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# The application of process mining in determining employee well-being

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## Abstract

The monitoring of well-being has become increasingly popular in the last decade as higher employee well-being leads to better performance and reduces the number of burnouts. Surveys and interviews are the most popular instruments for determining well-being. However, a drawback of these instruments is that they are cross-sectional which makes it difficult to continuously monitor well-being. Process mining is a discipline that has the potential to measure well-being without this drawback. Based on data from (process-aware) information systems process mining can discover, evaluate, enhance and monitor behaviour. This thesis investigates to what degree work-related parts of well-being can be determined with process mining. Job demands & resources influence well-being and are the work-related *parts of well-being* which are determined in this thesis.

A literature study revealed which job demands & resources are related to well-being and which of them could be measured based on process execution/human behaviour. We observed that five job demands & resources can be measured based on human behaviour, these five being: *workload, time pressure, monotonous work, autonomy* and *social support*. These five can measure *burnout, boredom* and *work engagement* to a great extend and are also related to *social, emotional* and *physiological well-being*. A structured literature study is performed to identify process mining techniques that focus on resources. We investigated if and which of the detected process mining techniques are related to selected job demands & resources. The process mining techniques are able to measure all the selected job demands & resources. *Social support* is the only job resource which could not be measured in its entirety.

Finally, a case study was conducted to examine whether process mining techniques can be applied to determine the job demands & resources. We observed that it is possible to measure aspects of well-being with process mining. Four of the five job demands & resources have a medium or high correlation with the key strain or motivation that it should measure. Time pressure is the job demand that has no significant relation with its strain burnout. To conclude, three out of the five job demands & resources can be measured entirely using process mining and one partly.



**Keywords:** Process mining, Employee well-being, Job demand-resource model, Organisational mining and Resource mining

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## Definitions

| **Definitions** | |
|---|---|
| Organisational/ resource mining | Process mining techniques that focus on gaining information about resources or organisational structures, are referred to as organisational mining in this report (van der Aalst & Song, 2004). |
| aspects of well-being \|job demands & resources | These are variables that can be used to indicate the well-being of a person. The JD-R model calls these aspects that influence well-being "job demands & resources" (Bakker & Demerouti, 2007). |
| Variables of process mining | Process mining techniques can be applied to gain a certain outcome. These outcomes often contain quantitative and/or qualitative variables, such as number of cases, activity duration, number of handovers. These variables are referred to in this paper as "process mining variables". |
| Trend | "A trend is a pattern found in time series datasets; it is used to describe if the data is showing an upward or downward movement for part, or all of, the time series" (*Trend \| Statista*, n.d.). |
| Distribution | "In descriptive statistics it stands for the (absolute or relative) frequency of the values of a variable. A frequency distribution describes statistical data" (*Distribution \| Statista*, n.d.). |

# 1 Introduction

On March 11, 2020 the World Health Organisation declared the coronavirus outbreak a global pandemic, beckoning the start of a period of struggle and adaptation. This period proved especially straining for healthcare workers as the influx of new patients drastically increased the workload of nurses (Mensinger et al., 2022; Morgan et al., 2022). Combined with the pre-existing shortage of nurses this led to a significant decrease in the well-being of nurses and other healthcare workers with a wave of burnouts as a result (Ahmadidarrehsima et al., 2022; Cheong et al., 2022; Mensinger et al., 2022). The rising interest in the well-being of employees is also observed in other fields among which education and the military (Alhasan et al., 2022; Cárdenas et al., 2022; Lahat & Ofek, 2020; Vogt et al., 2022). It is proven that the performance of employees is influenced by their well-being (Halaška & Šperka, 2018; Wright & Cropanzano, 2000).

Well-being is commonly measured with questionnaires or interviews (Rabbi et al., 2011). However, surveys and interviews capture cross-sectional information (Verhoeven, 2019), which makes continuous monitoring of employee well-being with these instruments expensive and time-consuming (Caruana et al., 2015). Furthermore, surveys are used to gather the perceived value of a target variable rendering them vulnerable to cognitive biases and increasing the possibility of user error (Rabbi et al., 2011).

The drawbacks of surveys can be overcome by techniques that rely on data from information systems. Information systems gather observed data continuously. Process mining has intersections with the fields of machine learning and business process management (van der Aalst, 2011, 2016). By combining aspects of the two fields, process mining can monitor employee behaviour based on digital data, which can continuously be gathered and monitored (van der Aalst, et al., 2012). The behaviour of employees can be analysed from different perspectives, one of those is the "organisational" perspective which focuses on resources and organisational structures. The primary benefit of process mining is that behaviour can be continuously monitored, which allows organisations to act when necessary. The effects of well-timed interventions are among others the improvement of employee well-being and a reduction in the number of burnouts (Kesarwani et al., 2020; West et al., 2016, 2018). Therefore, a few key aspects of process mining make it ideally suited for surveying employee well-being. However, despite the potential of process mining existing literature on the application of process mining for determining employee well-being is still sparse.

This study investigated if process mining can contribute to the measurement of employee well-being. The research gap to discover how *well-being* can be determined with process mining is at the moment too big for one master thesis to cross. Methods from the psychology domain which can be used to measure well-being have been examined. The *job demand- resource model (JD-R)* is a popular method to measure well-being and has been selected. The JD-R model measures well-being by investigating the aspects of well-being, these being *burnout, boredom* and *work engagement*. These aspects are determined based on job demands & resources. **This thesis investigates to what degree the job demands & resources can be determined with process mining.**

## 1.1 Research question

In this section we formulate and describe the research questions. The study aims to take the first steps in determining *well-being* using process mining. The intention is that other researchers expand on this research and that within a few years *well-being* can be determined through the use of process mining. To achieve the goal of this thesis, the following main research question (MRQ) is formulated:

| |
|---|
| MRQ: To what degree can the work-related job demands & resources be determined for employees with the use of process mining? |

The main research question can be decomposed into four research questions.

1. RQ1: What work-related job demands & resources influence well-being?

The JD-R model shows that the aspects that influence well-being are strains & motivations, which can be measured with job demands & resources. Well-being is a concept that has been extensively researched. The results from the past can be used to obtain an overview of what job demands & resources influence well-being. We investigated if these can be measured based on process execution (behaviour). The job demands & resources that can be measured are selected for further investigation. To answer RQ1, a literature research is performed on work-related job demands & resources that influence well-being.

2. RQ2: What information can be obtained with process mining techniques?

The aim of the second research question is to create an overview of all process mining variables which can be obtained with existing process mining techniques. A structured literature review is performed to investigate relevant process mining techniques. There are many process mining techniques with different goals. Some focus on discovering business processes while others try to enhance a process. Process mining techniques that focus on resources within an organisational context are especially interesting for this research. The structured literature review aims at creating an overview of the process mining techniques that focus on resources. When papers describe multiple techniques, all of them are described even if only one of them is about resources.

In this report, the results of process mining techniques are referred to as *"process mining variables"*. The structured literature review examines what process mining variables can be measured using the investigated techniques.

3. RQ3: Which process mining variables are related to job demands & resources?

The goal of the third research question is to identify connections between the process mining variables and the job demands & resources. The connection is made on the basis of what the job demands & resources entail according to the literature. A detailed explanation of the transformation procedure is provided in section 3.3.

4. RQ4: Which process mining variables related to the selected job demands & resources can be measured in a real-life scenario?

The goal of this research question is to investigate if the job demands & resources can be determined in a real-life application. The third research question investigates which process mining techniques are suited to obtain the relevant process mining variables for the selected job demands & resources. For the case study process mining techniques are applied, which are supported by tooling and executable using digital data commonly available in organisations.

In the second part of this research question, the job demands & resources are determined based on the process mining variables. Multiple steps are performed to transform the process mining variables into job demands & resources. The correlation between the job demands & resources measured with process mining and the strains & motivation measured with a survey is measured. This validates if the job demands & resources measure the strain or motivation that they are related to. Our expectation was that most but not all job demands & resources related to well-being can be measured with process mining.

