Process mining in multidisciplinary healthcare

Exploring the effect of process analysis on process thinking in a multidisciplinary outpatient clinic

Wendy Polderdijk
4077652

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Supervisors:
Prof.dr.ir. Hajo Reijers
Dr. Xixi Lu
Esmee Kester, Msc. (*UMC Utrecht*)

Utrecht University

Department of Information and Computing Sciences
Utrecht University
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Abstract

Interprofessional collaboration is an essential part of patient-centered healthcare. However, adopting a multidisciplinary approach to healthcare comes with a number of challenges, such as miscommunication and role blurring, due to a lack of insight in healthcare processes. Process mining techniques can be used to extract process models from event data, for the purpose of process analysis. While process mining has been applied to healthcare often, little research has been done to assess the impact of process analysis using process mining techniques on process thinking among healthcare providers. In this case study at the knee division of UMC Utrecht Mobility Clinic, patient pathway models were extracted from event data using process mining techniques. The extracted process models were analysed and demonstrated during semi-structured interviews with medical staff from the clinic. The results of these interviews suggest that process analysis stimulates process thinking and enables healthcare providers to envision and reflect on the application of process mining in their work. Additionally, variation in response to process analysis might be related to role characteristics, which implies that these should be taken into account when implementing process mining in multidisciplinary healthcare.

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Glossary

Business Process Management A paradigm involving the discovery, modelling, analysis and optimization of business processes. 1

case perspective A perspective of process mining that focuses on the characteristics of process variants. 13

control-flow perspective A perspective of process mining that focuses on the order of activities in a process. 13

enhancement A type of process mining techniques that aims to extend existing models with information regarding performance. 13

interprofessional collaboration Close collaboration between people from differing backgrounds, with differing expertises. 6

macrocognition Complex, collaborative cognition in novel situations, that relies on knowledge and ability, rather than routine and protocol. 9

multidisciplinary healthcare An approach to healthcare provision involving close collaboration between multiple specialisms. 6

organizational perspective A perspective of process mining that focuses on relationships between actors in the process. 13

principle of involvement A principle that highlights the importance of cultivating a sense of involvement among employees when applying BPM, as introduced by [5]. 9

principle of joint understanding A principle that highlights the importance of incorporating process thinking in the organization when applying BPM, as introduced by [5]. 2

process conformance A type of process mining techniques that aims to compare event data to an existing process model, in order to determine compliance. 2

process discovery A type of process mining techniques that aims to extract a process model from event data. 2

process mining A discipline of BPM that aims to extract process-related information from event data in an automated manner. 2

process mining technique A detailed, technical approach to extracting process information from event data, such as an algorithm. 12

process modelling A tool for analysing processes through visualisation. 3

process thinking A way of thinking that considers phenomena in an organization as dynamic and changing over time, considering process notions such as activities, events, and actors. 3

retention In the context of learning, retention can be defined as the comprehension of material being presented. 10

role blurring The dissipation of role boundaries due to misunderstandings regarding responsibility. 7

role interaction model A type of model used for social network analysis. 13

shared mental models A common understanding of processes, knowledge, and roles involved in a certain domain. 9

shared understanding A similar mental model regarding a certain domain among the actors involved, enabling them to conceptualise processes in terms of tasks, events, and roles. 3

social network analysis An application of process discovery techniques aimed at analysing communication flows and organizational structure. 12

spaghetti processes Unstructured processes lead to incomprehensible process models that resemble spaghetti, when not addressed properly. 12

transfer In the context of learning, transfer refers to the ability to apply knowledge gained from material being presented to problem-solving questions. 10

Acronyms

BPM Business Process Management. 2

CPAM Clinical Pathway Analysis Method. 13

CRISP-DM Cross-industry Standard Process for Data Mining. 19

CSF Critical success factor. 9

CTML Cognitive Theory of Multimedia Learning. 10

DSR Design Science Research. 16

IPC Interprofessional collaboration. 6

IPD Interactive Process Discovery. 14

MC Mobility Clinic. 1

MIIC Modified Index of Interdisciplinary Collaboration. 11

PCCM Patient-centered Care Measure. 11

RIPLS Readiness for Interprofessional Learning Scale. 11

UMC University Medical Center. 1

1 Introduction

In healthcare, collaboration between professionals with different backgrounds and specialties has become essential in the provision of patient-centered care [6]. Coordinated collaboration between healthcare professionals from different disciplines has proven to be beneficial to healthcare providers and patients, both in terms of perceived quality of care and treatment outcomes [7, 8, 9]. Furthermore, multidisciplinary collaboration among healthcare professionals has shown other beneficial effects, such as a decrease in surgical patients' duration of stay [7].

While some may associate the concept of multidisciplinary healthcare with geriatrics and elderly care, there are various other examples of multidisciplinary approaches in healthcare. One example is the Mobility Clinic (MC). Founded in 2014 by UMC Utrecht, the knee division of the MC consists of a team of orthopaedic surgeons, radiologists, physiotherapists, rheumatologists, orthopaedic cast technicians, sports medicine physicians, and doctor's assistants. Their goal is to treat patients with complex mobility problems. While originally focusing on knee problems, the MC has grown to include a Spine-centric division, which involves healthcare professionals, such as neurologists and neurologic surgeons, and a division focusing on complex ankle and foot issues. Through this multidisciplinary concept, the MC aims to provide newly referred patients with a diagnosis and a treatment plan in a single day. In order to do so, a patient may need to visit multiple healthcare professionals in one day. Key elements of this concept are the preliminary meeting between the various specialists, during which each case is discussed, and the bi-weekly shared consultation hours, during which the various specialists work in close proximity to one another. These elements distinguish the MC concept from other healthcare teams.

There are various challenges that come along with a high level of collaboration in healthcare. According to a recent evaluation report of the UMC Utrecht MC [10], for instance, staff criticized the lack of formal organization and express uncertainty regarding responsibilities. The report describes the difficulties that a "horizontally managed division" encounters in a "vertically structured organization", spanning from policy implementation to case evaluation. Additionally, the evaluation highlights the importance of regular monitoring and evaluation. There is a need for insight in patients' pathways through the MC, to facilitate evidence-based decision making. This is especially important, as the MC is collaborating with several hospitals to implement similar concepts elsewhere. Similar needs were expressed by healthcare providers in other studies [11] as well.

Multidisciplinary organizations and divisions focus on processes, as opposed to separate business activities. Managing these process-oriented organizations and divisions can be done through the application of Business Process Management (BPM) techniques. Process mining is an emerging discipline in BPM that aims to "*use event data to extract process-related information, e.g., to automatically discover a process model by observing events recorded by some enterprise system*" [12]. Process mining can be used to offer insight in the process, provide documentation, facilitate evidence-based decision making, or detect errors and bottlenecks, for example. Due to their complex and highly dynamic nature, healthcare processes are often interesting candidates for process analysis using process mining [13, 14, 15, 16, 17, 18]. Applications focus on process discovery [13, 14, 15], constructing pathways and workflows from event data, or process conformance [16], [17], by comparing mined pathways with existing guidelines and protocols. One case study even aims to use process mining and machine learning techniques to predict the next event in a patient's process [18].

In addition to this control flow perspective, process mining can also focus on the organizational perspective [12]. This is particularly interesting in the context of multidisciplinary healthcare. Through techniques such as social network analysis, collaborative networks can be visualized, and organizational structures can be discovered.

In the following sections, the research problem, research questions, and expected contribution of this research are stated. They are based on an exploratory literature study.

1.1 Problem statement

Research has shown that a collaborative, multidisciplinary approach to healthcare has a significant positive impact on perceived quality of care [7, 8, 9]. The rise of patient-centered healthcare has resulted in innovative multidisciplinary concepts in healthcare, which should be evaluated regularly in order to improve upon and develop [6]. These multidisciplinary concepts are horizontally structured, while the organizations they are adopted in are often vertically, or hierarchically, structured. Managing horizontal, process-oriented divisions presents new challenges due to cultural differences and communication errors, for instance [19]. There is often uncertainty about roles and responsibilities among healthcare managers as well as team members of multidisciplinary healthcare teams [10], [19, 20, 21]. Healthcare managers and providers have expressed a need for insight in patient pathways and organizational structure [10], [11]. Furthermore, researchers have expressed the need for studies "testing interventions at scale to develop a better understanding of the range of possible interventions and their outcomes" [9] in the context of improving interprofessional collaboration in healthcare.

According to Vom Brocke et al.'s "Ten principles of good business process management" [5], one essential element of managing process-oriented, multidisciplinary divisions is "the principle of joint understanding". Implementing

BPM approaches, such as Six Sigma or business process modelling, tends to divide employees, as only few are trained in the process management techniques and terminology used. As a result, some actors in the process may not have an adequate understanding of the roles, goals, challenges, or chain of activities involved. This leads to communication errors, tension and conflict among professionals, and resistance to change [19], [22]. Ubaid et al. state that "everybody participating in the BPM project, especially senior management, should understand the drivers of change" [23]. The need for research into cultivating insights in processes has also been stated by Langley [24] in their paper on the importance of *process thinking* in strategic organizations. They define process thinking as "*considering phenomena dynamically - in terms of movement, activity, events, change, and temporal evolution*". Process thinking is a shared understanding of processes, and the ability to apply this knowledge in strategic problem solving. The importance of employee involvement has also been highlighted by other researchers, albeit using varying terminology, such as "employee empowerment" and "business drivers understanding" [23], [25]. Rosemann et al. mention the aspect of culture in BPM, which includes the elements "process values and beliefs", "process attitudes and behavior" and "responsiveness to change" [26].

In the context of process analysis, process modelling is a method that is often applied to create insight and foster a shared understanding [23]. Process models encourage users to conceptualize processes in a uniform language. However, it can also be regarded as complex and difficult to understand for stakeholders who are inexperienced with the technique [27]. These conflicting properties lead researchers to question the appropriateness of process models as a tool for creating joint understanding of BPM practices throughout the process chain [27]. Moreover, the task of gathering information through interviews with domain experts, and converting this into process models, is quite labor-intensive. Process mining, in particular process discovery, supports the automatic extraction of process models from event data. Healthcare is a popular context for process mining since its processes are complex and highly dynamic [28]. Recommendations have been made to outline the unique value proposition that process mining can offer to healthcare, in terms of improving transparency [29].

1.2 Research questions

1.2.1 Main research question

From the problem statement, the following main research question is derived:

How can process analysis by process mining be used to improve a shared understanding of processes in multidisciplinary healthcare departments?

This research addresses the problem statement by analysing the effect of process analysis for creating a shared understanding of processes in multidisciplinary healthcare in a case study at the knee division of UMC Utrecht's Mobility Clinic.

1.2.2 Sub-questions

In order to answer the main research question in a structured manner, the main research question is divided into sub-questions. These sub-questions guide the research, following guidelines for the empirical cycle in Design Science Research by Wieringa [1]. This methodology will be further explained in section 3.

Before the effect of process analysis on shared understanding can be measured, it is first determined how a shared understanding of business processes can be assessed. The first research sub-question addresses this issue.

Q1. How can a shared understanding of business processes in multidisciplinary healthcare departments be assessed?

By answering the first sub-question, an instrument for assessing a shared understanding can be designed. The answer to this sub-question functions as a theoretical foundation for the assessment of a shared understanding of processes.

Next, the stakeholders of the MC knee are analysed. The second sub-question addresses the population of the research, their goals, and the problems they encounter.

Q2. Who are the stakeholders in a multidisciplinary healthcare department?

- ***What are the goals of the stakeholders?***
- ***What difficulties do they encounter?***

By answering the second sub-question, insights into the problem context of the research are gathered. This influences the design of the assessment instrument and provides additional perspectives to data selection and analysis.

The third sub-question addresses the application of process mining to the research context and its challenges and opportunities.

Q3. How can processes in multidisciplinary healthcare be analysed?

To answer this question, current methods, algorithms, and visualisations are analysed in order to determine relevance and applicability in the context of multidisciplinary healthcare departments. The results of this analysis guide the design of the process analysis that is executed as the treatment of the research.

The final sub-question addresses the effect of the process analysis on a shared understanding of processes among team members of a multidisciplinary healthcare department.

Q4. Does process analysis by process mining stimulate process thinking in multidisciplinary healthcare departments?

After the treatment is applied to the context, its effect on a shared understanding of processes is assessed. In this study, the treatment is a process analysis of healthcare processes in MC knee, based on a collection of process mining techniques.

