQ2) the most to the activities executed in the patient discharge process. These identified actors among others include nurses, medical assistants, pharmacist assistants and physician assistants. In addition, the actor interaction models gave us insight in how these actors collaborate. This can be used to by the hospital for resource allocation and potentially streamlining interactions between certain actors.

Furthermore, the results of this case study confirm that by comparing several departments concerned with the same process, we can find noticeable differences in case coverages. The subset of these identified activities has a commonality amongst them, namely they have an administrative nature. Moreover, tasks that are considered administrative are related to the preliminary discharge date (VOD), medication verification, medically ready date (MGD) and the advice that is given after certain paramedic consults. The results from this case study imply that activities that can be categorized as administrative are more likely to show noticeable differences between the departments.

Overall, the work in this thesis has shown that by applying process mining techniques to event log data and comparing the results from multiple departments that execute the same process independently, we can gain notable insights into how each organisational unit handles this process.

7 Discussion

7.1 Interpretation(s) of the results

Our findings related to the activity sequences found inside the discovered process models unfortunately cannot be considered actionable results, this pattern of results is consistent with previous literature [41]. This can be attributed to the fact that the found transitions between the activities are weak and implies that the data variance was too extreme to obtain an overall conclusive model. The high variance of the data was to a certain degree expected, past researchers have faced similar challenges in applying process mining techniques to healthcare event data [22, 42]. However, in our case this is further supported by the characteristics of the patient discharge process, which make it an exceptionally difficult process to map with the use of process mining. The process encapsulates multiple patient groups with each their own diagnostics track that most likely is executed in parallel with the discharge process. Therefore, the outcomes of the diagnostic processes will influence the course of the patient discharge process, resulting even greater variety amongst the event data.

Taken together it makes it difficult to determine if variations in the event log data between the departments is the cause for discrepancies in activity sequences or if the actual execution sequence of activities encapsulated by the patient discharge process, is in fact, different at each department.

In terms of future research, it would be useful to extend the current findings by examining a healthcare process with similar characteristics as the one in this study. This could potentially be achieved by using more extensive pre-processing techniques as demonstrated by the works of De Weerdt et al. [43] and Song et al. [44] by increasing the homogeneity of the data and as a result reduce the variance of the event logs. This will result in a more solid foundation for comparing process models between departments and could potentially lead to the production of more actionable results.

Moreover, our results related to the discovery of healthcare actors and interactions inside the healthcare process have potential intervention implications similar other works [19, 45] related to the social aspect of process mining. The hospital can use the results to get a clearer picture on which resources have highest degree of participation and interaction in the patient discharge process and potentially reallocate resources based on this.

Finally, we concluded that the subset of the activities where we observed discrepancies in case coverage are of an administrative nature. In our view, the most compelling explanation for this set of findings is related to characteristics of the healthcare domain. As investigated by the work of Lopez et al. healthcare professionals have to manage heavy and fluctuating workloads [46]. In addition, the mismatch between introduced technologies or policies and workflow behaviour are a common cause for workaround behaviour [47]. As a result, particularly administrative tasks might be subject to these workarounds and misplacing the input for this type of activity in a quick note instead of its designated place in the hospital information system. This can potentially negatively impact the completeness of the activity registration.

7.2 Limitations

No research is perfect, and we recognize at least three potential limitations concerning the results of this study. A first limitation concerns the usage of event data. The data used in this study was extracted from the hospital information system. Therefore, all the actions that are taken by the healthcare professionals are only reflected by what it registered inside the system. Any oral information exchange that might indicate a step in the process are thus invisible to the researcher and cannot be considered when analysing the results.

A second potential limitation concern is data quality as the ‘garbage in – garbage out’ principle holds for process mining endeavours in a healthcare setting. Therefore, the main stakeholders that will benefit from process mining results should be aware of these limitations and the researcher should try their best to show what can and cannot be implied from the produced results.

The third potential limitation concerns the fact that protocols and guidelines can change over time. The way healthcare processes are executed could change due to factors such as the season, busier seasons

might alter the process to cope with higher influx of patients or other external factors such as the COVID-19 pandemic can also impact the process execution is unknown ways. This makes difficult to gain conclusive insight, as there are many variables at play that could influence the outcome of these studies.

Despite these limitations, this study can be seen as a first step in comparing hospital departments with the application of process mining and we hope that further research can improve the findings in this area.

7.3 Recommendations for the hospital

We have several recommendations for future process mining endeavours at the ETZ hospital.

The results of this study have indicated that the discovered process models are inconclusive in reflecting the behaviour of the patient discharge process. In the future, more conclusive process models could be generated by paying attention to the following elements:

Picking the process

The patient discharge process consists of activities that are executed for all types of patients. This results in extreme variety in the data it makes it very challenging to extract data-driven process models that properly reflect reality. Therefore, we recommend the hospital to carefully consider the type of process they want to deploy process mining for. Smaller more structured processes will be more suitable as the variety between cases will be lower and will likely result in more conclusive process models that have a more realistic representation of reality. Larger and more unstructured processes like the patient discharge process can still be used, however they will require an extensive pre-processing phase to make the data more suitable for process mining.