## 1.2 Contribution

The results of this study led to two theoretical and two empirical contributions:

1) We have proved to what extent burnout, boredom, work engagement and the well-being types are measurable based on digital process execution.
2) We have proposed process mining variables to determine the job demands & resources that are measurable based on digital process execution.
3) We validated that four of the five job demands & resources determined with the process mining variables are related to the expected key strain or motivation.
4) We have made the application of measuring the job demands & resources with the process mining variables publicly available on GitHub.

This study set the first steps in determining well-being by proving that aspects of well-being (burnout, boredom, work engagement and the well-being types) are measurable with process mining to a certain extent. This makes it interesting for researchers to conduct research on this topic. Additionally, organisations can implement the application of measuring well-being with process mining. With the application, organisations can measure well-being continuously and act when necessary.

## 1.3 Structure of the thesis

The remainder of this paper is structured as follows: chapter 2 discusses the related work, chapter 3 describes the research design. Chapter 4 analyses the findings of the literature study. Chapter 5 describes the case study findings. Finally, the paper concludes with a brief recap and discussion of the primary findings in sections 6 and 7.

# 2 Related work

In order to apply process mining techniques on well-being, we need a thorough understanding of the research domain. This section introduces important definitions, theories and models on well-being and process mining.

## 2.1 Well-being

Well-being is defined as the quality of life for an individual (Crisp, 2021). The impact of activities on an individual's well-being can be investigated by asking the following question: is an activity good or bad for a specific individual? Happiness is seen as a part of well-being as it defines how content a person feels. Some researchers challenge the definition of well-being. Moore (1903), argues that well-being should be about what is **good in general** instead of what is **good for an individual**. For example, if a person wins a lottery then that is beneficial for him/her but not for the other lottery participants, therefore winning a lottery is not an inherently good activity. Scanlon (2000) makes a different objection, he argues that individuals participate in activities such as studies, which provide no benefits in the present but will be beneficial later on. Both arguments are countered by Crisp. He states that well-being is about individuals and that "good for" can also indicate activities that benefit individuals in the future. Utilitarianism is the term used when talking about what is good and bad for the human race (Held, 2006). Well-being is discussed in this paper according to the "eudaimonic" view of well-being (Lent, 2004). The eudaimonic view has its roots in philosophy. The other popular view on well-being is the hedonic view, which has its roots in psychology. Whereas eudaimonic well-being contains everything that is good for an individual (such as personal goals) hedonic well-being only measures what is pleasurable for an individual.

### *Theories of well-being*

There are three main theories on well-being: hedonistic, desire and objective list theories (Appleby & Sandøe, 2002). The hedonistic and desire theories are related to the hedonic view on well-being whilst the objective list theory is related to the eudaimonic view(Crisp, 2021; Lent, 2004). The hedonistic theory states that well-being is determined by the pleasure and pain which an individual experiences (Bentham, 1996). According to the desire theory, well-being can be determined by the number of desires that are satisfied. Both the hedonistic theory and the desire theory are subjective since the desires, pleasures and pains can vary per individual. The objective list theory states that there is a list of factors, and that well-being is determined by the number of satisfied factors (Fletcher, 2013; Rice, 2013). This list is the same for all humans and therefore, objective. This research uses the objective list theory perspective on well-being. We measure a number of observable factors to predict well-being. The other two theories focus on the subjective aspects of well-being. These can be measured with surveys instead of process mining. The eudaimonic view aligns better with this study than the hedonic view, as the eudaimonic view also considers aspects such as personal growth and goals which can be found in a work environment. The three theories have some commonalities. It can be assumed that individuals gain pleasure by satisfying objective factors (objective list theory) or desires (desire theory).

### *Different types of well-being*

Because well-being is a very broad topic it is often divided into multiple categories. *Mental well-being* is an individual's ability to function in society and realise his/her capabilities (World Health Organization, 2018). Keyes (2002) created a model to measure mental well-being. According to him, mental well-being is about *emotional well-being* and the presence or absence of positive functioning in life. Positive functioning can be measured with *psychological* and *social* well-being. The well-being categories physical, emotional, psychological and social are explained below.

- *Physical well-being* is determined based on how a person functions physically. Heavy physical activities, working out, eating patterns and diseases are key indicators of physical well-being (Emmons & McCullough, 2003).
- The mood, self-esteem and emotions of individuals are related to *emotional well-being* (Fredrickson & Joiner, 2002). The work-related well-being scale can be used to measure emotional well-being (Demo & Paschoal, 2016). According to this scale, emotional well-being contains anxiety, comfort, pleasure, displeasure, enthusiasm, and depression. Diener (1984) created the tripartite model of subjective (emotional) well-being. The model defines frequently positive affect, infrequent negative affect, and cognitive evaluations as the three distinct components that are related to emotional well-being. According to Reis et al. (2016) important indicators of emotional well-being are relatedness and autonomy.
- Ryff (1989) created an instrument to measure psychological well-being. *Psychological well-being* consists of six elements: personal growth, autonomy, purpose in life, self-acceptance, environmental mastery, and positive relations with others (Ryff & Singer, 1998).
- *Social well-being* is determined by how individuals function in communities and social structures (Keyes, 1998). It contains five dimensions: social coherence, social actualization, social integration, social acceptance, and social contribution. Larson (1993) describes similar indicators for social well-being, according to him social well-being can be divided into social adjustment and social support. Social adjustment is about: satisfaction with relations, adjustment to a new environment and performance in social roles. Social support can be indicated by the number of social relationships and the importance of each relationship.

#### *Conclusion well-being*

In this research we are interested in the objective list theory, which investigates what objective elements are satisfied to determine the well-being of individuals. The objective list theory is part of eudaimonic well-being. Eudaimonic well-being is about what is good for an individual. The other type of well-being is hedonic, which is measured by the amount of pleasure that an individual experiences. Hedonic well-being contains the desire and hedonic theories. The different types of well-being that can be measured are physical, emotional, psychological and social well-being.

## 2.2 Process mining

Organisations use information systems such as Enterprise Resource Planning (ERP), Customer Relationship Management (CRM) and Business Process Management Systems (BPMS) to support employees in process execution (van der Aalst, Adriansyah, de Medeiros, et al., 2012). Most information systems log the actions that employees perform on the information system. These interactions with an information system are called events. The system often stores additional information for each event such as the timestamp and performer. By doing this the systems can create an overview of all events performed in the system. This overview is called an event log. Process mining can be applied on an event log if it contains the variables; case id, activities, and timestamps. Process mining is a discipline that uses process models and data from event logs to analyse, compare and monitor the behaviour of process participants i.e., process execution (van der Aalst, 2016). Process mining techniques can, among others, discover:

1. Which activities are performed in the process.
2. Which activities are performed for which case.

3. The process/ the sequence of the activities (based on the timestamp).
4. The duration of a case.

Table 1 illustrates an event log from a call centre that solves IT-related incidents. In this example, incidents are the cases and multiple activities are performed to solve an incident.

| Incident id | Activities | Timestamp | Resources |
|---|---|---|---|
| 1 | Register call | 2022-01-04 16:05:44 | Jan |
| 1 | Call solved | 2022-01-04 16:07:44 | Jan |
| 2 | Register call | 2022-01-05 17:01:00 | Lien |
| 2 | Connect known solution | 2022-01-05 17:03:00 | Lien |
| 2 | Call solved | 2022-01-05 17:04:00 | Lien |

*Table 1, illustration of an event log.*

There are three major process mining tasks: process discovery, conformance checking, and process enhancement. (van der Aalst, Adriansyah, & van Dongen, 2012). Process discovery discovers the business process and describes the process characteristics based on an event log (van der Aalst, Adriansyah, & van Dongen, 2012). An organisation can investigate if the discovered process is desirable and based on that they can optimise their process. Conformance checking analyses if the interactions in an event log can be replayed in the process model. This technique can be used to analyse whether the targeted process is being followed and to identify the deviations. Process enhancements techniques identify process parts that are useful for further optimisation. This is applied by identifying bottlenecks based on the timestamps in the event log. The tasks can be investigated from different perspectives, according to Song and Van der Aalst (2004) the perspectives are: process, organisational and case perspective. Van der Aalst et al. (2012) decompose the process perspective into the control-flow and time perspectives.

