

MASTER

Process mining in healthcare mining for cost and (near) incidents

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Process Mining in Healthcare

Mining for cost and (near) incidents

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Abstract

In healthcare, care processes are standardized using so-called care paths. The actual patient's care processes can conform to these care paths or can deviate from them. In this research, it is tested whether patient's care processes that deviate more from the care path, introduce higher costs and more incidents. This thesis will investigate the relation between conformance, incidents and costs in a healthcare context. The research is performed at the Isala hospital in Zwolle, Netherlands.

Process mining techniques are used to measure conformance of the patients care process with the model of the care path. Conformance is measured on two levels: process-wide and activity-based. The trace fitness variable is used as a process-wide variable and alignments are used to measure the activity-based conformance. To measure costs, three methods are considered: Activity Based Costing (ABC), Time-Driven Activity Based Costing (TDABC) and Resource Consumption Accounting (RCA). Finally, incidents are retrieved from the VIM system of Isala.

The methods to measure conformance, incidents and costs are implemented in a toolset, based on existing software (ProM [7], RapidMiner [9] and Disco [1]). The toolset gives insight in the care processes of a hospital by calculating a feature set and enhanced event log. These two data formats can be used to analyze the care process. The toolset is applied on a case study. Based on the data of this case study, incidents are not significantly related to the number of activities, costs or conformance.

Costs increased significantly with a decrease in conformance. Moreover, specific alignments of activities were linked to higher costs and a lower conformance. Clustered activities (activities that act as a group by being repeated or skipped together) have a high influence on conformance. Activities with an occurrence between 10% and 90% made the biggest difference on the total cost of patient's care process. Furthermore, it is expected that expensive and clustered activities have an influence on costs, if these activities are repeated or skipped. However, this effect was not seen in the case study, since there were no clusters with a high repetition.

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Chapter 1

Introduction

In hospitals, patients often follow specific care processes. It can be questioned whether these care processes lead to more efficient provision of care and a higher quality of care. Process mining techniques are used to get more insight in care processes. In this thesis, the effect of process mining on costs and incidents is investigated. A case study is performed at Isala in Zwolle, one of the biggest hospitals in the Netherlands.

1.1 Context

Hospitals have many care processes. For these processes, it is important to know how they are really executed. This information can be retrieved by process mining. A distinction is made between a care process in a hospital (e.g. diagnosing and treating a tumor) and the actual patient's care process (e.g. an intake, followed by a scan, making of a treatment plan and several radiation therapies). A patient's care process is an instance of the care process.

This research is performed at the Isala hospital, which has 5.300 employees and more than 800 beds. Each year, Isala handles 500.000+ visits to the out-patient clinic and over 89.000 clinical admission and day treatments. In order to keep the level of care as high as possible, Isala participates in scientific research.

1.2 Problem description

The motivation for this study originates from opportunities to improve efficiency and quality of care by making better use of the available data in healthcare enterprises [20]. For instance, event logs can be used to analyze and improve care processes. In recent years, healthcare processes have been defined to standardize healthcare in so-called care paths [19]. By using care paths, different steps of a patient's treatment can be predicted more accurately. The care path can be used to improve the department's logistics and planning process. Subsequently, this can lead to an improved utilization of personnel and other resources.

A question that arises is whether the introduction of a care path improves the quality of care and lowers costs. The presence of a well defined care path for a process does not guarantee a high level of care.

In practice, doctors can let patients deviate from a care path (on purpose or by accident). Process mining can give insight in such deviations. Patient specific activities are recorded in event logs. Each activity in a patient's care process (e.g. getting a CT scan) is logged in these event logs with at least a patient ID and a timestamp. By applying process mining techniques, these event logs are used to create a model of the actually followed care process. These models are then compared to the pre-designed care paths to analyze the deviation.

The costs of a care path can be estimated by looking at various paths patients take in the event logs. Different routes can have different costs allocated to them. However, there are multiple

approaches to allocate costs to an activity or process. Whereas the fixed costs of an activity might be straightforward, allocating process-wide variable costs or overhead costs to activities can be a challenge. The key is to find the most suitable costing method for process mining event data.

Isala wants to know whether conformance has an influence on incidents and costs. In case non-conformance results in higher costs and an increased number of incidents, it may be useful to intervene in the execution of the care process (e.g. motivate people to adhere to guidelines and protocols). On the other hand, if non-conformance leads to lower costs and fewer incidents, it can be investigated what deviations from the care path are actually beneficial.

To illustrate, see Figure 1.1. Assume this is data from a care process.

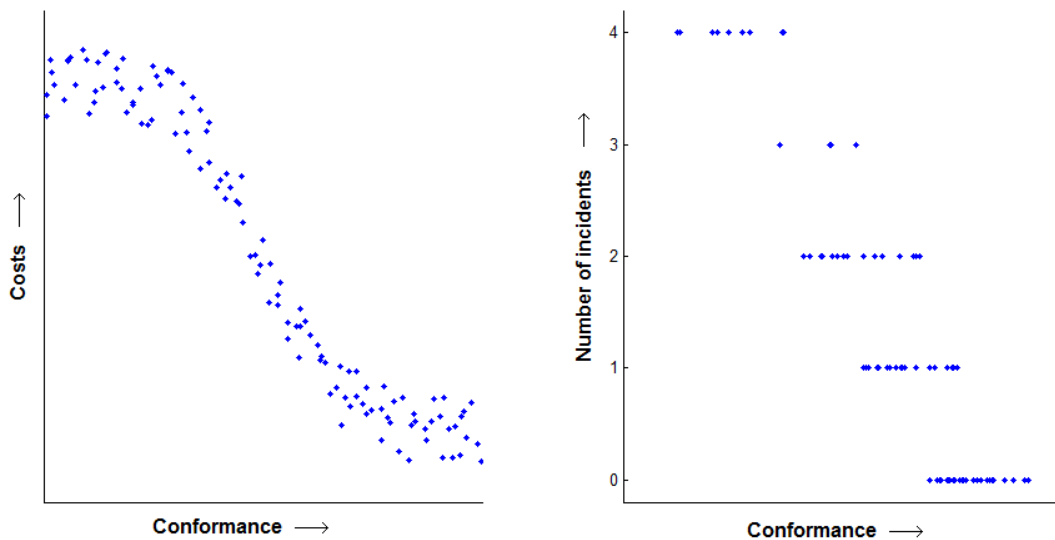


Figure 1.1: Example data to visualize the relation between conformance, incidents and costs

On the left, it is clearly visible that a higher conformance leads to lower costs. On the right, patients with more incidents during their care process have a lower conformance than patients with fewer incidents. That would mean that it is advisable to adhere to the care process, since that would lead to lower costs and less incidents.

Subsequently, for a care process it is interesting to regularly monitor its conformance to the associated care path. Monitoring allows a department to gain insight in the care process and make changes to the execution of the care path. A department wants to know whether the performance of the process stays the same, improves or even decreases. This needs to be checked periodically.

1.3 Research questions

Based on the problem description in Section 1.2, various research questions and tasks can be identified. The first challenge in this thesis is to link conformance to costs and incidents. In order to do this, conformance, costs and incidents will have to be measured. Based on this challenge, the following research questions can be defined:

- Investigate the relationship between process conformance on the one hand and incidents and costs on the other hand:
 - What method can best be used to measure conformance?
 - What method can best be used to measure costs?

- What method can best be used to measure incidents in a care path?
- How can conformance, costs and incidents be compared to each other?

Based on patient data, a department wants to see their performance on conformance, costs and incidents. A tool is needed that applies the methods to calculate these three variables and compare them. This leads to the research questions below:

- Describe an approach to monitor a care process, based on which the performance on conformance, costs, and incidents can be determined
- Create a toolset that aids the management in monitoring the care path processes
 - What input data are required for the tool?
 - What meaningful results can be presented to the end-user?
 - How is the toolset realized?

To validate the results, process experts are asked for feedback on the obtained results. Therefore, the final research question is:

- Do the results and conclusions found in this study make sense in practice?

1.4 Hypotheses

To define what relations are to be tested, a series of hypotheses are formulated. Costs (Def. 1), incidents (Def. 2) and conformance (Def. 3) are the three variables that will play a central role in this thesis. These will be described further on in this chapter in more detail.

Definition 1 (Costs) *Sum of the expenses for each activity in a patient's care process, including costs of the resource(s) performing the activity and optionally overhead costs, material costs and fixed costs.*

Definition 2 (Incidents) *Unintended event during the care process that led, could lead or (still) may lead to harm to the patient [21].*

Definition 3 (Conformance) *The degree in which a patient follows the care path. A patient that perfectly follows the care path has a conformance of 1 and a patient that deviates from the care path has a lower conformance. The more the patient deviates from the care path, the lower the conformance will be (with a minimum value of 0).*

What effect will a high conformance have on the incidents and costs? The philosophy behind a care path is to standardize the care process for patients with similar medical conditions. Care providers will be more familiar with the care process if they know what to expect. Also, by standardizing a care process, it becomes possible to forecast more efficiently. Therefore, it can be expected that a care path introduces fewer and less severe incidents and lowers costs. Based on that, the following hypotheses are formulated:

Hypothesis 1 *A higher conformance (a patient that deviates less from the care path) leads to fewer incidents in a patient's care process.*

Hypothesis 2 *A higher conformance leads to less severe incidents in a patient's care process.*

Hypothesis 3 *A higher conformance leads to lower costs in a patient's care process.*

Another interesting variable to take into account is the complexity of the patient's care process. The complexity variable of the patient's care process can be measured in multiple ways. In this study, a simple definition of complexity is used:

Definition 4 (Complexity) *number of activities in a patient's care process.*

A patient with a complex care process will probably use more resources of the hospital, leading to higher costs. Also, it is expected that patients with more activities have a higher chance of having an incident. Assume that every activity has a chance x (between 0 and 1) to cause an incident. In that case, the chance of having no incidents ($p(NI)$) for a patient with n activities is calculated as follows:

$$p(NI) = (1 - x)^n \quad (1.1)$$

Therefore, more activities (a higher n) lead to a lower chance of not having an incident ($p(NI)$). For example, if every activity has a 10% chance to lead to an incident ($x = 0,1$) and there are two patients: one with five activities ($n = 5$) and one with ten activities ($n = 10$) in his care process, the chances of not having an incident are approximately 0,59 and 0,35 respectively.

It is trivial to investigate the relation between the complexity and costs, since both of them are based on the number of activities. Therefore, the hypotheses for the complexity of a patient's care process are:

Hypothesis 4 *A patient with more activities in the care process has a higher number of incidents.*

Hypothesis 5 *A patient with more activities in the care process has more severe incidents.*

An illustration of these hypotheses can be seen in Figure 1.2. A (+) stands for a positive relation and a (-) stands for a negative relation.

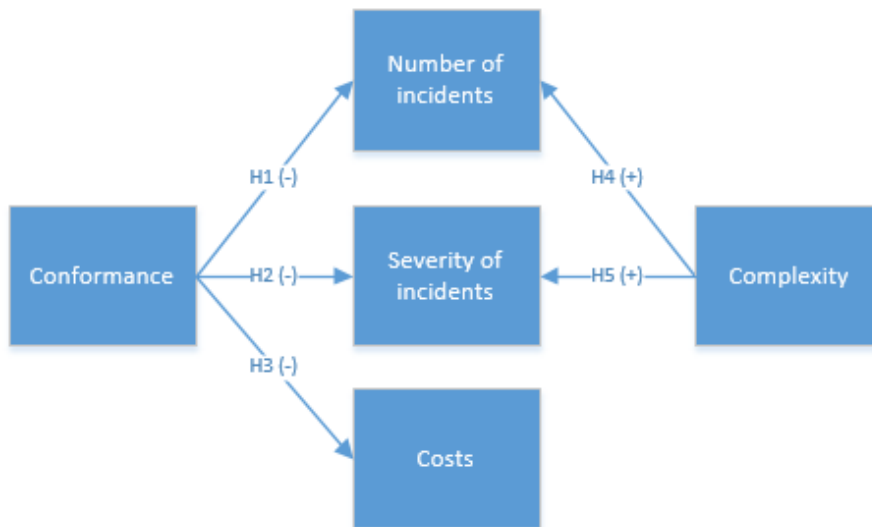


Figure 1.2: Hypotheses

1.5 Scope

Data in this study is retrieved from the Radiotherapy department at Isala. The process that is investigated is limited to the intake of new patients, the diagnosis of possible tumors and the making of a plan to treat the tumor. The actual radiation therapies are out of the scope. For this thesis, the process ends with the first radiation therapy.

The case study is applied on historical patient data between February 2013 and February 2014. These data contains the activities performed by the patients, based on which the patient's care process can be identified.

Furthermore, incident and cost data (e.g. salaries, cost of specific activities) is used. This is required to relate conformance, incidents and costs.

Process mining techniques will be applied on these data. Process mining is a broad field. A part of it, conformance checking, is used to what degree a patient follows the care path. This will be explained in more detail in Chapter 2.

1.6 Outline

An overview of the chapters can be seen in Figure 1.3.

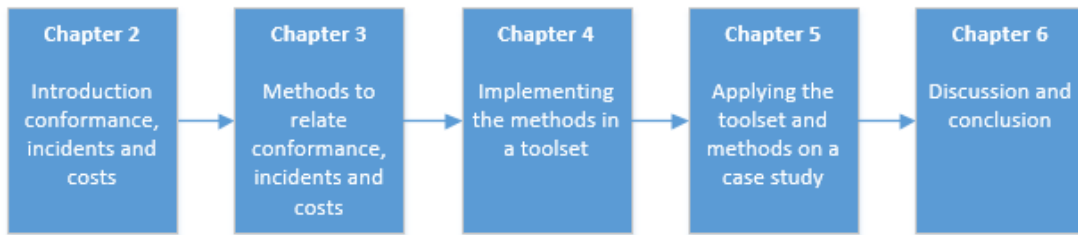


Figure 1.3: Outline chapters

First, Chapter 2 will give an introduction to the process mining techniques used in this study and introduces methods from literature to measure conformance, incidents and costs. Conformance checking is a part of process mining. For costs, three methods are considered (Activity Based Costing, Time-Driven Activity Based Costing and Resource Consumption Accounting). Also, the incident reporting system (VIM) is described.

The approach to relate all variables to each other are explained in Chapter 3. The data that is needed are described and a costing method is selected.

Chapter 4 describes the software and concept of the tool that is created to aid in monitoring a care process. Then, a general overview of the functionality of the tool is given.

Next, the tool is applied on a case study performed at the Radiotherapy department of Isala. The results of this study are described in Chapter 5.

Finally, this thesis is concluded with a discussion and conclusion (Chapter 6).

An overview of the content of the thesis can be seen in Figure 1.4. Data is extracted, transformed and loaded (ETL) from the HIS (Healthcare Information System) to retrieve event logs, incident data and cost data. Based on the guidelines and protocols (e.g. care paths), conformance checking techniques can be applied in order to get conformance data. For the cost, incident and conformance data, a theoretical framework to relate these data to each other and a theoretical definition of two data formats (an enhanced event log and feature set) is designed. This framework is realized in a toolset, that outputs the two data formats. Finally, the toolset is applied on a case study at Isala and the results are evaluated.

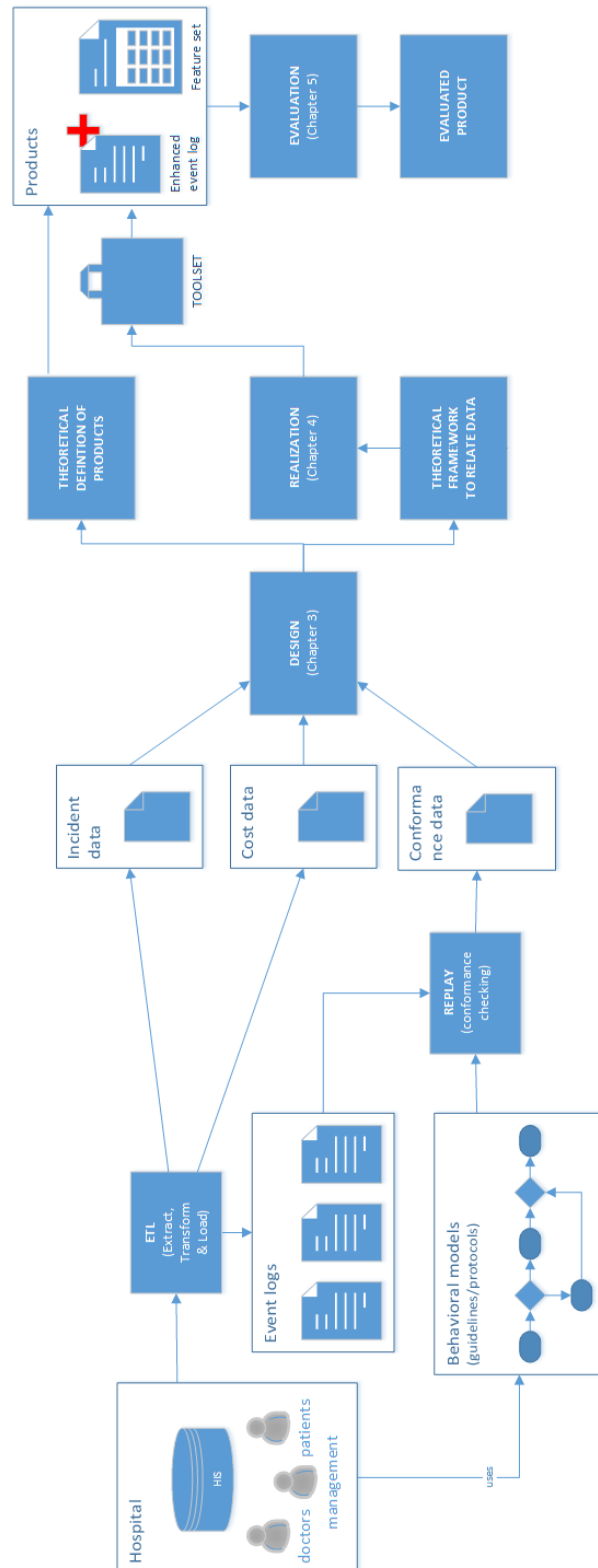


Figure 1.4: Overview thesis

Chapter 2

Preliminaries

This chapter covers previous research on which this study is based. First, some of the basics of process mining is introduced (Section 2.1). Conformance checking (a part of process mining) is described in more detail, since it plays a central role in this study. Conformance measures how closely patients follow a care path. To calculate conformance, alignments are used. Alignments indicate which activities are done and if these activities are done conforming to the care path.

In this study, it is investigated whether conformance has an influence on the number of incidents during a patient's care process. Therefore, the incident reporting system used at Isala is described in this chapter (Section 2.2). Furthermore, if activities in a patient's care process are known, patient-specific costs can be determined. The costing method used at Isala and various costing methods from literature are explained (Section 2.3).

2.1 Process mining

2.1.1 Basics of process mining

The "Process Mining Manifesto" [26] defines process mining as follows: "techniques, tools, and methods to discover, monitor and improve real processes by extracting knowledge from event logs commonly available in today's (information) systems".

An event log is a list of all activities performed in a process. In a hospital, information about a patient's care process is recorded in event logs. These event logs contain so called traces, in which activities are grouped per patient. Besides activities, also the resources and timestamps of these activities are recorded. An example of an event log with one activity is displayed in Table 2.1. This activity consists of two events, one recorded at the start ("start") and one at the end ("complete") of the activity.

Patient ID	Activity	Resource	Timestamp	Lifecycle
199281	CT Scan	P. Johnson	01-01-2014 09:00:00	start
199281	CT Scan	P. Johnson	01-01-2014 09:30:00	complete

Table 2.1: Example Event Log with "start" and "complete" timestamp

Process mining includes the following activities (Figure 2.1) [26]:

- Discovery: "based on an event log, a process model is defined. For example, the α -algorithm [14] is able to discover a Petri net by identifying process patterns in collections of events."
- Conformance checking: "analyzing whether reality, as recorded in a log, conforms to the model and vice versa. The goal is to detect discrepancies and to measure their severity."

- Enhancement: "A process model is extended or improved using information extracted from some log. For example, bottlenecks can be identified by replaying an event log on a process model while examining the timestamps."

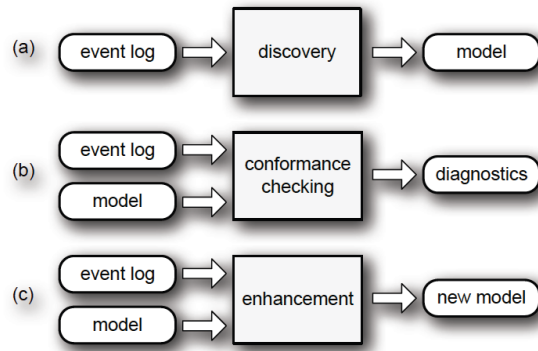


Figure 2.1: Discovery, conformance checking and enhancement in process mining

Conformance plays a central role in this thesis and is therefore described in more detail.

2.1.2 Conformance checking

Conformance checking determines to what degree the behavior in the model is reflected in the event log. Conformance checking consists of four quality criteria [13]:

1. Fitness: "the discovered model should allow for the behavior seen in the event log"
2. Precision: "the discovered model should not allow for behavior completely unrelated to what was seen in the event log"
3. Generalization: "the discovered model should generalize the example behavior seen in the event log"
4. Simplicity: "the discovered model should be as simple as possible"

In the context of this thesis, the model is the care path. A distinction is made between "process fitness" and "trace fitness". Process fitness is based on the whole event log, whereas trace fitness is calculated for each trace (in this case: a patient) separately. For this study, conformance is measured per patient. Therefore, trace fitness is used.

Precision and generalization give insight in whether the care path is under- or overfitting. A care path is underfitting if it describes too broad behavior or overfitting if the behavior is too detailed and doesn't generalize. Simplicity is high if the care path is the "simplest process model" to explain the behavior in the event log [13].

In this study, improving the care path is out of the scope. It is assumed that the care path is well constructed. Therefore, only fitness is considered as a measurement of conformance.

Fitness is calculated based on "alignments". Alignments indicate whether activities in the care path are performed as expected. Alignments consist of three types of moves [27]:

1. Log move (short: L move): the activity is not expected to occur according to the model, but was recorded in the event log.
2. Model move (short: M move): the activity is expected to occur according to the model, but was not recorded in the event log.

3. Log+Model move (short: LM move): the activity is expected to occur according to the model, and was indeed recorded in the event log.

For example, consider Table 2.2. In the event log, activities A, B, C, D and E are recorded. However, according to the model, activities B, C, F, D and E were expected (in that order).

Event Log	A	B	C	D	E
Model	B	C	F	D	E

Table 2.2: Alignments example (not aligned)

Comparing activities vertically, it can be seen that the event log and model are not aligned correctly. A correct alignment is found by adding "no steps" (\gg) to either the event log or model (Table 2.3) [27].