1.3 Expected contributions

The expected contributions of this research are the empirical data on the appropriateness of process analysis as a tool for fostering a shared understanding of processes [5], which is one of two key components of collaborative practice: understanding and appreciating professional roles and responsibilities [9], [19]. This data will provide insights into the effect of process analysis on a shared understanding of processes among actors in the process and contribute to the presentation of the unique value proposition of process mining in healthcare [29]. Furthermore, it offers qualitative evaluation of interprofessional collaboration, that takes context into account [8].

In order to determine which research methods and instruments are appropriate to fulfill the research goal, the problem context is studied carefully. In the next chapter, a detailed description of literature reviews on three topics is given, as well as the insights that were gathered from these reviews. They provide answers on the first two sub-questions, as well as guide the design of the treatment and the assessment instruments.

2 Background

Three key concepts are analysed in literature to provide scientific background for the research. First, a literature study was conducted to examine what has been written about the opportunities and challenges of a multidisciplinary approach to healthcare. Second, the concept of shared understanding was explored, both in general and in the context of healthcare. Third, through a literature study, capabilities of current process mining techniques and methods were investigated. For each literature study, a literature study protocol was defined to minimize bias and improve reproducibility. A more detailed description of the approach to literature review can be found in section 3.1.2.

2.1 Multidisciplinary healthcare

In the literature, a term often used interchangeably with multidisciplinary healthcare is *"interprofessional collaboration"* (IPC). Collaboration between healthcare professionals is an essential part to patient-centric healthcare and has proven to have a positive effect on perceived quality of care [7]. In addition to patients, interprofessional collaboration is also beneficial to healthcare providers, as it is reportedly related to higher work engagement, lower error rates, and decreased intention to leave [8].

2.1.1 Challenges

A high level of collaboration in patient diagnosis and treatment does come with a number of challenges. For instance, in a recent study by Dahlke et al. [30], issues such as differing routines, differing knowledge between disciplines, and professional hierarchies are mentioned as barriers to effective patient-centered care provision. Furthermore, participants highlight the importance of healthcare professionals being *"on the same page"*. This is especially important when answering questions from the patient, as giving conflicting advice is detrimental to a patient's trust in their care givers. Healthcare professionals from different backgrounds and perspectives might propose different solutions to the same problem. Competition among these professionals may impede goal alignment.

The relevance of professional hierarchies and goal alignment as factors in interprofessional collaboration is also stated in a paper by Morley et al. [31] on determinants for collaboration in healthcare. They differentiate between structural determinants, psychological determinants, and educational determinants for collaboration. These determinants may either encourage or discourage effective interprofessional collaboration, depending on their prioritization and management.

Structural determinants are the opportunities for collaboration through physical and organizational environments. An example of a structural restriction for collaboration is the physical space of a multidisciplinary clinic, and lack thereof [10], [32]. Other examples of structural determinants are schedules, communication tools and set time slots.

Psychological determinants concern the willingness of team members to adapt their style of working to serve a common goal as a collaborative effort. In their paper, Morley et al. [31] specifically highlight the importance of role valuing, trust, and mutual respect in collaborative efforts. One's ability to reflect on their role and effectively communicate their role to others contributes to these aspects.

The final determinants mentioned by Morley et al. [31] are *educational determinants*. This refers to the ability of team members to collaborate effectively and efficiently. In a study by Suter et al. [19], 60 healthcare professionals were interviewed on competencies for collaborative care provision. This resulted in two core competencies being identified.

The first competency is *"understanding and appreciating professional roles and responsibilities"*. This involves managing expectations within a team, as well as recognizing functional boundaries and balancing the need of the individual and the team. Participants in the study mentioned their struggle with finding their place in collaborative practice and its negative effects. As Suter et al. [19] state, *"some respondents freely admitted that they are not as informed as they should be, which made them realize that their role may be misunderstood by others as well"*. Misunderstandings regarding role boundaries can lead to tension, defensive attitudes and resistance to collaboration. Furthermore, according to Brown et al. [22], *"role blurring"* is a serious risk for professional conflict and burnout.

The second competency is *"communicating effectively"*, which refers to capabilities in conflict resolution, professional terminology, and negotiation, among other communication skills. The research by Suter et al. [19] also states that there is *"evidence of a link to positive patient and provider outcomes"* for both competencies.

In addition to these determinants, there may also be systemic barriers that impede effective communication and collaboration. Examples of systemic barriers are institutional policies, medical regulations, and physical environment aspects that are beyond the control of the organization [31].

By gaining insight in the challenges and barriers to multidisciplinary healthcare, an understanding of the research domain is created. For the purpose of this research, the focus will be on the psychological and educational determinants of multidisciplinary healthcare, and how they are affected by process analysis. The influence of these determinants and competencies are also apparent in the context of this research, as noted in the 2020 evaluation report of the MC [10]. During the process analysis, this domain understanding is needed to find possible explanations for observations.

2.1.2 Opportunities

The current advancement and increased popularity of multidisciplinary concepts for healthcare have introduced some research opportunities as well. In a literature review by Pomare et al. [8], the researchers state that although there were numerous comparable studies, both qualitative and quantitative, there were many inconsistencies between the outcomes of studies with similar outcome factors. They mention that *"context played an important role in understanding inconsistency"*. For example, there may be differences between what is considered a beneficial effect in patient care. When using *length of stay* as a measurement for quality of care, it must be considered that for some types of patients, increased length of stay might lead to fewer re-admissions down the line. Furthermore, multidisciplinary concepts are often created to deal with more complex cases, when compared to regular medical teams, which inhibits accurate performance comparison. Pomare et al. [8], therefore, recommend the use of qualitative- and mixed-method approaches to researching multidisciplinary healthcare concepts, as well as taking context into account when evaluating interprofessional care.

This sentiment is echoed by Reeves et al. [9], whose study concerned the evaluation of strategies to improve interprofessional collaboration. The researchers conclude that there is *"not sufficient evidence to draw clear conclusions on the effects of IPC interventions"*. They attribute this to a lack of a proper measurement for effectiveness in collaboration and suggest future research should focus on conceptualizing and measuring the impact of interventions in collaborative healthcare.

When evaluating multidisciplinary healthcare through process analysis, as opposed to metrics such as length of stay, context is considered. Furthermore, by regularly extracting and analysing process models, a benchmark can be developed to investigate the effects of IPC interventions over time. This indicates the added value of applying process mining techniques for process analysis and confirms the appropriateness of process analysis as a tool for evaluation and analysis of multidisciplinary healthcare concepts such as the MC.

2.2 Shared understanding in collaboration

Adopting a process-oriented, collaborative approach to working requires effective management of business processes. Consequently, multiple researchers have defined critical success factors (CSFs) for effective BPM. Although there are similarities in these CSFs, terminologies differ [23]. The importance of employee alignment, involvement, and education is mentioned by Vom Brocke et al. [5] who propose ten principles of good BPM. Among those principles are the principle of involvement and the principle of joint understanding. The principle of *involvement* addresses the threatening nature of organizational change. The researchers highlight that a sense of involvement in process-oriented working affects commitment and ownership. Furthermore, a lack of involvement impacts the level of resistance within the organization. The principle of *joint understanding* refers to the importance of incorporating process-thinking in the organization when applying BPM approaches. Each actor in the process should be able to conceptualize the process in terms of tasks, events, roles, and other process notions. Fostering a shared understanding among employees enables effective communication and empowerment. The influence of these factors is also mentioned by Buh et al. [25] in their research on CSFs in different stages of BPM adoption. They refer to it as *"empowerment of employees"*, *"educated, trained, and motivated employees"* and *"well-communicated and clearly defined objectives, purpose and plan"*. Similar notions are echoed in a chapter of the *"Handbook on Business Process Management"* by Rosemann et al. [27] called *"The six core elements of business process management"*. People, specifically their communication skills and process management knowledge, as well as culture, specifically process values and beliefs and process attitudes and behavior, are among the six core elements that are defined.

2.2.1 Assessing shared understanding

Although many researchers agree that a shared understanding of processes and process-oriented working among actors and stakeholders are key elements of successful BPM, they highlight the lack of a unified approach to assessing the level of shared understanding. In his book, *"Macrocognition in Teams: Theories and Methodologies"*, Letsky [33] elaborates on the concept of *shared mental models* and how they relate to macrocognitive processes. In this context, macrocognition refers to complex, collaborative cognition in novel situations, which relies heavily on knowledge and ability, as opposed to routine methods. This makes it applicable in healthcare, since medical processes are known for being dynamic, highly autonomic, ad-hoc, and complex [28], [34]. A key element of macrocognitive processes is shared mental models. Shared mental models refer to a common understanding of processes and the knowledge and roles involved. Letsky states that *"measuring mental models is one of the largest issues facing the field"* [33].

In his book [33], Letsky touches on a number of attributes of mental models that may be interesting to assess. He also highlights the difficulty and lack of validated methods for measuring these characteristics. One dimension of shared mental models he mentions is accuracy. This refers to how similar an individual's mental model is to that of an expert. Another dimension of shared mental models is the *degree of integration*. This concerns the overall match between stakeholders' mental models, as opposed to comparison with an expert on the process. As Letsky states, *"the degree of integration represents the amount of detail commonly held by the team members"* [33]. Mental models have previously been assessed by Smith-Jentsch et al. [35] in a study that aimed to compare accuracy and consistency of mental models in air traffic. They asked air traffic controllers to rank strategies to apply to certain scenarios, as well as assign percentages on an scale from 0% to 100% with increments of 10. Among other statistics, averaged squared Euclidean distance was used to measure mental model agreement. In their study they concluded that mental model consistency is more important than accuracy in terms of matching. Thus, it is more important to agree on the ranking of strategies, than it is to agree on the percentage of trust associated with the strategy.

In another study by Simon et al. [36], using qualitative questionnaires, researchers conclude that the positive relationship with team performance is stronger for shared mental model accuracy than for shared mental model similarity. This indicates that it is not only necessary for team members to improve shared understanding through converging views on processes and process-oriented working, but that is there is an added benefit to enriching shared understanding with information and data, such as models.

In order to determine the learning outcome of such enrichment, the Cognitive Theory of Multimedia Learning (CTML) by Mayer [37] can be applied. CTML defines two variables that are relevant when assessing whether meaningful, fragmented, or no learning has occurred: *retention* and *transfer*. Retention refers to the comprehension of the explanative material, which enables the learner to answer direct, simple questions about the material at hand. Transfer can be defined as the ability to apply the knowledge gained from the explanative material to problem-solving questions. If the learner's level of retention is high, while the level of transfer is low, only fragmented learning occurs. If both retention and transfer are high, meaningful learning occurs. This can also be seen in table 1, which was adapted from Reijers et al.'s [4] interpretation of CTML.

Outcome	**Cognitive description**	**Performance**	
		Retention	**Transfer**
No learning about domain	No understanding of process	Poor	Poor
Fragmented learning about domain	Surface understanding of process, incorporated into working memory only	Good	Poor
Meaningful learning about domain	Deep understanding of process integrated into long-term memory and combined with existing knowledge	Good	Good

Table 1: Understandability outcomes according to Reijers et al. [4].

2.2.2 Shared understanding in healthcare

In the context of healthcare, there are many studies that involve measuring the perception of collaboration [7], [19], [30], [38]. Several instruments for measuring the degree of patient- centered working have been introduced. Sidani et al. [39] propose the patient-centered care measure (PCCM), which can be used to assess implementations of patient-centered care through surveys. However, this research and the resulting questionnaire focus on shared decision-making involving the patient, as opposed to collaboration between medical professionals. The modified index of interdisciplinary collaboration (MIIC) by Oliver et al. [40] would be more appropriate in the context of this research, as it aims to quantify professionals' perception of IPC and encourage actors to reflect on their role in the organization.

Although these instruments are able to assess how stakeholders feel about the level of collaboration in their working environment, they do not capture the level of insight stakeholders may have in the processes they are involved in. In a study by Hudson et al. [41] on promotion of role clarification in a healthcare context, the roles and responsibilities subscale of the Readiness for Interprofessional Learning Scale (RIPLS) [42] is used to assess overall role clarification among members of multidisciplinary healthcare teams. Additionally, participants answered six questions, designed to assess their understanding of the roles of the other professionals in their team. These questions, such as *"How would you rate your understanding of the role of the physiotherapists within the healthcare team?"*, were answered by rating items on a five-point scale, from 'limited' to 'strong'.