Process Mining was discovered in the late 1990s. Process discovery is the first task that could be performed with process mining (van der Aalst, 2020). Capabilities such as decision mining, conformance checking, time prediction and organisational mining were discovered in the next decennium. Van der Aalst states the following about the tool support of these functionalities: “These capabilities are still considered to be cutting edge and not supported by most of the commercial Process Mining tools” (van der Aalst, 2020, p. 182). Commercial process mining tools tend to not update their functionality to the state of the art for reasons such as speed and simplicity (van der Aalst, 2020). The consequence is that the limitations of these techniques are still dealt with in practice and that ‘new’ capabilities such as conformance checking are often not supported.

### *Similar studies*

We found no studies in the literature that managed to measure well-being with process mining. However, there are studies that have taken steps in the direction. For example, the work in progress of Tang & Matzner (2020) investigates if humanistic values can be measured with process mining. Based on the equity theory they state that job satisfaction and distress are influenced by:

- High waiting and service times.
- Unfairly distributed workload.
- Breaches of compliance.

They measure these elements with bottleneck discovery, social network analyses and conformance checking. The elements that they investigate are relevant for this study and the ones that are related to a selected job demand or resource are measured in this study. Their focus differs from ours as we are interested in the measurement of well-being instead of humanistic values. Therefore, we also investigate other elements than Tang & Matzner. Lantow et al. (2019) investigated the state of social mining with a structured literature study in 2019. They investigated sources from the abstraction & citation database Scopus. Their search term investigates sources with the subjects *organisational-* and *social mining* and focuses on *social network analyses.* We decided to perform our own SLR because we wanted to identify all techniques that could be applied with process mining and focused on resources. Two additional reasons are:

1) The paper of Lantow et al. (2019) does not specify the inclusion and exclusion criteria. Therefore, we don't know if sources which would be relevant for us were excluded.
2) Their SLR was held three years ago. We want to make sure that the newest process mining techniques are obtained.

Our SLR focused on finding techniques which can be applied to measure parts of the selected job demands & resources.

In addition, there are studies in the discipline machine learning that focus on measuring well-being. For example, the study of Rabbi et al. (2011) which tries to determine physical and mental well-being with the use of mobile sensors. Text mining is another interesting technique which can be used to determine opinions, moods and stress of individuals (Nijhawan et al., 2022). These applications can continuously gather and monitor information i.e., just as process mining they do not have the drawbacks of surveys. It is interesting to investigate the potential of process mining for measuring well-being. Because the studies on themselves have not managed to measure well-being completely and they investigate well-being from a different perspective. Sensors examine physical activities and responses of the body (such as heart rate), text mining investigates opinions/thoughts and process mining investigates the behaviour during digital activities.

### *Conclusion Process Mining*

Process mining techniques analyse processes based on event logs. There are three types of process mining tasks process discovery, conformance checking and, process enhancement. There are multiple techniques proposed to perform each of the process mining tasks. The outcome of process mining techniques is in this paper referred to as process mining variables. The process mining tasks can be investigated from different perspectives.

# 3 Research methods

This section describes how each of the research questions is answered. Research question 1 is answered by conducting a detailed literature study. For research question 2 we perform a structured literature review according to the guidelines of Kitchenham et al. (2009). The third research question is answered based on the results of research questions 1 and 2. Finally, research question 4 is answered based on a case study performed according to the guidelines outlined by Runeson & Höst (2009). The project was performed in collaboration with a research group, which included four process mining experts and two Human Resource Management experts.

## 3.1 RQ1: determining the job demands & resources that influence well-being

Research question 1 explores which work-related job demands & resources influence well-being. HRM & psychology methods that specify how well-being can be measured, have been examined. The examined methods are the *OECD well-being framework* (OECD, 2017), the *job demand-resource model* of Demerouti et al. (2001a) and the multi-dimensional framework for measuring "equitable and sustainable well-being" (Bacchini et al., 2021).

The job demand-resource model of Demerouti et al. (2001a) was selected for this study, because of its popularity (more than 5000 citations on Scopus (Demerouti et al., 2001a)) and its flexibility. The other two frameworks focused on well-being outside & inside work but do not have the flexibility to focus solely on work-related well-being, making them less suitable for this research. The JD-R model is a famous and established model that is often used to measure parts of well-being. Bakker & Demerouti (2007) reviewed the model and proved that it can be used to measure well-being. In this study, the JD-R model is used to give a solid foundation to measure work-related well-being. The model is visualised in figure 1.

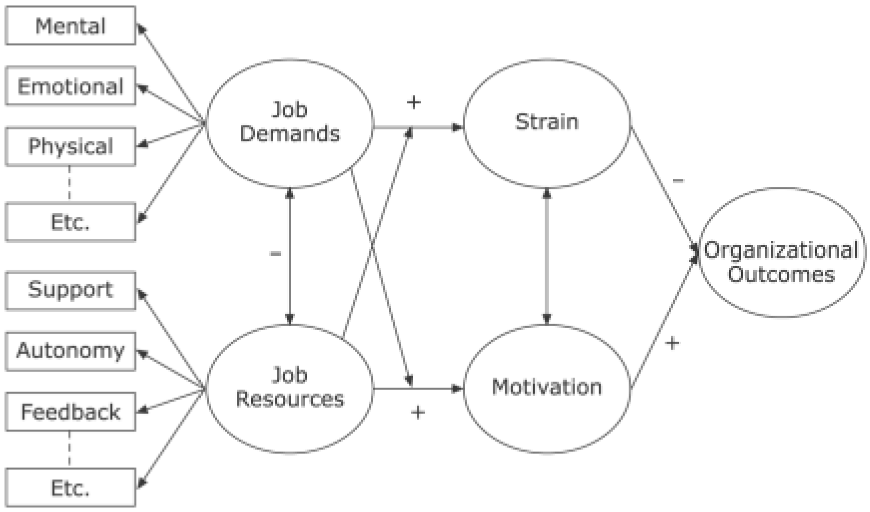



*Figure 1, the job demands-resource model of Bakker & Demerouti (Bakker & Demerouti, 2007).*

Job demands & resources can be filled to meet the needs of the target situation (Bakker & Demerouti, 2007). The model specifies what kind of information is required in each part of the model. On the right side the output variable, *organisational outcome* is presented. In the middle the relationships between *job demands, job resources, strains* and *motivation* are described. On the left, the researcher can specify the job demand & resources that influence the specified strain and motivation. As mentioned in the related work, well-being is viewed in accordance with the objective list theory. In this study, the aspects considered are the job demands & resources which are objectively measured using process mining.

*Strains and motivation to measure well-being*

With the job demand-resource model, well-being can be measured with the strains "*burnout*" and "*stress*" and the motivation "*work engagement*" (Guest, 2017; Maslach et al., 2003). The model shows how job demands & resources are balanced and what their effect is on the strains and motivation. Bakker et al. (2005), also indicate that *burnout* is highly related to well-being. They observe that high job demands and low job resources are the primary reasons for *burnout* (Bakker et al., 2005; Schaufeli & Bakker, 2004). Most studies agree that the job demand 'exhaustion' is the main factor for *burnout* (Demerouti et al., 2001a; Maslach et al., 2003).

*Procedure for answering research question 1*

Research question 1 investigates which job demands & resources influence well-being. According to Diener (1984), there is a high number of elements that influence subjective well-being. To keep the study comprehensible we investigated which job demands & resources cover each of the *well-being types, burnout, boredom* and *work engagement*. *Burnout*, *boredom* and *work engagement* were investigated because multiple studies showed that they have a strong connection with well-being.