Event Log	A	B	C	\gg	D	E
Model	\gg	B	C	F	D	E
Alignment	L	LM	LM	M	LM	LM

Table 2.3: Alignments example (aligned)

Alignments indicate where deviations can be found. The first activity in the model is "B", whereas the first activity in the event log is "A". The activity "B" in the event log is preceded by "A". Activity "A" is inserted in the event log, but not present in the model. Therefore, a Log move is made. Both the event log and model then have activities "B" and "C". These are aligned correctly (Log+Model move). Then, activity "F" should occur according to the model, but is not present in the event log. Therefore, a Model move is made. Finally, activity "D" and "E" are aligned correctly as well (Log+Model move). In summary, activity "A" is now aligned with a Log move and activity "F" is aligned with a Model move.

Consider a case with A being all activities recorded in an event log. Let bag A_m be the activities skipped according to the model (Model moves). Bag A_l is a subset of A , consisting of the activities inserted in the care process not according to the model (Log moves).

$fcostM$ and $fcostL$ are the cost of skipped and inserted activities respectively.

Trace fitness is then calculated as one minus the ratio between cost of skipped/inserted activities and total cost considering all activities in A as Log moves [17]:

$$fitness = 1 - \frac{\sum_{m \in A_m} fcostM(m) + \sum_{l \in A_l} fcostL(l)}{\sum_{a \in A} fcostL(a)} \quad (2.1)$$

A fitness value ranges from 0 to 1. A trace fitness of 1 indicates that a patient followed the care path perfectly.

For the example in Table 2.3, cost $fcostL$ and $fcostM$ are considered to be 1 for all activities. Then, trace fitness is 0,6:

$$fitness = 1 - \frac{2}{5} = 0,6 \quad (2.2)$$

2.2 Incidents

During the care process of a patient, incidents may occur. Both the number and severity of incidents are taken into account in this study.

At Isala, a system called VIM [23] is used to report and keep track of incidents. VIM stands for 'Veilig Incident Melden', which translates to 'Reporting Incidents Safely'. At the clinic, incidents are discussed monthly by a VIM committee.

The VIM system assigns a score between 1 and 4 to an incident, indicating its severity. This score is based on the impact and frequency of that incident. When an incident is reported, the clinician also gives an estimation of this impact and likelihood of that incident to reoccur. The score is then derived from the risk matrix (shown in Table 2.4).

↓ Likelihood \ Impact →	Insignificant	Minor	Moderate	Major	Catastrophic
Almost certain	2	2	3	4	4
Likely	2	2	3	4	4
Possible	1	2	3	4	4
Unlikely	1	1	2	3	4
Rare	1	1	2	3	4

Table 2.4: VIM Matrix

An incident which occurs more often has a higher VIM score than incidents that are less likely to happen again. Moreover, an incident with a higher impact, has a higher VIM score.

For example, when an incident is rare and has an insignificant impact, the incident score is 1. An incident with a major impact and which is likely to happen again, has an incident score of 4.

2.3 Costs

Patient-specific costs need to be calculated. The costing method used at Isala and various costing methods from literature are considered. Each method is explained with a leading example. These methods will be compared to each other and evaluated in the next chapter.

2.3.1 Costing methods at Isala

The costing method of Isala is similar to other hospitals in the Netherlands. Hospital costs are covered by insurance companies. Treatments are invoiced in 'packages' (DOTs). Instead of seeing the care process of each patient as unique, it is classified as a DOT [2].

Treatments are split up into two segments: the A-segment and B-segment. For the A-segment, national guidelines state how much treatments cost. For the B-segment (the 'free' segment), a hospital is free to determine their own prices (to compete with other hospitals). About 70% of the treatments are part of the B-segment. Since the costs of treatments in the A-segment are fixed, DOTs only have to be calculated for treatments in the B-segment.

The price of a DOT is based on the costs of an average patient (e.g. resources, medicines, buildings). The costs are therefore neither patient-specific nor activity-specific.

2.3.2 Costing methods from literature

Costing methods that can be applied to process mining are found in literature. At Queensland University of Technology (Australia), research has been performed on cost-awareness in process mining by Nauta (2011) and subsequently Wei Zhe Low (2011) [25, 28, 15].

They propose three costing methods for a process mining problem: ABC (Activity Based Costing), TDABC (Time-Driven Activity Based Costing) and RCA (Resource Consumption Accounting). These costing methods are explained on the basis of a leading example. The data is imaginary, but roughly based on the case study at the Radiotherapy department described in Chapter 5. This is done, since some methods require an extensive method to collect the required data (e.g. interviews) in order to work. In this chapter, the methods are introduced. The weaknesses and strengths of each method are covered in Chapter 3.

For this example, it is assumed that there are 6 employees, working 40 hours per week, 40 weeks per year. In total, employees work 576.000 minutes per year. It is assumed that employees cost 60.000 euro on average per year. Therefore, the total salary costs are 360.000 euro.

ABC (Activity Based Costing)

Kaplan and Burns (1987) introduced a method called ABC [11].

Standard Application

By means of interviews, employees indicate what percentage of their time is used on each activity. Based on these percentages, assigned costs can be calculated. This is done by dividing salary costs of the whole process over the various activities, based on the percentage of time employees are busy with that activity. An example is given in Table 2.5. Note that the values in column *# Time* would normally be retrieved from interviews.

Activity	% Time	Assigned Cost	Quantity	Var. costs	Fixed costs	Total costs
Intake	5,2%	18.720	2000	9,36	15	24,36 euro/intake
Surgery	9,4%	33.840	600	56,40	400	456,40 euro/surgery
Consultation	5,6%	20.160	1600	12,60	20	32,60 euro/consultation
Scan	6,3%	22.680	1200	18,90	150	168,90 euro/scan
Planning	12,5%	45.000	1200	37,50	50	87,50 euro/planning

Table 2.5: ABC standard application example

By means of interviews, resources of the department stated that they spend 5,2% of their time on the activity "Intake". The assigned costs for this activity are therefore 5,2% of 360.000 euro, which is 18.720 euro. Since 2000 intakes are performed during one year, variable costs per intake are 9,36 euro. Fixed costs for this activity are 15 euro/intake. Therefore, total costs are 24,36 euro/intake.

Kaplan and Burns [22] concluded that their ABC method was less effective in large scale businesses. In practice, it can be hard to maintain and difficult to implement, since ABC requires many parameters [24]. Therefore, a (simpler) version of the ABC method was introduced in 2005: Time-Driven ABC (TDABC) [22].

TDABC (Time-Driven ABC)

The TDABC method is simpler compared to the ABC method and requires only two steps:

1. Estimating costs per time unit of capacity
2. Identify cost drivers for each activity

Standard Application

As stated before, yearly salary costs are 360.000 euro and employees work 576.000 minutes per year. Therefore, costs per minute of supplying capacity is $360.000/576.000 = 0,63$ euro/minute.

Next, for each activity the average duration is calculated. This can be done by means of interviews or by retrieving the data from event logs. When these durations are known, costs for a certain activity are calculated by multiplying the duration with the costs per minute. This gives the results shown in Table 2.6.

Activity	Duration (minutes)	Costs per minute	Fixed costs	Total costs
Intake	15	0,63	15	24,45 euro/intake
Surgery	90	0,63	400	456,70 euro/surgery
Consultation	20	0,63	20	32,60 euro/consultation
Scan	30	0,63	150	168,90 euro/scan
Planning	60	0,63	50	87,80 euro/planning

Table 2.6: TDABC standard application example

In Table 2.6, the duration of an intake was 15 minutes. Since costs per minute are 0,63 euro and fixed costs are 15 euro, total costs are $15 * 0,63 + 15 = 24,45$ euro/intake.

Note that this example does not differentiate between different types of resources. A doctor can be more expensive than a secretary. For each event in the event log, it is known what resource performed the activity. This resource can be a single entity or a resource group (in case multiple entities performed the activity). To make a distinction between the costs of different resources, the costs/minute are calculated per resource type. For example, see Table 2.7. A distinction is made between the costs/minute for a doctor and a secretary.

Resource	Cost / minute
Doctor	1,50
Secretary	0,90

Table 2.7: Distinction between the cost/minute for different resources: doctors are more expensive per minute than secretaries

RCA (Resource Consumption Accounting)

Resource Consumption Accounting (RCA) is based on three pillars [18]:

1. RCA calculates costs based on resources (# FTEs)
2. RCA gives an output that can be converted to a cost price per activity
3. RCA recognizes that costs are fixed or variable

Standard Application

Assume that in total, 120.000 euro is budgeted for intakes and consultations. 1 FTE is allocated to perform intakes and 1 FTE for consultations. RCA splits the total budgeting over the activities, based on the amount of resources allocated to them. That means that both intake and consultation get 60.000 euro as budget. Costs per activity can be calculated using the number of activities per year. In the example, there are 2000 intakes and 1600 consultations per year. Therefore, the costs are 30,00 euro/intake and 37,50 euro/consultation.

2.4 Summary

In this chapter, methods to measure conformance, incidents and costs were introduced. These variables can be determined for individual patients in a care process. The results of the various costing methods are similar. Only the input data used by the methods to calculate the costs are slightly different. In the next chapter, the differences, strengths and weaknesses between the costing methods are covered.

Chapter 3

An approach to relate conformance, costs, and incidents

With the methods described in the previous chapter, it is possible to measure conformance, incidents and costs for a patient's care process. Incidents are retrieved from the VIM system. Costs and conformance can be calculated based on an event log.

In this chapter, the four costing methods introduced in Chapter 2 (method of Dutch hospitals, ABC, TDABC and RCA) are evaluated based on a set of criteria (Paragraph 3.1). In this evaluation, the differences, strengths and weaknesses of each costing method are covered. Based on these criteria, the most appropriate method for this study is selected.

Data are required to monitor a care process. Two data formats are described: an enhanced event log and a feature set (Section 3.2 and 3.3).

The enhanced event log is an event log enriched with conformance, incident and cost data. This event log can be used as input for process mining techniques.

A feature set is used to investigate whether there is a relation between the variables. These relations are investigated to be able to accept or reject the hypotheses (Figure 1.2). The methods used to relate the variables are described in the final part of this chapter (Section 3.4).

Finally, an overview of the approach is shown (Section 3.5). This overview will be extended in the following chapters.

3.1 Costs

In the previous chapter, various costing methods were explained. First, their application in a process mining study is shown. Next, criteria are described based on which the costing methods are evaluated and compared to each other.

3.1.1 Application for process mining

For each of the costing methods from literature, it is described how the presence of an event log affects the application of the method. It is investigated whether information needed for the methods can be retrieved from event logs. For example, the activities in a patient's care process and the duration of the activities.

Costing method Isala

The costing method based on declarable DOTs is focused on process-wide averages. These averages are based on the bigger (more expensive) activities in the process (of which the price is already known). An event log is of no use for this method, since the information in the log is too detailed.

ABC (Activity Based Costing)

In case this method is applied in a process mining study, information can be retrieved from the event log. Instead of having to interview employees, the percentage of time a resource is occupied with a specific activity can be derived from the log in case "start" and "complete" timestamps are recorded.

For example, the duration of activity A can be calculated by taking the difference between the "start" and "complete" timestamps. The total amount of time resource R spend on activity A ($\sum duration_{A,R}$) is calculated by taking the sum of all the durations of activity A. To calculate the percentage of time spent on activity A by resource R ($f(A, R)$), this sum is divided by the total amount of time resource R spent on all activities ($\sum duration_{ALL,R}$):

$$f(A, R) = \frac{\sum duration_{A,R}}{\sum duration_{ALL,R}} * 100\% \quad (3.1)$$

In case the "start" or "complete" timestamps are unknown, durations can not be calculated from the event log. Often only "complete" timestamps are recorded. For example, activity "Troubleshoot incident" in Figure 3.1 misses a "start" timestamp.

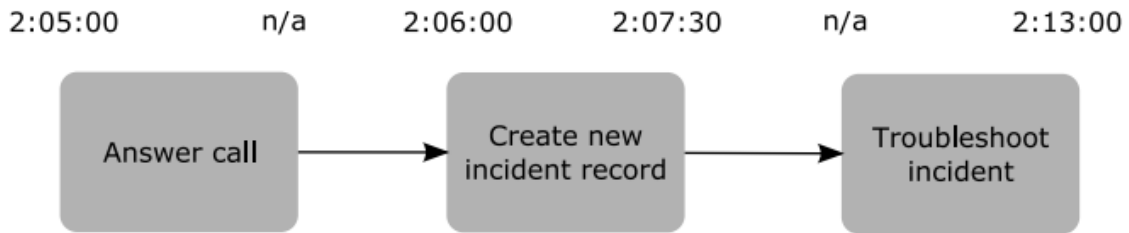


Figure 3.1: Incomplete log

The duration can be calculated by taking the difference between the "complete" timestamps of this activity and the previous activity. However, part of this time can contain waiting time for the activity "Troubleshoot incident". It is unknown what fraction of this time consists of waiting time for that activity and what fraction consists of the actual time spend on the activity. If either the "start" or "complete" timestamp is unknown for an activity, a fixed (average) value of the duration of this activity has to be used. These values can be retrieved from interviews.

Another limitation of the ABC method is that the event log may not contain all activities a resource performs. The percentage of time a resource spends on an activity can only be estimated from the event log assuming the resource worked full-time on activities in the event log. This can be resolved by interviewing employees about the time they spend on the activities present in the event log. For instance, it can be known that an employee works for 1 FTE at a department. In case a (sub)process of that department is investigated, interviews can be used to know what fraction of time the employee spends on that (sub)process. Then, this fraction can be multiplied with the yearly salary to get the actual costs per year for that (sub)process.

Furthermore, for this method, average costs are calculated per activity. Costs are identical for all instances of an activity.

TDABC (Time-Driven ABC)

Similar to the ABC method, the event log is used to calculate the duration of activities. However, compared to the ABC method, TDABC calculates the costs of an activity based on the actual duration. Variable costs are calculated per minute instead of an average per activity.

RCA (Resource Consumption Accounting)

The RCA method is based on budgets, the number of FTEs allocated to activities and the number of activities performed within a certain time span. The latter variable can be retrieved in a process mining study, by counting all activities present in the event log. However, the budget and allocated FTEs can not be derived from the event log. To do so, extra information would have to be added to the event log. Therefore, the standard application would be the same as the application for process mining with an event log.

3.1.2 Method selection

To select the best costing method for this study, selection criteria are formulated.

The selection criteria are:

- Data requirement
- Accuracy
- Use of event log

In the evaluation, these three criteria are given a "good" (+), "neutral" (0) or "weak" (-) score. The method that has the best overall score is considered the best method and used to measure the variable "costs".

Data requirement

This criteria determines how much data are needed to calculate costs and how much effort it takes to get the data. For example, it can be very time consuming if the information comes from interviews. A method scores "good" on this criteria if it does not require a lot of data and effort to collect the data (performing well on both aspects). If it performs well on one of these aspects, it scores "neutral" and if it performs badly on both aspects, it scores "bad".

The costing method of Isala only requires general information about the more expensive activities in a process. Cheap administrative activities have a relatively low effect on the total cost of a care process and are often not taken into account [2]. The method does not require a lot of information and the information is not hard to collect. Therefore, this method scores "good" on data requirement.

The amount of data required for the three other methods is similar. All methods require precise information about costs per resource or FTE. Therefore, all methods score bad on the aspect "amount of data". For the ABC and TDABC method, information about the duration of activities can be retrieved from event logs in case "start" and "complete" timestamps are recorded. However, for the ABC method, the fraction of time the resource spends on the (sub)process has to be known. Therefore, ABC scores "bad" on this criteria. RCA and TDABC score "neutral".

Accuracy

Accuracy focuses on how detailed the resulting cost values are. Is the method activity-based or process-wide? Does the method return estimations for the activities or are the returned values more specific? A "good" score is given if the method differentiates between multiple instances of the same activity based on duration and resource. A method scores "neutral" if the method calculates a score for each activity separately and it scores "bad" if the method only calculates the average costs of the whole process.

In the costing method used at Isala, the prices of a DOT are based on an estimation of the costs of an average patient's care process. In this study, costs have to be calculated in more detail.

A patient skipping a specific activity needs to have an influence on the costs of that patients care process. This distinction can not be made with the costing method Isala currently uses. Therefore, it scores "bad" on accuracy.

Since the data of this study is based on patient data, the variability of the duration within an activity is larger. Take for example the construction of a car on a conveyor belt. Every activity will take roughly the same time, since every car should be similar to each other. However, a patient does not have this property. Two patients with similar symptoms can follow the same care path with the same activities, but one patient can have a longer intake meeting with the doctor than another patient. Therefore, the use of the variable 'cost per minute' is more precise than the variable 'cost per activity'. Even though both patients (or their insurance company) will pay the same for the DOT, costs that are made by the hospital are not identical. TDABC scores better on accuracy than ABC and RCA, since it takes both the duration and resource into account. TDABC scores "good" on this criteria and the other two methods score "neutral".

Use of event log

Since this is a process mining study and the event log is available, the costing method should preferably be able to derive costs from the event log. To what degree can an event log ease the difficulties of retrieving information? If the data required for the method is greatly reduced with the presence of an event log, a method scores "good". If only a few aspects of the event log can be used for the method it scores "neutral" and if an event log is of no use, it scores "bad".

All methods make use of the data available in event logs, except for the method of Isala. TDABC and ABC use the durations of activities and the total amount of time a resource spent on the activities (therefore, scoring "good"). The only data from the event log that is used by RCA is the amount of activities in the specific timespan. RCA scores "neutral" on this criteria.

Based on the evaluations of each method, Table 3.1 shows an overview of the scoring on the three criteria. The scoring possibilities are: + (good)/0 (neutral)/- (weak). An overall score is calculated by looking at the average score for all three criteria (rounded up).

Criteria	ABC	TDABC	RCA	Isala
Data requirement	-	0	0	+
Accuracy	0	+	0	-
Use of event log	+	+	0	-
Overall (average)	0	+	0	0

Table 3.1: Method evaluation

Based on these evaluations, TDABC is the most appropriate costing method to use as a measurement. It has a higher overall score than the two other methods.

With the methods described in this chapter, the variables conformance, incidents and costs can be determined for each patient's care process. The values of these variables will be added to the event log. This can be seen in Section 3.2.

3.1.3 Feedback Isala on TDABC

According to the evaluation, the TDABC costing method appears to be the best choice. But, in order to use the method for this study, it has to be applicable at Isala. In an interview with a financial expert, it was confirmed that TDABC can be used as an alternative costing method [2]. TDABC was considered practical, since it uses a logical allocation of costs.

In order to be able to monitor a care process, data about the execution of the process has to be collected. In Sections 3.2 and 3.3, two data formats are introduced that can be used for monitoring: an enhanced event log and a feature set.

3.2 Enhanced event log

In Section 2.1, it was explained that an event log contains all activities of all patients in a care process. The patient’s care process is also known as the ‘trace’ of the patient. A trace contains all activities (‘events’) recorded for that patient. An event contains an optional ”start” and/or ”complete” timestamp and can be performed by a resource. Some event logs also contain timestamps for aborting (”abort”) and scheduling (”schedule”) an activity, but this is out of the scope of this study.

An event log is extended with information about conformance, incidents and costs. An overview of the resulting event log is shown by means of an UML Class Diagram (Figure 3.2). An UML Class Diagram relates different entities or concepts to each other.

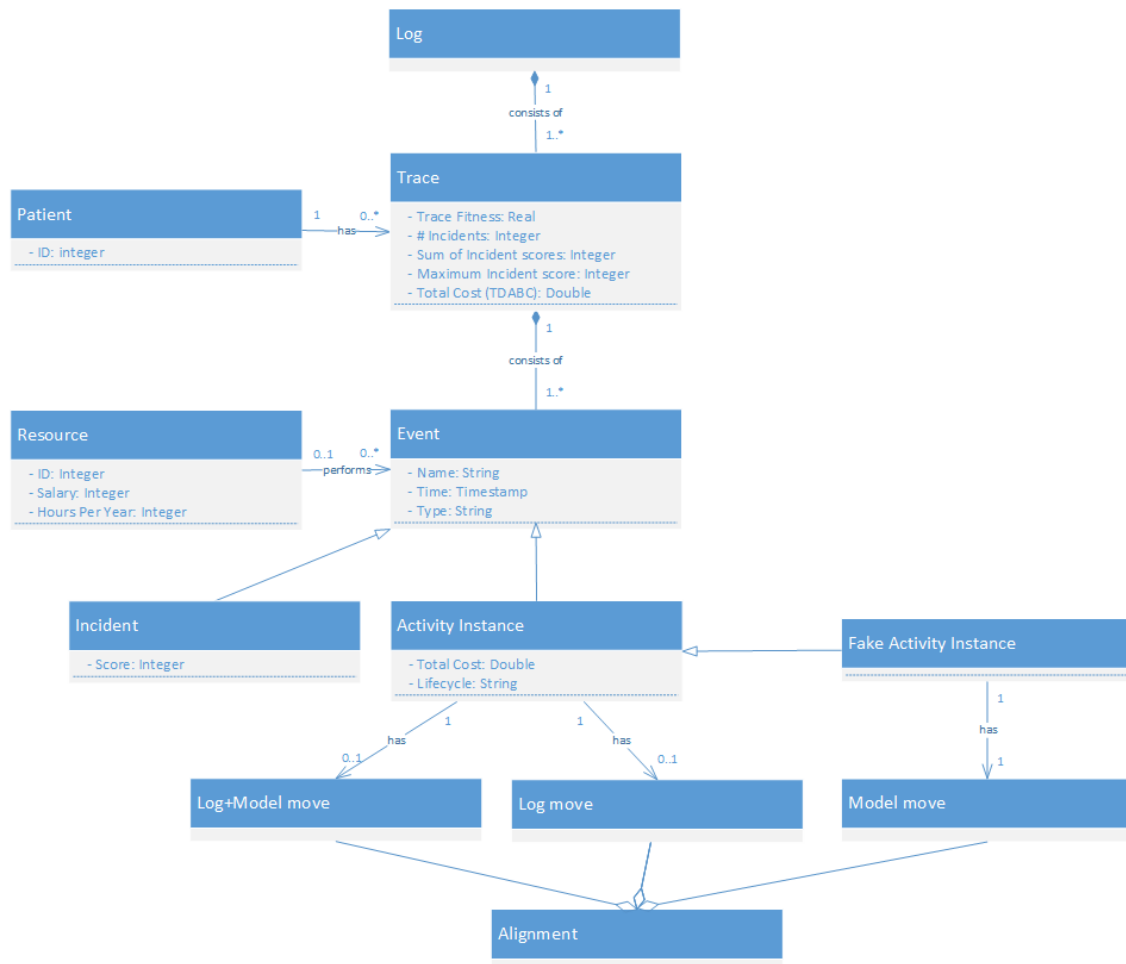


Figure 3.2: UML diagram: enhanced event log

A log consists of one or more traces, each belonging to a single patient. A trace conforms to a model, based on which the trace fitness is calculated. A trace consists of one or more events. A resource can be associated with this event. To be able to use the TDABC method, the salary and hours per year of this resource have to be known (in order to calculate the costs per minute).