Activity registration

To maximize the results of process mining projects it is important that the activity registration for the hospital is up to par. Preferably data that is mostly automatically registered have the potential to give the most reliable results.

Guidelines and protocols

Discovering process models of unstructured health care processes is inherently complex. This makes the validation process of the generated models essential in making sure that the models accurately represented

the sequence of activities as they are executed in reality. Therefore, the availability of finished hand-made process models can be a great help in ensuring this is the case. We would not advise investigating processes that have little protocol documentation available beforehand.

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Appendix A – SQL query used for the data collection process.

Selection of the databases across the HIS.

```
WITH OPN AS(


SELECT HSP.PAT_ENC_CSN_ID
,HSP.HOSP_ADMSN_TIME
,HSP.HOSP_DISCH_TIME
,SPEC.NAME
FROM DBO.PAT_ENC_HSP            HSP
LEFT JOIN DBO.CLARITY_ADT       ADT ON ADT.PAT_ENC_CSN_ID = HSP.PAT_ENC_CSN_ID
                                                                                AND
ADT.EVENT_TYPE_C = '2'
                                                                                AND
ADT.EVENT_SUBTYPE_C IN('1','3')
LEFT JOIN DBO.ZC_SPECIALTY      SPEC ON '0' + ADT.PAT_SERVICE_C = SPEC.SPECIALTY_C
WHERE 1=1
--AND ADT.PAT_SERVICE_C = '330'
AND ADT.PAT_SERVICE_C IN('308','313','330')
AND YEAR(HSP.HOSP_ADMSN_TIME) IN('2021','2020')
--AND HSP.HOSP_ADMSN_TIME > '2022-05-01'
AND HSP.HOSP_ADMSN_TIME IS NOT NULL
--AND HSP.PAT_ENC_CSN_ID = '87292448'
),
EVENT_DATA AS(
SELECT PAT.PAT_MRN_ID
,OPN.PAT_ENC_CSN_ID
,EEI.EVENT_TYPE [EVENT_TYPE]
,ZET.EVENT_NAME
,EEI.EVENT_TIME AS [EVENT_TIME]
,EMP.NAME AS [EMP_NAME]
,SER.PROV_TYPE
,'' [DEPARTMENT_NAME]
,'' [SPEC_NAME]
,EEI.REC_ADMIT_STATUS_C
,ZRAS.NAME [ZRAS_NAME]
,ROW_NUMBER() OVER ( PARTITION BY OPN.PAT_ENC_CSN_ID, EEI.EVENT_TYPE
                                                                        ORDER BY
OPN.PAT_ENC_CSN_ID ASC, EEI.EVENT_TYPE ASC, EEI.EVENT_TIME DESC
                                                                        ) AS "RIJNR"
FROM OPN
JOIN ED_IEV_PAT_INFO                    EPI ON OPN.PAT_ENC_CSN_ID = EPI.PAT_ENC_CSN_ID
JOIN PATIENT                            PAT ON EPI.PAT_ID = PAT.PAT_ID
JOIN ED_IEV_EVENT_INFO                  EEI ON EPI.EVENT_ID = EEI.EVENT_ID
JOIN ED_EVENT_TMPL_INFO                 ZET ON EEI.EVENT_TYPE = ZET.RECORD_ID
JOIN CLARITY_EMP                        EMP ON EEI.EVENT_USER_ID = EMP.USER_ID
LEFT JOIN DBO.CLARITY_SER       SER     ON SER.PROV_ID = EMP.PROV_IDLEFT JOIN ZC_REC_ADMIT_STATU ZRAS  ON
ZRAS.REC_ADMIT_STATU_C = EEI.REC_ADMIT_STATUS_C


WHERE 1=1
AND EEI.EVENT_TYPE IN('35210','35320')
),
```

```
OPN_DATA AS(

SELECT OPN.NAME                         [SPECIALISME]
,PAT.PAT_MRN_ID                         [PATIENT_NUMMER]
,ORD.PAT_ENC_CSN_ID                     [PATIENT_CSN]
,OPN.HOSP_ADMSN_TIME                    [OPNAME_DATUM_TIJD]
,OPN.HOSP_DISCH_TIME                    [ONTSLAG_DATUM_TIJD]
,'STAP_1_ORDER' AS                      [ONDERDEEL]
,ORD.ORDER_INST                         [DATUM_SORT]
,ORD.ORDER_PROC_ID                              [ONDERDEEL_ID]
,ORD.DISPLAY_NAME                               [OMSCHRIJVING]
,NULL                                           [STATUS THUISMEDICATIE]
,ORD.ORDER_INST                                 [ORDER_DATUM]
,NULL                                           [FLOWSHEET_OPGENOMEN]
,NULL                                           [FLOWSHEET_GENOTEERD]
,NULL                                           [FLOWSHEET_NAAM]
,NULL                                           [FLOWSHEET_WAARDE]
,NULL                                           [FLOWSHEET_WAARDE_DATUM]
,NULL                                           [FLOWSHEET_WAARDE_TIJD]
,NULL                                           [ORDER_VRAAG]
,NULL                                           [ORDER_ANTWOORD]
,NULL                                           [ORDER_ANTWOORD_DATUM]
,NULL                                           [ORDER_OPMERKING]
,NULL                                           [ADT_AFDELING]
,NULL                                           [ADT_SPECIALISME]
,SER.PROV_NAME                                  [ACTOR_NAAM]
,SER.PROV_TYPE                                  [ACTOR_FUNCTIE]
FROM ORDER_PROC                         ORD
LEFT JOIN  PATIENT              PAT     ON PAT.PAT_ID = ORD.PAT_ID
JOIN                OPN                         OPN     ON OPN.PAT_ENC_CSN_ID = ORD.PAT_ENC_CSN_ID
LEFT JOIN CLARITY_EMP           EMP ON EMP.USER_ID = ORD.INSTNTOR_USER_ID
LEFT JOIN CLARITY_SER           SER ON EMP.PROV_ID = SER.PROV_ID
WHERE 1=1
--AND ORD.PAT_ENC_CSN_ID = '87167737'
AND ORD.FUTURE_OR_STAND IS NULL
--AND CONVERT(DATE, ORD.ORDER_INST, 105) = '2021-11-12'
AND ORD.PROC_ID IN
(
379,
383,
88576,
385
)
UNION ALL
SELECT DISTINCT
OPN.NAME                                [SPECIALISME]
,PAT.PAT_MRN_ID                         [PATIENT_NUMMER]
,PE.PAT_ENC_CSN_ID                      [PATIENT_CSN]
,OPN.HOSP_ADMSN_TIME                    [OPNAME_DATUM_TIJD]
,OPN.HOSP_DISCH_TIME                    [ONTSLAG_DATUM_TIJD]
,'STAP_2_3_5_FLOWSHEET'                 [ONDERDEEL]
,MEAS.RECORDED_TIME                     [DATUM_SORT]
,MEAS.FLO_MEAS_ID                       [ONDERDEEL_ID]
,DAT.DISP_NAME                          [OMSCHRIJVING]
```