The job demands & resources that correspond to the strains (*burnout* and *boredom*) and the motivation (*work engagement*) are investigated based on previous literature. The study of Bakker et al. (2003) examined similar strains and motivation. Their job demands & resources were compared with the elements that could cause or prevent the strains and motivation according to other literature. The elements that are mentioned by both types of literature are selected as job demands & resources. The investigation of which job demands & resources cover the *well-being types* is performed, based on the characteristics of the *well-being types*.

The second step investigates which of the selected job demands & resources can potentially be measured with process mining. Process mining can only measure that which is measurable based on process execution/participants' behaviour. Therefore, the job demands & resources which cannot be measured based on behaviour were excluded. Research question 3 analyses to what degree the remaining job demands & resources can be measured with process mining.

## 3.2 RQ2: obtaining an overview of relevant process mining techniques

A Structured Literature Review (SLR) is performed to analyse the current organisational mining techniques. The identified techniques are investigated to discover what information can be obtained by applying them. The results of the Structured Literature Review are used in the third research question to investigate which process mining results relate to job demands & resources.

### 3.2.1 Data collection procedure for the structured literature review

This section explains the procedure through which papers were selected for the structured literature review. The procedure consists of five iterations. The first three iterations are part of a larger structured literature review which was performed by two scientists. They created a list of papers on process mining techniques centred around communication between resources. The last two iterations were performed by the author of this report and were used to select the relevant papers for this research. The difference with the first three iterations is that the goal changed from *analysing all papers about process mining that have some relation with resources within organisational context* **to** *analysing papers that describe* ***process mining techniques that focus on resources within organisational context as the main topic***.

For the structured literature review the search engines Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar were used. Multiple search iterations have been performed to select the relevant sources. The first iteration was used to fine-tune the search term and find the relevant sources. The final search term used is *("process mining" OR "workflow mining" OR "event log") AND ("resource" OR "originator" OR "staff" OR "actor" OR "employee" OR "organisational" OR "organizational").* The results of the search engines were ordered on relevance. Then the first 300 sources of each search engine were selected. This first iteration resulted in 1246 sources.

In the **second iteration,** the duplicates were removed, after which 923 sources remain. In the **third iteration**, exclusion and inclusion criteria were set up to filter out irrelevant papers. The inclusion criterion is "IC1: the paper has explicit attention for process mining techniques that focus on resources within an organisational context". The exclusion criteria are:

- EX1: The full text of the paper is not available.
- EX2: The paper is not written in English.
- EX3: The paper has not been published in a peer-reviewed scientific journal or peer-reviewed conference proceedings.
- EX4: The paper is a literature review, one-pager, executive summary, abstract, editorial, research proposal, interview, poster, call for papers or table of contents.
- EX5: The paper focuses on process mining in an organisational context, but a human resource-related topic is insufficiently part of the core of the paper.
- EX6: The paper focuses on a human resource-related topic, but process mining in an organisational context is insufficiently part of the core of the paper.
- EX7: The paper neither focuses on a human resource-related topic, nor on process mining in an organisational context at the core of the paper.

The papers were screened independently by two researchers and their differences in the screening were settled in a discussion. The **third iteration** resulted in the selection of 199 relevant papers. The papers with meta-information (author, date etc.) were described in an excel sheet.

The excel sheet with the 199 papers was subjected to an additional selection process. This was done to make sure that only the relevant papers for this research are selected and to make the structured literature review feasible for the given timeframe. In the additional selection process, the papers were evaluated on the used inclusion and exclusion criteria and new criteria. To make sure that only those papers were selected, the following exclusion criteria were setup:

- EX8: The title of the paper does not indicate that the paper revolves around organisational mining. (applied in the fourth iteration).
- EX9: The paper focuses on the allocation of employees (applied in the fifth iteration).
- EX10: The paper is inaccessible with a student Utrecht University account.

### 3.2.2 Analyses procedure for the SLR

This section provides a detailed description on how the last two iterations were performed. The set-up is visualised in figure 2. In the Excel file, the 199 papers were described alongside their characteristics: authors of the paper, article title, source title, book series title, document type, conference title, author keywords, abstract, publication year, volume, issue, start page, end page and page range.

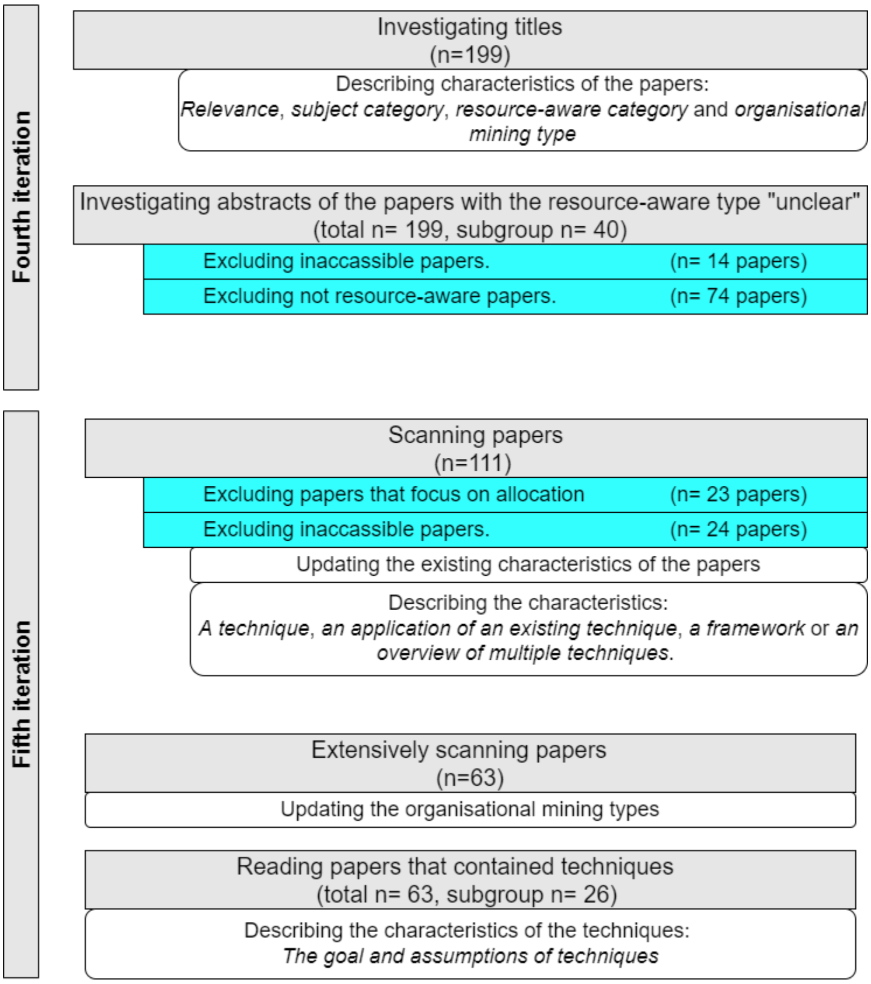



*Figure 2, SLR set-up. Grey= Iterations and sub-iterations, blue= exclusion criteria, white= categorising or updating existing categories. The letter 'n' refers to the number of papers that are investigated in a phase or excluded by an exclusion criterion.*

In the **fourth iteration**, the article titles were read and the characteristics information was extended with: *relevance*, *subject category*, *resource-aware category* and *organisational mining type*. The category *relevance* indicates the significance of the paper for this research. The main focus of each paper was described in the *subject* category. The *resource-aware* category indicates whether the focus of the paper is on resources in an organisational context. Papers of which it was difficult to determine if they contained information about resources in an organisational context (based on the title) were given the value "unclear". Papers which include information on resources were further categorised by their mining type. The *mining type* explains how the papers affected resources or organisational structures. The categories created for the mining type were: allocation, clustering, organisational model, social graph, similar tasks, anomaly, unknown, broad, resource behaviour and specialised. The last three mining types are ambiguous and further explained in table 2.

| Process mining type | Explanation |
|---|---|
| Broad | Multiple mining types discussed in one article. |
| Resource behaviour | Identification or optimalisation of behaviour. |
| Specialised | Focuses on an organisational mining topic that is not discussed in other articles. |

*Table 2, mining types.*

In the second part of the fourth iteration, the abstracts of the 40 papers with the *resource-aware* value "*unclear"* were read. The papers were searched on the internet and for each source was determined whether it was accessible with a student UU account. This step excluded 14 papers. Based on the abstracts the *subject*, *relevance* and *resource-aware category* were updated. *The resource-aware category* of the papers was not allowed to stay in the category “unclear”. They were changed to the category value *resource-aware* or *not resource-aware*. The fourth iteration ends by excluding the inaccessible papers and the papers that were *not resource-aware*. After the fourth iteration the list of papers consists of 111 articles.