An event can either be a reported incident or an instance of an activity [13] in the care path (e.g. "CT scan"). This is stored in the parameter "Type" of the class "Event". Each instance of an activity has an alignment. It can either be a Log+Model move, Model move or Log move. An activity that is present in the event log can not have a Model move. Therefore, a fake activity is added that represents a skipped activity. For each activity, the total number of each of the moves is known.

At the level of a trace, information about the patient's care process is stored (e.g. total costs of the patient's care process), whereas on the level of events the activity-specific data is stored (e.g. total costs of the activity). An example can be seen below.

```
<trace>
  <string key="concept:name" value="199281" />
  <string key="Total Cost (euro)" value="30.0" />
  ... (other trace-level information)
  <event>
    <string key="concept:name" value="A" />
    <string key="Total Cost (euro)" value="10.0" />
    ... (other event-level information for activity A)
  </event>
  <event>
    <string key="concept:name" value="B" />
    <string key="Total Cost (euro)" value="20.0" />
    ... (other event-level information for activity B)
  </event>
</trace>
```

In this example, a log is shown for one patient with ID 199281. Since a trace belongs to a patient, the patient ID is stored at the level of the trace (variable *concept:name* with value *199281*). In this example, the trace consists of two activities: activity *A* and *B*. The names of the activities are stored at the level of the event (variable *concept:name* with values *A* and *B* respectively). The total costs of the activities are stored in the variable *Total Cost (euro)*. Activity *A* costs 10 euro and activity *B* costs 20 euro. The total costs of all activities is stored at the level of the trace, which is 30 euro (variable *Total Cost (euro)*). Whenever information is added to the level of the trace, it is inserted as a new line in the trace (above the first `<event></event>` tag). Information about a specific activity is stored within the `<event></event>` tag of that activity.

The attributes of the "Trace" class in Figure 3.2 are added at the level of the trace, including the related patient data (class "Patient") and the alignments (class "Alignment"). The events are added to the corresponding trace. For each event, the attributes of class "Event" are added, including the incident score or total costs and lifecycle (depending on whether the event is an incident or an instance of an activity).

In the sections below, it is explained in more detail how incident, cost and conformance data are added to the log.

Incidents

First, all incidents reported during a patient's care process are retrieved from the VIM system. An incident in the VIM system contains a patient ID, incident score and timestamp (Table 3.2).

Patient	Incident Score	Timestamp
199281	1	02-01-2014 11:00:00
199281	3	03-01-2014 12:15:00
299281	4	10-01-2014 14:30:00

Table 3.2: Example VIM export: incident data

An incident can be seen as a new event that occurs at some point in a patient's care process.

Incidents are therefore added to the event log with a specific timestamp (Table 3.3). With these timestamps, incidents can be linked to activities.

Patient ID	Name	Resource ID	Timestamp	Score
199281	Incident	-	02-01-2014 11:00:00	1
199281	Incident	-	03-01-2014 12:15:00	3
299281	Incident	-	10-01-2014 14:30:00	4

Table 3.3: Incident data added to events. *Score* is an attributes of the class "Incident" in the UML.

At the level of a trace, incident data about the patient's care process is added. The number of incidents, the sum of incident scores and the maximum incident score are added to this level (Table 3.4). These attributes can also be seen in the UML "Trace" class (Figure 3.2). The sum of incident score is only interesting if a patient has multiple incidents in his care process. For example, a patient having 4 incidents with score 1, 1, 1 and 4 can be distinguished from a patient having incident with score 4, 4, 4 and 4 (number of incidents and maximum incident score would be the same for both patients).

With this parameter, the average incident score can be calculated by dividing the sum of incident scores by the number of incidents. Minimum incident score is not considered, because incidents with a higher score have more impact and/or occur more frequently (Table 2.4).

From the example in Table 3.3, the following incident data is derived at trace level (Table 3.4).

Patient ID	Sum of incident scores	Maximum incident score	# incidents
199281	4	3	2
299281	4	4	1
399281	0	0	0

Table 3.4: Incident data added to the trace. *Sum of incident scores*, *Maximum incident score* and *# incidents* are attributes of the class "Trace" in the UML.

Patient 199281 had two incidents, with an incident score of 1 and 3 respectively. Patient 299281 had one incident with a score of 4. Patient 399281 had no incidents during his care process (number of incidents = 0).

The variables in Table 3.4 are bound to the patient's care process and not specific activities. Therefore, these are added at the level of the trace. This can also be seen in Figure 3.2, since the variables are attributes of the class "Trace".

Conformance

Conformance is calculated by aligning the trace to the model. The fitness value is added to the trace level of each patient. Furthermore, for each patient, the alignments of all activities are determined and added to the trace. An example with one activity "X" is shown in Table 3.5.

Patient ID	Trace fitness	X (Log+Model move)	X (Log move)	X (Model move)
199281	0,74	1	2	0
299281	0,90	1	0	0
399281	0,71	0	0	1

Table 3.5: Conformance data added to the trace. *Trace fitness* is an attribute of the class "Trace" in the UML and alignments (class "Alignment") are related to class "Trace".

Patient 199281 had activity "X" three times in his care process (once according to the care path with move LM and twice not according to the care path with move L). Patient 299281 had

activity "X" conform to the care path (move LM) and patient 399281 skipped activity "X" (move M).

Costs

Finally, costs are calculated using the TDABC method. For each activity in the trace of a patient, resource and duration are known. The duration is either the difference between "start" and "complete" timestamp or an average duration if one of the timestamps is unknown.

For each resource, "costs per minute" are known and for each activity, the "fixed costs" are known. Then, by multiplying the duration with the costs per minute and adding the fixed costs, the costs per activity are calculated. These data are added to the event log to each event (Table 3.6).

Patient ID	Activity Name	Resource ID	Timestamp	Lifecycle	Total cost
199281	CT Scan	133	01-01-2014 09:00:00	start	0
199281	CT Scan	133	01-01-2014 09:30:00	complete	145

Table 3.6: Cost data added to events. *Total cost* is an attribute of the class "Activity Instance" in the UML.

Patient 199281 had the activity CT scan in his care process. Since the "start" and "complete" timestamps were known, the duration of the activity was derived from the event log (30 minutes). Costs of the resource are 1,50 euro / minute and fixed costs of the scan are 100 euro. Then, the costs for this activity are $1,50 * 30 + 100 = 145$ euro. These costs are added to the event log. Note that these costs are only added at the row with the "complete" timestamp to avoid counting the costs twice.

Total costs belonging to a patient's care process are calculated by taking the sum of the costs of each activity. The total costs are added to the trace in the event log (Table 3.7).

Patient ID	Total cost (TDABC)
199281	281,20
299281	250,48
399281	319,33

Table 3.7: Cost data added to the trace. *Total cost (TDABC)* is an attribute of the class "Trace" in the UML.

3.3 Feature Set

An event log is three dimensional (a log contains multiple traces containing multiple events). This is not optimal for data analysis, where typically a two-dimensional format is used. So, data has to be transformed to a two dimensional format. Therefore, a feature set is created. Note that a feature set contains all the data from the trace level of the enhanced event log. An overview can be seen in Figure 3.3.

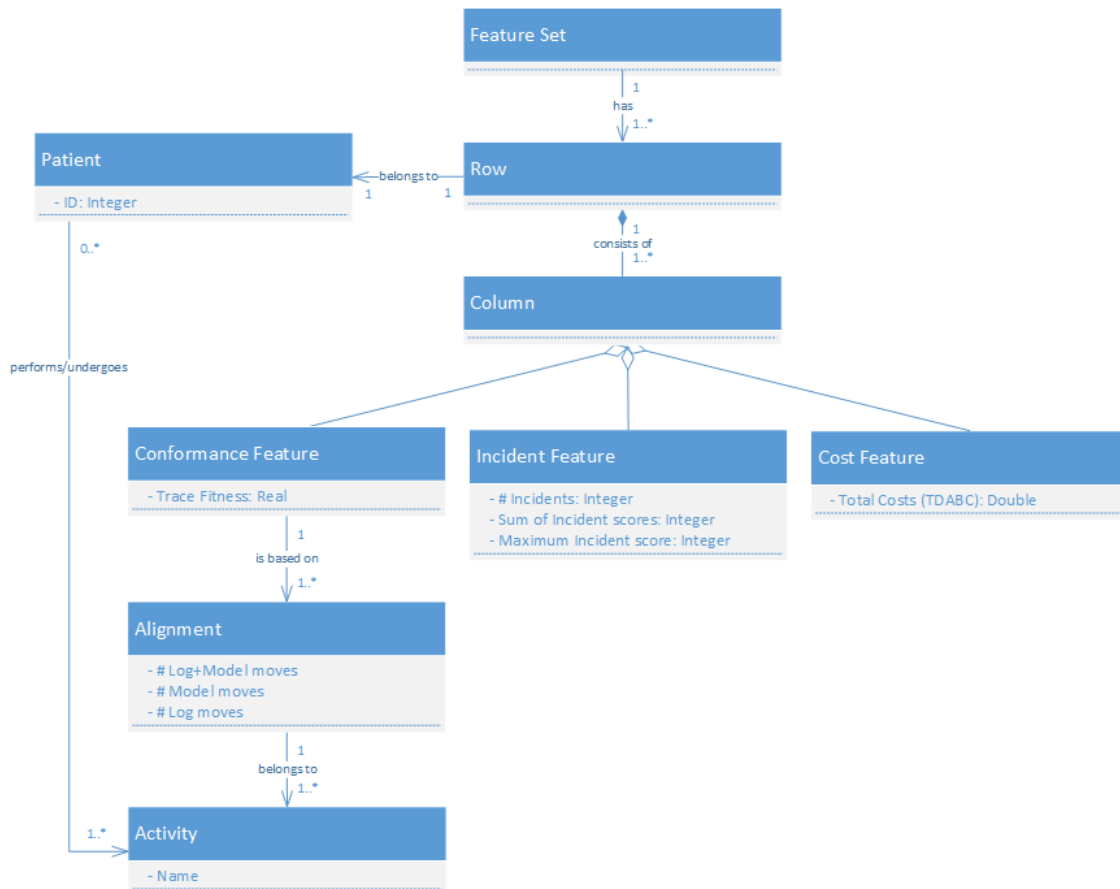


Figure 3.3: UML diagram: feature set

The features set contains a set of features (columns) for a list of patients (rows). In summary, a row in the feature set has the following columns:

- ID (*Patient*)
- # Activities (*Patient*)
- # Incidents (*Incident feature*)
- Sum of incident scores (*Incident feature*)
- Maximum incident score (*Incident feature*)
- Total costs (TDABC) (*Cost feature*)
- Trace fitness (*Conformance feature*)
- For each activity: # Log+Model moves (*Conformance feature*)
- For each activity: # Model moves (*Conformance feature*)
- For each activity: # Log moves (*Conformance feature*)

A part of a feature set can be seen in Figure 3.4.

Row No.	Patient ID	Sum Incident Scores	# Incide...	Max Incident Score	Total Costs (TDABC)	Trace Fitness	# Activities
706	0386367	5	2	4	288	0.742	22
781	0504263	2	2	1	258	0.828	20
1194	0427812	8	2	4	228	0.852	18
1294	0161005	5	2	4	213	0.760	16
7	0291763	1	1	1	223	0.923	17
34	7684436	1	1	1	228	0.926	18
62	5141916	4	1	4	198	0.885	17
63	0059183	4	1	4	198	0.885	17
81	4778201	1	1	1	228	0.815	18
83	8579563	1	1	1	228	0.815	18
148	4819593	4	1	4	228	0.852	18
149	7076774	1	1	1	228	0.852	18
175	4675243	1	1	1	218	0.885	17
184	5019219	1	1	1	218	0.846	17
191	9942769	1	1	1	60	0.909	13
203	0089746	1	1	1	258	0.833	21
262	4358027	4	1	4	228	0.852	18
283	7057424	4	1	4	203	0.826	14
343	7123608	1	1	1	268	0.867	21
344	2320620	1	1	1	268	0.867	21
365	10154213	4	1	4	223	0.931	20
370	0226006	4	1	4	228	0.852	18

Figure 3.4: Screenshot feature set (taken from RapidMiner)

The features in the feature set are used to accept or reject the hypotheses and test the relations on significance.

3.4 Calculating the relations

The feature set is used to find relations between conformance, incidents and costs. Before data analysis is performed, outliers are removed from the data set. Then, the relations are investigated on two scopes: process-wide and activity-specific.

In the process-wide analysis, the data of all patients are used to see whether there is a relation between conformance, incidents, costs and the number of activities. This is done with a correlation test. A care process can consist of multiple care paths. If there are paths with different characteristics, these paths have to be analyzed separately. Therefore, a path comparison analysis is conducted as well in the process-wide scope.

The activity-specific analysis will zoom in on single activities and clusters of activities. A cluster analysis is used to investigate whether there are activities that act as a cluster (e.g. activities that are skipped or repeated together). Then, alignments are used to examine in more detail which activities lead to differences in conformance, incidents and costs. Another way to look at individual activities is by using Decision Trees (this concept will be explained in detail below).

First, the outlier analysis will be described. Both the path comparison and the decision tree analysis both use the a Wilcoxon's rank-sum test to determine whether two groups differ significantly. Therefore, this will be covered next.

Then, the process-wide analyses will be covered, followed by the activity-specific analyses.

3.4.1 Outlier analysis

The goal of the outlier analysis is to make the data set more homogeneous and to remove patients with extraordinary behavior (behavior that is not part of the usual patient flow). The outlier analysis uses boxplots to identify extreme cases. Therefore, boxplots are made to find outliers for each variable.

Data points are considered an outlier if the point do not lie within the lower and upper "outer fence" (LOF and UOF). The range of these outer fences are calculated based on the first and third quartile of the boxplot. 75% of the data points lie below the first quartile and 25% lie below the third quarter. The range of the fences are calculated as follows:

$$IQR = 3rd\ quartile - 1st\ quartile \quad (3.2)$$

$$LOF(k) = 1st\ quartile - k * IQR \quad (3.3)$$

$$UOF(k) = 3rd\ quartile + k * IQR \quad (3.4)$$

With the parameter k , the accepted range is made wider or smaller. A visual example of the upper outer fence (UOF) can seen in Figure 3.5. In this example (and in the case study), a value of 3 is used for k .

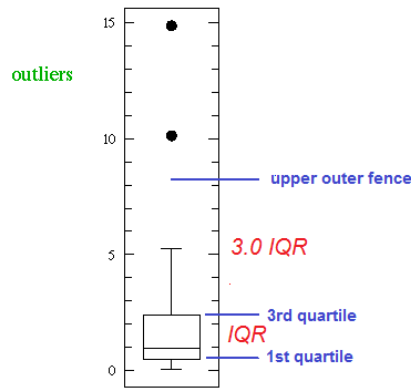


Figure 3.5: Boxplot example with the upper outer fence ($k = 3$)

In this example, the two black dots represent the extreme cases and would be removed from the data set.

3.4.2 Wilcoxon rank-sum test

A Wilcoxon rank-sum test is used to test whether two groups (e.g. patients) differ significantly.

In this study, Wilcoxon rank-sum tests are used to compare patients with and without incidents in their care process. For example, to test whether there is a significant relation between incidents and costs, patients can be divided into two groups: patients with and without incidents in their care process. The Wilcoxon rank-sum test is then used to test whether both groups have an significant difference in costs.

The test gives a p-value on how significantly the groups differ. In this study, a p-value below 0,05 is considered significant.

With a Wilcoxon rank-sum test, it is determined whether there is a significant difference between the medians of both groups [12]. The test is unpaired (data that is compared is not from the same group) and non-parametric (it makes no assumptions about the distribution of the data). However, in order to use this test, it is assumed that the distributions of both groups are the same.

3.4.3 Process-wide analyses

Path comparison

To compare two or more paths with each other, the mean, standard deviation and median of each variable (cost, conformance # incidents, # activities) is calculated. Then, the Wilcoxon's rank-sum test is used to see whether there are paths that are significantly different. If this is the case, these paths are analyzed separately.

Furthermore, the occurrences of activities in each of the paths are investigated. This gives insight in whether there are specific activities that occur more often in one path as another. Some activities might be characteristic for one of the care paths. Also, if an expensive activity is often skipped in one of the paths, this might have an influence on the average costs of that path.

Correlation test

For each patient's care process, the values of all variables are known. The most direct way to see whether there are relations between the variables is to perform a correlation test. This can then be used to accept or reject the Hypotheses. For example, Hypothesis 1 states that a higher conformance leads to fewer incidents in a patient's care process. Whenever a positive correlation is found between conformance and number of incidents, this Hypothesis could be accepted.

Two correlation tests are used in the case study: Pearson's Product-Momentum Correlation and Spearman's Rank-Order Correlation. The biggest difference between these tests is that Pearson's test is based on a linear relation (Figure 3.6), whereas Spearman's test is based on a monotonic relation (Figure 3.7).

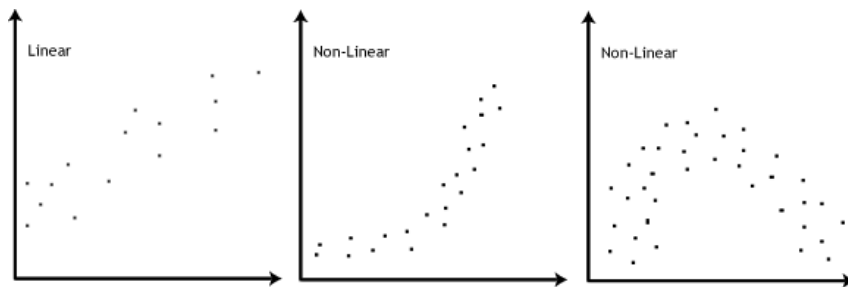


Figure 3.6: Linear and non-linear relations Pearson's [5]

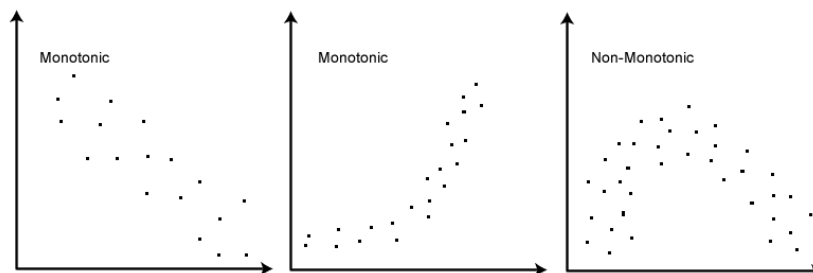


Figure 3.7: Monotonic and non-monotonic relations Spearman's [5]

A monotonic relationship has the following properties:

- if one of the variables increases, the other variable increases too, or
- if one of the variables increases, the other variable decreases.

In the example, the third figure is non-monotonic. With an increase in the value on the horizontal axis, the value on the vertical axis first increases, then decreases.

It is not guaranteed that the relation between costs, conformance and incidents is linear. For example, an exponential relation between incidents and costs is possible. Therefore, testing whether the relation is monotonic (Spearman's test) is more suitable in this study. The only other assumption for Spearman's test is that the data is ordinal (data can be ordered), interval (difference between values is meaningful) or ratio (a scale with a meaningful zero value. Whenever the value is equal to zero, it means that there is "none"). This requirement is not violated in this study. Therefore, Spearman's correlation test is chosen over Pearson's correlation test. Pearson's test is only used if the relation between variables is expected to be linear.

A correlation coefficient of -1 suggests a perfectly negative relation between two variables, a coefficient of 0 suggests that there is no relation and a coefficient of 1 suggests that there is a positive relation. Examples can be seen in Figure 3.8.

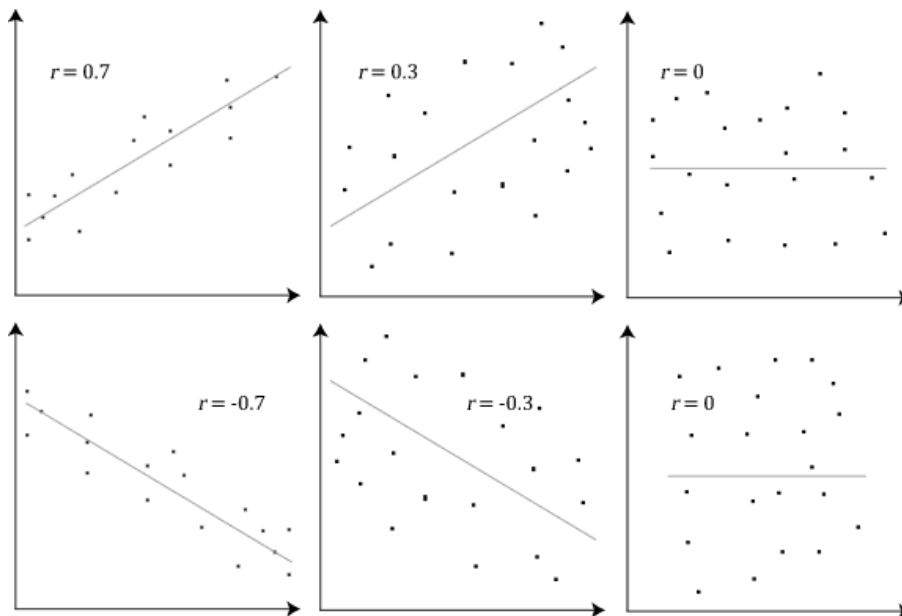


Figure 3.8: Examples for correlation values [5]

3.4.4 Activity-specific analyses

Cluster analysis

In the cluster analysis, it is investigated whether there are activities that act as a group. For example, one skipped activity can lead to another activity being skipped as well. If this happens in most cases, these two activities are considered to form a cluster together. Clusters are interesting to investigate, since clustered activities can have a higher influence on the conformance, incidents and costs.

The cluster analysis uses a more detailed scope to look at the relation between costs, conformance and incidents. Process mining techniques provide insight in where the patient's care process deviates from the care path. This information is stored in alignments. For each patient, it is known what activities are skipped. Also, for the activities that are performed, it is known whether it has been corresponding to the care path (move LM) or not (move L).

Deviations from the care path can be individual activities or clusters of activities. For example, a doctor wants to have another consultation with a patient to have a better diagnosis. The original

consultation can be performed according to the care path (thus having an move LM). However, the second consultation is a deviation from the care path (move L). Requiring a second consultation can lead to other activities that are repeated as well (e.g. informing the patient). This has an impact on the variables costs and conformance. Therefore, it is interesting to examine what activities are clustered and in what frequency they occur.