Selecting order data.

Selecting questionnaire data.

Questionnaire data.

```
,NULL                                   [STATUS THUISMEDICATIE]
,NULL                                   [ORDER_DATUM]
,MEAS.RECORDED_TIME                     [FLOWSHEET_OPGENOMEN]
,MEAS.ENTRY_TIME                        [FLOWSHEET_GENOTEERD]
,DAT.DISP_NAME                          [FLOWSHEET_NAAM]
,MEAS.MEAS_VALUE                        [FLOWSHEET_WAARDE]
,CASE WHEN MEAS.FLO_MEAS_ID IN('15411','20470') THEN
                    CAST(DATEADD(D,CAST(MEAS.MEAS_VALUE AS NUMERIC),'1840-12-31') AS DATE)
                    ELSE NULL END [FLOWSHEET_WAARDE_DATUM]
,CASE WHEN MEAS.FLO_MEAS_ID IN('15412','3042210235') THEN
                    CAST(DATEADD(S,CAST(MEAS.MEAS_VALUE AS NUMERIC),0) AS TIME)
                    ELSE NULL END [FLOWSHEET_WAARDE_TIJD]
,NULL                                           [ORDER_VRAAG]
,NULL                                           [ORDER_ANTWOORD]
,NULL                                           [ORDER_ANTWOORD_DATUM]
,NULL                                           [ORDER_OPMERKING]
,NULL                                           [ADT_AFDELING]
,NULL                                           [ADT_SPECIALISME]
,SER.PROV_NAME                                  [ACTOR_NAAM]
,SER.PROV_TYPE                                  [ACTOR_FUNCTIE]
FROM IP_FLWSHT_MEAS MEAS
INNER JOIN IP_FLWSHT_REC REC     ON REC.FSD_ID = MEAS.FSD_ID
INNER JOIN PAT_ENC PE                       ON REC.INPATIENT_DATA_ID = PE.INPATIENT_DATA_ID
JOIN OPN                                                    ON PE.PAT_ENC_CSN_ID = OPN.PAT_ENC_CSN_ID
INNER JOIN PATIENT PAT                      ON PE.PAT_ID = PAT.PAT_ID
INNER JOIN IP_FLO_GP_DATA DAT    ON MEAS.FLO_MEAS_ID = DAT.FLO_MEAS_ID
LEFT JOIN CLARITY_EMP           EMP                 ON EMP.USER_ID = MEAS.TAKEN_USER_ID
LEFT JOIN CLARITY_SER           SER                 ON EMP.PROV_ID = SER.PROV_ID
WHERE 1=1
AND MEAS.FLO_MEAS_ID IN(
'20470'
,'16360'
,'16361'
,'20471'
,'15399'
,'3042210235'
,'15400'
,'15417'
,'3042210260'
,'15401'
,'15416'
,'15402'
,'15406'
,'3042210243'
,'30422102044'
,'15407'
,'15408'
,'15409'
,'15411'
,'15412'
,'3042210236'
,'30422102042'
,'3042210239'
,'30422102040'
```

```
,'3042210241'
,'3042210237'
,'3042210238'
,'3042210247'
,'15413'
,'15415'
,'3042210245'
,'3042210246'
,'3042210248'
,'3042210249'
,'3042210250'
,'3042210251'
,'3042210252'
,'3042210253'
,'19644'
,'6040400000023'
,'304130000143'
,'3041300524'
,'304221012'
,'304221014'
,'304221015'
,'304221017'
,'304221019'
,'304221020'
)
UNION ALL
```