The abstracts of the remaining papers were read in the **fifth iteration**. In this step, the *subject*, *relevance* and *mining type category* were updated. Additionally, it is described whether the paper concerns: *a technique*, *an application of an existing technique*, *a framework* or *an overview of multiple techniques*. The information of the papers which describe a technique is extended with the *goal of the technique*, here it is stated whether the goal of the paper is to gain information about a process or to optimise a process. This analysis shows that most of the techniques that tried to optimise the process belong to the mining type *allocation of employees*. The optimization of a process is irrelevant, for this research, because it gives no information that can be used to determine well-being. Therefore, exclusion criterion 8. which excluded all papers that focussed on the *allocation of employees,* was added. After the fifth iteration the list was reduced to 87 relevant papers.

The 87 selected papers were obtained through the UU database and for each paper we reported if they were accessible in English. This resulted in the exclusion of an additional 24 papers. The chapter’s results, discussion and conclusion of the remaining 63 papers were read. This resulted in the conclusion that many papers corresponded to multiple values in the *subject category*. Therefore, the *subject category* values *organisational models*, *social graphs* and *similar tasks* were removed. The papers that contained these values also related to the category value *organisation structures*, *social networks* or *clusters*. The previously mentioned categories were updated and for each paper, the content was summarised in a few sentences.

The 26 papers that reported on new techniques were fully read. The techniques were divided into the categories: *causality handovers*, *causality subcontracting*, *clusters with causality*, *causality with special event types*, *joint activities*, *joint cases* and *others*. In addition, the goals and assumptions of each technique were explained. Based on the information contained in the 63 selected papers the second research question (*What information can be obtained with process mining techniques?*) was answered. An overview of the selected papers is presented in appendix 9.1.

## 3.3 RQ3: connecting the process mining techniques to the job demands & resources

This section describes how process mining variables were transformed into job demands & resources. The information from the first two research questions was used to determine how the well-being related job demands & resources can be measured through the use of process mining. Based on the job demands & resources of research question 1 the connection between the process mining variables and the job demands & resources was determined. A three-step transformation procedure was developed to transform the process mining variables into job demands & resources (see figure 3). The third research question investigates to what degree the selected job demands & resources can be measured with process mining.

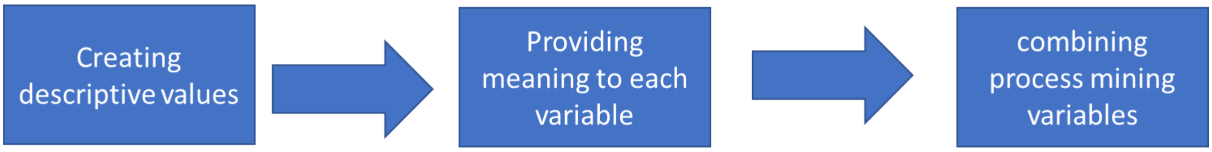



*Figure 3, transformation procedure*

### *Step 1, Creating a descriptive value from continuous values*

The goal of the first step is to obtain one value per performer for all process mining variables for the targeted timeframe. This is achieved by applying descriptive statistics to the process mining variables. The variables are categorised both on an employee or employee cluster and on a specified timeframe. Descriptive statistics is selected for its simplicity and flexibility. The variables can be aggregated with the method that we are interested in, for some this could be the mean, while for others it could be the standard deviation. The simplicity becomes clear when we compare it with the discretization method "micro aggregation" (Schmid et al., 2007). This method divides the data into A groups and takes the mean for each group, the techniques are then applied to each group. The micro aggregation method gives A results for each technique, while "normal" descriptive statistics gives one result per technique.

### *Example step 1*

Table 3 illustrates an example of the first step. *First,* the process mining variable of interest is selected. *Second,* the descriptive statistic is specified. Examples of relevant descriptive statistics are mean, median, mode, variance, standard deviation, skewness, maximum value and minimum value. The meaning of the process mining variable can vary depending on the descriptive statistic that is applied to it. For example, the mean activity duration gives an indication of the work speed of an employee while the variance activity duration gives an indication of the distribution between long and short activities. *In the third* step, the target for whom the process mining variable is measured is decided. In most cases, the objective is to measure the process mining variable separately for all employees. *Lastly,* the timeframe is specified.

| **Process mining variable** | **Which descriptive statistic** | **Which employee or employee cluster** | **Which timeframe** |
|---|---|---|---|
| Activity duration | Mean | All employees (for this example there are three employees: employees A, B and C) | Month |
| *Outcome: employee A has this month a mean activity duration of 40 minutes.* | | | |
| *Outcome: employee B has this month a mean activity duration of 45 minutes.* | | | |
| *Outcome: employee C has this month a mean activity duration of 38 minutes.* | | | |

*Table 3, the example of step 1.*

It is also possible to investigate what happens per employee cluster instead of per employee. As values are measured per employee, this can be done by taking the mean of the sum of employees. For example, the mean activity duration for table 3 is measured under the assumption that employees A, B and C belong to cluster 1.

*Outcome: employee cluster 1 has a mean activity duration of 41 minutes this month.*

Step 1 results in a single value for each process mining variable for each employee or employee cluster for a specified timeframe.

### *Step 2, Creating information: providing meaning to each variable*

The second step transforms values of the process mining variables into meaningful values (information) through the use of baselines. A baseline determines when a value is high, average, or low. However, in literature there are no papers that specify baselines for process mining variables to measure job demands & resources. For this reason, we decided to take the mean of each process mining variable as the baseline. The difference between the baseline and the value of an employee is determined by the standard deviation. The calculations are the same as the Z-score formula. The study of Bin Mohamad et al. (2013) proved that the z-score is an effective formula for standardizing. The Z-score can be seen as distance because it shows how much variance/distance lies between performers.

### *Example step 2*

The outcome of the example in step 1 was that *cluster 1 has a mean activity duration of 41 minutes*. Assuming that *workload* is specified as a job demand and that *activity duration* is an indicator of the *workload.* The above information cannot be used to state whether cluster 1 has a high or low activity duration.

However, the evaluation of the activity duration of employees A, B and C can be determined by comparing their outcomes with the baseline (see table 4). The baseline is the mean activity duration of the employees, which is 41 minutes in this example. Based on the standard deviation (STD) the distance from the mean is 3.6 minutes. This information enables us to state that employees A and B have a high activity duration which corresponds to a high *workload* while employee C has a low activity duration which corresponds to a low *workload*. The distance determines how high or low the activity duration and corresponding *workload* are.

| **Employees** | **Average activity duration** | **Distance in STD (Z-score)** |
|---|---|---|
| Employee A | 40 min | (40-41)/3.6= 0.28 |
| Employee B | 45 min | 1.11 |
| Employee C | 38 min | -0.83 |
| Baseline: Mean of the average activity duration:  41 min | | |
| Baseline: standard deviation: 3.6 min | | |

*Table 4, the example of step 2.*

In the previous example, activity duration is used as an indicator of *workload*. However, it cannot determine *workload* by itself. To determine the *workload* multiple process mining variables need to be combined. For example, the combination of *activity duration* and *the number of activities* performed provides an improved indication of *workload* compared to just *activity duration*.