An example of a cluster analysis for move $L \geq 1$ can be seen in Figure 3.9. A chart is shown for activity "A", "B" and "D". On the x-axis, all activities in the model are listed ("A", "B", "C" and "D") and on the y-axis the number of occurrences of the move $L \geq 1$ for each activity is shown. Each bar chart shows what other activities had move $L \geq 1$ while the activity shown above the chart had move $L \geq 1$.

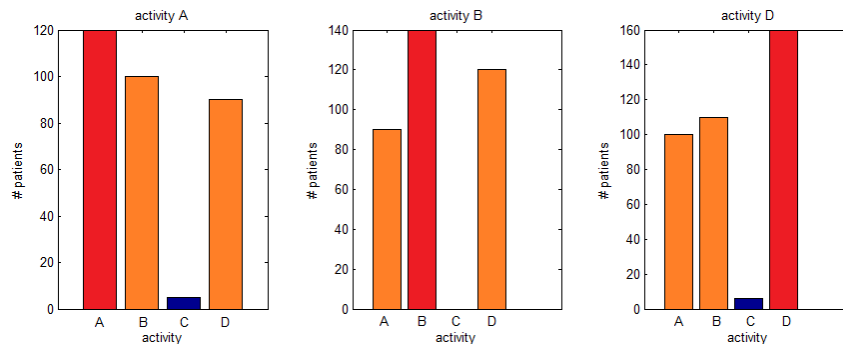


Figure 3.9: Cluster example: activities "A", "B" and "D" are clustered. Whenever activity "A" has a Log-move, activity "B" and "D" have one as well (left chart). The same effect is seen for activity "B" (middle chart) and "D" (right chart).

The left chart shows that activity "A" had a Log move (move $L \geq 1$) in 120 cases. To find clusters, all activities that also had an $L \geq 1$ when activity "A" had $L \geq 1$ were counted. For instance, in the 120 cases where "A" had $L \geq 1$, activity "B" had $L \geq 1$ in 100 cases, activity "C" had $L \geq 1$ in 5 cases and "D" had $L \geq 1$ in 90 cases. That would suggest that activity "A", "B" and "D" are clustered for move $L \geq 1$, but activity "C" is not. So, in most cases activity "A" had move $L \geq 1$, activities "B" and "D" had a move $L \geq 1$. This does not mean that this is also the other way around. Therefore, a graph is plotted for activity "B" and "D" as well (middle and right chart). Based on these graphs, a cluster of "A", "B" and "D" can also be deduced.

The red bar is activity "X" and the other bars are the other activities with the same misalignment as activity "X". Clustered activities are yellow if they have the same misalignment in more than 20% of the cases and orange in case its more than 33%.

Decision Tree

Activities (and their alignments) can be directly related to costs, conformance and incidents. For example, it can be found that the presence of activity "X" in a patient's care process is characteristic for a patient with an incident. To find these kind of relations, a decision tree analysis is done.

To illustrate a decision tree analysis, an example is given for the variable "incidents" (Figure 3.10). Patients are divided into two groups, based on the presence of an incident in their care process (group "true" or "false"). Then, the decision tree analysis tries to find activities that are characteristic for one of these groups. In the example, activities "X", "Y" and "Z" are found to be characteristic for one of the groups.

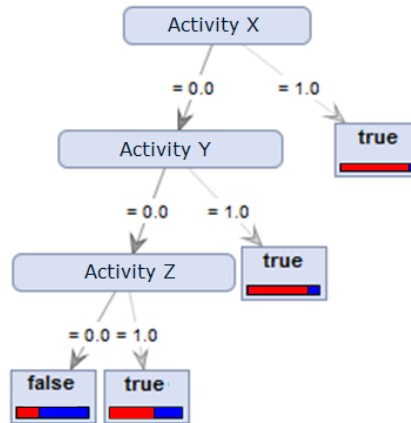


Figure 3.10: Decision Tree example

Activity "X" was found in the highest leaf of the tree. The highest leaf in a decision tree corresponds to the activity that is the best predictor. If activity "X" is present (value = 1.0), the decision tree predicts that the patient has an incident during his care process (group "true"). If the activity is not present (value = 0.0), activity "Y" is found in the second leaf (as the second-best predictor). Activity "Y" can be read as the following: if activity "X" is not present (value = 0.0) and activity "Y" is present, the tree predicts that the patient has an incident during his care process (group "true"). Note that the bar below "true" is not entirely red. This means that there was a small group of patients without incidents (blue part of the bar) under this condition.

If both activity "X" and "Y" are not present, activity "Z" is a predictor for incidents. However, the groups of this leaf are even less uniform.

It is possible to calculate an accuracy of the decision tree. This accuracy indicates what percentage of the cases is predicted correctly by the decision tree. The goal of this study, however, is not to build one decision tree to represent the patient data, but to find activities that are characteristic for one of the groups. Accuracy of the tree is therefore not essential in this study, but is still used to validate the trees on a global level. A tree with a very low accuracy (e.g. 10% of the cases are predicted correctly by the tree) is obviously useless. For this study, a threshold for accuracy of 70% is used to consider a decision trees valid. Decision trees are used to find interesting activities, that are characteristic for high or low conformance, costs and number of incidents.

If a decision tree is found, these activities are marked as candidate activities. In the next iteration, these activities are no longer taken into account, in order to find new candidate activities. This is repeated, until no decision tree is found anymore. Lower leaves in the tree are based on a subset of the data. For example, activity "Z" in Figure 3.10 is a decision point under the conditions that "X=0.0" and "Y=0.0". All cases that either have "X=1.0" or "Y=1.0" are not taken into account for this decision point. To reduce this nested behavior, a maximum depth of a decision tree is set to three. This could also be set to another value (e.g. two or four), but in this study a depth of three is considered to be the correct balance between having too little information and too much behavior in the tree.

After all iterations, candidate activities that are characteristic for one of the groups are known. For these activities, the differences between the values of the two groups are tested on significance (with a Wilcoxon rank-sum test).

3.5 Overview of the approach

Figure 3.11 shows what approaches are used to relate conformance, incidents and costs to each other.

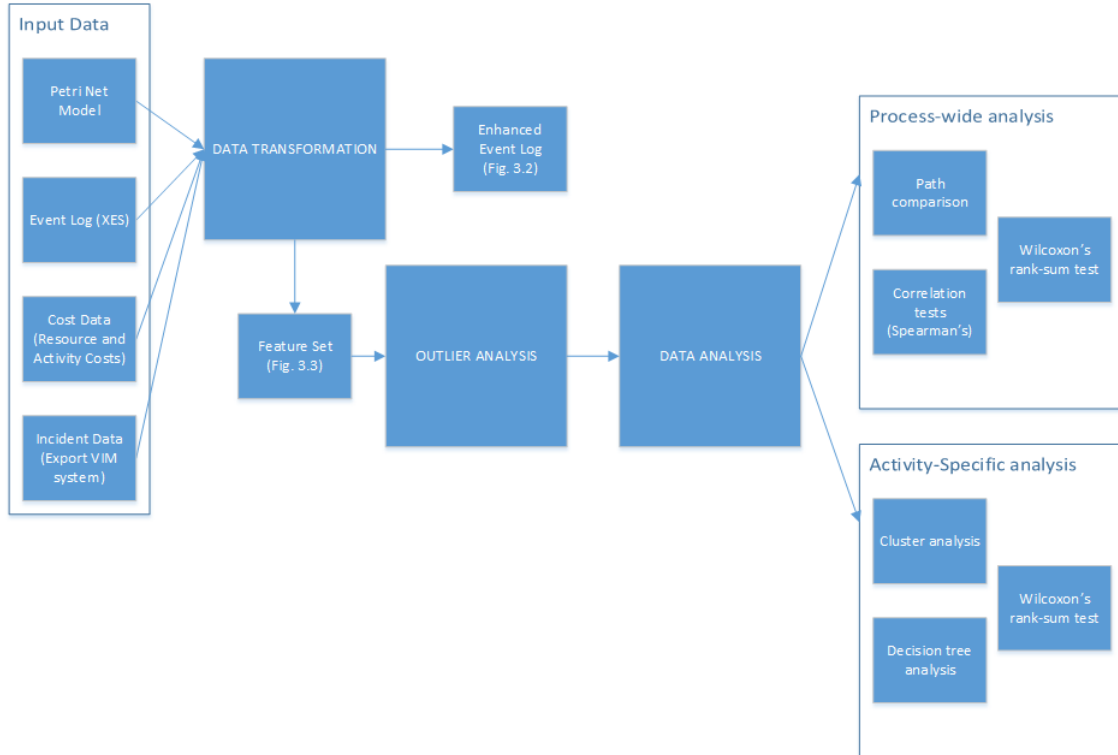


Figure 3.11: Overview approach

3.5.1 Input data

The input data consist of:

- An event log (Table 2.1).
- A model of the expected care path (used to calculate the conformance of the patient’s care process).
- Cost data to use the TDABC method, consist of two parts:
 - The cost/minute per resource(group) (Table 2.7)
 - The fixed cost and (optionally) the duration per activity (Table 2.6). In case ”start” or ”complete” timestamps are absent in the event log, the duration per activity is required as well. In that case, the average duration per activity is determined based on interviews with process experts.
- Incident data exported from the VIM system.

3.5.2 Data transformation

In the data transformation block in Figure 3.11, several things happen:

- Calculating the costs and conformance per patient, using TDABC and conformance checking.

- Determining the number of incidents, sum of incident scores and maximum incident score per patient, based on the export of the VIM system.
- Generating the feature set and enhanced event log:
 - Cost, incident and conformance data are added to the enhanced event log and incidents are added to the event log as events (see Section 3.2).
 - Cost, incident and conformance data are listed per patient in a feature set (see Section 3.3).

3.5.3 Output data & analyses

The feature set is used as input for analyses.

First, outliers are removed from the feature set to make the data more homogeneous. Then, a process-wide analysis and activity-specific analysis are done to investigate the relations in detail.

Note that the enhanced event log is not used in this study. Incidents are added to the event log with a timestamp. This makes it possible to use process mining techniques to discover a new process with incidents. It is interesting to know whether there are incidents that are often located in a specific part of the process. A simplified example can be seen in Figure 3.12. By adding incidents to the event log as events, a process discovery algorithm (e.g. the Fuzzy miner of Disco [1]) can be used to see where these incidents occur. In this example, the incident occurs between the activities *Plan afronden* and *Plan controle fys*.

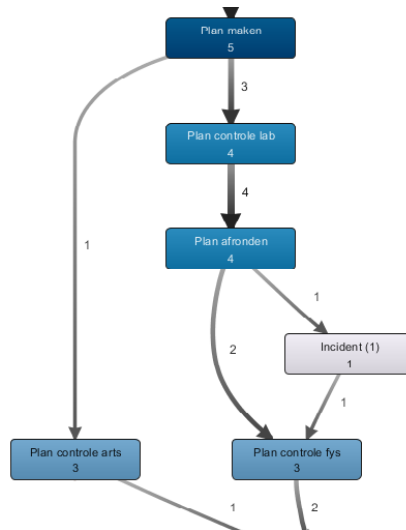


Figure 3.12: Process mined with incidents added to the event log as events

This requires timestamps to be known for the incidents. Without timestamps, it is impossible to add incidents in the correct position in the event log, since it is unknown between what activities the incident happened.

3.6 Summary

In this chapter, the approach to relate conformance, incidents, costs and number of activities was described. The TDABC costing method is selected to measure the costs of a patient’s care process. To relate the variables, a feature set, containing the values for each patient, is created. This feature set is used as input for various analyses. These analyses are used to find (significant) relations between conformance, costs and incidents (see Figure 3.11 for an overview).

Chapter 4

Realization of the approach

This chapter describes the concept and functionality of the toolset. The toolset consists of a collection of existing software. It is explained what software is used to implement the approaches described in the Chapter 3 (Section 4.1). Finally, an overview is given of the main functionality of the toolset, including screenshots of the output (Section 4.2).

4.1 Software selection

In the previous chapter, an overview was given of the approaches to relate conformance, incidents and costs. In Figure 4.1, the software that is used is added. Also, the boundaries of what is implemented in the toolset are shown with a dashed line. The toolset reads the input files, transforms the data and outputs a feature set and enhanced event log. To realize this, a collection of existing software is used.

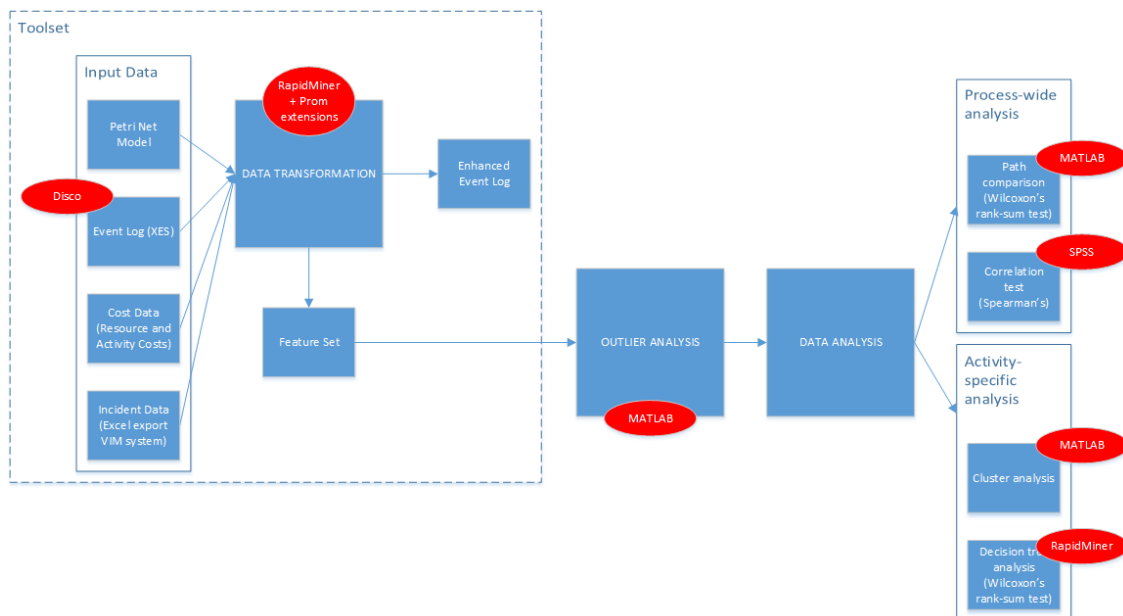


Figure 4.1: Overview of the implementation: boundaries of the toolset are shown (dashed line) and it is indicated what software is used for the various parts

In order to use process mining techniques, ProM 6 [7] and Disco [1] are used in combination with RapidMiner 5 [9]. ProM is a process mining platform with over 500 process mining plugins.

The most interesting plugin for this study is "Replay a Log on Petri Net for Conformance Analysis" [16]. This plugin takes the event log and model as input and calculates the conformance (both fitness and the alignments).

Disco is a commercial process mining toolset that is able to deal with large datasets. In this study it is used to convert the patient data to event logs and filter the event logs. Since Disco requires licenses, this might be an issue. There are employees at Isala that have access to a license for Disco, but KeyValue [4] can be used as a free alternative.

RapidMiner allows the user to make workflows. First, it is explained why these workflows are required. The realization of the workflow is described in Section 4.2.

With RapidMiner's workflow, the user does not have to start all analyses (e.g. ProM algorithms) separately. Instead, a user can press a single button to run the whole workflow. These workflows consist of "Operators", which can be seen as building blocks of the workflows. These Operators can exchange input and output data. An alternative to RapidMiner is KNIME. However, a selection of plugins of ProM are available as Operators in RapidMiner, due to the efforts of R. Mans [8]. This allows the user to execute a series of ProM plugins in one workflow. For this reason, it is more convenient to use RapidMiner in this study.

The decision tree analysis is also performed in RapidMiner. Unfortunately, Spearman's correlation test, Wilcoxon rank-sum test and the analysis of clustered activities can not be done in RapidMiner. Therefore, additional software is used (taking the feature set as input). Spearman's correlation test is done in SPSS [10] [12] and Wilcoxon rank-sum test and the cluster-analysis are performed in Matlab [6].

4.2 Workflow

4.2.1 Main functionality

The toolset is implemented as a workflow in RapidMiner 5 and uses the ProM extension to be able to run ProM algorithms within the environment of RapidMiner. The main functionality can be seen in Figure 4.2.

While the toolset is built mostly from existing software, some functionality had to be coded manually. Functionality that was not available was programmed in Java (in combination with the "Execute script"-operator of RapidMiner). This custom functionality consists of:

- Creating arrays in order to easily sort data per patient and loop through all the data.
- Building the feature set by calculating for each patient: the costs with TDABC, the incident data (# incidents, sum of incidents scores and maximum incident score) based on the VIM export per patient and conformance based on the conformance checking plugin
- Enhancing the event log by connecting the events with the available cost data and adding incidents as events to the log.

On the highest level of abstraction, the toolset consists of six sub-processes:

- Input data: In Figure 4.1, it is shown that incident and cost data are used as input for the toolset. These data are read from an excel input file. Furthermore, all ProM related import/algorithm processes are placed in this subprocess. Conformance of the event log with the model is calculated here.
- Transform Data: Data is joined together based on the patient ID key and pivoted in such a way that the transform scripts can use it. Scripts loop through the data and build the feature set. Also, the event log is enhanced with conformance, incident and cost data.
- Export Data: The enhanced event log is written back to XES format and exported to disk. The feature set is returned as an Excel file.

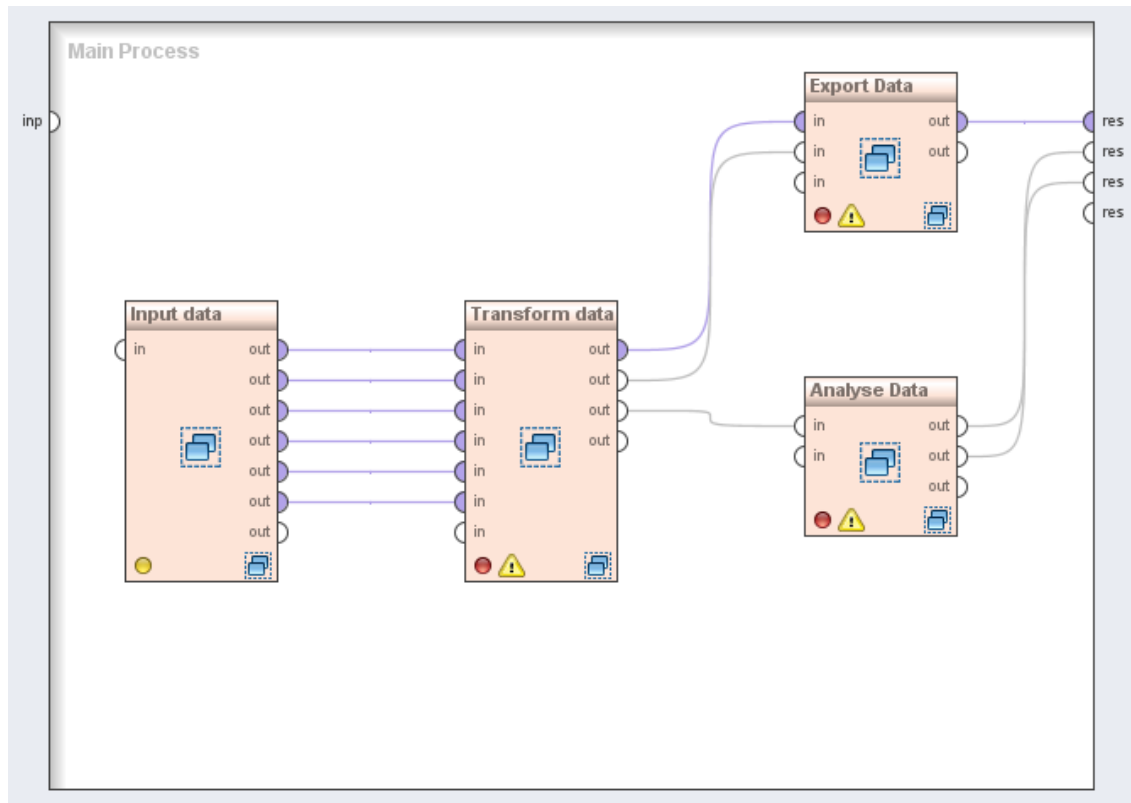


Figure 4.2: Toolset: Main functionality of the implementation in RapidMiner

- **Analyse Data:** This is a simplified analysis of the data, based on the functionality present in RapidMiner. Based on the patient data of the 'Transform Data' step, patients are split up in groups (e.g. low vs high conformance) by aggregation. Then, the other variables (e.g. sum of incident score, total costs) are determined for both groups of patients. This gives insight in the correlations between costs, incidents and conformance. Note that this is not the detailed analysis that is applied on the case study (using Matlab and SPSS). However, Matlab and SPSS work directly with the output of the toolset.

In short, the product that is delivered to Isala is able to output the feature set and enhanced event log, based on their data (patient data and VIM). Furthermore, a simple analysis can be performed to analyze the influence of high/low conformance, incidents and costs. It all works within the environment of RapidMiner.

Each sub-process is described in more detail in Appendix A.

4.2.2 Screenshots output

As shown in Figure 4.1, the toolset outputs a feature set and enhanced event log. The enhanced event log is visualized with the "Log Inspector" of ProM 6. The "Log Inspector" gives an overview of the content of the event log (see Figure 4.3 for a screenshot).

0359714 18 events		Attributes for event 1	
Start	#1 complete @Start 08.03.2013 10:50:22.000	Activity: Start	Chklist: Start
Aanmelddatum	#2 complete @57 08.03.2013 10:50:22.000	Compleet: Start	Conformance: 0.8695652173913043
QCL openen	#3 complete @57 08.03.2013 10:53:53.000	Duratie (minuten): ?	Incident score: ?
DBC openen	#4 complete @244 08.03.2013 11:26:07.000	Kosten / minuut: ?	MaxIncidentScore: 4.0
Incident (4)	#5 complete @? 08.03.2013 00:00:00.000	NumberOfIncidents: 1.0	SumIncidentScores: 4.0
Statusnr+D invoeren	#6 complete @244 18.03.2013 10:44:15.000	TotalCosts: 90.0	Vaste kosten: ?
CT-sim afwerken	#7 complete @70 03.05.2013 12:57:27.000	conceptname: Start	creator: Fluxicon Disco
Introductie Pinnacle	#8 complete @70	lifecycle:transition: start	org:resource: Start
		time:timestamp: 2013-03-08T10:50:2	

Figure 4.3: Screenshot of the enhanced event log (taken from the "Log Inspector" of ProM 6)

In the red rectangle, the (extra) attributes in the log can be seen (e.g. NumberOfIncidents). Also, an incident that is added as an event to the log can be seen in the blue eclipse.