Due to the lack of validated instruments that quantitatively assess a shared understanding, the focus of the research is on qualitative assessment. However, existing instruments that are used for evaluating the perception of IPC can be used for the purpose of domain analysis. As the literature indicates that there is added benefit to improving a shared understanding with information and data [36], by using models for example, CTML [37] can be applied to assess what level of learning occurs among team members when presented with process information.

2.3 Process mining

Process modelling is a widely used tool for analyzing and improving understanding of processes [27]. Process models can be used to communicate more effectively, instruct employees, and discover bottlenecks and workarounds. However, gathering information on processes through interviews and creating process models manually are very labor intensive tasks. Fortunately, techniques have been developed to ease the creation of process models. *Process mining* is a technique that aims to extract process models from event data, or as Van der Aalst states, *"exploit event data in a meaningful way"* [12]. In his book, *"Process mining: Data science in action"*, he mentions various benefits from extracting process models from data. For example, using data as a source for process modelling, as opposed to expert interviews, requires less involvement of domain experts, which is often costly. Furthermore, process mining links process monitoring to diagnosis for process redesign, enabling iterative BPM.

2.3.1 Process mining techniques

Van der Aalst [12] differentiates between three types of process mining techniques: *process discovery*, *conformance checking*, and *enhancement*. These techniques are often used in combination for process analysis. The first type of process mining techniques is *process discovery*. Discovery algorithms aim to automatically construct process models based on event logs containing activities, timestamps, and resources. For example, the α-algorithm [43] produces Petri nets when given a set of example executions of a process.

As the amount of input data and complexity of the processes increase, the readability of automatically generated process models decreases [12]. This could result in the creation of *spaghetti processes*. These are models of unstructured processes, named for the resemblance that a resulting process model might have to spaghetti, when simple process discovery techniques are applied. Spaghetti process models are unreadable and without adaptation unsuitable for process analysis. The counterpart to a spaghetti process is a lasagna process, which is highly structured, resulting in a simple process model. To combat spaghetti process models, other discovery techniques have been proposed, such as the Heuristic miner [44]. The heuristic miner is able to detect decision points and parallel activities from dependency relations and abstract from outliers and noise. This algorithm is especially suitable for event logs that have a limited variation of activities. Alternatively, the Fuzzy miner was introduced by Günther et al. [45] to deal with processes that lacked structure, but also involved many different activities. The Fuzzy miner groups cases according to correlation and significance metrics, simplifying models by clustering similar cases and leaving out clusters of unimportant cases.

A different application of process discovery is *social network analysis* [46]. This type of discovery techniques focuses on the resources in event logs, which are the actors who are executing certain activities. Based on resource data, a social network can be constructed. Social network analyses using process mining techniques have been applied in various fields, such as change management [47], social commerce [48], education [49], and healthcare [14], [50], [51]. Examples of metrics used in social network analysis are handover of work between two actors, which is an indication of possible causality, number of joint cases, which is an indication of working relations, and number of joint activities, which is an indication of role similarity [46], [52]. Another application of social network analysis is the construction of role interaction models, as illustrated by Alvarez et al. [53] in their study on role interaction in the emergency room. Role interaction models are similar to workflow models, but visualize how a process moves through the various actors involved, instead of activities.

The second type of process mining techniques that Van der Aalst [12] defines is *conformance checking*. This involves comparing existing process models with event logs, in order to detect discrepancies between the model and real-life executions of the process. Conformance checking is applied to make sure that rules and regulations are followed and to locate any deviations. In healthcare contexts, conformance checking has been applied for example to perform deviation analysis [16], [17].

The third type of process mining techniques in the list by Van der Aalst [12] is *enhancement*. The goal of enhancement techniques is to extend or improve on a process by introducing new data perspectives, for the purpose of finding bottlenecks and workarounds, for instance.

Examples of process mining perspectives are the *control-flow perspective*, that focuses on the order of activities in a process, the *organizational perspective*, that focuses on relationships between actors in processes, and the *case perspective*, that focuses on the characteristics of a case and its differentiating qualities in comparison to other cases [12].

In this research context, process discovery techniques are applied to extract process models. As role characteristics and communication are so important in multidisciplinary healthcare, social network analysis is also an essential part of the process analysis. Conformance checking is not suitable for application to the context of this research, as there are currently no existing process models available for comparison.

2.3.2 Process mining in healthcare

Due to their complex and dynamic nature, healthcare processes are popular subjects in process mining literature [28]. For instance, Caron et al. [34] have introduced the Clinical Pathway Analysis Method (CPAM), specifically for application of process mining techniques in the context of healthcare. CPAM is designed for assessing compliance with guidelines and analyzing adverse events. One of the key elements of CPAM is the involvement of medical experts in the process mining process. After initial exploratory pathway analysis, medical confirmation is sought after through a review by medical experts and externalization of knowledge. Following this phase, advanced pathway analysis, such as bottleneck analysis, conformance checking, and performance analysis can be performed.

The concept of involving domain experts in the process of process model creation has also been incorporated in a process mining technique by Dixit et al. [54] called *"Interactive process discovery"* (IPD). This technique differs from its peers by involving domain experts in the actual mining phase of process discovery, as opposed to eliciting information from experts before or after creating the process model. It has been applied to healthcare in a case study by Benevento et al. [55], where it was concluded that interactive process discovery allowed for accurate and compliant process models. One of the disadvantages to high involvement of domain experts in process mining is the required time input, which can be costly.

In a recent paper by Martin et al. [29], which followed from an international brainstorm seminar, recommendations are made to promote process mining in healthcare by improving usability and understandability. One recommendations is to *"present the unique value proposition of process mining in healthcare"* [29]. They state that process mining improves transparency through inductive insights, which potentially effects role and department boundaries. Another recommendation is to *"start from real-world healthcare problems"* [29]. They mention the design science research methodology, which focuses on the creation and study of an artifact that solves a problem from a specific context. Martin et al. emphasize the need to reflect on the implications in healthcare that may come from the analyses and state that *"close ties are needed between process mining researchers and healthcare practitioners"* [29], a principle that design science research also accentuates.

2.4 Literature summary

While multidisciplinary collaboration in healthcare has proven to be beneficial to both patients and healthcare professionals, it offers challenges as well [7], [8]. It is subject to ineffective communication, cultural differences, and a lack of understanding of roles and responsibilities [30], [31]. These challenges are also found in other process-oriented, collaborative approaches to business [23]. Multiple principles and critical success factors for business process management that are identified in research concern employee involvement, empowerment, and shared understanding [5], [23, 25, 26]. Furthermore, research indicates an added benefit to accurate shared understanding of processes, rather than relying solely on similar views on processes [36].

Process mining aims to extract information on processes from event data [12]. It facilitates evaluation that takes context into account, a need that has been expressed in the context of healthcare[9]. Applications of process mining include process discovery, which uncovers process models and offers insights in case variants and activity ordering, among others. Additionally, process mining techniques, such as social network analysis using handover-of-work metrics

[46], [52] or role interaction models [53], can be used to study organizational and communicative structures, which might provide information on roles and responsibilities in a multidisciplinary team. Due to the complex, dynamic nature of healthcare processes, healthcare has been a popular field of application for process mining [28]. The literature indicates that in order to improve the potential of process mining in healthcare, its unique value proposition must be explored [29].

These insights that were gained through the literature review shape the design of the research. From the literature, it can be concluded that an instrument for quantitatively assessing a shared understanding among team members has yet to be designed or compounded from various sources, since there is no validated tool currently in existence. As the design and validation of such a tool would be too extensive to fit the scope and time limitations of this research, the focus is on qualitative assessment through interviews, supported by a survey. The survey design is based on elements of the MIIC [40] and the RIPLS [42], as well as the challenges of multidisciplinary healthcare that were discussed in section 2.1. Furthermore, from the literature, the appropriateness of various process mining techniques for fostering a shared understanding was derived, which guide the design of the treatment that is applied. Process discovery techniques will be used to extract process models, as well as role interaction models for the purpose of social network analysis. In the next chapter, the research design, the research methods that are applied, and the instruments and tooling that is used are explained.

3 Research methods

As recommended by Martin et al. [29], the design of this research follows guidelines for empirical research according to the Design Science Research (DSR) paradigm, as explained by Wieringa [1]. The phases of this research correspond to Wieringa's empirical cycle. According to this cycle, research involves applying a treatment to an object of study, followed by data collection according to pre-specified measurement, in order to fulfill a knowledge goal. In this research, the treatment is a process analysis containing process models and the object of study is a multidisciplinary healthcare department. The knowledge goal of this research is to determine the appropriateness of process modelling as a tool for creating shared understanding in a specific context. Based on this knowledge goal, it can be stated that the research aims to validate a design and can be viewed as part of a higher-level design or engineering cycle.

The research is a case-based study. As opposed to sample-based studies, case-based studies focus on architectural structures instead of statistics. Due to time constraints, the treatment is applied to only one case, classifying the research as a single-case mechanism experiment [1].

In figure 1, the phases of the empirical cycle are visualised. For this research project, one iteration of the empirical cycle is performed. The applied research methods are grouped according to the corresponding phase of the research. In the following sections, these research methods are explained in detail.

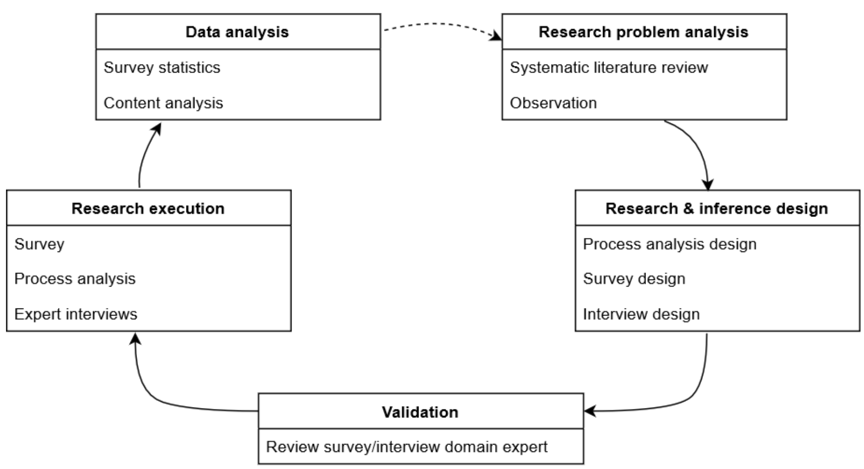


Figure 1: The empirical cycle [1] and corresponding research methods applied in this research

3.1 Research and inference design

3.1.1 Research context

The object of this study is the knee division of UMC Utrecht's Mobility Clinic, a horizontally structured, multidisciplinary out-patient clinic for patients with complex knee issues. Their aim is to provide new patients with a diagnosis and a treatment plan in a single day, by streamlining the patient process through intensive inter-specialist collaboration. Specialists involved in the clinic include orthopaedic surgeons, physiotherapists, orthopaedic cast technicians, and sports medicine physicians, among others. Recently, there has been a thorough evaluation of the concept, which uncovered the need for insight in patient flows and organizational structure [10].

In order to gain understanding of the unique concept that is the MC, observation was done by attending approximately 20 hours of consultation. The days consisted of sitting in on multidisciplinary preliminary consultation, as well as consults with patients. Time was spent with various medical specialists, who were prompted to reflect on their experience with the MC. Two days were spent in the MC knee division, while the third day was spent in the MC spine division. This was done to provide insight in the generalizability of observed phenomena.

3.1.2 Literature review

In order to analyse the research problem, a systematic literature review of three key concepts was performed. The result of this review provides background on relevant developments in multidisciplinary healthcare and process mining, as well as a scientific basis for the research design. First, the opportunities and challenges of multidisciplinary healthcare were analysed. Then, the importance of a shared understanding was researched. Lastly, a literature study on the capabilities of process mining techniques and applications was performed.

For each literature study, a literature study protocol was defined to minimize bias and improve reproducibility. The literature study protocols were created based on guidelines by Kitchenham [56]. Conducting a systematic literature study involves several phases. In the first phase, the study was planned. This plan includes the goal of the literature study, which databases and search terms are used, and which search strategies are applied. Additionally, in- and exclusion criteria for research papers were defined. The next step was to conduct the literature review by searching and applying the defined criteria. Finally, the resulting literature was analysed and coded. A synthesis that describes insights relevant to the research problem was written, which will provide a foundation for the research to build upon. The protocols can be found in tables 2, 3 and 4. The synthesis of each literature study, as well as a summary of the three topics, can be found in chapter 2 of this thesis.