Order data.

```
SELECT DISTINCT
OPN.NAME                                [SPECIALISME]
,PAT.PAT_MRN_ID                         [PATIENT_NUMMER]
,ORD.PAT_ENC_CSN_ID                     [PATIENT_CSN]
,OPN.HOSP_ADMSN_TIME                    [OPNAME_DATUM_TIJD]
,OPN.HOSP_DISCH_TIME                    [ONTSLAG_DATUM_TIJD]
,'STAP_4_ORDER' AS                      [ONDERDEEL]
,ORD.ORDER_INST                         [DATUM_SORT]
,ORD.ORDER_PROC_ID                      [ONDERDEEL_ID]
,ORD.DISPLAY_NAME                       [OMSCHRIJVING]
,NULL                                           [STATUS THUISMEDICATIE]
,ORD.ORDER_INST                                 [ORDER_DATUM]
,NULL                                           [FLOWSHEET_OPGENOMEN]
,NULL                                           [FLOWSHEET_GENOTEERD]
,NULL                                           [FLOWSHEET_NAAM]
,NULL                                           [FLOWSHEET_WAARDE]
,NULL                                           [FLOWSHEET_WAARDE_DATUM]
,NULL                                           [FLOWSHEET_WAARDE_TIJD]
,CQQ.QUEST_NAME                                 [ORDER_VRAAG]
,OSQ.ORD_QUEST_RESP                             [ORDER_ANTWOORD]

,CASE WHEN CQQ.QUEST_NAME IN('ETZ VERWACHTE ONTSLAGDATUM') THEN
                    CAST(DATEADD(D,CAST(OSQ.ORD_QUEST_RESP    AS NUMERIC),'1840-12-31') AS DATE)
                    ELSE NULL END [ORDER_ANTWOORD_DATUM]

,OSQ.ORD_QUEST_CMT                              [ORDER_OPMERKING]
,NULL                                           [ADT_AFDELING]
,NULL                                           [ADT_SPECIALISME]
```

```
,SER.PROV_NAME                                  [ACTOR_NAAM]

,SER.PROV_TYPE                                  [ACTOR_FUNCTIE]

FROM ORDER_PROC                                 ORD

LEFT JOIN  PATIENT                      PAT     ON PAT.PAT_ID = ORD.PAT_ID

JOIN                OPN                                 OPN     ON OPN.PAT_ENC_CSN_ID =
ORD.PAT_ENC_CSN_ID

LEFT JOIN  ORD_SPEC_QUEST       OSQ ON ORD.ORDER_PROC_ID = OSQ.ORDER_ID

LEFT JOIN  CL_QQUEST            CQQ     ON CQQ.QUEST_ID = OSQ.ORD_QUEST_ID

LEFT JOIN CLARITY_EMP                   EMP ON EMP.USER_ID = ORD.INSTNTOR_USER_ID

LEFT JOIN CLARITY_SER                   SER ON EMP.PROV_ID = SER.PROV_ID

WHERE 1=1

--AND ORD.PAT_ENC_CSN_ID = '87167737'

AND ORD.FUTURE_OR_STAND IS NULL

--AND CONVERT(DATE, ORD.ORDER_INST, 105) = '2021-11-12'

AND ORD.PROC_ID IN

(

365,

72350,

132512

)

UNION ALL
```