The feature set is exported to Excel and outputted directly by the toolset. The screenshot shows the output in RapidMiner itself (Figure 3.4).

As described in Section 3.3, the feature set has columns for the patient, incident, cost and conformance feature. The columns # Log, Log+Model and Model moves are optional (not included in the screenshot).

4.3 Summary

In this chapter the realization of the toolset is described. Based on a concept, the toolset is implemented as a workflow in RapidMiner. ProM algorithms are available as operators in the environment of RapidMiner [8]. Disco is used to transform the data set to an event log. For the more detailed analyses, SPSS and MatLab are used.

Finally, a main overview of the functionality of the toolset is described. The toolset consists of operators of RapidMiner and custom scripts to build the feature set and event log.

Chapter 5

Application in the Isala hospital

In this chapter, the case study is described (Section 5.1). The approaches described in Chapters 2 and 3 are applied on this case study. First, the usual patient flow through the process is explained. The analysis is based on the feature set retrieved from the toolset. The analysis consists of three parts: an outlier analysis (based on which cases are removed from the feature set), a process-wide analysis and a activity-specific analysis (Sections 5.2, 5.3 and 5.4 respectively). The mapping between the various parts and the sections is also depicted in Figure 5.1.

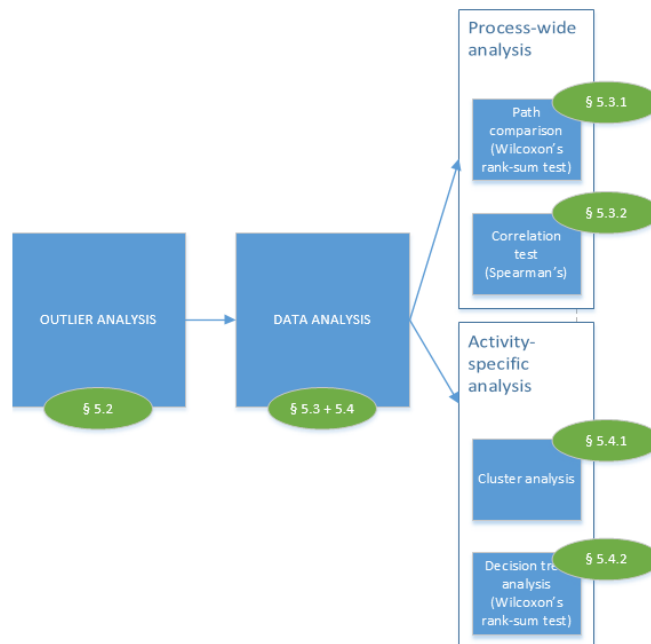


Figure 5.1: Mapping of analyses and sections

The hypotheses formulated in Figure 1.2 are tested with Spearman’s correlation test and Wilcoxon rank-sum tests. The correlation coefficients between the conformance (trace fitness), number of incidents, total costs and number of activities are calculated. This gives an indication which Hypotheses can be accepted or rejected.

Alignments of activities are used to find individual or clustered activities that have an influence on conformance, costs and/or incidents.

5.1 Scenario case study

The case study is based on patient data from the Radiotherapy department at Isala. This department treats patients that possibly have a tumors. Scans (CT or Sim) are performed to locate a tumor. Patient data were taken from a period between the 1st of February 2013 and the 1st of February 2014.

A new patient is first scheduled for a consultation with a doctor. During this consultation, it is determined whether the patient will go through a quick or regular trajectory (Figure 5.2).

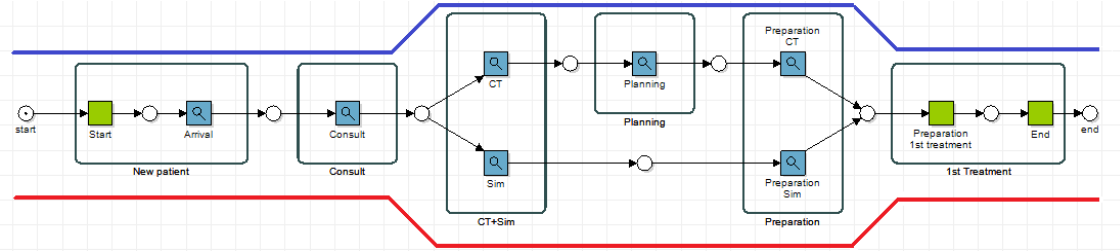


Figure 5.2: Model with CT-scan (path 1, blue) & Sim-scan (path 2, red).

Patients in the regular trajectory undergo a CT-scan (path 1), whereas patients in the quick trajectory undergo a Sim-scan (path 2). The main difference between these two trajectories is that path 1 includes a more detailed CT scan and a planning process. In this process a detailed plan is designed for the treatment of the tumor. Since acute patients (patients with a more life-threatening condition) need to be treated immediately, this detailed planning process is skipped in path 2.

For both paths, data of the scans are inserted in software that controls the radiation angles and intensities. After that, the radiation therapy (treatment) can start. However, the scope of this case study ends at the first treatment.

In this case study, 1265 patients followed care path 1 and 250 patients followed care path 2.

Costs of each activity were calculated with the TDABC method. Since the event logs of the case study do not contain "start" timestamps, an average duration of each activity was retrieved from interviews with an expert of Isala [3]. Appendix C shows the parameters of the TDABC method on which these costs per activity were based.

5.2 Outlier analysis

To make the patient data more homogeneous, preprocessing steps are required. This is done to make sure that results are not affected by extraordinary behavior in the data. A few extreme cases may have a big impact on the relation between conformance, incidents and costs. To counteract this, outliers are analyzed and (partly) removed from the data set.

Outliers with regard to costs and # activities are investigated with boxplots. The boxplots are based on the total costs of a patient's care process. The costs can be examined in more detail by looking at the outliers based on alignments. Costs are calculated based on the activities that are performed. Therefore, outliers are also investigated based on the activities that are skipped, repeated or performed extra (outside of the care path).

5.2.1 Outliers based on boxplots

In path 1, there were 86 outliers. The threshold of an outlier can be derived from the lower and upper fence of a boxplot (Section 3.4.1). In this case, an outlier has costs higher than 370 euro or lower than 265 euro (Figure 5.3). For path 2, a case is considered an outlier if the costs are higher than 135 euro or lower than 70 euro.

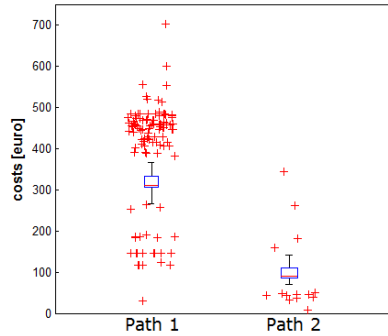


Figure 5.3: Boxplot Costs: outliers with regard to the costs.

30 of the outliers in path 1 were also considered outliers with respect to the number of activities (more than 25 activities, Figure 5.4).

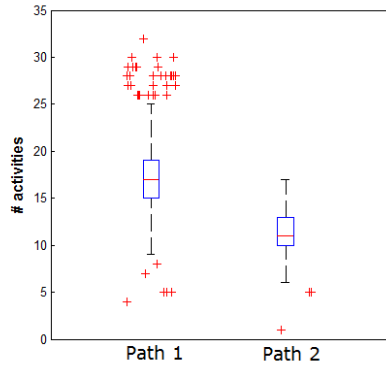


Figure 5.4: Boxplot # Activities: outliers for the number of activities.

For care path 1, 23 outliers had costs lower than 265 euro. Seven of these patients had less than 9 activities in their care process.

Similarly, 10 patients in path 2 had costs lower than 70 euro. Three of these patients were also considered outliers regarding to the number of activities (less than 6 activities).

Outliers with respect to the number of activities were removed from the data set, since in those cases, higher or lower costs are not caused by specific activities. For the remaining outliers, alignments of the activities were analyzed.

5.2.2 Outliers based on alignments

According to both care paths, activities do not occur more than once in a patient's care process. Therefore, it is not possible to have more than one Log+Model or Model moves in a patient's care process. Figure 5.5 lists the possible combinations of moves in a patient's care process.

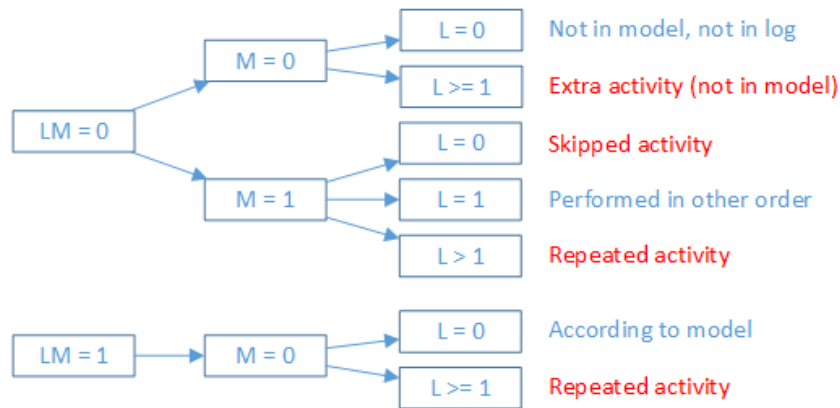


Figure 5.5: Possible combinations of moves in a patient’s care process (LM = # Log+Model moves, L = # Log moves, M = # Model moves)

Table 5.1 lists the activities that are skipped, repeated or performed extra (outside the normal activities in the care path). These activities have a direct influence on the costs: skipped activities lead to lower costs, while repeated and extra activities lead to higher costs. However, note that it is possible that skipping an activity in a patient’s care process may lead to extra generated costs in a later part of that same patient’s care process.

For the outliers in path 1, certain activities are repeated. One of those activities was *CT-sim afwerken*, which was repeated in 22 cases. This key activity for path 1 has relatively high costs (≈ 140 euro). Fifteen patients skipped this activity.

For about 30 patients, the planning process was repeated. This is verified at Isala and appears to be normal behavior for some patients [3]. In that case, the plan is adjusted and the planning process has to be redone. This can be seen in the column with repeated activities in Table 5.1, where activities from the planning process were repeated 14 to 36 (*Plan maken* and *Plan controle lab*) times in path 1.

One patient had the activity *Simulatie afwerken* in his care process, despite following care path 1. This is a key activity for care path 2, with costs of approximately 38 euro.

In path 2, there were no outliers with high costs. All seven outliers with low costs skipped the activity *Simulatie afwerken* in their care process.

The scans are seen as the key activities in each of the care paths. The usual patient flow should contain one scan. Repeating or skipping scans in the care process is considered to be extraordinary behavior [3]. Since the goal of this outlier analysis is to make the data more homogeneous, this behavior should be omitted. Therefore, all patients repeating or skipping these key activities were removed from the data set.

Approximately 30 patients repeated activities in the planning process. However, activities in the planning process are not considered key activities. Therefore, these patients are not removed from the data set as outliers.

Activity	Costs per activity	Outliers path 1			Outliers path 2
		High (56)		Low (16)	Low (7)
		Extra	Repeated	Skipped	Skipped
DBC openen	2,3	0	5	0	0
Scannen	4,6	0	3	2	0
Statusnr+D invoeren	2,3	0	5	1	0
CT-sim afwerken	139,99	0	22	15	0
Introductie Pinnacle	7,99	0	36	9	0
Plan maken	63,95	0	36	0	0
Plan controle lab	7,99	0	31	0	0
Plan afronden	2,66	0	28	8	0
Plan controle fys	15,48	0	19	0	0
Plan controle arts	22,36	0	14	0	0
Invoer MQ+MQ check	7,99	0	19	0	0
Invoer Theraview	7,99	0	21	0	0
Controle MQ+MQ check	7,99	0	18	0	1
Controle Theraview	5,33	0	19	0	0
Vrbereiding 1e bestr	5,33	0	0	0	0
QCL openen	2,3	0	5	0	0
Simulatie afwerken	37,99	1	0	0	7
Screendump getekend?	2,66	0	0	0	0
ME berekening	7,99	0	0	0	0
Controle ME-berek.	5,33	0	0	0	0
Aanmeldform geprint	2,3	0	3	1	0
Chipsoft controleren	7,45	0	3	1	0
Brief verstuurd	14,91	0	3	0	0
Doorsturen plan	5,33	0	1	0	0
Invoer XVI	7,99	0	0	0	0

Table 5.1: Repeated, skipped and extra activities of outliers. Many activities in the planning process were repeated. High and low costs were also caused by repeated or skipped scans. Path 2 only had outliers on the lower end, caused by skipped activities.

5.3 Process-wide analysis

In this analysis, both care paths are compared to each other and it is investigated whether variables conformance, costs, incidents and number of activities are related. This is done with Wilcoxon rank-sum tests.

5.3.1 Path comparison

After the outliers were removed, 1192 patients remained in path 1 and 237 patients in path 2. Further analysis is done on this filtered data set.

Variables costs, conformance, incidents and number of activities were compared for the two different care paths (Table 5.2). Wilcoxon's rank-sum test is used to see whether the groups differ significantly.

	Path 1			Path 2			Significantly different?
	Mean	St. Dev.	Median	Mean	St. Dev.	Mean	
Costs	322	47,2	311	95	26,1	89	Yes (p = 0,00)
Conformance	0,80	0,08	0,81	0,83	0,09	0,85	Yes (p = 0,00)
# Activities	17	3,1	17	11	2,1	11	Yes (p = 0,00)
# Incidents	0,08	0,28	0	0,00	0,06	0	Yes (p = 0,00)

Table 5.2: Comparison of path 1 versus path 2 regarding costs, conformance, number of activities and number of incidents. For all variables, there was a significant difference between both paths.

All variables were significantly different for patients in care path 1 compared to care path 2. Costs and number of activities were significantly higher for path 1 compared to path 2 (Figure 5.3 and 5.4). This is expected, since the planning process is absent in path 2.

Also, the number of incidents were significantly higher for path 1 compared to path 2. Only one patient following path 2 had an incident reported during his care process. For path 1, the number of patients with incidents was 98 (7,7%). Four of these patients had two incidents, while the others had only one incident reported.

Median conformance was significantly lower for path 1 compared to path 2 (Figure 5.6).

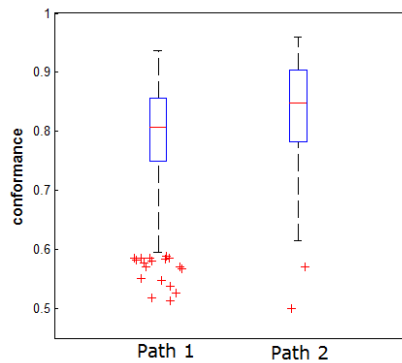


Figure 5.6: Boxplot Conformance: path 1 versus path 2. Conformance was significantly lower for path 1.

Figures 5.7 and 5.8 show the average occurrence of each activity in the two different care paths. Activities were also grouped by color, based on their costs (low: < 10 euro, medium: 10 - 30 euro, high: > 30 euro).

Activities *CT-sim afwerken*, *Plan maken* and *Simulatie afwerken* are the most expensive activities in the process.

The majority of the activities were performed approximately once on average. Note that some activities were performed more than once on average (e.g. *Introductie Pinnacle* in path 1 has a value > 1), since they were done according to the model (with move LM) and repeated later in the care process (with move L).

The occurrences are similar for both paths. Activities *Sim afwerken*, *Screendump getekend?*, *ME berekening* and *Controle ME-berekening* are only performed in path 2. These activities are related to a Sim scan. Activities *Invoer Theraview*, *Controle Theraview*, *Doorsturen plan*, *Invoer XVI*, *Controle XVI*, *CT-sim afwerken* and activities of the planning process are only performed in path 1.

Activities *Aanmeldform geprint*, *Invoer XVI*, *Doorsturen plan*, *Brief verstuurd* and *Chipsoft controleren* were performed less frequently. Activities *Aanmeldform geprint*, *Brief verstuurd* and

Chipsoft controleren are performed by a doctor. In practice, not all doctors register these activities.

Activities *Invoer XVI*, *Controle XVI* and *Doorsturen plan* are only performed for patients with a more severe form of cancer [3]. The occurrence of these activities is therefore relatively low.

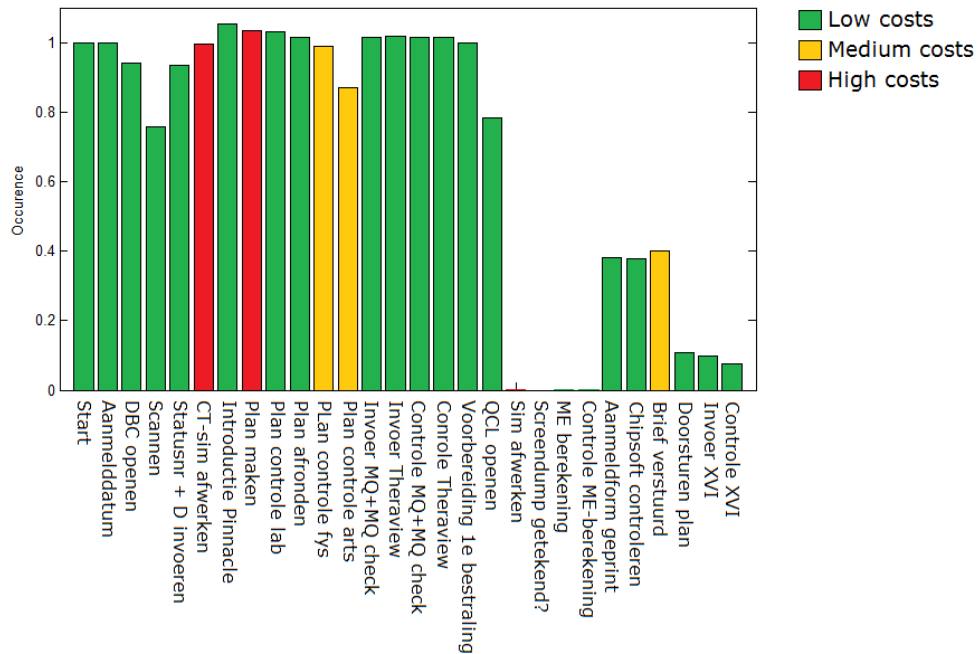


Figure 5.7: Occurrence of all activities (path 1), grouped in low, medium and high costs.

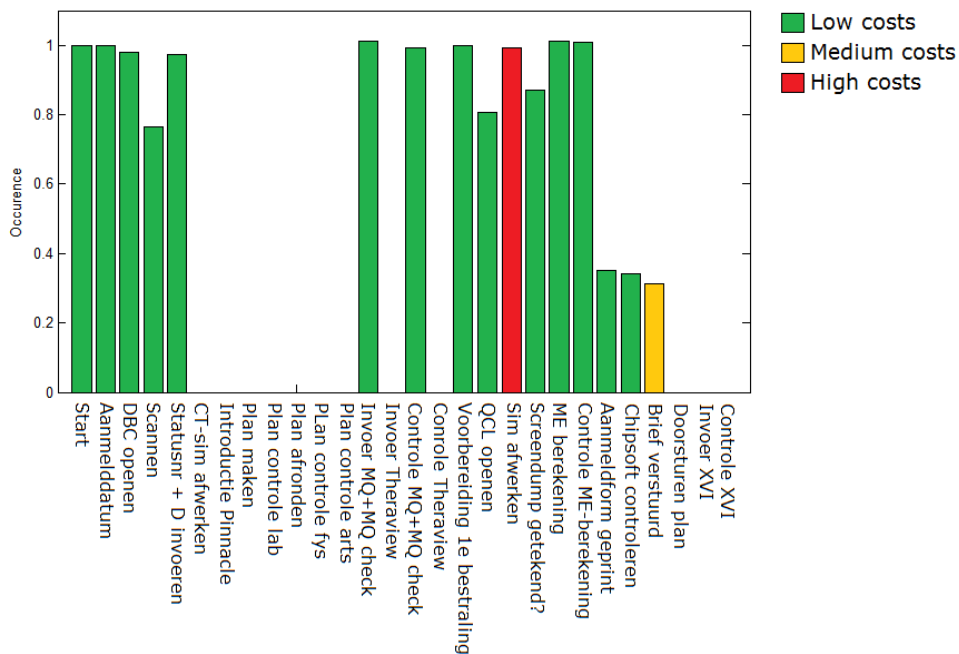


Figure 5.8: Occurrence of all activities (path 2), grouped in low, medium and high costs

Figures 5.7 and 5.8 give insight in the differences between both care paths. While the occurrence of the activities are fairly similar, some activities are only performed in one of the two care paths. Since the characteristics of both care paths are so different, it would be incorrect to merge the patient data of both paths. Therefore, the analysis of these care paths were done separately.

5.3.2 Correlation test

In this part of the data analysis, a correlation test is used to determine how closely costs and the number of activities are related. Moreover, it is investigated whether conformance has a significant (negative) effect on the costs of a patient’s care process (Hypothesis 3).

Since the number of incidents is almost always one or zero, a Wilcoxon rank-sum test is used to investigate whether number of activities, conformance and costs are different for the group of patients with and the group without incidents. Similarly, this is done regarding severity of incidents, since the score is often one or four. The results of this analysis are used to accept or reject Hypotheses 1, 2, 4 and 5.

Costs versus number of activities

For both care paths, costs increased significantly with the number of activities (Figure 5.9). Spearman’s correlation coefficients were 0,80 ($p=0,00$, $n=1192$) and 0,92 ($p=0,00$, $n=237$) respectively (Tables 5.3 and 5.4). Since the relation between costs and # activities appears to be linear, Pearson’s correlation coefficients were also calculated. This coefficient was 0,92 ($p=0,00$) for care path 1 and 0,95 ($p=0,00$) for care path 2.

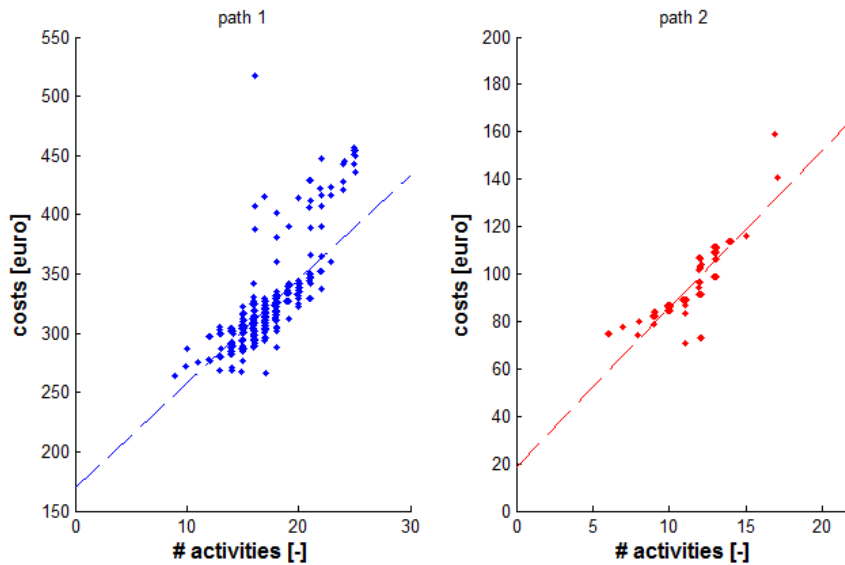


Figure 5.9: Scatterplot Costs versus number of Activities. For both paths, costs increased almost linearly with the number of activities (Pearson’s correlation coefficients: 0,92 and 0,95.)