Plan	*Goal*	Investigate opportunities and challenges of a multidisciplinary approach to healthcare
	Databases	Scopus, PubMed, Google Scholar
	Search terms	"*collaboration*" AND "*healthcare*", "*multidisciplinary*" AND "*healthcare*"
	Search strategy	Forward and backward snowballing
	In- & exclusion criteria	English/Dutch language; Published between 2005-2020; Available through UU account; Reviews, case studies, methodologies
Analysis	*Coding method*	Thematic analysis

Table 2: Literature review protocol for review of multidisciplinary healthcare

Plan	*Goal*	Explore concept of shared understanding and assessment methods
	Databases	Scopus, IEEE, Google Scholar
	Search terms	"*shared understanding*", "*understanding*" AND "*measuring*", "*understanding*" AND "*assessment*"
	Search strategy	Forward and backward snowballing
	In- & exclusion criteria	English/Dutch language; Published between 2000-2020; Available through UU account; Reviews, case studies, methodologies
Analysis	*Coding method*	Thematic analysis

Table 3: Literature review protocol for concept of shared understanding

Plan	*Goal*	Investigate capabilities of process mining techniques and methods, in the context of collaboration
	Databases	Scopus, IEEE, Google Scholar
	Search terms	*"process mining"* AND *"multidisciplinary"*, *"process mining"* AND *"technique"*, *"process mining"* AND *"network"*, *"process mining"* AND *"collaboration"*, *"process mining"* AND *"healthcare"*, *"process mining"* AND *"financial"*
	Search strategy	Forward and backward snowballing
	In- & exclusion criteria	English/Dutch language; Published between 2010-2020; Available through UU account; Reviews, case studies, methodologies
Analysis	*Coding method*	Thematic analysis

Table 4: Literature review protocol for review of process mining techniques

3.1.3 Survey

A survey was designed to assess the current level of insight in patient flows in the MC knee division. A number of questions were based on the Modified

Index of Interdisciplinary Collaboration by Oliver et al. [40], while others were derived from the Readiness for Interprofessional Learning Scale by McFadyen et al. [42]. As all participants were either native speakers or fluent in Dutch, the questions were translated accordingly. The design of the survey is detailed in table 5. Altogether, there were four categories of questions. First, participants were prompted to reflect on their own level of insight in the MC. The second category of questions pertained to their own role and responsibilities, while the third reflected on their understanding of other specialists' roles and responsibilities. The fourth question required the participants to rank a number of factors, derived from observation and literature study, based on their effect on collaboration in the MC. The first three categories of questions were answered using a 5-point Likert scale, while the final part of the survey required grouping and ranking within that grouping.

Question category	Number of statements/factors	Topic	Measurement type
1	11	Level of insight in the MC	5-point Likert scale
2	6	Understanding own role and responsibilities	5-point Likert scale
3	8	Understanding colleague's roles and responsibilities	5-point Likert scale
4	14	Factors influencing collaboration in the MC	Grouping in 3 categories, ranking within

Table 5: Survey design

After validation, the survey was sent out to all MC knee team members. This included orthopaedic surgeons, sports medicine physicians, physiotherapists, orthopaedic cast technicians, and doctor's assistants. The responses were anonymous on a personal level, but participants were required to indicate their role in the MC. In total, 24 team members completed the survey. The results of the survey were compared to the observations made during the interviews, in order to assess generalizability.

3.1.4 Process analysis

A key component of this research project is the *process analysis*. The goal of the analysis is to provide insight in the patient pathways through the MC, from the moment they are referred to the clinic until the final visit. The approach for process analysis follows the *CRISP-DM cycle*, a widely adopted framework for data mining [3]. In figure 2, the CRISP-DM cycle is visualised.

First, through research methods such as literature review and observation, *business understanding* of the research context is gained. In the *data understanding* phase, initial data collection is done, in close collaboration with domain experts. In this phase, it is important to get familiar with the data and assess data quality. In the *data preparation* phase, the raw data is transformed to the dataset that will be the input for the mining algorithm. This involves data cleaning, data enhancement, and attribute selection. The next step is *data mod-*

eling. In this phase, the dataset is given to a mining algorithm, which produces a model. Depending on the complexity of the dataset, a project often requires going back and forth multiple times between the data preparation phase and the modeling phase. Finally, the result of the modeling phase is evaluated. This could lead to another instance of the CRISP-DM cycle, or result in deployment of the model.

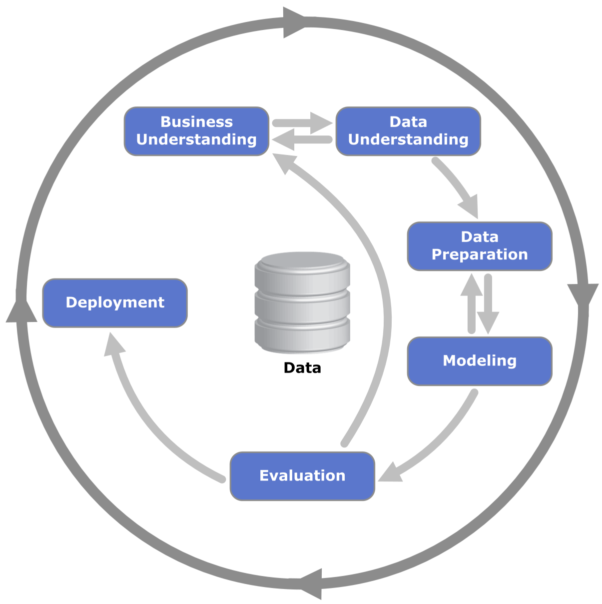


Figure 2: The CRISP-DM cycle [2] according to Wirth et al. [3]

Data selection The first step of data selection was selecting the right sources to pull data from. In collaboration with two domain experts, a business intelligence specialist from UMC Utrecht and the healthcare coordinator of the MC, a set of relevant agendas was selected. These agendas pertain to certain specialisms involved in the MC, correlate with the MC knee consultation hours, and contain scheduling information of patients and specialists. From these agendas, all patient identification numbers were selected, as well as the dates of the first instances of these patients in the MC, from 2015 to 2020.

The next step was to gather all instances of the selected patient-IDs in UMC Utrecht's agendas. All agendas were selected as a source, to detect communication flows throughout the hospital. This includes specialisms that may not be included in the multidisciplinary preliminary consults. Before data extraction, a time frame for relevant data needed to be determined. One of the difficulties that were encountered during this phase was the lack of completion registration. There was no attribute or data source that could identify if and when a patient's case was finished. Consequently, after consulting a domain expert, a time window was determined: from three months prior to the first contact in the MC, until three years after. This time window was chosen to include any data on referral if the patient was referred to the MC internally. The limit of three years was chosen because it was thought not uncommon for patients of the MC to receive a conservative treatment plan on their first visit, only to return in a year's time for surgical treatment after all. Furthermore, the waiting list for orthopedic surgery is quite long.

Data preparation After selecting and extracting the raw data, it has to be transformed into the event log that will be the input for the process mining algorithm. This transformation involves cleaning, formatting, and filtering, as well as many iterations between data preparation and model building.

First, the raw data was cleaned and formatted. Duplicate instances, which were corrections of earlier registrations in the set, were removed based on matching attributes. Additionally, the timestamps for the instances were joined with the dates and formatted according to standards. Then, a number of activities were abstracted using an abstraction table. An example of an abstraction is the generalization of specific radiology imaging activities. In the raw dataset, these activities were registered under the name of the body part that was the subject of the image, such as "*KNEE LEFT*" or "*PELVIS*". The distinction between imaging types could be derived from an attribute called *subagenda*. After abstraction based on *subagenda*, the imaging activities were registered as "*X-ray*" or "*MRI*", for example.

The next step in data preparation was to enhance the dataset with referral data. Information on sources of referral to the MC were extracted from an insurance-related dataset and transformed into an activity. The activity name contained the word "*referral*" and the role of the referring party. This could either be a general practitioner, an external medical specialist, an internal medical specialist, or a doctor's assistant. For each patient-ID, a referral activity was added to the dataset. Some patient-IDs corresponded to multiple referral activities, these were all added to the dataset as well.

The final step of data preparation was filtering. First, infrequent activities were removed from the dataset, as activities that occur only a few number of times are highly unlikely to be relevant to the healthcare processes in the MC. Furthermore, the dataset still included over 20 different attributes. While containing interesting information, these were not all relevant to the process mining task at hand. A selection of relevant attributes was made. A translated example excerpt of the resulting event log can be found in table 6.

PatientID	Agenda	Appointment	Datetime
22146	General practitioner	Referral GP	00:00 23-04-2018
22146	Orthopaedics	Second opinion	13:00 21-06-2018
56432	Radiology	X-Ray	14:00 15-03-2019
56432	Orthopaedics	First consult	14:30 15-03-2019
66599	Cast technician	Brace fitting	15:15 06-09-2019

Table 6: Example excerpt of the resulting event log

Process visualisation The resulting event log was used as input for two process mining tools. First, the dataset was uploaded to Disco. Disco applies a process discovery technique, Fuzzy miner [45], that was developed to handle unstructured event data with many different activities. It applies the Fuzzy miner to the dataset, after mapping certain data attributes to process components. This mapping can be seen in figure 3. In order to create a control-flow model, the "*appointment*" column was mapped to activity, while "*agenda*" was mapped to resource. This resulted in a complex web of activities and relationships. Using the sliders, a level of relevant frequency was selected so that the model would include the most relevant activities, but remain readable. While using this mapping, the tool enabled variant analysis as well by showing and elaborating on the most frequent paths in the MC.

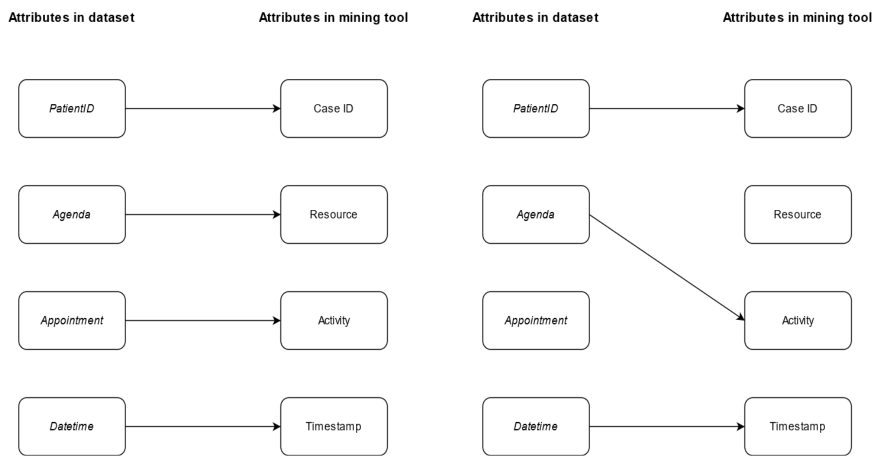
By mapping the *agenda* attribute to activity instead of the *appointment* attribute, a role interaction model was extracted that represents the communication flows between the various specialisms in the dataset. This model was built for the purpose of social network analysis, which offers insight in the specialisms that might be involved in a patient's pathway.

Additionally, the event log was translated to the eXtensable Event Stream (XES) [57] format to provide input for the ProM tool. In ProM, the log visualiser package was used to explore the data and compare variants. The *agenda* column was marked as the activity, while the *patient-ID* and *datetime* column were matched to case-ID and start time respectively.

A screenshot of the tool and the created models can be found in Appendix A.

3.1.5 Interviews

Five team members of the MC knee division were interviewed on their level of insight in the MC, as well as their views on the usability of process mining in their work environment. The participants were selected based on their role, as



(a) Mapping for control-flow model (b) Mapping for role interaction model

Figure 3: Attribute mapping

well as their availability and willingness to be interviewed. Each team member has a different role in the MC. Among the interviewees were an orthopaedic surgeon, a sports medicine physician, a physiotherapist, an orthopaedic cast technician and a doctor's assistant. Each interview lasted between 45 and 60 minutes, was conducted in the Dutch language, and was done either digitally or in person at UMC Utrecht. Four interviews were done on the same day, while the fifth was done one week later due to scheduling issues. All interviews were recorded for analysis.