Questionnaire data.

```
SELECT DISTINCT

OPN.NAME                        [SPECIALISME]

,PAT.PAT_MRN_ID                 [PATIENT_NUMMER]

,PE.PAT_ENC_CSN_ID              [PATIENT_CSN]

,OPN.HOSP_ADMSN_TIME            [OPNAME_DATUM_TIJD]

,OPN.HOSP_DISCH_TIME            [ONTSLAG_DATUM_TIJD]

,'STAP_6_FLOWSHEET'             [ONDERDEEL]

,MEAS.RECORDED_TIME             [DATUM_SORT]

,MEAS.FLO_MEAS_ID               [ONDERDEEL_ID]

,DAT.DISP_NAME                  [OMSCHRIJVING]

,NULL                           [STATUS THUISMEDICATIE]

,NULL                           [ORDER_DATUM]

,MEAS.RECORDED_TIME             [FLOWSHEET_OPGENOMEN]

,MEAS.ENTRY_TIME                [FLOWSHEET_GENOTEERD]

,DAT.DISP_NAME                  [FLOWSHEET_NAAM]

,MEAS.MEAS_VALUE                [FLOWSHEET_WAARDE]

,CASE WHEN MEAS.FLO_MEAS_ID
IN('3042210806','304172009','3042210815','3042210809','3042210818','304172011','304172010','3042210916','3
042210918') THEN

                    CAST(DATEADD(D,CAST(MEAS.MEAS_VALUE AS NUMERIC),'1840-12-31') AS DATE)

                    ELSE NULL END [FLOWSHEET_WAARDE_DATUM]

,CASE WHEN MEAS.FLO_MEAS_ID IN('3041720091','3042210816','3042210810') THEN

                    CAST(DATEADD(S,CAST(MEAS.MEAS_VALUE AS NUMERIC),0) AS TIME)

                    ELSE NULL END [FLOWSHEET_WAARDE_TIJD]

,NULL                                           [ORDER_VRAAG]

,NULL                                           [ORDER_ANTWOORD]

,NULL                                           [ORDER_ANTWOORD_DATUM]

,NULL                                           [ORDER_OPMERKING]

,NULL                                           [ADT_AFDELING]

,NULL                                           [ADT_SPECIALISME]

,SER.PROV_NAME                                  [ACTOR_NAAM]

,SER.PROV_TYPE                                  [ACTOR_FUNCTIE]

FROM IP_FLWSHT_MEAS MEAS

INNER JOIN IP_FLWSHT_REC REC            ON REC.FSD_ID = MEAS.FSD_ID

INNER JOIN PAT_ENC PE                           ON REC.INPATIENT_DATA_ID = PE.INPATIENT_DATA_ID
```

```
JOIN OPN                                                    ON PE.PAT_ENC_CSN_ID =
OPN.PAT_ENC_CSN_ID

INNER JOIN PATIENT PAT                          ON PE.PAT_ID = PAT.PAT_ID

INNER JOIN IP_FLO_GP_DATA DAT           ON MEAS.FLO_MEAS_ID = DAT.FLO_MEAS_ID

LEFT JOIN IP_FLT_DATA TPL          ON MEAS.FLT_ID = TPL.TEMPLATE_ID

LEFT JOIN CLARITY_EMP          EMP                          ON EMP.USER_ID = MEAS.TAKEN_USER_ID

LEFT JOIN CLARITY_SER          SER                          ON EMP.PROV_ID = SER.PROV_ID

WHERE 1=1

AND TPL.TEMPLATE_NAME LIKE '%TPZ%'

UNION ALL
```

Selecting ADT actions

```
SELECT

OPN.NAME                                        [SPECIALISME]

,PAT.PAT_MRN_ID                                 [PATIENT_NUMMER]

,OPN.PAT_ENC_CSN_ID                             [PATIENT_CSN]

,OPN.HOSP_ADMSN_TIME                            [OPNAME_DATUM_TIJD]

,OPN.HOSP_DISCH_TIME                            [ONTSLAG_DATUM_TIJD]

,'ADT-ACTIES' AS                                [ONDERDEEL]

,ADT.EFFECTIVE_TIME                             [DATUM_SORT]

,NULL                                           [ONDERDEEL_ID]

,ET.NAME                                        [OMSCHRIJVING]

,NULL                                           [STATUS THUISMEDICATIE]

,ADT.EFFECTIVE_TIME                             [ORDER_DATUM]

,NULL                                           [FLOWSHEET_OPGENOMEN]

,NULL                                           [FLOWSHEET_GENOTEERD]

,NULL                                           [FLOWSHEET_NAAM]

,NULL                                           [FLOWSHEET_WAARDE]

,NULL                                           [FLOWSHEET_WAARDE_DATUM]

,NULL                                           [FLOWSHEET_WAARDE_TIJD]

,NULL                                           [ORDER_VRAAG]

,NULL                                           [ORDER_ANTWOORD]

,NULL                                           [ORDER_ANTWOORD_DATUM]

,NULL                                           [ORDER_OPMERKING]

,DEP.DEPARTMENT_NAME                            [ADT_AFDELING]

,SRV.NAME                                       [ADT_SPECIALISME]

,SER.PROV_NAME                                  [ACTOR_NAAM]

,SER.PROV_TYPE                                  [ACTOR_FUNCTIE]

FROM CLARITY_ADT                        ADT

JOIN OPN                                        OPN       ON OPN.PAT_ENC_CSN_ID = ADT.PAT_ENC_CSN_ID

LEFT JOIN DBO.PAT_ENC_HSP       HSP       ON HSP.PAT_ENC_CSN_ID = OPN.PAT_ENC_CSN_ID

JOIN PATIENT                                    PAT ON ADT.PAT_ID = PAT.PAT_ID

JOIN ZC_EVENT_TYPE                      ET        ON ADT.EVENT_TYPE_C = ET.EVENT_TYPE_C

LEFT JOIN CLARITY_EMP                   EMP       ON EMP.USER_ID = ADT.USER_ID

LEFT JOIN DBO.CLARITY_DEP       DEP ON DEP.DEPARTMENT_ID = ADT.DEPARTMENT_ID

LEFT JOIN ZC_PAT_SERVICE        SRV ON SRV.HOSP_SERV_C = ADT.PAT_SERVICE_C

LEFT JOIN DBO.CLARITY_SER       SER       ON SER.PROV_ID = EMP.PROV_ID

WHERE 1=1
```