Correlation (n=1192)	Conformance	# Activities	Total Costs
Conformance	-		
# Activities	-0,24	-	
Total Costs	-0,23	0,80	-

Table 5.3: Spearman’s correlations coefficients for path 1. Conformance, number of activities and costs were significantly correlated ($p=0,00$)

Correlation (n=237)	Conformance	# Activities	Total Costs
Conformance	-		
# Activities	-0,34	-	
Total Costs	-0,35	0,92	-

Table 5.4: Spearman’s correlations coefficients for path 2: Conformance, number of activities and costs were significantly correlated (p=0,00)

Costs vs Conformance

Costs decreased significantly with an increasing conformance (Figure 5.10). In the blue graph, a subgroup is visible with high costs and low conformance. These cases are the outliers that repeated the planning process (these were not removed in the outlier analysis). Spearman’s correlation coefficients were -0.23 (p=0,00) and -0,35 (p=0,00) for care path 1 and 2 respectively (Tables 5.3 and 5.4). In Figure 5.10, no clear linear or monotonic relation can be seen.

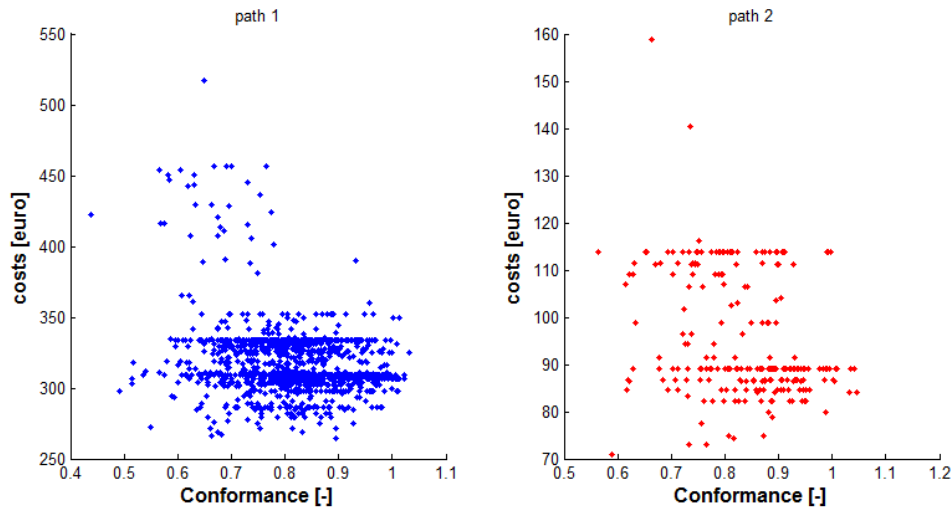


Figure 5.10: Scatterplot Costs versus Conformance. Costs decreased significantly with an increase in conformance (Spearman’s correlation coefficient: -0,23 and -0,35)

Incidents

As seen in Table 5.2, there were almost no incidents reported in path 2 (only 1 incident was reported). The number of incidents in path 1 was almost always 0 or 1. There were only four patients with 2 incidents reported during their care process. Therefore, the maximum incident score was almost always similar to the average incident score. Most incidents had a score of 1 or 4. For that reason, the groups were divided based on the maximum incident score (MIS) < 2, 5 or ≥ 2, 5.

Incident/no incident

Patients were split up into two groups: a group with incidents (I, 90 patients) and a group without incidents (NI, 1102 patients). For these groups, the median of conformance, costs and number of activities were compared using a Wilcoxon rank-sum test (Table 5.5 and Figure 5.11).

Variable	Median group I (n=90)	Median group NI (n=1102)	Significantly different?
# Activities	17	17	No (p = 0,26)
Costs	317	309	No (p = 0,10)
Conformance	0,81	0,81	No (p = 0,17)

Table 5.5: Wilcoxon’s rank-sum test incident versus no incident: groups are not significantly different

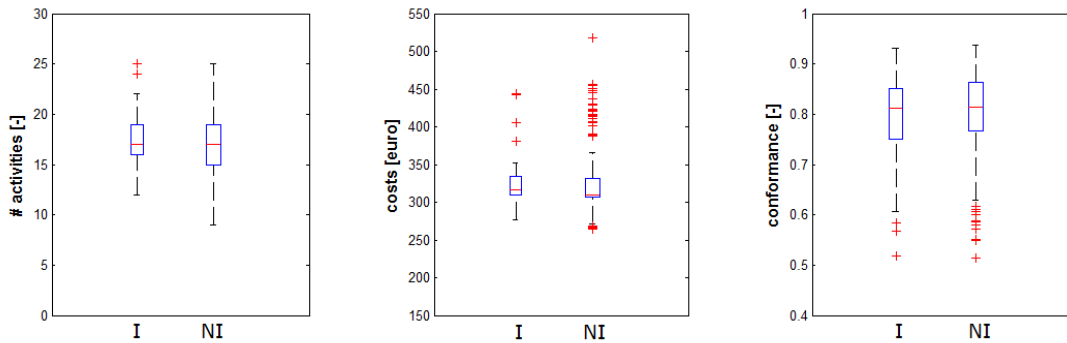


Figure 5.11: Boxplot incident versus no incident: no significant difference

There were no significant differences between conformance, costs or the number of activities comparing patients with incidents to patients without incidents.

High vs low maximum incident score

The group of patients with incidents was also divided into two groups. One group with a maximum incident score (MIS) lower than 2,5 and the other group with MIS higher than or equal to 2,5. A Wilcoxon rank-sum test was also performed on these two groups (Table 5.6 and Figure 5.12). As stated before, a Wilcoxon rank-sum test uses median values to determine whether the groups differ significantly.

Variable	Median MIS <2 (n=48)	Median MIS >2 (n=42)	Significantly different?
# Activities	16	17	No (p = 0,83)
Costs	309	310	No (p = 0,79)
Conformance	0,82	0,81	No (p = 0,51)

Table 5.6: Wilcoxon’s rank-sum test high versus low incident score: groups are not significantly different

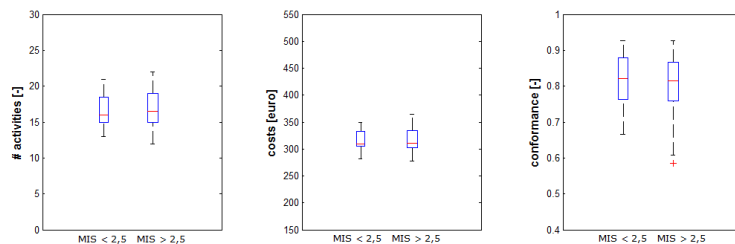


Figure 5.12: Boxplot high versus low incident score: no significant difference

Also, the severity of an incident was not related to conformance, costs or the number of activities. No significant differences between the values of these variables were found comparing the groups with high and low maximum incident score.

Feedback from Isala

Only relations between costs, conformance and number of activities were found. As expected, costs increase linearly with the number of activities. Costs decreased with an increase in conformance. This complies with Hypothesis 3. The other Hypotheses, relating incidents to the other variables, could not be confirmed in the process-wide analysis. These Hypotheses will be investigated in more detail in the activity-specific analysis.

A process expert at Isala [3] was asked for feedback on the results of the process-wide analysis. It was expected that more incidents and more severe incidents would lead to higher costs. However, it was hard to give an explanation on such a broad subject. Therefore, the feedback is focused on the activity-specific analysis. The outcomes of that analysis are verified with the process expert and asked whether the found results comply with experiences in practice. The feedback will be marked with "[3]".

5.4 Activity-specific analysis

This part of the data analysis focuses on the effect of individual and clustered activities on the variables conformance, incidents and costs.

First, it is investigated whether activities are repeated or skipped as a cluster.

Then, decision trees are used to investigate whether specific activities can be linked to differences in costs and conformance. Even though no relation was found between incidents and the other variables, it is also determined whether specific activities are related to incidents.

5.4.1 Cluster analysis

It is investigated for what activities misalignments are clustered. A cluster of activities that are often misaligned together can have a big impact on the conformance.

Whenever an activity is repeated or skipped, other activities may also be repeated or skipped (see Figure 5.5).

Clusters for move L=1

The first cluster (Figure 5.13) consists of three activities (*Statusnr+D invoeren*, *Scannen* and *DBC openen*) that are performed at the beginning of the care process. This is the case for both paths.

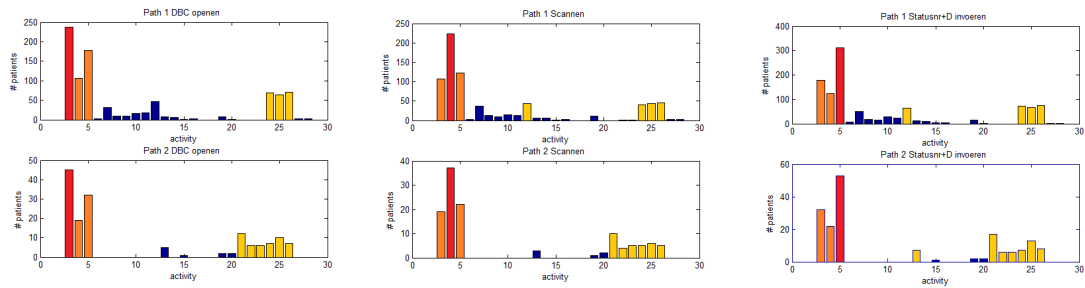


Figure 5.13: Log-move Cluster 1 (top: path 1, bottom: path 2): Activities *Statusnr+D invoeren*, *Scannen* and *DBC openen*. Whenever one of these activities was misaligned with a Log-move, the other two were often misaligned with a Log-move as well.

In practice, these activities are performed sequentially by the secretary [3]. So if one of these activities is misaligned in the process, the other activities are often misaligned as well. Activities *Aanmeldform geprint*, *Chipsoft controleren* and *Brief verstuurd* were also present in all graphs (yellow bars). These activities are related to the first cluster, since these activities are often performed directly after the tasks of the first cluster.

These activities also form a cluster (Figure 5.14), since they are performed sequentially by a doctor [3].

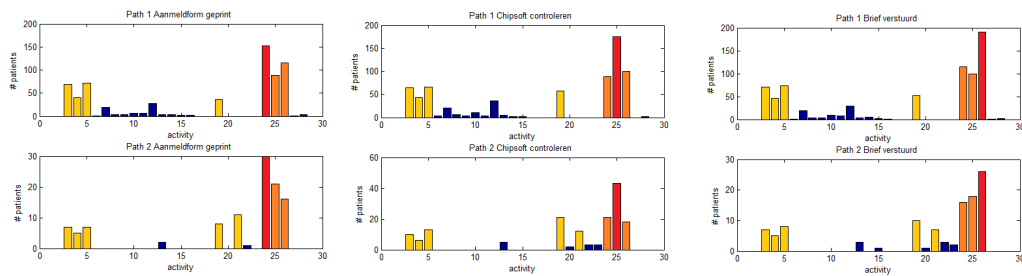


Figure 5.14: Log-move Cluster 2 (top: path 1, bottom: path 2): Activities *Aanmeldform geprint*, *Chipsoft controleren* and *Brief verstuurd*

Activities in the third cluster (Figure 5.15) are all part of the planning process in care path 1.

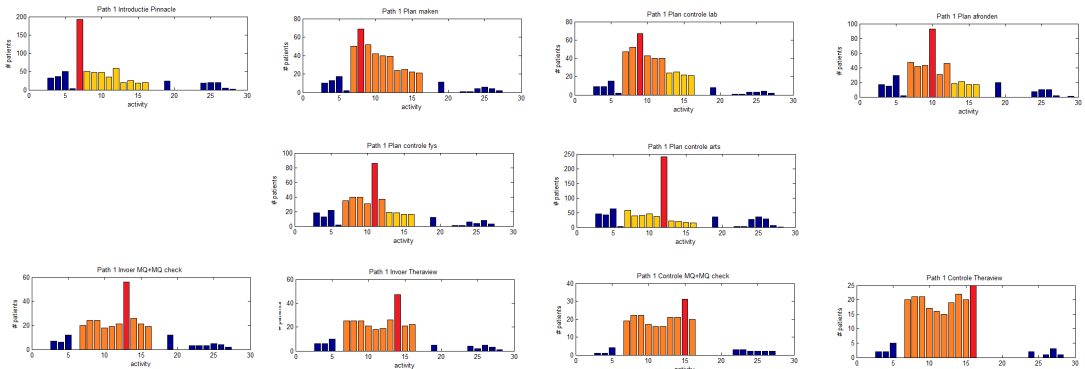


Figure 5.15: Log-move Cluster 3: activities in the planning process.

The first activities in the planning process (*Introductie Pinnacle*, *Plan maken*, *Plan controle lab*,

Plan afronden, *Plan controle fys* and *Plan controle arts*), are more often misaligned than the activities *Invoer MQ+MQ check*, *Controle MQ+MQ check*, *Invoer Theraview* and *Invoer Theraview*. In practice, this difference can be explained. The order in which the first activities in the planning process are executed is often not conform to the care path [3].

Note, that not all activities in this cluster show the same effect. *Introductie Pinnacle* and *Plan controle arts* often had a misalignment separately. This can be seen on the y-axis of those activities, since a lot more patients had a misalignment for those activities than for the other activities in the cluster (≈ 200 versus 30).

Clusters for repeated activities

It is interesting to know whether the previously found clusters come from common misalignments (when activities in a cluster are performed in the wrong order) or from repeated activities.

For these activities, only the third cluster was found again (Figure 5.16).

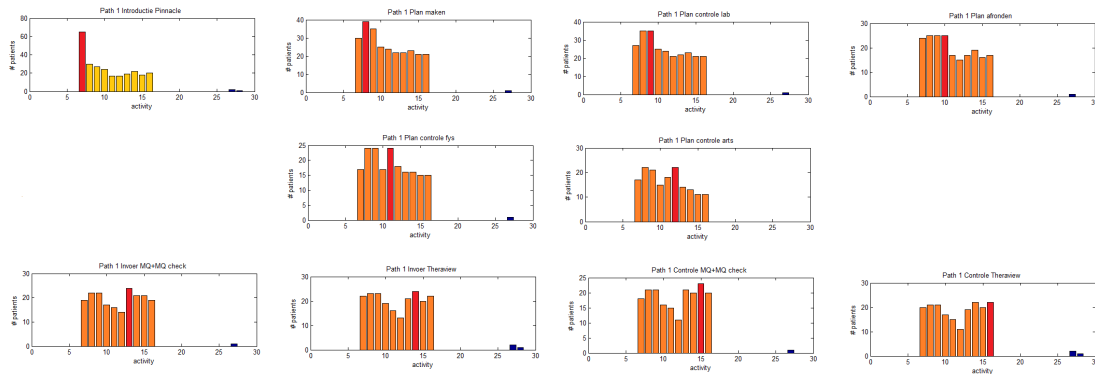


Figure 5.16: Repeated activities in cluster 3: Planning process

All activities in the planning process form a cluster. When one of the activities is repeated, the other activities are often repeated as well. Whenever a plan is rejected, a new plan is drafted. In this case, the whole planning process is repeated.

This cluster was also visible in the outlier analysis (Table 5.1). In that table it was seen that about 30 patients repeated the planning process.

The frequency of repetition of the planning process is similar to the frequency of misalignments for activities *Invoer MQ+MQ check*, *Controle MQ+MQ check*, *Invoer Theraview* and *Invoer Theraview*. Misalignments (move $L=1$) for these activities are only caused by repetition. Since the activities follow the "four-eyes-principle" (activity is verified by a second person), it is expected that these activities form pairs. For the other activities in cluster 3 only part of the misalignments were caused by repetition of the planning process. These activities are not always performed in a fixed order. It is a difficult part of the care process to describe [3].

Clusters for skipped activities

No clusters were found for skipped activities. Activities were skipped individually. Similarly, no clusters were found for move $M \geq 1$.

The activity closest to a cluster was *DBC openen*. However, all activities fall below the threshold of occurring in 20% of the cases.

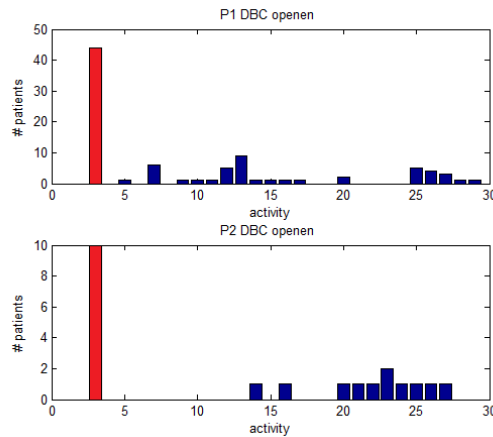


Figure 5.17: Skipped activities example (no clusters found)

5.4.2 Decision trees

With decision trees, the relations between conformance, incidents and costs were investigated on a more detailed scope. Decision trees were built for all variables. However, for incidents no decision trees were found.

Based on the decision trees, candidate activities were selected and tested on significance with a Wilcoxon rank-sum test (as described in Chapter 3). All trees related to conformance had an accuracy of approximately 70% and all trees related to costs had an accuracy of approximately 90%. Therefore, no trees were removed based on accuracy.

Conformance

For path 1 and path 2, median value (0.81) was used as threshold to divide patients in a high ("true" in the decision tree) and low ("false") conformance group. Figures 5.18 and 5.19 show the iterations of the decision tree analysis for both paths, based on which the candidate activities were selected.

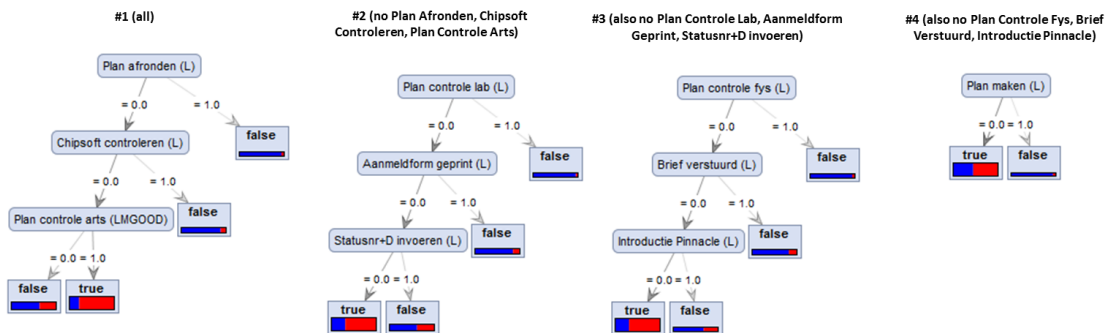


Figure 5.18: Decision tree (Conformance) (path 1). Patients were split up in groups with a conformance lower than and higher or equal to 0.81. Accuracy of all trees is $\approx 70\%$.

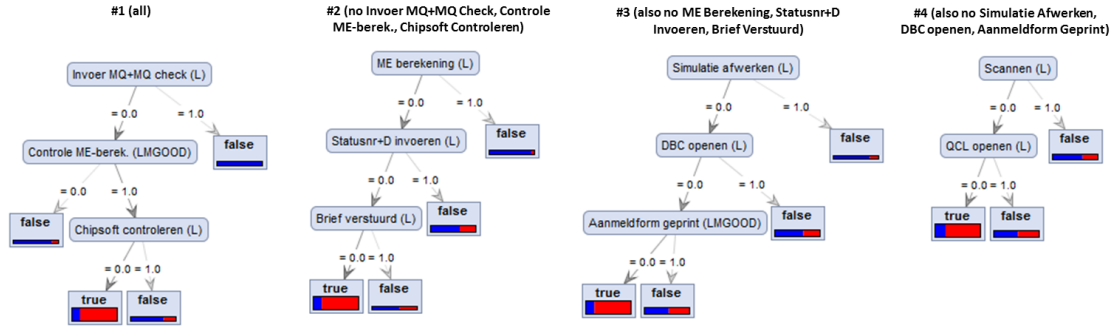


Figure 5.19: Decision tree (Conformance) (path 2). Patients were split up in groups with a conformance lower than and higher or equal to 0.81. Accuracy of all trees is $\approx 70\%$.

Since the conformance was based on alignments, it is trivial to see that an activity with move LM was linked to a higher conformance and move L to a lower conformance. This effect was seen for all activities in the decision tree except for *Aanmeldform geprint*. However, this was caused by the preceding leaves in that tree. Individually, *Aanmeldform geprint* with move LM was linked to a higher conformance.

All candidate activities influence the conformance significantly (Table 5.7). The effect on conformance (\uparrow or \downarrow) is based on the decision trees. If the tree predicts that the presence of an activity (value = 1.0) leads to a higher conformance (group "true"), the activity has a positive effect (\uparrow). Otherwise, the activity has a negative effect (\downarrow).

Activity	Move(s)	Path	Effect on conformance	p	In Cluster?
Plan afronden	L	1	\downarrow	0,00	Yes, cluster 3
Chipsoft controleren	L	1	\downarrow	0,00	Yes, cluster 2
Plan controle arts	LM	1	\uparrow	0,00	Yes, cluster 3
Plan controle lab	L	1	\downarrow	0,00	Yes, cluster 3
Aanmeldform geprint	L	1	\downarrow	0,00	Yes, cluster 2
Statusnr+D invoeren	L	1	\downarrow	0,00	Yes, cluster 1
Plan controle fys	L	1	\downarrow	0,00	Yes, cluster 3
Brief verstuurd	L	1	\downarrow	0,00	Yes, cluster 2
Introductie Pinnacle	L	1	\downarrow	0,00	Yes, cluster 3
Plan Maken	L	1	\downarrow	0,00	Yes, cluster 3
Invoer MQ+MQ check	L	2	\downarrow	0,00	Yes, cluster 3
Controle ME-berek.	LM	2	\uparrow	0,00	No
Chipsoft controleren	L	2	\downarrow	0,00	Yes, cluster 2
ME berekening	L	2	\downarrow	0,00	No
Statusnr+D invoeren	L	2	\downarrow	0,00	Yes, cluster 1
Brief verstuurd	L	2	\downarrow	0,00	Yes, cluster 2
Simulatie afwerken	L	2	\downarrow	0,00	No
DBC openen	L	2	\downarrow	0,00	Yes, cluster 1
Aanmeldform geprint	LM	2	\uparrow	0,01	Yes, cluster 2
Scannen	L	2	\downarrow	0,01	Yes, cluster 1
QCL openen	L	2	\downarrow	0,00	No

Table 5.7: Candidate activities for high or low conformance (all activities had a significant effect on conformance)

Most of the activities are part of a cluster. If one of the activities in these clusters is misaligned, it creates a chain-reaction of other misaligned activities leading to a significantly lower conformance. In care path 2, individual activities (*QCL openen*, *ME berekening*, *Controle ME*

berek. and *Simulatie afwerken*) with a misalignment (move L=1) had influence on the conformance. This was not the case for care path 1, since only clustered activities showed a significant effect on conformance. If more and bigger clusters of activities are present in a care process, it is expected that individual activities have less influence.