For the interviews, a semi-structured approach was taken to encourage interviewees to elaborate on their comments and views. There were three sections to the interview. First, interviewees were asked to reflect on their insight in the MC knee division, specifically on its multidisciplinary aspects and their expectations of the patient flows. In the second part, the process analysis was demonstrated. This part of the interview was scripted, to ensure every interviewee received the same information. However, to facilitate a natural learning environment, the interviewees were able to ask questions and inquire more about the tool after the demonstration. During the demonstration, interviewees were shown the control-flow model in Disco, the most frequent patient pathways through the MC, the log visualisation in ProM, and the role interaction model in Disco.

For the third part of the interview, the goal was to determine whether the interviewees were able to understand the process analysis and incorporate process thinking in their own mental framework. In order to assess this, three types of understandability questions were asked, based on the framework used by Reijers et al. [4], adapted from Mayer [37].

A high level of retention indicates that a person understands what has been presented. For this purpose, interviewees were asked straightforward questions that required them to interpret the process model components. Example questions are "*Which referral activity is performed most often?*" or "*What activity follows most often after a second opinion?*".

A high level of transfer means that a person has gained knowledge from the presentation and is able to apply this new knowledge to problem-solving. For healthcare providers, it is not the goal to gain a skill set meant for process analysts. Ideally, they would be able to translate the process analysis to their reality, understand the value of process modelling, and be stimulated to form hypotheses and theories to test using these techniques. Interviewees were prompted to explain certain phenomena captured in the process models, imagine factors that could influence the accuracy of the models, and come up with applications or recommendations for the process analysis techniques to be used in the context of the MC.

In the context of this research, a third type of questions was added: *reflection*. This prompted interviewees to reflect on the commonalities and differences between their expectations of the patient pathways and the pathways shown in the analysis.

3.1.6 Data analysis

The interviews were transcribed and coded using nVivo, a tool for qualitative analysis. The interview transcriptions were subjected to content analysis, which involves coding based on an existing conceptual framework, to which concepts are added that are found during interpretation.

The results of the survey were analysed using statistical metrics such as mean, median, and variance. The survey serves as support for any conclusions drawn based on role, because it provides statistical reinforcement of role correlation, as opposed to personality.

3.2 Validation

Various steps are taken to improve the validity of the research design. In order to enable comparison between the participants of the interviews, the demonstration part of the interview was performed according to a script. This ensured each participant was shown the same visualisations and received the same information, so discrepancies in understanding could not be attributed to differing experiences.

In order to improve the validity of the inference, the results of the survey are compared to the observations from the interviews. The survey provides statistical background for the various roles' level of insight and reflection. The results offer support for any explanations of observations in the interviews based on role characteristics.

Furthermore, both survey and interview script were subjected to review by a domain expert before deployment, as advised by Laue et al. [58]. This was done to minimize assumptions regarding use and comprehension of terminology. Any terminology relating to process management should be explained before usage, so possible confusion regarding the process analysis is not caused by presumption or miscommunication.

Another measure that was taken to improve validity was to schedule the interviews on the same day. This was done to mitigate the risk of participants discussing their interview experiences with each other, possibly causing them to gain process knowledge from a source other than the process analysis. Unfortunately, one of the interviews had to be scheduled on a different day, but as the reason for this was the participant's absence due to illness, the risk of this participant meeting with a colleague to discuss the interviews beforehand was still limited.

In conclusion, the research approach has been designed carefully in regards to validity. Efforts were made to reduce the influence of external factors and ensure the appropriateness of the instruments used. However, some limitations to the research remain. These are discussed in detail in section 5.2. In the next chapter, the results of the executed research design are discussed.

4 Results

In this section, the results of the research are discussed and explained. During the interview, the process analysis was demonstrated to the participants. Screenshots of the process models that were shown can be found in Appendix A. As previously mentioned in section 3.1.5, the interview can questions can be divided into three categories; retention, reflection, and transfer. The results of these questions are therefore grouped accordingly. In table 7, details regarding interview participants, duration, and setting are shown. A detailed design of the interview and the script of the process analysis demonstration can be found in Appendix B.

Participant	**Role**	**Sex**	**Years active in MC**	**Interview duration**	**Setting**
1	Orthopaedic surgeon	M	6	51 min.	Digital
2	Sports medicine physician	M	6	62 min.	Digital
3	Orthopaedic cast technician	M	6	52 min.	In person
4	Physiotherapist	M	6	38 min.	In person
5	Doctor's assistant	F	6	36 min.	Digital

Table 7: Interview details

4.1 Retention

After demonstrating the process analysis to the interview participants, the first objective was to assess their retention of the analysis. Participants were prompted to interpret basic elements of the models that were shown and translate them to context. In this way, the general readability of the process models could be gauged.

Overall, 4 out of 5 participants (1, 2, 4, 5) were immediately able to interpret the basic elements of the process models. The participants identified activities and sequence relationships between them, as well as quantitative data on certain activities. Notably, these participants did differ in their display of curiosity after the demonstration of the process analysis. Two participants (1, 2) reacted very positively to the analysis, showing immediate interest and curiosity, while others (4, 5) reacted in a more neutral manner. The curious participants did not even require any prompting or encouragement, but started interpreting the models straightaway. Not only were they able to read the models correctly, one participant (1) was even able to recognize the limitations of the model right away as well. They (1) stated that they "*can read the model, but it does elicit lots of questions*". They (1) then proceeded to question the accuracy of the model, as well as the limits, mentioning the lack of external data sources in the context of patient pathways that go beyond UMC Utrecht. The other two participants (4, 5), who reacted more neutrally to the analysis, were able to correctly translate elements of the model after being asked for process information, but refrained from asking questions after the analysis.

However, one participant (3) seemed to have difficulty in reading and interpreting the process model. Before the demonstration, the participant already mentioned a lack of confidence and experience with medical data. After the demonstration, they (3) stated: "*of course, I will not be able to immediately understand this, but it seems like a nice overview*". When directly prompted to interpret a certain aspect of the model, the participant struggled to state an interpretation, again expressing doubt and citing lack of experience with data analysis as an explanation. Notably, the participant seemed to over-complicate their interpretation, rather than actually seeming under-qualified to interpret. Despite their difficulty, the participant did express seeing patterns in the process analysis, adding "*You can definitely recognize a certain outline, very nice to see*".

Ultimately, 4 out of 5 participants (1, 2, 4, 5) showed ability to read and translate the model, immediately after the demonstration. While one participant (3) struggled to comprehend at first, they were able to understand basic concepts after further assistance. Consequently, retention has been established for the participants. According to the model of understandability outcomes by Reijers et al. [4] shown in table 1, for these participants, fragmented learning about the domain has been achieved, at the minimum.

4.2 Reflection

In the next part of the interview, participants were encouraged to reflect on the process analysis in the context of their own mental model. Their mental model had previously been discussed in the first part of the interview, as well as examined through the survey. The participants' mental models shared some similarities. For example, when asked about variation in the MC, each participant mentioned the numerous protocols in place, and expressed confidence that these protocols were generally followed. However, nearly every participant mentioned some sort of trade-off between a protocol-guided approach and a personal, patient-centered approach, stating phrases such as "*We have many protocols and guidelines, but every patient is different*" (5). This is also reflected in the survey. When asked to rate statements on a scale from 1 to 5, ranging from *totally disagree* to *totally agree*, participants rated the statements "*I follow a protocol in the execution of my tasks*" and "*My colleagues from other specialisms follow a protocol in the execution of their tasks*" 3.85 and 3.75 on average. One participant (2) also mentioned the challenges of high variation in healthcare processes, particularly complicating the work of the clinic's support staff.

When asked to compare their expectations of the analysis to the results, most participants indicated that despite the existence of protocols, they were not surprised at the level of variation that the data showed. Two participants (1, 2) related the level of variety to case complexity and the purpose of university medical centers, stating that healthcare of a more standardized manner was often referred to other hospitals or private clinics. These facilities often have much shorter waiting lists, a major benefit for the patient. Additionally, teaching hospitals' services are generally much more expensive for insurance companies, due to the complexity of the cases they handle. One participant (4) related the variation and complexity to the selection and filtering methods used to create the input dataset. They wondered whether the selection method and the filter on the dataset should have been more selective, in order for a streamlined model to appear. This indicates that the participant was able to understand the construction of the process analysis and reflect on the factors that might affect the accuracy of a model.

Participant 3 expressed surprise at the level of variation shown by the process analysis. They interpreted the high variation as an indication that protocols may not be followed as closely as they had expected, and that a personal approach was taken more often. Furthermore, the difference between their expectations and the analysis seem to confirm for them that their level of insight in the patient flows in the MC was rather low. In the first part of the interview, this had been stated by the participant, who said that they "*do not have the level of insight that the doctor's assistants or orthopaedic surgeons have*". This was indicated by their colleagues in the survey as well. While doctor's assistants and orthopaedic surgeons rated the statement "*I know what processes occur in the MC*" 4.0 and 4.5 on average respectively, the average rating of the group of orthopaedic cast technicians amounted to 3.6. Notably, there seemed to be some variation among orthopaedic cast technicians regarding self-assessed level of insight. While most technicians *agreed* or *totally agreed* with the previous statement, one *disagreed*.

Furthermore, participant 3 echoed the statements made by participant 4, relating the complexity of the model to the many specialisms included in the dataset. They wonder whether focusing solely on knee-related specialisms might uncover a simpler model, but also acknowledge the possible loss of relevant information when doing so.

4.3 Transfer

The objective of the final part of the interview was to determine whether participants were able to translate the process analysis results to reality and integrate the knowledge gained from the process analysis with their mental models. For this purpose, three indications of knowledge transfer were established. First, participants that have achieved meaningful learning about the domain should be able to come up with explanations for observations in the process analysis. Additionally, they should be able to reflect on possible applications of process analysis in the MC. Lastly, participants should be able to discuss how they envision the use of process analysis in their work routines. Reviewing the possible integration of process analysis in the MC relates to the psychological determinants that were discussed in section 2.1, namely the willingness of the participants to adapt their work style for a collaborative effort.

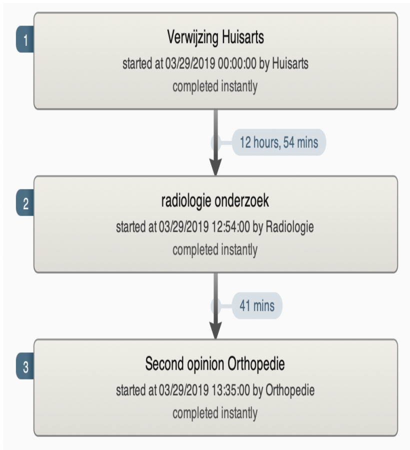
To assess whether these indications were present, participants were shown fragments of the models and noteworthy phenomena and asked to provide possible explanations. They were also encouraged to reflect on possible factors that could influence the accuracy of the analysis. Furthermore, participants were given an example of a hypothesis that had been stated at the start of the research, namely "*general practitioners refer unsuitable patients to the MC more often than external medical specialists*", for which supportive indications could be found in the analysis. They were then prompted to come up with their own hypotheses, theories, and recommendations for further use of the process mining techniques. Lastly, participants were asked how they envisioned the use of such tooling in the MC and who should be the intended user.

4.3.1 Explaining observations

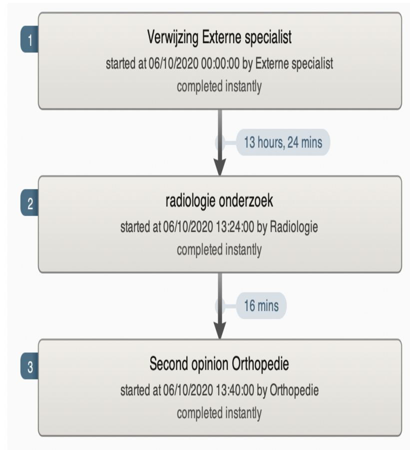
First, participants were shown the most frequent process variants in the dataset. These were a set of short patient paths, consisting of a referral by either a general practitioner or an external medical specialist, followed by an X-ray and a consult with an orthopaedic specialist. Screenshots of the most frequent variants can be seen in figure 4.