Selecting medication verification data

```
AND ADT.EVENT_TYPE_C IN('1','2','3','5')

AND ADT.EVENT_SUBTYPE_C IN('1','3')

UNION ALL

SELECT

OPN.NAME                                [SPECIALISME]

,EVT.PAT_MRN_ID                         [PATIENT_NUMMER]

,OPN.PAT_ENC_CSN_ID                     [PATIENT_CSN]

,OPN.HOSP_ADMSN_TIME                    [OPNAME_DATUM_TIJD]
```

```
,OPN.HOSP_DISCH_TIME                    [ONTSLAG_DATUM_TIJD]
,'EVENT-ACTIES' AS                      [ONDERDEEL]
,EVT.EVENT_TIME                         [DATUM_SORT]
,EVT.EVENT_TYPE                         [ONDERDEEL_ID]
,CASE WHEN EVT.EVENT_TYPE = '35320' THEN 'STATUS THUISMEDICATIE'
           WHEN EVT.EVENT_TYPE = '35210' THEN 'STATUS ONTSLAGMEDICATIE'
           ELSE NULL
           END AS [OMSCHRIJVING]
,EVT.ZRAS_NAME                                  [STATUS THUISMEDICATIE]
,NULL                                           [ORDER_DATUM]
,NULL                                           [FLOWSHEET_OPGENOMEN]
,NULL                                           [FLOWSHEET_GENOTEERD]
,NULL                                           [FLOWSHEET_NAAM]
,NULL                                           [FLOWSHEET_WAARDE]
,NULL                                           [FLOWSHEET_WAARDE_DATUM]
,NULL                                           [FLOWSHEET_WAARDE_TIJD]
,NULL                                           [ORDER_VRAAG]
,NULL                                           [ORDER_ANTWOORD]
,NULL                                           [ORDER_ANTWOORD_DATUM]
,NULL                                           [ORDER_OPMERKING]
,NULL                                           [ADT_AFDELING]
,NULL                                           [ADT_SPECIALISME]
,EVT.EMP_NAME                                   [ACTOR_NAAM]
,EVT.PROV_TYPE                                  [ACTOR_FUNCTIE]
FROM EVENT_DATA EVT
JOIN OPN                                        OPN       ON OPN.PAT_ENC_CSN_ID = EVT.PAT_ENC_CSN_ID
WHERE 1=1
AND EVT.RIJNR = '1'
)
SELECT *
FROM OPN_DATA
ORDER BY OPN_DATA.PATIENT_CSN DESC, OPN_DATA.DATUM_SORT ASC
```

Appendix B – activity selection.

Q1. Is the activity present in the designed PDP process?

Q2. Does the activity fall inside the scope of the PDP?

Activities highlighted yellow have been divided and re-clustered. Orange highlighted cells are activities that have been relabelled.

Activity	Frequency	Q1	Q2	#
ADT-activities (Admission Discharge Transfer data)	**151661**			
Ontslag	48613	Yes	Yes	1
Opname	48606	Yes	Yes	2
Overplaatsen in	51453	Yes	Yes	3
Patiëntupdate	2989	No	No	
Event-acties	**59164**			
Status ontslagmedicatie	37605	Yes	Yes	4
Status thuismedicatie	21559	Yes	Yes	5
Stap_1_Order (Questionnaire data)	**22869**			
Consult dietetiek	3119	Yes	Yes	6
Consult diëtetiek	1548	Yes	Yes	6
Consult ergotherapie	4403	Yes	Yes	7
Consult fysiotherapie	9066	Yes	Yes	8
Consult fysiotherapie - mobiliseren	24	No	No	
Consult fysiotherapie - ademhalingsoefeningen	122	No	No	
Consult fysiotherapie - contractuurpreventie	182	No	No	
Consult fysiotherapie - mobiliseren	181	No	No	
Consult fysiotherapie - overig	117	No	No	
Consult fysiotherapie- ademhalingsoefeningen	51	No	No	
Consult fysiotherapie- contractuurpreventie	27	No	No	
Consult logopedie	3342	Yes	Yes	9
ETZ KL CONSULT ERGOTHERAPIE	1	No	No	
Screening valrisico	686	No	No	
Stap_2_3_5_Flowsheet (Questionnaire data)	**38870**			
1e- lijns therapie	160	No	No	
Advies ontslag - ergotherapie	2299	Yes	Yes	10
Advies ontslag - fysiotherapie	5755	Yes	Yes	11
Advies ontslag - logopedie	718	Yes	Yes	12
Advies RA	83	Yes	Yes	13
Advies SO	71	Yes	Yes	14
Anders (toelichting)	8	No	No	
Apotheek: Recepten nodig	667	No	No	
Bloedsuikermeting	640	No	No	
Datum (gepland)	1045	No	No	
Diëtetiek	39	No	No	
Ergotherapie	91	No	No	
Frequentie thuiszorg	101	No	No	
Fysiotherapie	135	No	No	