### *Step 3, combining process mining variables to gain a value for an aspect of well-being*

Step 3 combines the process mining variables to get a single value for each job demand & resource. No precedent was found in the literature on how to transform the results of process mining techniques into job demands & resources. Therefore, the process mining variables are given equal weights.

### *Example step 3*

Let us assume that the *workload* can be measured by a combination of activity duration and the number of activities. The number of activities is specified in table 5 and the *workload* is calculated in table 6. The distances of both process mining variables are summed up to obtain a value for the *workload*. The + and – sign signify if an employee has a high or low *workload* and the specific values determine how high or low the *workload* is.

| **Employee** | **Number of activities** | **Distance in STD** |
|---|---|---|
| A | 60 | (60-46)/15.1= 0.93 |
| B | 48 | 0.13 |

| | | |
|---|---|---|
| C | 30 | -1.06 |
| Baseline: Mean of the average activity duration: 46 | | |
| Baseline: standard deviation: 15.1 | | |

*Table 5, specification of the number of activities.*

| Employees | Distance activity duration (mean) | Distance number of activities | Workload |
|---|---|---|---|
| A | 0.28 | 0.93 | 0.28+0.93 = 1.21 |
| B | 1.11 | 0.13 | 1.11+0.13 = 1.24 |
| C | -0.83 | -1.06 | -0.83 -1.06 = -1.89 |

*Table 6, calculating the workload.*

In this example employees A and B have a high *workload*, whereas employee C has a low *workload*. Whilst based on the number of activities one might expect employee A to have the highest *workload* in reality employee B has an even higher workload. This shows that a combination of variables provides a more complete and detailed summary of the actual *workload*.

## 3.4 RQ4: case study design

This section describes the case selection, data collection process, analysis process and validity threats of the case study. The case study is used to answer RQ4: *Which process mining variables related to the selected job demands & resources can be measured in a real-life scenario?* The first three research questions answer to what degree well-being can be measured with process mining. The fourth research question investigates whether it is feasible to measure well-being with process mining.

### 3.4.1 Case selection

The case selection was performed based on three criteria. The first criterion is that the case must represent a department that is commonly found in organisations. The second criterion is that there must be variety in the well-being of employees in the department. The third criterion is that the department must contain multiple employees that perform similar tasks.

The departments *Support* and *User Collaboration Services* (USC) of the IT Service (ITS) of Utrecht University (UU) were selected as the case. These departments satisfied all criteria. The department *Support* is an IT service desk which is commonly found in organisations. The department *User Collaboration Services* delivers IT support for the systems Workplace Engineering, Printing, Office365, Citrix, Windows Workstations, and MacIntosh management. Last year the workload of the selected departments increased because of new IT and Covid19 developments. These developments required additional tech support and resulted in increased requests for laptops and other carrying devices (Manager of Support, personal communication, 16 December 2021). The employees of these departments also need to handle complaints and are responsible for solving incidents within a specified timeframe. Furthermore, employees of the departments *Support* and *User Collaboration Services* perform similar tasks and therefore satisfy the third criterion.

On 16 December the author of this paper had a conversation with the manager and an employee of the department Support, who explained the work procedure of IT service (Manager of Support & employee of Support, personal communication, 16 December 2021). The main task of the department *Support* is to gather and solve all ICT-related incidents encountered by UU employees and students. Tasks that are too difficult for the *Support* department are assigned to second-line IT departments. The second-line departments specialise in a specific IT domain (e.g. networks). The *Support* department consists of 20 employees of which 8 have a permanent contract and 12 are students. The *User*

*Collaboration Services* department is a second-line department and is roughly equal in size to the *Support* department.

The process of gathering and solving incidents is called the *Incident management* process. Related processes are the *Problem management* and *Change management*. The incoming incidents are referred to as calls. The *Support* department receives calls from one of five channels: telephone, WhatsApp, e-mail, self-service or (physical) desk. The systems that ITS uses and their purpose is described in table 7.

| **Tools used** | **The tool is used for** |
|---|---|
| TopDesk | TopDesk is the main Service Management Tool used by ITS. It supports activities such as registering calls (for all channels), monitoring calls, communication with clients, distribution to the second line, and the status of the call. |
| Interaction connect | Interaction connect provides an overview of all incoming telephone calls and allows the phone to be answered or stopped. |
| Outlook (non-personal server) | Outlook provides an overview of all incoming emails. However, emails are not answered through Outlook. The outgoing emails (that contain the solution or confirmation) are sent through TopDesk. |
| Reporting | Reporting is a collaborative platform for WhatsApp. In addition to the functionalities of WhatsApp, Reporting can give an overview of all incoming messages, divide messages among employees and assign messages to other departments. |
| MS teams | MS teams is used for all internal communication that doesn't apply to one specific case. |
| Telephone exchange | Telephone exchange gathers all data regarding the phone, the duration of a phone call, the number of calls, etc. |

*Table 7, tools used by the department Support (employee of ITS, personal communication, 16 December 2021).*

The Data from TopDesk is used with the consent of the ITS. Additionally, a survey is conducted on the employees of the departments Support and UCS in a parallel study. The employees of these departments freely decided whether they wanted to participate in the survey. The researchers involved in this study signed a non-disclosure agreement. The agreement states that the personal information of the participants is not allowed to be reported outside the UU.

### 3.4.2 Data collection procedure case study

The well-being of the employees in the case study is determined through both process mining and a survey. This section describes how the data for the case study is collected.

Runeson & Höst (2009) categorise data types into three distinct categories: first-, second- and third-degree data types. Surveys are a first-degree data type. This means that the researcher can directly obtain information from subjects. The survey data used in this study is collected by another scientist. Process mining is applied on archival data gathered from the information systems of ITS. This is considered third-degree data type because the researcher can only use data that is already gathered.

The archival data is obtained from TopDesk, this program is used to report information on calls from all channels. The dataset contains information such as a description of the issue, the provided solution, and the personal information of the client. TopDesk is also used by the second line operators as they continue working on a call after the first line operator has delegated the issue to their department. The system records an overview of all online activities that are performed to solve a call. Therefore, the TopDesk dataset includes the event log for the entire incident process, from incident to solution. Unfortunately, the database is not all-inclusive as a known quality issue is that employees stop reporting on cases that they can solve immediately. This user error is especially prevalent in times when there are a lot of clients waiting on hold (Manager of ITS, personal communication, 16 December 2021).

After the privacy regulations were agreed upon, a dataset from TopDesk was created. The assembly of the dataset was done in discussion with the author of this report, who requested to include certain attributes in the dataset. The dataset contains data over a one-year period and is constructed with the purpose of testing whether the job demands & resources can be determined with process mining.