Participants were asked to provide possible explanations for such short processes. Each participant was able to come up with at least one explanation: patients that followed one of the short pathway variants had been referred to the MC because the referring doctor had recognized an indication for surgery, but after the preliminary multidisciplinary consult and examination, the orthopaedic surgeon concluded that there was no indication after all. Participant 5 also mentioned that in the case of a second opinion, MC doctors might agree with the initial diagnosis and treatment plan, and refer the patient back to the specialist that gave the first opinion for treatment. Another participant (4) contemplated the possibility of the patient's care pathway being continued at a different hospital or healthcare provider, but also expressed that referral to external orthopaedic surgeons was uncommon and only external physiotherapists were referred to often.

Reflecting on factors that could possibly affect the accuracy of the process analysis proved to be a challenging task for most participants. Participants 3,



(a) Short path with referral by general practitioner



(b) Short path with referral by external specialist

Figure 4: Screenshot of variants shown during demonstration

4 and 5 expressed difficulty at coming up with any factors. One participant (4) asked for an example factor and agreed that data quality and registration might affect accuracy. However, another participant (3), who was not given the example, stated: "*I think that is a very difficult question, because if the dataset is so big, the analysis will be accurate regardless of registration mistakes. A common thread can definitely be found*". Other participants (1, 2) were able to relate accuracy to data registration and selection. Participant 1, for example, stated: "*The input data either makes or breaks the analysis. If the data is incorrect, so are the conclusions. So, where does the data come from? Have you selected the right sources?*". They also mention the effect that filtering might have on the accuracy of the analysis.

4.3.2 Imagining possible applications of process analysis tools

Throughout the interview, 4 out of 5 participants (1, 2, 3, 4) were able to recognize the usefulness of the tool and make numerous recommendations regarding data enhancement or focus. Most recommendations can be grouped into three central themes.

Change in treatments One of the topics mentioned often by various participants during the interviews was the change in treatments that were provided by the MC knee division. Until recently, the MC was known for its research and execution of knee joint distractions for patients below the age of 65, who suffer from arthrosis in the knee. During this procedure, the knee joint is temporarily distracted by a few millimeters, in order to allow the cartilage to regenerate. However, due to developments in research, this treatment is no longer covered in basic insurance contracts. Additionally, the MC knee division has been recognized as a center of excellence in research in osteochondritis dissecans, a rare condition affecting the knee. Participant 1 mentions that these phenomena should be visible in the data as well, suggesting to compare the variant frequency over time. They also state that the process mining tools should be used for monitoring changes in frequency of certain activities such as MRI imaging and brace application, so shifts in trends and patterns can be detected.

Referral and triage Another concept that was frequently mentioned during the interviews was referral and triage. 4 out of 5 participants (1, 2, 3, 4) recognized the problem of "*incorrect referral*", or referral of patients that were not suitable for the purpose of the MC. Participant 5, when asked about this issue, expressed surprise that their colleagues found this a problem, as triage is performed before patients enter the clinic, which should minimize the amount of incorrect referrals. The purpose of triage is to determine which specialist should see the patient, as well as assess in which time frame the patient has to be seen. During the interview, it became clear that triage was a complex topic in multidisciplinary healthcare, and some participants (2, 3, 5) expressed uncertainty as to how exactly triage was performed in the MC, and who was responsible.

Participant 4 recognized the possibilities that process mining techniques could offer with regards to incorrect referral. They suggested that process mining could be applied to evaluate the effects of educating referring doctors, such as general practitioners. They went on to explain that this could be done by reviewing variants that included referral by general practitioners and comparing them over time.

Remarkably, when asked about the possible applications of the tooling shown, one participant (2) considered the limitations of the tooling and discussed an application they thought out of reach for the analysis techniques used. They stated: "*What this tool is not able to tackle, I believe, is that there are a lot of patients who come here, who do not belong here yet. They should have been treated more adequately before coming here. That is related to triage, which has been done inadequately*". The current data selection indeed does not contain information on who performed triage, nor on what information the triage is based. The feasibility of such a research focus is dependant on the type and amount of triage data. This includes what is registered during triage and the availability of a patient's doctors' reports and imaging data. These remarks indicate that the participant was not only able to reflect on the possible application of process analysis, but able to recognize its limitations as well.

Financial aspect The third topic that came up during the interviews was the financial aspect of the MC. As previously mentioned, treatment in a multidisciplinary outpatient clinic in a teaching hospital can become quite expensive. This sentiment was echoed by multiple participants (1, 2, 3), specifically with regard to variation and complexity; "*If you make increase complexity, for yourself or for the outpatient clinic, you reduce profits*", as participant 3 stated. Participant 1 recognized the value of the process analysis in relation to complexity and costs: "*It would be good for management to see this, this level of complexity. They often tend to think that the knee is very straightforward, but this analysis can show that it is indeed very complex*". Participant 2 stated that high variation complicates work for support staff, as well as increase costs. They recommended that the dataset be enhanced with financial data, so variants can be analysed based on their costs. They added that "*everything has a price tag in the end. Especially management would be interested in that aspect: how much does it cost, and can we do it for less?*".

There were other recommendations made that do not fall into the three categories mentioned. For example, participant 3 discussed a phenomenon regarding the waiting list for the MC. They stated that "*sometimes, the waiting list in itself is a solution*", as patients experience improvement of their condition or drop out of the waiting list due to other reasons. The participant proposed to analyse whether the amount of time spent on the waiting list might affect the patient's subsequent pathway.

Participant 1 mentioned another possible future application of process mining techniques in the MC: *prediction*. They suggested using the tool to make predictions regarding a patient's pathway, based on referral and other healthcare activities: "*For example, if a patient is referred by a specialist, then the chance of needing surgery is* x*, if referral is done by a general practitioner, the chance is* y*. What are the chances that a patient has to visit a sports medicine physician? Or needs another X-ray? Or needs a brace? These* apriori *chances would be interesting to analyse*".

One participant (5) was unable to come up with any possible applications of process mining techniques such as the ones used for the demonstrated process analysis. After some encouragement, they demonstrated once more that they did comprehend the process analysis and was able to correctly interpret the model, but they still struggled to think of hypotheses or theories to investigate using the tool. Notably, the participant had been very clear and confident in their reflection on their role in the MC and the MC itself, but seemed to become less certain and assertive as the interview progressed. Their answers to the questions became shorter and contained more expressions of doubt, frequently stating that some questions may be out of their area of expertise.

4.3.3 Incorporating process analysis tools in current work

In the final part of the interview, participants were encouraged to reflect on the usability of process mining techniques in the MC. More specifically, they were asked whether they saw value in the process analysis, as well as if and how they would incorporate the use of such tooling in their own day-to-day work. Furthermore, if they could not imagine themselves working with these tools, they were asked to discuss what type of roles would be more appropriate to be the intended end user.

Most participants stated that the process analysis would be of use for management, by supporting decision making and policy. For example, participant 1 stated that "*it is very important for management to know where patients come from and where they are going*". Participant 2 mentioned that insights provided by the analysis could show management that the high costs of multidisciplinary healthcare are justified, as it involves complex processes. Furthermore, participant 2 suggested that the tool and techniques should be used in knee-related education as well. They added that students could offer fresh perspectives on the analysis and pose interesting questions.

Regarding the use of the tooling by medical specialists directly, opinions differed. For example, participant 1 and 2 both expressed the need for medical specialists to have insight in their own patient flows. However, participant 4 stated: "*If I encounter efficiency problems in my work, I do not need a model to detect that and find a solution. For people in overarching roles such as management, it would make sense that they would require a model or a data analysis to detect inefficiencies. Using such a tool would make sense for them*". They added that management and medical specialists might require different levels of detail in a process analysis: "*You should simplify it and categorize it in order to make it usable for specialists. Management-wise, it would be more useful to have such an extensive analysis*".

Participant 3 also seemed conflicted on how to incorporate the use of process mining tooling in the MC. On one hand, they mentioned that "*there is only a fine line between doctors and managers, doctors are kind of like managers these days*", and they acknowledged that the tooling could provide medical specialists with insight in their patient flows. On the other hand, the participant stated that the tooling would not be as useful to them as to others, as orthopaedic cast technicians "*only operate at the end of the chain*", and require orthopaedic surgeons and sports medicine physicians to perform examination and provide diagnoses.

One participant (5) was not able to envision the use of process analysis techniques such as the ones used in the demonstration in the MC. They could not imagine using the tooling themselves and were unable to come up with hypotheses or theories to investigate using process mining. Furthermore, they were not sure that people in coordinating roles would have the knowledge and expertise to incorporate the use of such tooling in their day-to-day work. They concluded that "*it might be something for the medical specialists*".

In table 8, a summary of the levels of transfer that occurred for each participant is shown. Overall, 4 out of 5 participants were able to use the knowledge gained through the demonstration to conceptualize and reflect on process analysis in the MC.

Participant	**Transfer**			**Overall**
	Explaining observations	**Imagining possible applications**	**Incorporating process analysis tools**	
1	Good	Good	Good	Good
2	Good	Good	Good	Good
3	Good	Good	Good	Good
4	Good	Good	Good	Good
5	Good	Poor	Poor	Poor

Table 8: Indications of knowledge transfer for interview participants

4.4 Summary

Overall, 4 out of 5 participants were immediately able to read the models and understand the process analysis, performing well during the retention part of the interview. The participant that struggled to interpret the models correctly at first had indicated a lack of confidence in their data skills, but was able to grasp the basic elements after some more guidance. All participants were able to reflect on the analysis in comparison to their own mental models. Some participants were even able to reflect on possible explanations for differences, such as data selection and filtering.

Regarding transfer, each participant was able to interpret and find an explanation for phenomena seen in the analysis, but reflecting on factors that could affect the accuracy of the analysis proved to be difficult for 3 out of 5 participants. When asked to come up with recommendations, 4 out of 5 participants were able to recognize the possible added value of the tools. Furthermore, 2 participants were able to accurately describe a possible research set up using process mining techniques, while a third participant was able to reflect on the limitations of the tools. Only 1 participant said they had trouble envisioning the use of process mining techniques in the MC. Finally, when discussing the possible manner of use of the tools, opinions differed. 4 out of 5 participants considered the tools useful for management, while 2 out of 5 stated that medical specialists should apply the tools as well. 1 participant disagreed, as they saw no value in the tools for medical specialists. 1 other participant could see the benefits of the tool when used by medical specialists, but added that this did not apply for their specific specialism.

After relating the results of the interviews to the understandability outcomes adapted from Reijers et al [4], it can be assessed that for 4 out of 5 participants, meaningful learning about the domain has occurred. This is shown in table 9. For 1 participant, the outcome of the demonstration was fragmented learning about the domain. Consequently, 4 out of 5 participants showed multiple examples of process thinking after the demonstration by reflecting on the analysis and describing possible future applications of process mining techniques in the context of the MC.

Participant	**Retention**	**Reflection**	**Transfer**	**Learning outcome**
1	Good	Good	Good	Meaningful learning
2	Good	Good	Good	Meaningful learning
3	Good (after further assistance)	Good	Good	Meaningful learning
4	Good	Good	Good	Meaningful learning
5	Good	Good	Poor	Fragmented learning

Table 9: Learning outcomes of interview participants

5 Discussion

In this section, the implications of the results of the research are discussed. Their validity is assessed by relating them to current literature. Furthermore, the limitations of the research are considered, as well as challenges that were encountered during the execution of the research plan. Lastly, recommendations are made for future work.

5.1 Implications

Process analysis using process mining techniques can stimulate process thinking in multidisciplinary healthcare. While literature often mentions that certain approaches can provide insight in processes and support decision making, little research has been done to assert the suitability of process analysis using process mining techniques as a tool to encourage process thinking throughout the process chain. In this study, healthcare providers were given a demonstration and explanation of process analysis tools in order to analyse its impact on their ability to communicate and reflect on processes. During the interviews, each participant displayed their ability to interpret process models and relate the analysis to their own experiences in the MC. Furthermore, 4 out of 5 participants showed examples of process thinking by coming up with possible applications of process mining techniques and envisioning the integration of process analysis tools in the MC. They were able to take the knowledge on processes gained through the demonstration and apply it to communicate the challenges they face in their work. Moreover, participants were able to describe possible research designs using the process analysis tools, in order to analyse these challenges.