Costs

For this analysis, patients were split up into two groups: high costs and low costs. Again, median values were used as threshold. For path 1, the threshold was 310 euro and for path 2 it was 88 euro. Figures 5.20 and 5.21 show the decision trees.

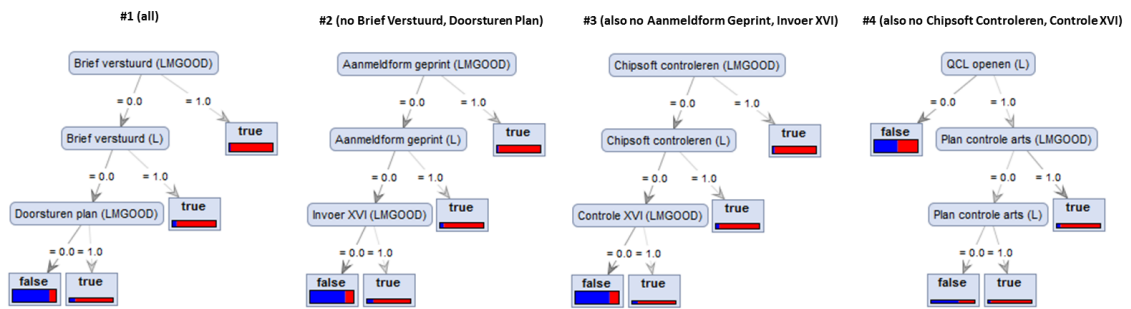


Figure 5.20: Decision tree (Total costs) (path 1). Patients were split up in groups with costs lower than and higher or equal to 310 euro. Accuracy of all trees is $\approx 90\%$.

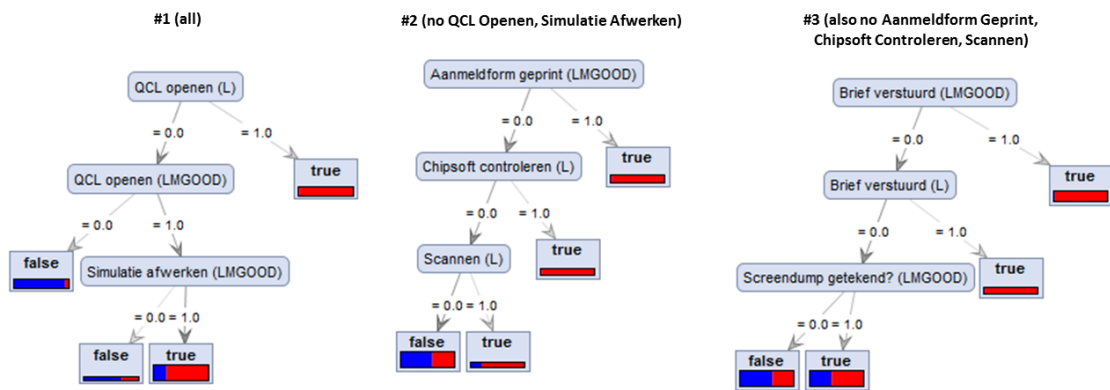


Figure 5.21: Decision tree (Total costs) (path 2). Patients were split up in groups with costs lower than and higher or equal to 88 euro. Accuracy of all trees is $\approx 90\%$.

Logically, all candidate activities lead to higher costs (\uparrow), since they had move L or LM. However, not all activities had a significant influence on the costs (Table 5.8).

Activity	Move(s)	Path	Effect on costs	p	In Cluster?
Brief verstuurd	LM + L	1	↑	0,00	Yes, cluster 2
Doorsturen Plan	LM	1	↑	0,00	No
Aanmeldform geprint	LM + L	1	↑	0,00	Yes, cluster 2
Invoer XVI	LM	1	↑	0,00	No
Chipsoft controleren	LM + L	1	↑	0,00	Yes, cluster 2
Controle XVI	LM	1	↑	0,00	No
Plan controle arts	LM + L	1	↑	0,00	Yes, cluster 3
QCL openen	L	1	↑	0,10	No
QCL openen	LM	2	↑	0,32	No
QCL openen	L	2	↑	0,00	No
Simulatie afwerken	LM	2	↑	0,82	No
Aanmeldform geprint	LM	2	↑	0,00	Yes, cluster 2
Chipsoft controleren	L	2	↑	0,00	Yes, cluster 2
Scannen	L	2	↑	0,22	Yes, cluster 1
Brief verstuurd	LM + L	2	↑	0,00	Yes, cluster 2
Screendump getekend?	L	2	↑	0,12	No

Table 5.8: Candidate activities for high costs (tested on significance with Wilcoxon rank-sum test)

Activities that are characteristic for a care process with high costs were activities with an occurrence between 10 and 90 % (see Figures 5.7 and 5.8), not necessarily activities with high costs. If an activity is almost always or never present in a care process, it does not make a difference in costs, even if it is an expensive activity.

For care path 1, activities *Doorsturen Plan*, *Invoer XVI* and *Controle XVI* are performed sequentially according to the care path. An XVI is only performed for patients with a more life-threatening condition [3]. This would comply with these activities having lower occurrence and therefore being more decisive for the costs.

Note that patients with very high and low costs were already removed from the data set as an outlier. For these patients, expensive scans were repeated or skipped.

Clustered activities did not show a significant influence on costs. Only clustered activities with relatively low occurrence had an effect on costs. For the biggest cluster (cluster 3), only *Plan controle arts*, which had an occurrence of 90%, showed a significant effect. Other activities in the planning process had a high occurrence of approximately 100%.

It is expected that clustered activities that are often repeated (occurrence > 100%) do have a significant effect on costs. However, in only 1,7% of the cases (20 out of 1200), the planning process was repeated.

Incidents

Since most of the patients do not have incidents in their care process (1128 out of 1254, 90%), a decision tree analysis that evaluated all leafs in the tree to "no incidents" has a high accuracy (since 90% of the patients fall into that group). It is possible that a decision tree finds a very specific subgroup that contains most of the patients with incidents. However, no decision tree was found for the variable "incidents".

Differences in occurrence of activities between patients with and without incidents were visualized in a bar-graph for the different alignments (Figures 5.22, 5.23 and 5.24). This was also done for the differences between patients with severe and non-severe incidents (Figures 5.25, 5.26 and 5.27). Note that in the latter, all of these patients had an incident.

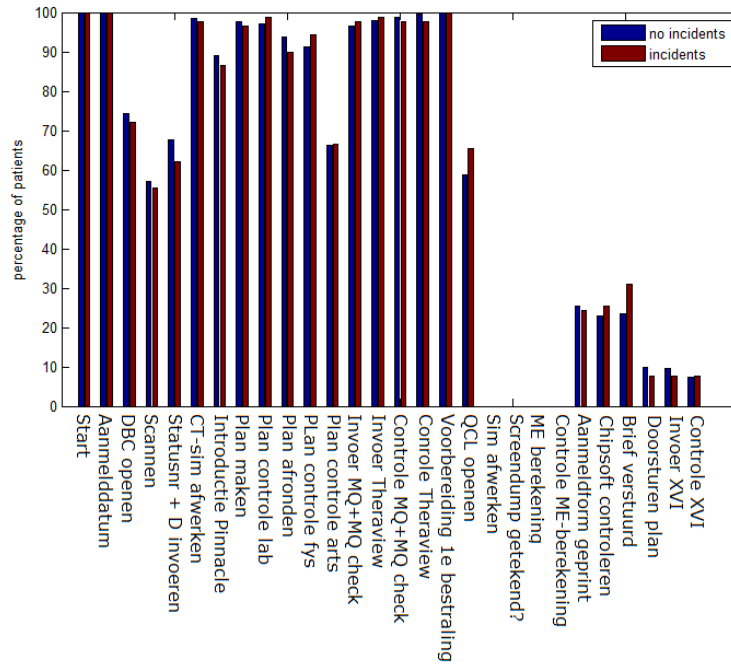


Figure 5.22: Incidents vs no incidents: occurrence of move LM in both groups. No significant difference between the groups was found.

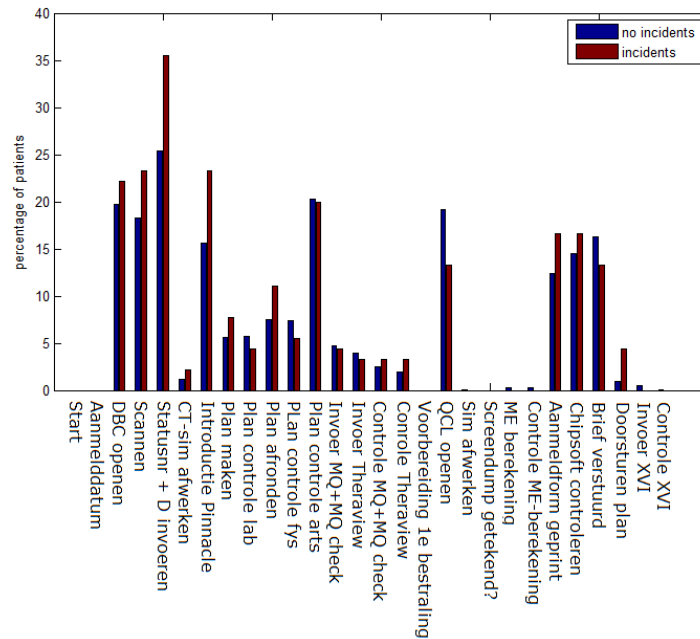


Figure 5.23: Incidents vs no incidents: occurrence of move L in both groups. No significant difference between the groups was found.

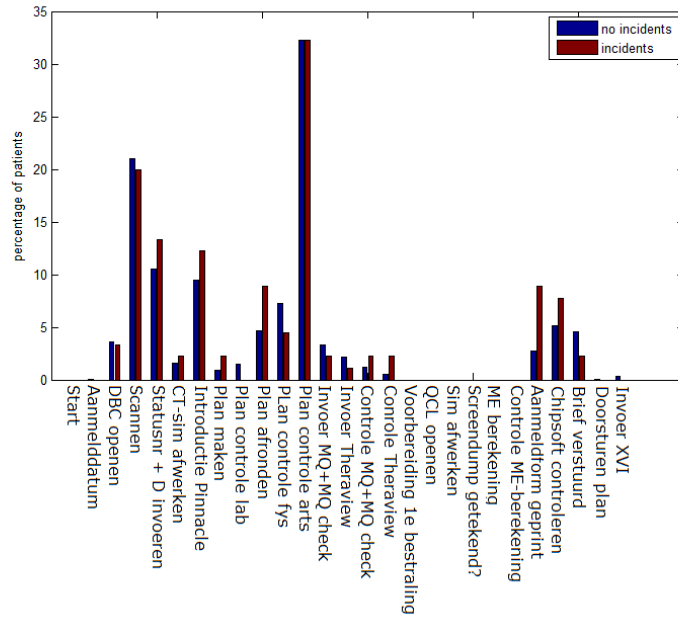


Figure 5.24: Incidents vs no incidents: occurrence of move M in both groups. No significant difference between the groups was found.

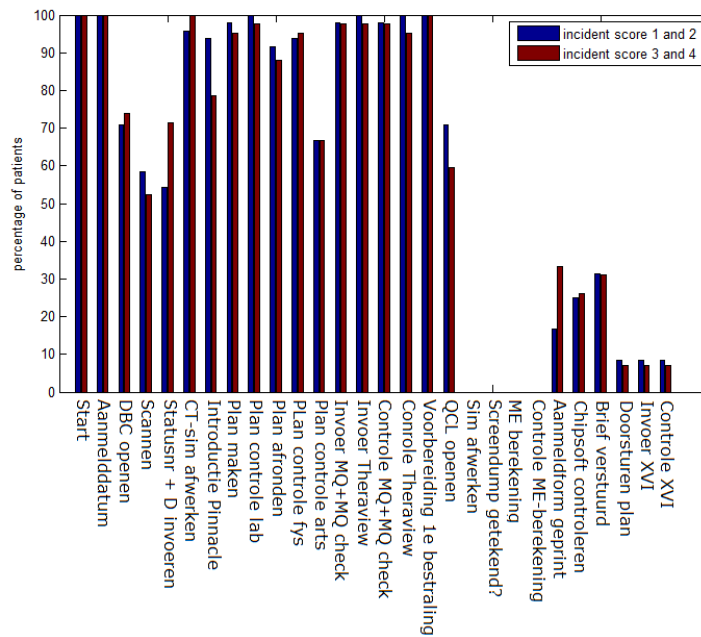


Figure 5.25: Severe vs non-severe incidents: occurrence of move LM in both groups. No significant difference between the groups was found.

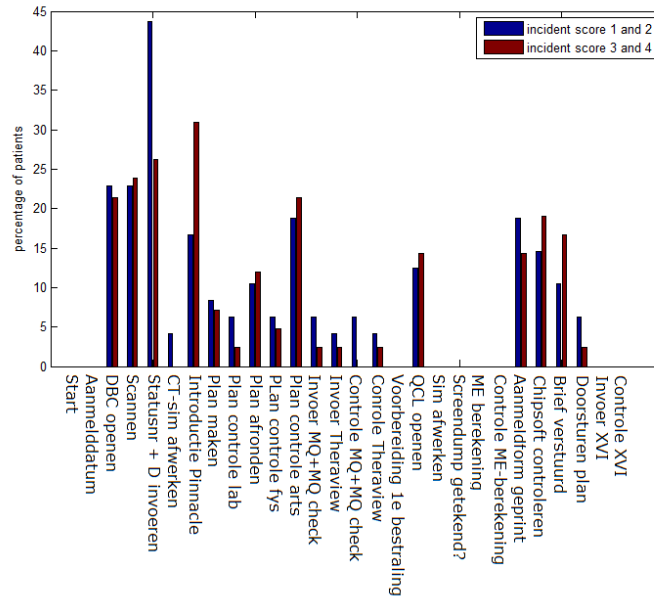


Figure 5.26: Severe vs non-severe incidents: occurrence of move L in both groups. No significant difference between the groups was found.

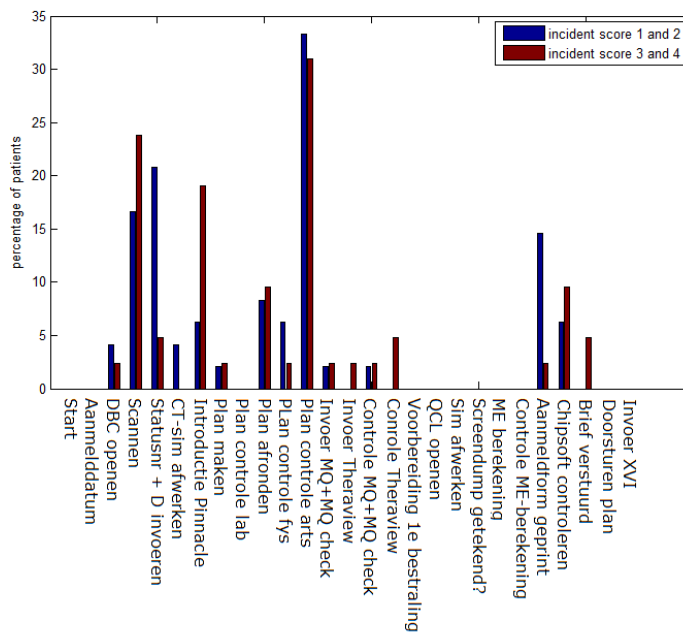


Figure 5.27: Severe vs non-severe incidents: occurrence of move M in both groups. Occurrence of *Statusnr+D invoeren* and *Aanmeldform geprint* with move M was significantly higher for incidents with a lower score.

There was a high similarity between the groups. For each activity in Figures 5.22, 5.23, 5.24, 5.25, 5.26 and 5.27, it was tested whether the blue bar (no incidents/incident score 1 and 2) was significantly different from the red bar (incidents/incident score 3 and 4). The percentages of both

bars are tested on statistical power. The (near) significantly different activities can be seen in Table 5.9.

Activity	Move	Occurrence score	Occurrence score	p
		≤ 2	> 2	
Introductie Pinnacle	LM	94	79	0,07
Aanmeldform geprint	LM	16	34,9	0,09
Statusnr+D invoeren	M	20	4,7	0,05
Introductie Pinnacle	M	6	18,6	0,13
Aanmeldform ge-print	M	16	2,3	0,02

Table 5.9: Activities with (near) significantly different occurrence for the groups with low and high incident score. No activities were found for the groups with or without incidents.

Between patients with and without incidents, no activities had a significantly different occurrence. Activities with a significant difference between patients with severe and non-severe incidents were *Statusnr+D invoeren* and *Aanmeldform geprint*. Occurrence of these activities with move M was higher for incidents with a lower score. In other words, skipping these activities is linked to less severe incidents.

In practice, incidents do occur often during activities *Statusnr+D invoeren* and *Aanmeldform geprint*. These incidents have a low impact in general, but the likelihood of the incident to reoccur is high [3]. However, according to Table 2.4, the score for these type of incidents (high likelihood and low impact) is not higher than 2. Therefore, the results of Table 5.9 can not be verified.

Moreover, incidents that occur in the planning, often have a bigger impact on the patient [3]. However, no significant differences in incident score were found for activities in the planning process.

5.5 Summary

In this chapter, the approaches to calculate the relations between conformance, incidents, costs and number of activities were applied on a case study. The results of these approaches are summarized in the next chapter (section "Case Study").

Chapter 6

Conclusion

Several choices were made to find an answer to the research questions. These choices will be discussed first (Section 6.1). Next, the strengths and weaknesses of the toolset are described (Section 6.2). In the previous chapter a case study was performed. The results of this case study are explained, viewed from the perspective of costs, conformance and incidents (Section 6.3). Then, the hypotheses formulated in Chapter 1 are validated (Section 6.4). These hypotheses are accepted or rejected, based on the results of the case study. This thesis is focused on costs, conformance and incidents. However, more interesting aspects can be considered for future work (Section 6.5).

6.1 Approach

During this thesis, several choices were made in how to answer the research questions. In this section, these choices are discussed. Four topics are covered:

- was the TDABC costing method the best choice?
- how usable was the incident data from the VIM system?
- Why was the relation between the costs and # activities so high?
- How was monitoring interpreted and realized in this study?

6.1.1 TDABC method

TDABC was selected as costing method. Compared to the other candidate costing methods (method of Dutch hospitals, ABC and RCA), this method was more accurate and could make better use of the event log.

To make use of the full capabilities of TDABC, both "start" and "complete" timestamps are required in the event log. However, the event log used in the case study did not contain "start" timestamps. The advantage of TDABC over RCA is therefore lost. Duration of activities was not based on the actual time per activity, but on a fixed duration estimated by an expert in the hospital. This is similar to the approach used in the RCA method to define costs per activity. In this method costs are not estimated as costs per minute, but directly as costs per activity based on budgets and allocated resources.

In hindsight, the RCA method might have been more suitable for this case study. However, in general, TDABC is still favorable over the RCA method. When "start" timestamps are recorded in the event log, TDABC gives a more patient specific estimation of costs compared to RCA and makes better use of the event log.

6.1.2 VIM system

The VIM system of Isala was used to extract incident data from the process. The data from this system was ideal for this study. Although no significant differences were found between incidents with a high or low score, it is still important to be able to differentiate between severe and non-severe incidents.

One remark on the VIM system is that incidents were logged in the VIM system with a date. A date makes it impossible to place an incident between activities if there are multiple activities performed on one day. Also, the incident date logged in the system was often not the actual date of the incident. Therefore, it is advisable to Isala to be more precise about the time an incident occurred (a timestamp instead of a date). This would make it easier to apply process mining techniques on incident data.

6.1.3 Cost versus # activities

In Figure 5.9, a high linear correlation was found between costs and the number of activities (0,92 for path 1 and 0,95 for path 2). If these variables are highly correlated, a logical question can be asked: why going through all the trouble of calculating the total cost of a patient's care process if simply counting the number of activities is sufficient as well? In the TDABC method, costs are directly generated from activities. Each activity has a duration, cost/minute and fixed costs. In the case study, the correlation between costs and # activities are high due to multiple reasons:

- Resources earn more or less the same salary per year, resulting in a similar cost per minute for each resource (only doctors are clearly more expensive).
- In most cases, activities are performed by the same resource(group), resulting in the same cost per minute for all instances of an activity.
- Activities are often present in most cases or in nearly any case (see Figures 5.7 and 5.8).
- Due to missing "complete" timestamps, average durations (estimated by a process expert [3]) were used instead of the difference between the "start" and "complete" timestamp.

All these reasons lead to a lower variance in costs. A higher variance in costs leads to a lower conformance between costs and # activities. While costs are still generated directly from activities, these variables would not be directly interchangeable. Therefore, as long as it is expected that activities differentiate in costs, it is important to keep both costs and # activities in mind.

6.1.4 Monitoring

Monitoring is one of the subjects in the research questions described in Section 1.3. Monitoring can be seen as analyzing a trend over time for specific parameters (e.g. costs). Graphs can be created that give a historical view. For example, a graph with the average total costs of a patient's care process, calculated for each month. Then, peaks and drops in the graph can be analyzed and investigated.

However, in this thesis, monitoring is seen on a broader scope. The toolset does not output graphs that visualize the performance over time. Instead, it outputs a feature set that contains information about conformance, incidents and costs. Since it is known when patients started with their care process, the trend over time can be extracted from this feature set by filtering out the patients from a specific time span. This gives the user more freedom in what to monitor, since all the data is present in the feature set.

6.2 Toolset

In this thesis, methods are selected to measure conformance, costs and incidents. A toolset was created that applies these methods and gives the user the ability to relate these three variables to each other.

The toolset is applied on a case study and successfully gives insight in costs, conformance and incidents belonging to each patient's care process. By using the output of the toolset, it is possible to monitor the performance of a department and to spot any trends over time. Furthermore, process mining algorithms from ProM are available within the toolset [8].

Improvements of the toolset can be found in the visualization of the results. For example, the feature set is outputted as a table in RapidMiner. It is possible in RapidMiner to create charts from this feature set, but a user would preferably have a dashboard with all relevant data on the screen. This could be achieved by integrating RapidMiner into a Java application, using RapidMiner's API. However, this requires a significant amount of work.