Gezamenlijk advies ETZ	746	No	Yes	15
Insuline schema	644	No	No	
Is bestelling van hulpmiddelen noodzakelijk	611	No	No	
Is de achterban geïnformeerd?	1242	No	No	
Is de oorspronkelijke ontslagdatum (VOD) gehaald?	1392	No	Yes	16
Is instelling geïnformeerd?	979	No	No	
Is vervoer na ontslag geregeld?	1153	No	No	
Logopedie	54	No	No	
Machtiging/overdracht paramedici	511	No	No	
Moet er voor patiënt vervoer na ontslag geregeld worden?	1785	No	No	
MSVT	642	No	No	
Naam thuiszorgorganisatie	68	No	No	
Naam zorgorganisatie	798	No	No	
Ontslaglocatie	1597	No	No	
Overdracht	906	No	No	
Overige informatie m.b.t. ontslag	181	No	No	
Poliklinische afspraak	544	No	No	
Reden(en) waarom VOD niet gehaald is	503	No	No	
Specialisme(n)	1	No	No	
Terminaalverklaring	549	No	No	
Thuiszorg	950	No	No	
Tijd (gepland)	1027	No	No	
Tijd van ontslag	1296	No	No	
Trombosedienst	633	No	No	
Type thuiszorg	82	No	No	
Type vervoer	1150	No	No	
Verbandmiddelen e.d.	650	No	No	
Verwachte ontslagdatum	4976	No	No	
Warme overdracht	737	No	No	
Zuurstof	651	No	No	
Stap_4_Order (Order data)	**30236**			
Consult transferpunt	26860	Yes	Yes	17
Consult transferpunt SEH naar huis/extern	180			
ICC revalidatie geneeskunde	1504	Yes	Yes	18
ICC SO	1692	Yes	Yes	19
Stap_6_Flowsheet (Questionnaire data)	**57719**			
Actief wachtend sinds	363	No	No	
Afdeling	674	No	No	
Analyse en conclusie	2806	No	No	
Apotheek instelling	107	No	No	
Bijzonderheden	2643	No	No	
Datum aanmelding	1472	No	No	
Datum ingang nazorg	2294	No	No	
Datum levering	68	No	No	
Datum levering hulpmiddelen	141	No	No	
Datum medisch gereed bevestigd door afdeling	1737	No	Yes	20
Datum start verblijfsindicatie	47	No	No	
Datum van aanmelding bij locatie	379	No	No	
Datum verblijfsindicatie aangevraagd	107	No	No	

Datum WZD aangevraagd	14	No	No	
Datum WZD afgewezen	1	No	No	
Heeft de patiënt reeds een WLZ-indicatie of verwacht u die op de korte termijn te kunnen verkrijgen?	397	No	No	
Hulpmiddelen	170	No	No	
Hulpvraag uit order	2039	No	No	
Indicatie extramuraal	960	No	Yes	21
Indicatie intramuraal	914	No	Yes	22
Is de (medische) zorg thuis te verlenen?	395	No	No	
Is er een WLZ indicatie aanwezig?	573	No	No	
Is medische / verpleegkundige zorg noodzakelijk?	399	No	No	
Is opname (herstelzorg) noodzakelijk vanwege elkaar beïnvloedbare meervoudige problematiek	29	No	No	
Is ziekenhuiszorg wenselijk?	398	No	No	
Levering hulpmiddelen OPAT	72	No	No	
Locatie De Wever	744	No	No	
Locatie Hospice	95	No	No	
Locatie Maasduinen	1	No	No	
Locatie Schakelring	82	No	No	
Locatie 't Heem	8	No	No	
Locatie Thebe Zuidoost	36	No	No	
Locatie Volckaert	37	No	No	
Naam apotheek instelling	10	No	No	
Opmerkingen	7410	No	No	
Organisatie	1328	No	No	
Plaats levering	67	No	No	
Reden van wachten	1272	No	No	
Soort aanvraag	3128	No	Yes	23
Status aanvraag	1089	No	No	
Status WLZ indicatie	267	No	No	
Status WZD	28	No	No	
Thuisorganisatie	1237	No	No	
Tijdstip ingang nazorg	1550	No	No	
Tijdstip levering	61	No	No	
Tijdstip levering hulpmiddelen	125	No	No	
Toegekend sinds:	116	No	No	
Vervolg	4701	No	No	
Verwacht u dat de patiënt na opname weer naar huis kan?	397	No	No	
Voortgang	6103	No	No	
Voortgang analyse	4452	No	No	
Welke transferverpleegkundige heeft de aanvraag in behandeling?	3364	No	No	
WLZ	222	No	No	
WLZ indicatie	2	No	No	
WZD	114	No	No	
WZD toegekend sinds:	7	No	No	
Zijn er haalbare revalidatiedoelen en is er sprake van een kwetsbare ouderen met multi-problematiek	347	No	No	
Zonder zorg naar huis	120	No	No	