The results of this research show that medical specialists are able to comprehend, interpret, and conceptualise applications of process mining techniques for the analysis of multidisciplinary healthcare processes. This suggests that through the application of process mining techniques, process thinking in multidisciplinary healthcare can be stimulated. Process analysis can help healthcare providers in multidisciplinary healthcare to frame their experiences in the context of business processes. This offers them a new perspective from which to analyse the challenges they face. Additionally, by sharing the process analysis with all actors in the process chain, a common knowledge base and terminology is provided. This helps actors reflect on their role and effectively communicate their role to others [19]. One's ability to do so is considered a psychological determinant for collaboration in healthcare, influencing their willingness to adapt their style of working to serve a common goal [31]. This willingness to adapt was also prevalent during the study, as the interview participants were able to imagine various different types of integration of process analysis tools into their work environment.

In order to effectively use process analysis tools to stimulate process thinking, role characteristics should be taken into account. In this research, all participants were given highly similar, scripted demonstrations, but experienced differing learning outcomes. While some participants cited lack of confidence in data analysis, other participants specifically related their incomprehension or inability to see value to the role they played in the research context. One participant explicitly stated their theory that the level of detail of the process analysis should be tailored to the intended end user. This theory is supported by the research done by Martinez et al. [59] in the context of building process mining dashboards for operating rooms. They analysed staff expectations for the usability of such a dashboard, after grouping various roles into three categories: *technical*, *clinical*, and *managerial* staff. As they stated, "*Results showed different weights for the features in the process mining dashboard for each group*", which suggests the need for role adaptation in process mining applications in healthcare.

The next question would be "*How to categorize the various roles in multi-disciplinary healthcare in order to provide adaptation*?". Martinez et al. [59] distinguished between management functions, such as HR and reporting, clinical staff, such as doctors and nurses, and technical staff, such as data managers. However, it could be argued that there are more distinctions to be made between clinical staff. As stated by a participant of this research, "*doctors are kind of like managers these days*", complicating the distinction between clinical and management functions, as well as causing variation in the information needs of differing medical specialists. Another participant suggested that their position in the process, specifically the fact that they were only involved in the final part of the process, caused the process analysis to be less relevant to them. The nature of an actor's involvement in the process, as well as in the research context, might be cause for adaptation as well. In the *integrative framework of the factors affecting process model understanding* designed by Reijers et al. [4], the importance of considering user characteristics is included as well. Examples of intrinsic motivational attributes that may affect the learning process regarding process models are *attitude* and *self-efficacy*. During the interviews, much contrast could be found in these attributes of the participants; while some repeatedly expressed their uncertainty and lack of confidence, others showed great enthusiasm and curiosity. Moreover, one participant seemed to become less confident as the interview went on. So while empowering for some, the demonstration of process analysis tools might lead to insecurity and reduce empowerment for others.

5.2 Limitations

There are several limitations to this research that affect the validity of the conclusions that are drawn. In this section, these limitations and threats to validity are discussed.

5.2.1 Validity of the implications

First, construct validity is discussed. Construct validity pertains to the structure of the research and the research methods chosen, and the question whether what was measured is what was intended to be measured. In the context of measuring a shared understanding, a major threat to construct validity was the absence of a tried and tested measurement instrument. Originally, the research plan consisted of the design of a survey to measure a shared understanding before and after an intervention, in order to collect quantitative data on the concept. However, due to time limitations, the survey could not be properly validated before deployment, in order to produce significant quantitative data. For this reason, the main instruments used for assessing the impact of the process analysis on domain experts became semi-structured interviews, which offer qualitative data. In designing the interview script, the guidelines for designing and selecting understandability questions by Laue et al. [58] were considered. They mention the importance of adapting questions to the hypothesis and the participants involved. However, in the literature, no specific examples of understandability questions for medical experts could be found. To provide structure to the interview, the learning perspective on understandability of process models as adapted by Reijers et al. [4], as shown in table 1, was used as a framework for creating interview questions.

Furthermore, the implications that were made are subject to internal validity threats. The main threat to internal validity is the quality of the process analysis. To limit the risk of the process analysis providing little insight, a structured approach was taken to perform the analysis: an established framework for data mining, CRISP-DM [3], was applied. Additionally, the demonstration was given to a domain expert for review before it was used in the interview. However, no formal metrics or quantitative measurements were done to assess the quality of the process analysis. Additionally, in this research, only a small number of interviews were conducted. A spread of medical specialists and support staff was selected as participants, one of each role involved. With such quantities, it is difficult to relate differences in interpretation or impact exclusively to role. Variation could also be related to other characteristics such as attitude or personal experience [4], or even be affected by the measurement instrument. To mitigate this last threat, both the survey and the interview script were reviewed by a domain expert, to limit any misconceptions about terminology for example. In order to properly draw conclusions on process thinking based on role, more interviews should be performed with multiple participants who fulfill similar roles. However, due to time constraints, scheduling challenges, and COVID-19 related limitations, it was not feasible for this research to interview participants at a quantitatively significant scale. Additionally, during the interview, participants should be encouraged to reflect on other factors that might influence their reaction to the process analysis, such as confidence level and personal expectations.

Another type of validity to consider is external validity. External validity pertains to the question of generalizability. To what extent can the same results be expected when the research design is applied to a different context? This research was performed in a multidisciplinary outpatient clinic at UMC Utrecht. Although the concept of the MC is relatively new, and currently only applied at UMC Utrecht, multiple healthcare organizations have expressed interest in adopting the concept. Due to the structured approach to the research design, it would be reasonable to expect similar results if the research would be conducted at an architecturally similar concept in a different hospital.

5.2.2 Challenges in the research context

During the execution of the research plan, some challenges were encountered that influenced the progress of the research. The extraction of the data needed for the analysis proved to be a complicated process, as data ownership at UMC Utrecht turned out to be quite complex. First, their research data platform seemed like the suitable source to select from, as the required data attributes were included and anonymisation had already taken place. However, extracting large quantities of data from different departments was very costly. As the MC intended on continuing working with process mining techniques after the research, some time was invested into finding a feasible, efficient approach to extracting the data, that could be used long-term. Eventually, another source was found, but this brought along new issues regarding data attributes, that required some time to solve. Eventually, the analysis could be done, but the limited time left affected the level of detail that the analysis was able to have.

Another example of a challenge in the construction of the analysis was the lack of registration of completion. As there were no attributes or other data elements that marked a patient's pathway as "*completed*", it proved difficult to determine if and when a patient's pathway in the hospital had ended. Eventually, after consulting multiple domain experts, a time frame was selected. This method of determining a patient's path greatly affected the accuracy of the process analysis.

Finally, the COVID-19 pandemic had its effects on the research as well. During the peaks of the pandemic, non-urgent care was postponed, which included surgeries in the MC. During the interviews, the effects of COVID-19 came up multiple times, when discussing communication problems. Furthermore, due to the pandemic, several aspects of the research plan were altered. For instance, during the observation in the MC, it was not always possible to sit in on patient consults, as there was a maximum number of people allowed in one room. Additionally, some interviews had to be conducted digitally, due to health issues or working from home, for example.

5.3 Future work

In this section, some recommendations are made for future work. These recommendations are based on the implications of this research, the challenges encountered during the execution of the research plan, and the recommendations made by the domain experts during the interviews.

First, more research should be conducted on the understandability of process models, with a focus on medical experts. Until now, participants in quantitative understandability studies are often students or consultants who are experienced with, or at least have affinity with process models. However, the use of process models for analysis could extend to people with other backgrounds than IT or data. In order to stimulate process thinking throughout the process chain, the process analysis has to be shared with people from various types of backgrounds, types of jobs, and levels of experience with data. The variation in these groups are often not represented in understandability studies. Additionally, quantitative research should be done on the influence of role characteristics on the effects of process analysis.

Another possibility for future research is the design and validation of a measurement instrument, such as a survey, that can be used to assess a level of shared understanding, or process thinking, if specifically applied to the context of business processes. While this was originally part of the design of this research, the scope would have been too broad for the allotted time. The need for a structured approach to measuring a shared understanding was highlighted by Letsky [33] as well. The availability of a validated measurement instrument such as a survey would enable researchers to analyse the effects of interventions aimed at improving a shared understanding, both qualitatively and quantitatively.

Furthermore, the financial aspect of integrating a horizontal healthcare department in a vertically structured healthcare organization should be investigated. During the interviews, the financial challenges of the MC were mentioned multiple times, such as frequent discussion about which division is financially responsible for certain treatments. One of the recommendations that were made was to enhance the dataset with financial data, in order to analyse pathway costs and responsibility.

6 Conclusion

The aim of this research was to assess whether process analysis using process mining techniques could be used to improve a shared understanding of processes in multidisciplinary healthcare. In order to answer this main research question, several sub-questions were posed.

How can a shared understanding of business processes in multidisciplinary healthcare departments be assessed? First, an approach to assessing a shared understanding of business processes had to be determined. Through a systematic review of relevant literature, it was concluded that due to a lack of quantitative measurement instruments, the focus of the study had to be on qualitative assessment of a shared understanding of processes. Consequently, semi-structured interviews with domain experts were deemed an appropriate research method for achieving the research goal. By applying a learning theory known as CTML to structure the interviews, learning outcomes for each participant could be established.

Who are the stakeholders in a multidisciplinary healthcare department? The next sub-question concerned the stakeholders of the multidisciplinary healthcare department, their goals, and the challenges they encounter. Through observation, systematic literature review, and a survey, the problem context of the research was analysed. Several factors that influence collaboration in healthcare were identified, such as the willingness to adapt one's working style to suit a collaborative effort and the ability to effectively communicate one's role and responsibilities. These psychological determinants and educational determinants were considered during the design of the process analysis and interview script.

How can processes in multidisciplinary healthcare be analysed? The third sub-question pertained to the design of a process analysis in the context of multidisciplinary healthcare. As manual extraction of process models from event data can be time-consuming and costly, process mining techniques were applied. Various types and applications of process mining techniques were researched and discussed, such as process discovery, social network analysis, and conformance checking. Taking the results of the problem context analysis into account, a selection of suitable techniques was made. This included constructing a control-flow model using a Fuzzy miner in Disco, as well as log exploration in ProM. Additionally, considering the educational determinants that were previously discussed, a role interaction model was to be constructed in Disco for the purpose of social network analysis.

Does process analysis by process mining stimulate process thinking in multidisciplinary healthcare departments? The research design was executed during a case study at the knee division of UMC Utrecht's Mobility Clinic. Patient data was extracted and transformed into an event log, which was mined for processes. The resulting process models and analysis were demonstrated to 5 staff members of the clinic during semi-structured interviews. The goal of these interviews was to assess whether the process analysis stimulated process thinking among the participants. During the interviews, they were asked to reflect on the analysis and come up with recommendations for the application of process mining techniques in the MC. From these interviews, it can be concluded that process analysis can stimulate process thinking and enable medical domain experts to envision the use of process mining techniques in their multidisciplinary healthcare department. Furthermore, the variation in response might be related to role characteristics, so in future research, these must be taken into account.

How can process analysis by process mining be used to improve a shared understanding of processes in multidisciplinary healthcare departments? In conclusion, the results of the study suggest that through a demonstration of analysis of process models, a shared understanding of processes can be fostered for team members of a multidisciplinary healthcare department. Process analysis tools can enable medical specialists and other healthcare providers to conceptualize their experiences in the framework of process management and envision the application of process mining in their own working context. Furthermore, results imply that variation in the usefulness of process analysis tools for actors in the process chain may be linked to role characteristics, such as experience, self-efficacy, or position in the process.

The contribution of this research is the exploration of the unique value proposition of process mining in the context of healthcare, as well as insight in the understandability of process analysis for domain experts in multidisciplinary healthcare.