6.3 Case study

The two care paths studied in the case study were significantly different with respect to costs, conformance, incidents and number of activities. Path 1 had significantly higher costs and higher number of activities and significantly lower conformance than path 2. Furthermore, only one incident was reported for patients in path 2. Since the majority of patients in care path 1 had no or only 1 incident, no distinction was made between average, maximum or minimum incident score.

Within the two care paths, variables conformance, costs and number of activities were related to each other.

6.3.1 Costs

For both care paths, costs increased linearly with the number of activities (Pearson's correlation coefficients were 0.92 and 0.95 for path 1 and path 2 respectively).

As a first step of the data-analysis, outliers with very high and low costs were removed from the data set. These differences in costs were caused by repetition and omission of expensive, key activities in the care paths (*CT-sim afwerken* and *Simulatie afwerken*). However, after removing these outliers, decision trees showed that the occurrence of activities was more decisive regarding to the costs of a patients care process than the actual costs per activity. Activities with an occurrence between 10% and 90% were significantly more present in more expensive care processes.

Activities with a very low occurrence ($\approx 0\%$) or high occurrence ($\approx 100\%$) did not make a difference in costs, even if it was an expensive activity.

Clustered activities had a minor effect on costs. This might be caused by the low repetition of activities in these clusters (cluster 3 was repeated in only 1,7% of the cases). However, it is expected that repeated clustered activities have influence on the costs of a process. If one of the activities within a cluster is repeated, other activities are repeated as well, increasing the costs significantly.

6.3.2 Conformance

For both care paths, conformance decreased significantly with the number of activities (Spearman's correlation coefficients were -0,24 and -0,34 for path 1 and 2 respectively). This is expected, since care processes with a higher number of activities have more log-moves (leading to a lower conformance).

Clustered activities had a high influence on the conformance. Care processes with many and big clusters of activities are more sensitive regarding to conformance. If one of the activities in a cluster is misaligned, a chain-reaction in the cluster leads to a lower conformance. In path 1, both the number of activities and the number of clustered activities is higher than in path 2.

In path 1, two activities (*Introductie Pinnacle* and *Plan controle arts*) in the planning process often did not follow the care path. Since the planning process is not part of path 2, this might explain the significantly higher conformance in this path.

6.3.3 Incidents

Incidents could not be related to the number of activities or conformance in the case study. Also, the decision tree analysis was not suitable for the incident data. Occurrences of all activities were compared for a group with and without incidents and a group with severe and non-severe incidents. This resulted in few activities with significant differences between the groups. However, according to the process expert at Isala [3] and the VIM table (Table 2.4), these incidents should not have an incident score higher than two. Therefore, these results contradict with the expectations of Isala and can not be verified.

6.4 Validation of hypotheses

Based on the case study, Hypothesis 1, 2, 4 and 5 are rejected. The number and severity of incidents were not related to conformance or the number of activities. However, this might be caused by the lack of timestamps (only the dates were logged) in the incident data. For this reason, it could not be determined exactly where in the patient's care process the incident occurred. If this would be known, it could have been possible to connect incidents to specific activities or clusters of activities. Also, relatively low number of patients had an incident during their care process. Also, the variety of the number and severity of incidents was low (0 or 1 incident(s) and a score of either 1 or 4).

Hypothesis 3 can be accepted. In the case study, a significant correlation was found between costs and conformance. A higher conformance lead to lower costs. Deviations from the care path were often Log-moves and not Model-moves. This means that a misalignment leads to higher costs, since a Log-moves generates costs for a costing method, while Model-moves do not. Therefore, the opposite relation could be found if data would be used of a care process where a lot of activities are skipped. Still, there is a clear relation between costs and conformance.

6.5 Future work

More variables can be added to the analysis. The toolset returns a feature set to the user. Columns can be added to this feature set to relate other variable to costs, incidents and conformance.

First, information about (human) resources that performed activities in a patient's care process can be added to the feature set. The resources allocated to each activity are known in the event log. The "Case Data Extractor"-operator in the toolset shows for each patient what resources are linked to their activities. The presence of a resource in a patient's care process can be related to costs, incidents and conformance. However, this can quickly become complex if a patient had a lot of different resources. Also, it is unknown whether the activity that the resource performed did actually have any influence.

Another option is to link the responsible doctor to the patient. It is debatable, but the resource that has the most influence on the path a patient takes in their care process is the doctor. In a department there can be individual doctors that do not let their patients conform to the care path, but do whatever they deem best for their patients. Regardless of whether this is good or bad for the patient, an executive of a department might want to investigate this. By adding the responsible doctor to the trace of a patient, this new variable can be linked to conformance.

Another variable is the outcome (e.g. did the patient survive?) of the care process. It can be interesting to know whether a patient recovered from their original complaints. If a low conformance can be linked to a worse outcome, guidelines can be adjusted to conform more closely to the care path. These kind of insights are interesting to know and can be added to the toolset if data about the outcome is available.

Patient's satisfaction is another variable that can be investigated. A care path can lead to fewer incidents, but greatly reduce the patient's satisfaction.

6.6 Summary

In this thesis, methods to measure conformance, incidents and costs were discussed. Conformance checking is a part of process mining that contains methods to calculate the trace fitness and alignments for a patient's care process. For costs, Time-Driven Activity Based Costing (TDABC) was selected as the most appropriate costing method. Incident data were retrieved from the VIM system. Of these data, the number of incidents and incident scores (maximum and sum) were used.

Based on these methods, a toolset was created. The toolset successfully gives insight in the care processes of a hospital. Specific activities within a care process can be related to higher costs and conformance. More accurate recording of incidents might also indicate what activities lead to incidents and if these incidents are related to conformance or number of activities. In further research it would be useful to add additional information to event logs. Information about resources, the responsible doctor, outcome of the treatment and patient's satisfactory can give a more detailed insight in care processes in a hospital.

A set of research questions and hypotheses were formulated. In the case study, only Hypothesis 3 could be accepted: *A higher conformance leads to lower costs in a patient's care process.* Surprisingly, incidents did not have a significant relation with conformance, cost and number of activities.

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Appendix A

Workflow implementation RapidMiner: subprocesses

In Chapter 5, the high level implementation of the toolset was shown. In this Appendix, each subprocess is explained in more detail.

A.1 Input data

This step converts the cost and incident data from Excel sheets to Examplesets (Figure A.1). The 'Read Excel' operator is used. By using the 'Import Configuration Excel' option of that operator, the input parameters can be changed (e.g other input filepath, other sheets, other column headers).

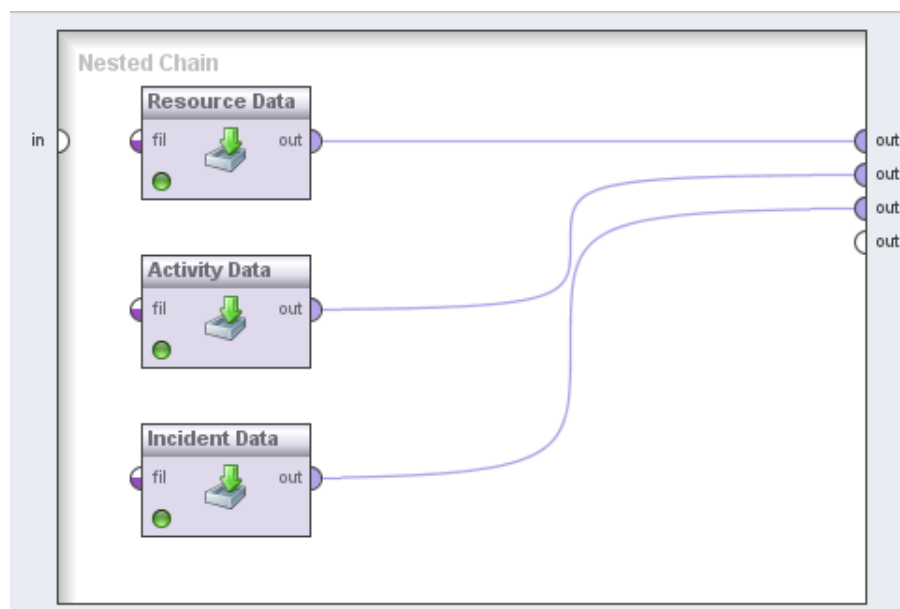


Figure A.1: Input data toolset (1): Cost (Resource and Activity) data and incident data are imported from Excel

Every ProM related operator is put in this sub-process (Figure A.2). These operators come from the ProM6 1.0.7 extension package available in RapidMiner (created by R. Mans) [8]. The event log is converted from XES to an ExampleSet. Furthermore, the Conformance plugin of A. Adriansyah [16] is used to calculate the conformance of the event log with the Petri Net model

and to determine the alignments of the traces. Moreover, the "Case Data Extractor" is used to retrieve the # activities in each patient's care process.

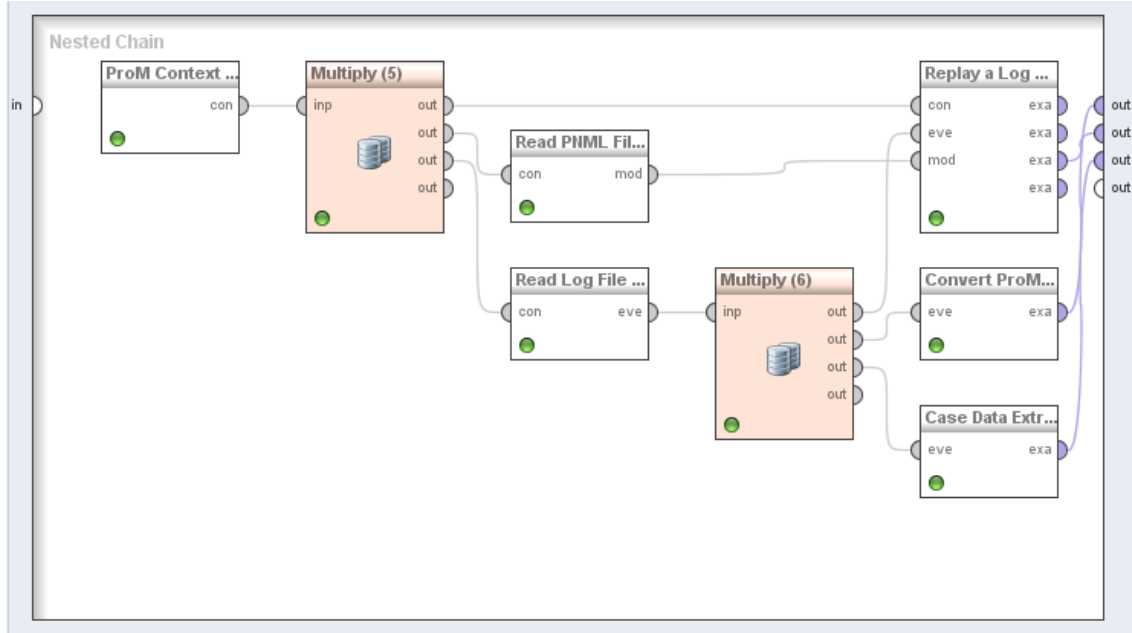


Figure A.2: Input data toolset (2): Event log and the model of the care path are imported with ProM extensions and trace fitness is calculated for each patient. Case data extractor is used to retrieve the # activities in each patient's care process.

A.2 Transform data

Each event in the event log has information of the patient ID, activity name and resource. The input data (cost data and resource data) has information about the cost/minute for each resource and duration and fixed cost of activities. These data are merged and pivoted in preparation to the second part of this sub-process. The second part uses script to generate the feature set and enhanced event log and require a specific input.

See Figure A.3 for an overview of the first part of this sub-process.

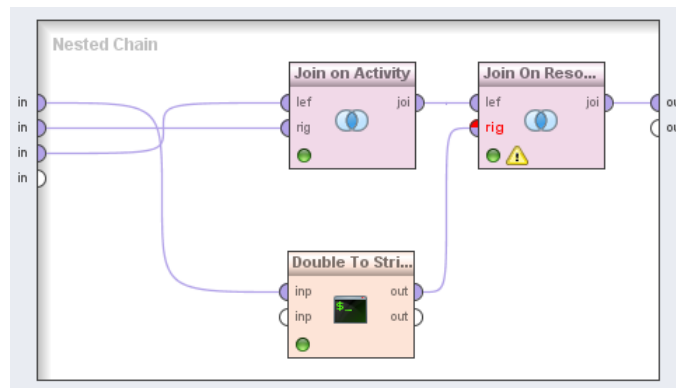


Figure A.3: Transform data toolset (1): data is merged and pivoted in order to allow the scripts to generate the feature set and enhanced event log

The patient data is created based on the various input data. The second part of this sub-process loops over all patients and activities and uses the TDABC costing method to calculate the total costs of the processes of each patient. Also, the incidents (and incident scores) are mapped to the patients. Optionally, the alignments of the activities for each patients are added. Based on these data, the feature set is generated by a custom script.

The event log is enhanced with the event information (cost/minute of the resource and duration of the activity). Also, incidents are added to the event log as extra events. Doing so, it becomes possible to use the event log to discover a new process with the incidents included. This can give insight if an activity is oftenly followed by an incident. Finally, if there are no complete events present in the event log, these are added based on the duration of the activity (which is known from the input files).

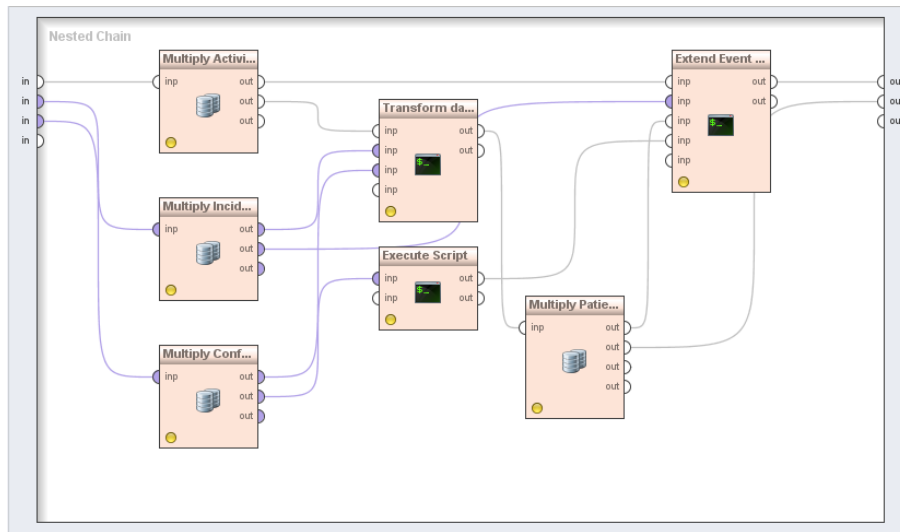


Figure A.4: Transform data toolset (2): enhanced event log and feature set are generated based on the prepared input data

A.3 Export data

The enhanced event log created in the sub-process "Transform Data" is converted back to XES format and written to disk. The feature set is exported as Excel file. The filepath of the outputted XES and Excel file can be changed in the operator itself (Figure A.5).

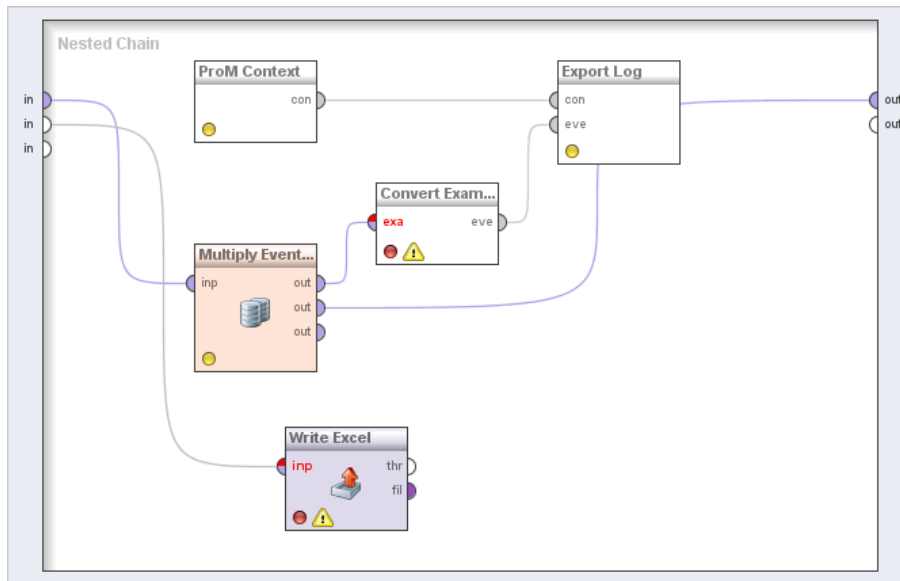


Figure A.5: Export data toolset: enhanced event log (XES) and feature set (Excel) are exported

A.4 Analyze data

The feature set contains information about the costs, incidents and conformance of each patient. It can be interesting to investigate whether patients with a care process that have a higher conformance, also have higher costs. This sub-process (Figure A.6) splits the patients in two groups. For example, one group with a high conformance (> 0.6) and one group with low conformance (≤ 0.6). The parameters to split up the groups can be changed in the 'Numeric to Binominal' operator. Then, by means of aggregation, the other variables are calculated (costs, incidents) for each group. This is not the analysis performed in Chapter 5. RapidMiner misses operators to perform all of those analysis. Therefore, the analysis is performed in MatLab and SPSS.

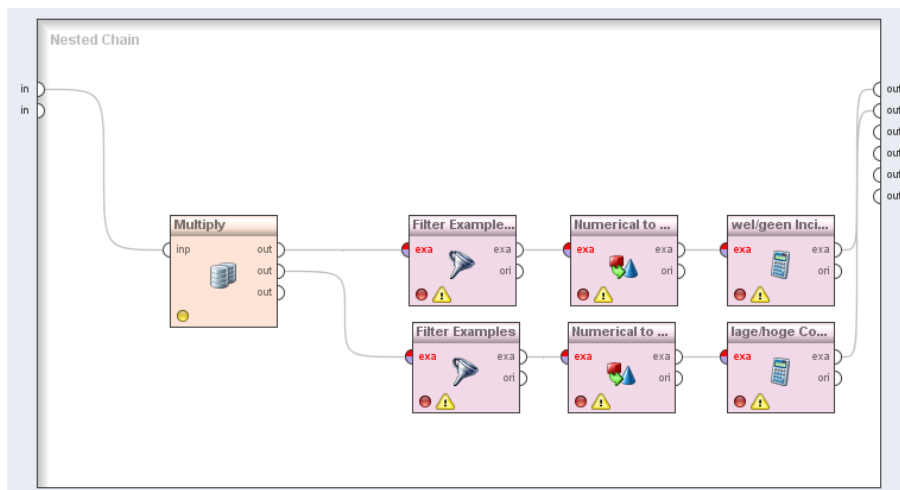


Figure A.6: Analyze data toolset: simple analysis to compare patients groups with high against low costs, # incidents and/or conformance

Appendix B

Decision trees: Rapidminer setup

The setup used to mine decision trees and subsequently measure their accuracy is described in this Appendix. The incidents, costs and conformance are attempted to explain based on the alignments (LM, M and L). The operators used in RapidMiner to do this are shown in Figure B.1

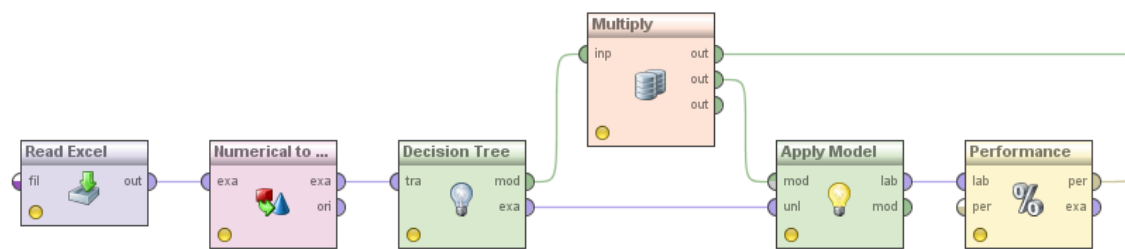


Figure B.1: Setup Alignments: Decision Tree

First, the feature set is imported via the 'Read Excel'-operator. Then, if the label variable is continuous, it is transformed in a binominal or polynominal variable. For example, the (continuous) variable costs is transformed in 'low' and 'high' costs. After that, in the 'Decision Tree'-operator, the label is selected (conformance, incidents or costs) and the attributes (the alignments of all activities). This operator builds the 'Decision Tree', with the setting that nodes need to have a minimum size of 10. After the decision tree is created, the 'Apply Model' and 'Performance' operators validate the decision tree on the data and return an accuracy parameter.

Appendix C

TDABC costs

The cost of each activity in the case study is calculated with the TDABC costing method. Table C.1 gives an overview of the average costs per activity and their occurrence in path 1 and 2.

Activity	Avg. Cost per minute	Fixed costs	Average duration (minutes)	Average costs (euro)	% patients Path 1	% patients Path 2
Aanmeldform geprint	0,46	-	5	2,3	39,0	34,0
Brief verstuurd	1,49	-	10	14,91	40,9	30,0
CT-sim afwerken	0,53	124	30	139,99	97,9	1,2
Chipsoft controleren	1,49	-	5	7,45	38,7	33,2
Controle ME-berekening	0,53	-	10	5,33	0,2	99,6
Controle MQ + MQ check	0,53	-	15	7,99	99,1	97,2
Controle Theraview	0,53	-	10	5,33	99,2	0
Controle XVI	0,53	-	10	5,33	7,5	0
DBC openen	0,46	-	5	2,3	92,8	96,8
Doorsturen plan	0,53	-	10	5,33	10,5	0
Introductie Pinnacle	0,53	-	15	7,99	98,5	0,8
Invoer MQ + MQ check	0,53	-	15	7,99	99	99,2
Invoer Theraview	0,53	-	15	7,99	99,4	0
Invoer XVI	0,53	-	15	7,99	9,6	0
ME berekening	0,53	-	15	7,99	0,2	99,2
Plan afronden	0,53	-	5	2,66	97,9	0,4
Plan controle arts	1,49	-	15	22,36	85	0,4
Plan controle fys	1,03	-	15	15,48	96,8	0,4
Plan controle lab	0,53	-	15	7,99	99,7	0,4
Plan maken	0,53	-	120	63,95	99,8	0,4
QCL openen	0,46	-	5	2,3	75,8	77,2
Scannen	0,46	-	10	4,6	74,3	75,6
Screendump getekend	0,53	-	5	2,66	0	83,6
Simulatie afwerken	0,53	30	15	37,99	0,2	94,4
Statusnr + D invoeren	0,46	-	5	2,3	91,5	95,6
Vorbereiding 1e bestraling	0,53	-	10	5,33	100	100

Table C.1: Activity Summary: cost parameters and occurrence in both paths

This table is also visualized in Figures 5.7 and 5.8.