Appendix C – Mean transition times

Internal medicine	
Transition	**Mean transition duration (hours)**
Preliminary discharge date → Admission	15.8
Admission → Status homeMed 3A	1.27
Admission → Status homeMed 1	0.18
Status homeMed 3A → IT	1.85
Status homeMed → Discharge	2
Status dischargeMed → Discharge	3.7
IT → Status dischargeMed	23.3
IT → Consult dietician	2.1
IT → Consult physiotherapist	14.8
IT → Consult transfer point	44.7
Consult dietician → Status dischargeMed	57.1
Consult transfer point → Decision care type (intra/extramural care)	15.4

Neurosurgery	
Transition	**Mean transition duration (hours)**
Preliminary discharge date → Admission	297.6 (12.4d)
Admission → Status homeMed 3A	0.71
Admission → Status homeMed 1	0.75
Status homeMed 3A → IT	2.5
Status dischargeMed → Discharge	2.1
IT → Discharge	1,51
IT → Status dischargeMed	18.2
IT → Consult physiotherapist	7.7
IT → Consult transfer point	25.3
Consult dietician → IT	11.2
Consult physiotherapist → Discharge advice PTP	15
Consult physiotherapist → Consult transfer point	17.6
Consult physiotherapist → Status DischargeMed	22.4
Consult physiotherapist → Consult ergotherapy	1.57
Discharge advice PTP → Status DischargeMed	20.8

Neurology (old)	
Transition	**Mean transition duration (hours)**
Preliminary discharge date → Admission	14
Admission → Status homeMed 3A	1.06
Admission → Status homeMed 1	0.13
Status homeMed 3A → IT	2.6
Status homeMed 1 → Discharge	1.53
Status dischargeMed → Discharge	5.3
IT → Consult physiotherapist	0.68
IT → Consult dietician	6.1
IT → Consult logopaedic	0.55
IT → Consult ergotherapy	0.9
Consult physiotherapist → Discharge advice PTP	18.4
Consult ergotherapy → Discharge advice PTP	16.5

Consult transfer point → Decision care type (intra/extramural care)	20.6
ICC rehabilitation specialist → Discharge advice PTP	17.2
Decision care type (intra/extramural care) → Status dischargeMed	19.2
Discharge advice PTP → Status DischargeMed	19.8

Neurology (new)	
Transition	**Mean transition duration (hours)**
Preliminary discharge date → Admission	14.7
Admission → Status homeMed 3A	1.09
Admission → Status homeMed 1	0.15
Status homeMed 3A → IT	1.33
Status homeMed 1 → IT	0.33
Status dischargeMed → Discharge	4.9
IT → StatusHomeMed 3A	0.86
IT → Consult physiotherapist	0.63
IT → Consult dietician	3.8
IT → Consult logopaedic	0.56
IT → Consult ergotherapy	1
Consult physiotherapist → Discharge advice PTP	15.3
Consult ergotherapy → Discharge advice PTP	11.1
Consult logopaedic → Discharge advice PTP	15.6
Consult transfer point → Decision care type (intra/extramural care)	4.2
Discharge advice PTP → Status DischargeMed	19.9
Discharge advice PTP → Collective advice ETZ	1.69
Discharge advice PTP → Consult transfer point	17.6
Discharge advice logopaedic → Discharge advice ergotherapy	0.25

Appendix D – Translation table healthcare professionals

Dutch	**English**
Verpleegkundige	Nurse
Apotheker assistant	Pharmacist assistant
Arts assistant	Physician assistant
Medisch assistent	Medical assistant
Fysiotherapeut	Physiotherapist
Verpleegkundig student	Nurse student
Ergotherapeut	Ergo therapist
Transfer verpleegkundige	Transfer nurse
logopedist	Logopaedic
Arts	Physician
Farmaceutisch consulent	Pharmacist

Appendix E – Data exploration results