### *3.4.3* Data preparation for TopDesk

The dataset of TopDesk contains 105 attributes. An overview and explanation of the attributes is presented in appendix 9.2. This research attempts to use attributes that are domain-independent and which can be obtained from event logs of processes where a client is served. In section 4.2 we investigated what kind of attributes are domain independent. Our event log contains 22 domain-independent attributes that are useful for determining the specified job demands & resources. The selected attributes are described in table 8.

| Number | Attributes | Explanation |
|---|---|---|
| 1 | CallNumber | Case id |
| 2 | ActivityStartDate | Activity start date |
| 3 | ActivityEndDate | Activity end date |
| 4 | CallDate | Case start date |
| 5 | CreationDate | Case start date |
| 6 | CompletionDate | Case end date |
| 7 | ClosureDate | Case end date |
| 8 | ActualDate | Case duration |
| 9 | Activity | Activities |
| 10 | Incident_Operator | Resource |
| 11 | Incident_OperatorGroup | Resource department |
| 12 | Performer (ActivityPerformerResource_Name) | Resource |
| 13 | Current_Incident_Operator | Resource |
| 14 | Current_Incident_Operator_Group | Resource department |
| 15 | Incident_Name_Reporting | Client Name |
| 16 | Priority | (SLA) Contract duration per case |
| 17 | SolvedwithinSLA | Contract achieved |
| 18 | Reopend | Number of reopened cases |
| 19 | Calltype | Case category |
| 20 | Category | Case category |
| 21 | Subcategory | Case category |
| 22 | Entry | Start point of a case (category) |

*Table 8, selected attributes from the event log. The attributes that are not used are coloured in orange.*

When exploring each of the attributes we found out that 20 attributes contained missing values (see figure 4). 15 of these attributes contained the same missing values. The missing values corresponded to certain cases which did not contain these attributes in any of their activities. Considering that the afflicted observations contained only a small fraction of the total 741942 observations we decided to omit them from the database.

```
: CallNumber(naam)                                 0
  Activity                                         0
  ActivityStartDate                                0
  ActivityEndDate                             657402
  Incident_Name_Reporting(aanmeldernaam)           2
  Incident_Phone_Reporting(aanmeldertelefoon)  283511
  Incident_OperatorGroup                        2489
  Incident_Operator                             2489
  Priority                                      2489
  Entry(soortbinnenkomst)                       2489
  CallType(soortmelding)                        2489
  Category(incident_domein)                     2489
  Subcategory(incident_spec)                    2489
  SolvedWithinSLADuration                      16801
  CurrentOperator                              86883
  CurrentOperatorGroup                          2489
  ActivityPerformerResource_Name                2504
  CreationDate(dataanmk)                        2489
  CallDate(datumaangemeld)                      2489
  ClosureDate(datumafgemeld)                    2489
  Total_Reopens                                 2489
  CompletionDate(datumgereed)                   2489
  ActualDuration                                2489
  dtype: int64
```

*Figure 4, an overview of the missing values per attribute.*

The attribute Activity End Date contained missing values for more than 50% of all observations. As such, it is unfeasible to work with this attribute, which lead to the decision to remove the attribute as a whole. The third resource attribute “Current_Incident_Operator” contained many missing values and the values it did report suffered from a high correlation with the attribute Incident_Operator. For this reason, the attribute “Current_Incident_Operator” and the related attribute “Current_Incident_OperatorGroup” did not provide additional information and were removed from the database.

After the initial data cleaning, three attributes still contained missing values (displayed in figure 5). The observations that contained missing values for the two resource attributes were dropped because they contained only a small portion of the total number of observations. However, the empty values of the SolvedWithinSLA duration were left in the dataset.

```
Incident_Name_Reporting(aanmeldernaam)           2
ActivityPerformerResource_Name                  15
SolvedWithinSLADuration                      14312
```

*Figure 5, an overview of missing values.*

The attribute names were simplified and the attributes that contained dates were changed to “datetime 64[ns]”. Due to missing end dates, it was not possible to calculate activity duration on the difference between start and end date. We decided to calculate the activity duration based on the difference between the start time of the activities from the same case. However, as a consequence, the activity duration now includes the waiting time, which can give a wrong interpretation of the results. The case duration is calculated based on the difference between the CallDate and CompletionDate, this shows the duration between when the problem occurred and when it was solved. The four case times attributes are defined as:

- The CallDate describes when the case is sent in by the client.
- The CreationDate corresponds to the date when a resource starts handling the case.
- The CompletionDate describes the date when a resource notifies that the problem is resolved.

- The ClosureDate specifies when the case is officially closed, the client has a few days after the problem is resolved to confirm that the problem is actually solved.

The majority of the time the cases are already solved before the ClosureDate. As such, the additional waiting time would give an unrealistic representation of the case duration. For this reason, we select the CompletionDate as the formal end time (employee ITS, personal communication, 2021). The difference between the CreationDate and the CompletionDate is the amount of time that a resource worked on the case and the difference between the CallDate and the ClosureDate is the amount of time that the case is open. The cleaned dataset contains 17 attributes and 739436 activities. A second dataset has been created from TopDesk with the same attributes for the period 01-01-2022 till 18-04-2022. The second dataset contains information about the three months before the survey was conducted.

The dataset is filtered to include only real performers (not departments or systems) from the department's Support and User Collaboration. Real performers are defined as employees which have worked more than 40 hours in the period of 2020-2022 or more than 20 hours in the period 01-2022 to 04-2022. The required work hours are less for the second period because the period is shorter. The employees that do not satisfy the condition are labelled as "unknown", they were not removed because that could result in incomplete cases.

### 3.4.4 How are the process mining techniques applied?

Process mining techniques are applied to the TopDesk dataset to obtain process mining variables that have a relation with the selected job demands or resources. The transformation procedure as described in 3.3 was applied for the process mining variables in the case study. In this section we describe the event log, tools & frameworks and process mining techniques that are applied in the case study.

*The event log of our case*

The discovered incident management process model was compared with the one designed by IT Service of Utrecht University. The process models are visualised in appendix 9.3 and a simplified visualisation is presented in figure 6. We observe that the discovered process includes the activity "Action added on Incident", while the designed process described all the actions that can be added to the incident. Because of that many activities are not recorded in the discovered process, resulting in a less informational process model.

Therefore, the activities will not be used to investigate the variation in the processes. The attributes "Entry" and "CallType" give information about the cases, these attributes are used to examine the variation in the processes. Additionally, we cannot apply process mining variables that investigate deviations between the design and discovered process.

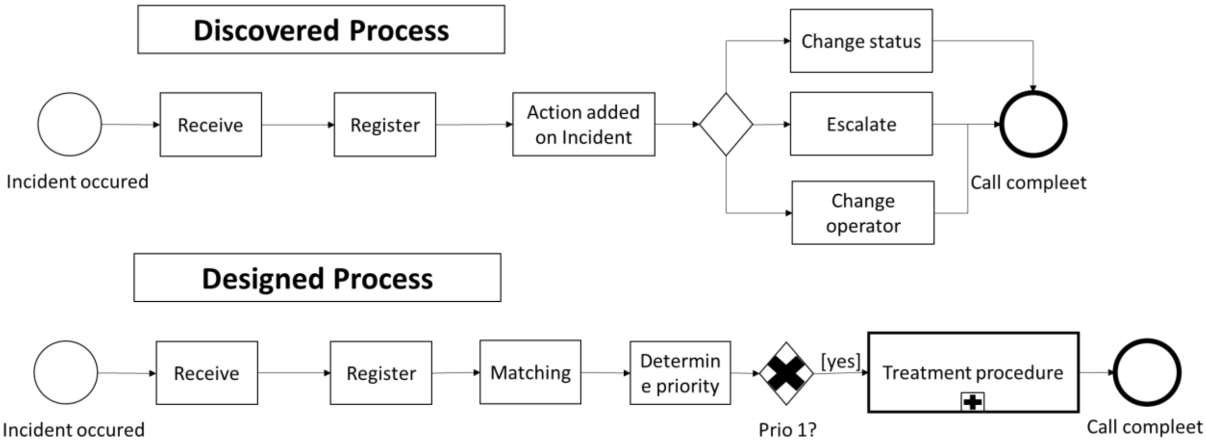



*Figure 6, Comparison of the discovered and the designed process model*

### *The tools and frameworks*

The process mining techniques were applied with the tool Disco and the framework ProM. These tools are recommended by Van der Aalst (2016). According to the author, Disco is fast and easy to use, whilst ProM has many functionalities which allow the user to analyse the event log for a variety of purposes.

Disco was applied to discover the process model with its characteristics. The discovered process model provides a basic understanding of the process. Disco has a filter functionality which can be applied to filter on variants, categories and time. The resulting process model and its characteristics give an overview of how the employees perform and can be exported to Python.