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A Screenshots Process analysis tools

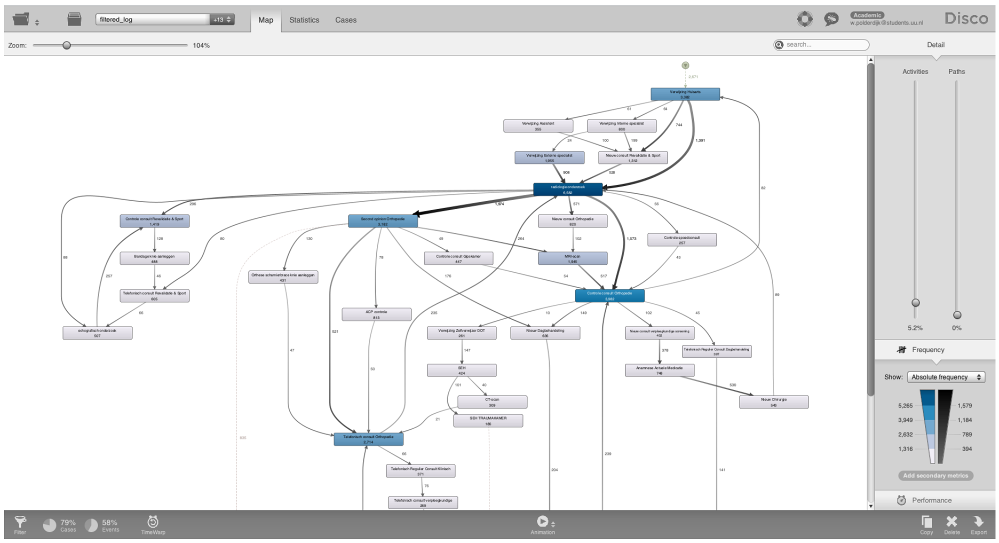

Figure 5: Control-flow model in Disco

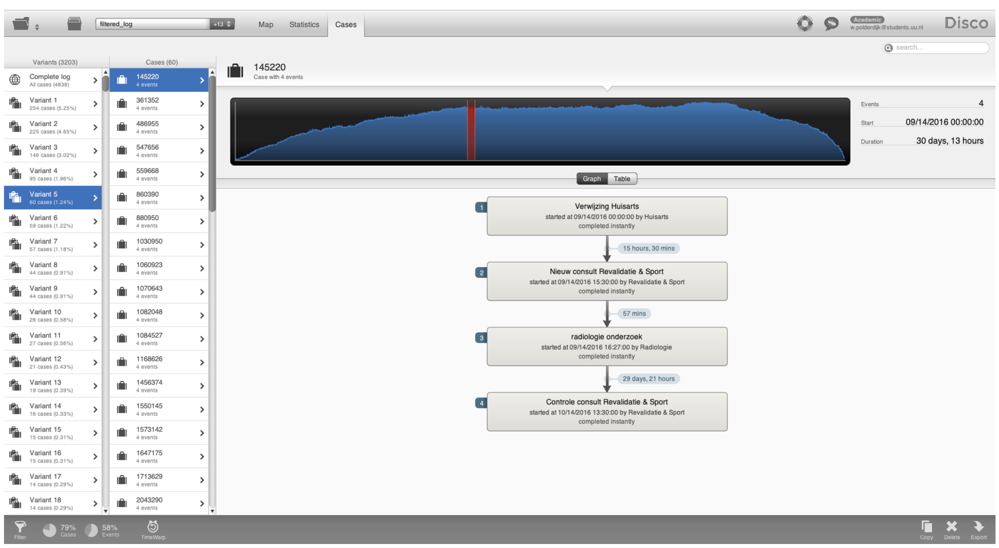

Figure 6: Variant analysis in Disco

Figure 7: Log exploration in ProM

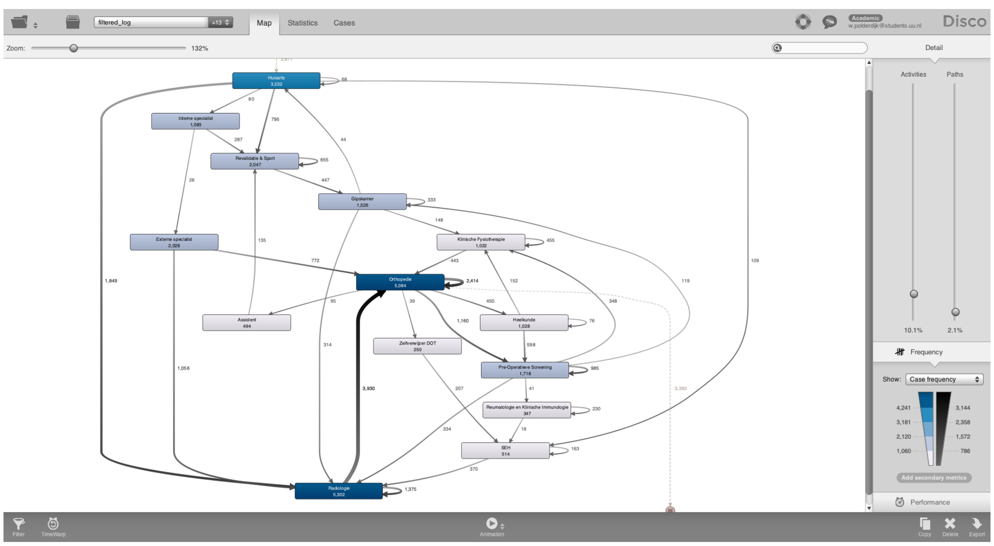

Figure 8: Role interaction model in Disco

B Interview design

Introductie
In dit interview gaan we het hebben over de patiëntstromen door de Mobility Clinic. Ik ben benieuwd naar uw inzicht in de patiëntstromen en communicatie in de Mobility Clinic. Daar ga ik eerst wat vragen over stellen. Daarna zal ik een demonstratie geven van de procesanalyse waar ik de laatste tijd aan gewerkt heb, waarbij ik wat uitleg over processen en procesmodellen, en hoe deze door middel van process mining tot stand komen. Vervolgens heb ik wat vragen over deze procesanalyse en ben ik benieuwd naar uw indruk van de procesmodellen en process mining, en hoe dit gebruikt kan worden in de Mobility Clinic.

Eigen beeld patientstromen

- Volgen veel patiënten dezelfde routes of volgt ieder een uniek pad?
- Ziet het merendeel van de patiënten behandelaars van meer dan 1 specialisme?
- Langs welke afdelingen/specialismen van het UMC Utrecht gaan patiënten van de Mobility Clinic?
- Hoeveel patiënten zien voor dezelfde klachten meer dan 2 soorten specialisten?
- Wat voor problemen staan effectieve samenwerking in de Mobility Clinic in de weg?

Demonstratie
Een proces bestaat uit een aantal activiteiten die in een bepaalde volgorde worden uitgevoerd. De activiteiten worden uitgevoerd door een zorgmedewerker van een bepaald specialisme. In deze omgeving wordt het specialisme aangeduid met het woord ‘resource’. Een patiënt, in deze omgeving een ‘case’ genoemd, volgt een pad langs deze activiteiten. In een model staan een aantal activiteiten en een aantal paden langs de activiteiten. Een pad doet niet per se alle activiteiten aan, en kan sommige activiteiten meerdere keren beslaan. Zo kan een patiënt bijvoorbeeld meerdere controleconsults hebben.

Dit model is gebouwd op basis van een dataset die als volgt tot stand kwam. Eerst zijn alle patiëntnummers die bij de Mobility Clinic zijn geweest geselecteerd. Vervolgens zijn alle afspraken die die patiënten in het UMC Utrecht hebben gehad, bij elk specialisme, vanaf hun eerste bezoek aan de Mobility Clinic tot aan maximaal 3 jaar daarna, aan de dataset toegevoegd. Elk specialisme is hierbij meegenomen, omdat dat informatie kan verschaffen over andere specialismen die wellicht meer betrokken zijn bij de MC dan aanvankelijk gedacht.

Uiteindelijk zijn er ruim 6000 patiënten met 80.000 afspraken of verrichtingen geselecteerd.

Niet alle afspraken zijn relevant voor de Mobility Clinic. Activiteiten en specialismen die maar enkele keren voorkwamen in de dataset zullen geen deel uitmaken van frequente processen in de MC, dus kunnen weggefilterd worden. Daarnaast is de dataset verrijkt met verwijzersinformatie.

(Control-flow model) Vervolgens is de dataset geupload in deze omgeving, Disco. Disco gebruikt een algoritme om een procesmodel te bouwen waarin de meest voorkomende volgorden van activiteiten te zien zijn. De blauwe labels zijn de activiteiten. De intensiteit van de kleur en het getal in het label geven aan hoeveel cases (patiënten) deze activiteit aandoen. De pijlen geven het pad aan. De getallen bij de pijlen geven aan hoeveel cases dit pad volgen. Met de sliders hiernaast kun je bepalen hoeveel van de activiteiten (top 0-100 activiteiten) en hoeveel van de gelopen paden tussen deze activiteiten (top 0-100 paden) er zichtbaar zijn. Wanneer niet alle activiteiten en paden getoond worden, kan het dus kloppen dat de getallen bij de paden en activiteiten incompleet lijken.

De eerste observatie die je kan doen is dat het procesmodel erg veel activiteiten en mogelijke paden bevat. *(Sliders maximum)* Op deze manier is het procesmodel onleesbaar. Dit is een indicatie van de complexiteit van de zorgprocessen, zoals wellicht te verwachten valt van een academisch ziekenhuis. Omdat de MC patiënten met complexe knieproblemen en co-morbiditeit behandelt, zijn er maar enkele veelvoorkomende zorgpaden te identificeren. Een bepaald pad, een volgorde van een aantal activiteiten, wordt een 'variant' genoemd. Frequente paden, variants die door veel cases gevolgd worden, zijn over het algemeen korte paden, zoals een patiënt die verwezen wordt door een huisarts of externe specialist, een radiologieonderzoek doet en een enkele consult of second opinion krijgt. Dat betekent niet dat het merendeel van de patiënten die doorverwezen worden zo'n kort pad volgen. Patiënten die langere routes afleggen, leggen 'uniekere' paden af, waardoor deze niet terug te zien zijn als veelvoorkomende variants. Omdat korte paden uit weinig activiteiten bestaan, is er ook minder variatie. Tussen de populaire paden zijn ook een paar langere processen te vinden. Zo herken je in een variant het pad van een patiënt die ACP-injecties krijgt. *(Variant 17/18/19)*

(ProM Log exploration met rollen) Hier zie je paden die patiënten afleggen langs verschillende specalismen. Elk specialisme heeft zijn eigen kleur. Hier valt bijvoorbeeld op dat een patiënt voorafgaand aan een afspraak bij de Orthopedie meestal langs de Radiologie-afdeling gaat. Patiënten die naar een specialist van Revalidatie en Sport gaan, hebben juist vaker daarná een afspraak op de Radiologie.

(Role interaction model) Dit is een model van de paden die patiënten afleggen tussen de verschillende specialismen. Door de sliders aan te passen,

worden meer specialismen toegevoegd, op volgorde van frequentie. Door middel van animatie kan je goed zien hoe frequent patiënten zich tussen bepaalde specialismen bewegen. Je ziet ook de specialismen naar zichzelf verwijzen. Een patiënt die bijvoorbeeld zo'n lijn van Orthopedie naar Orthopedie volgt ziet niet per se twee verschillende orthopeden, maar heeft wellicht gewoon twee keer een afspraak bij de Orthopedie, zonder tussendoor iemand van een ander specialisme te zien.

Retentie

- Uit welke elementen bestaat een proces?
- *Control-flow model*
- Hoeveel patiënten zijn verwezen door de huisarts?
- Welke activiteit volgt er het vaakst op een radiologieonderzoek? Hoeveel patiënten lopen dit pad?
- Welke activiteit gaat er het vaakst voorafgaand aan een MRI-scan? Hoe veel patiënten lopen dit pad?
- *Role interaction model*
- Welke specialismen worden het vaakst bezocht in de MC?
- Tussen welke specialismen is er veel interactie?

Reflectie

- Waarin komt het procesmodel overeen met je eigen beeld van de patiëntstromen in de MC?
- Waar zie je dat in terug?
- Waar zitten de verschillen tussen je eigen beeld en het procesmodel?
- Waar zie je dat in terug?

Transfer

- Een van de meest voorkomende paden bestaat uit een verwijzing van huisarts of externe specialist, gevolgd door een bezoek aan de Radiologie en daarna een afspraak bij de Orthopedie. Daarna stopt het pad. Wat zijn mogelijke verklaringen van zo'n kort proces? Welke factoren zouden de betrouwbaarheid van deze modellen kunnen beïnvloeden? Zijn er voorbeelden die je binnen je eigen rol bent tegengekomen?

- Een voorbeeld van een hypothese die voorafgaand aan dit onderzoek was gesteld is "Huisartsen verwijzen vaker patiënten die niet geschikt zijn voor een behandeling in de Mobility Clinic dan externe specialisten". Kan je meer voorbeelden noemen van vragen die je kunt stellen of hypothesen die je kunt testen door middel van process mining en procesmodellen?
- Hoe zou zo'n procesanalyse u kunnen helpen in uw werk?
- Voor welke rollen zou het gebruik van zo'n procesanalyse een nuttige toevoeging zijn?