The process mining variables related to the job demands (*workload, time pressure, monotonous work*) and the job resource *autonomy* were explored with Disco. However, Disco lacks the ability to specify what statistics to calculate, to calculate activity time without the attribute “activity end date”, and to group on multiple categories. The programming language Python with the libraries Pandas and Numpy was used to calculate the process mining variables from the (filtered) event log. The code was created in the open-source integrated development environment (IDE) Jupiter Notebook and the package management was simplified by using the open-source distributor Anaconda. The program language Python was selected because it is the most popular programming language for data science and the research group had prior experience working with this programming language (Piatetsky, 2019; TIOBE, 2022). The Python code for all functions is publicly available on GitHub.

Van Dongen et al. (2005), created the ProM framework so that all process mining techniques can be applied from one platform. Process mining techniques can be added to the ProM framework as a plugin. ProM gives an overview of all available techniques and allows users to apply multiple techniques and compare the results. In this study ProM plugins that analyse the communication between performers were applied to determine process mining variables related to the job resource *social support*. The plugins were applied in ProM to visualise the sociograms.

### *Global overview of the (process mining) techniques that are applied to gain the results*

Disco is constructed with a built-in process discovery technique which creates a process model from an event log. The process model was used to explore the process mining variables. The characteristics of the process are required to calculate the job demands and resource *autonomy*.

ProM has five built-in organisational mining techniques which correspond to the techniques: *causality handover, special event causality, joint tasks, causality subcontracting,* and *joint cases*. The *special event causality* does not correspond to one of the selected job demands & resources, the other four techniques are applied in this research. The techniques in ProM 6.11 visualise their result as a sociogram. Furthermore, ProM 5.2 visualises the numeric results. However, these results cannot be exported. Therefore, Python was used to replicate the ProM techniques and to calculate the Z-scores on the obtain numeric results.

### 3.4.5 Survey

In addition to process mining a survey was performed. The survey measured the job demands & resources that were selected for further investigation (see section 4.1). These job demands & resources correspond to the data measured with process mining. Additionally, the survey measured the strains, motivation and outcome of the participants. These aspects were measured so that additional information can be provided to IT Service. The survey was published on 7 April 2022 and was open for about two weeks. The survey was filled out by 16 respondents. The majority of the correspondents are employees with permanent contracts. The average scores of the job demands & resources measured by the survey are described in table 9. The highest possible score is 5 and the lowest possible score is 1. The higher the value the more the job demand/ resource occurs. For example, a score of 5 on "*workload*" implies that an individual perceives his/her workload as high.

| Job demand/ resource | Score | Standard deviation |
|---|---|---|
| Workload | | |
| Time pressure | | |
| Monotonous work | | |
| Autonomy | | |
| Social support | | |

*Table 9, results of the survey (personal information removed).*

### 3.4.6 Analysis procedure

The objective job demands & resources results measured with process mining are compared to the subjective job demands & resources results obtained from the survey. The expectation is that the absolute values of the distributions differ, but that they display similar trends (the percentage a line increases or decreases). Unfortunately, it is not possible to validate the process mining measurements by testing this expectation. However, by calculating the Pearson correlation coefficient, we can investigate whether there is a positive correlation between the objective and subjective job demand/ resource. The strength of the relations is interpreted according to the guidelines of Dancey & Reidy which is mentioned in the article of Akoglu (2018). They state that a correlation of 1 is perfect, between 0.9 and 0.7 is strong, between 0.6 and 0.4 is medium and below 0.4 is weak.

Additionally, is Pearson's correlation measured between the objective job demands & resources and the subjective strains and motivation. These correlations indicate if the job demands & resources measure what is expected of them. The hypothesis is that the expected relations have a correlation with each other with an effect size of 0.4 or higher. The hypothesis can be seen as a validity test since it checks if the objective job demands & resources measure what they should. Based on literature are the expected key relations:

- Workload and burnout
- Time pressure and burnout
- Monotonous work and boredom
- Autonomy and work engagement

- Social support and work engagement

Furthermore, the job demands should negatively influence the motivation and the job resources should positively influence the strains. Pearson's effect size is used to identify the strength of a relation.

## 3.5 Validity threats

This section describes the three validity threats affecting this study and the mitigating actions performed to minimise the threats.

*The first validity threat* is the incorrect or insufficient selection of job demands & resources used to measure well-being. To mitigate this threat we investigate what job demands & resources are related to *well-being types, burnout, boredom* and *work engagement*. The job demands & resources of the JD-R model were selected based on a study that applied the model to measure the strains and motivation related to well-being, and studies that state what job demands & resources influence well-being. However, it could still be the case that not all job demands & resources related to well-being are measured. Well-being is a broad subject and not all relevant job demands & resources are known. The purpose of this study is to investigate to what degree parts of well-being can be measured with process mining. As such, it is less important that all aspects of well-being are investigated.

*The second validity threat* is that the selected process mining variables do not measure the job demands & resources. There is no existing literature in which process mining variables are used to measure the job demands & resources. To mitigate this threat, we investigated what each job demand & resource entails. Then the process mining variables that measure these job demands & resources are selected based on logical reasoning and sparring with the project team.

*The third and final threat* is that the archival data is gathered for a different purpose than the one analysed in this study. A consequence of this could be that the archival data does not contain all the required information to answer the research question of this study. However, after the initial analysis we found that the data contains the required information to calculate most of the process mining variables.

# 4 Results of the literature study

In this chapter, the results of the research are described. The first two research questions are answered using a literature study. The results of the literature studies are combined to answer the third research question. The results of the case study (research question 4) are discussed in section 5.

## 4.1 RQ1: What work-related job demands & resources influence well-being?

In this section, the job demands & resources are specified for the job demand-resource model (JD-R model). Bakker et al. (2003) measured similar outcomes, strains and motivation with the JD-R model. They applied the model to measure the *outcomes* absenteeism and personnel turnover, the strain *burnout*, and the motivation *work engagement* for a call centre. The job demands & resources used in that study are *workload, time control, changes in tasks, social support, supervisory coaching, emotional demands, computer problems* and *performance feedback*. These job demands & resources have been investigated if they could be of value for this study. Boredom is selected as an additional strain because it is proven that *boredom* has a negative effect on well-being (Watten et al., 1995). According to Elpidorou (2017), a little bit of boredom can have a positive effect on well-being. The study of Sulea et al. (2015) indicates that *burnout, boredom* and *work engagement* are three forms of well-being.

### *Job demands related to burnout: workload & time pressure*

*Workload* is the first selected job demand as it has been used in multiple studies to predict employee burnouts (Bakker, Demerouti, & Schaufeli, 2003; Schaufeli & Bakker, 2004). Furthermore, *workload* is a big part of the Job content scale developed by Karasek (1998). Hernandez et al., describe the influence of workload on well-being as follows: "Excessive exposure to high-workload tasks from work has frequently been associated with poorer psychological and physical well-being" (Hernandez et al., 2021, p. 2). Two indicators of *burnout* are exhaustion and occupational stress (Demerouti et al., 2001a; Yi et al., 2022). These aspects are not observable from event logs. Therefore, the job demands *workload* and *time pressure* are selected to proxy well-being since high *workload* and *time pressure* can lead to exhaustion and occupational stress (Bolliger et al., 2022; Wang et al., 2021). According to Bolligor et al. (2022) occupational stress can also be reduced with job resources such as *social support*.

### *Job demand related to boredom*

A known indicator of *boredom* is *monotonous work* (Loukidou et al., 2009). Smith (1981) proves that monotonous work is an important influencer of boredom. For this reason, *monotonous work* is selected as a job demand.

### *Job resources related to work engagement and burnout*

A cross-sectional study (de Jonge et al., 2001) proved that *social support* is a key aspect of well-being, and is increasingly important when work is carried out in close teams. In the literature *social support* is used to predict *burnout*, well-being and personnel turnover (Bakker, Demerouti, & Schaufeli, 2003; de Jonge et al., 2001; Karasek et al., 1998). According to Bakker et al. (2003b), is *autonomy* related to *work engagement*. This led to the selection of the job resources: *social support* and *autonomy*.

### *Selection of the* job demands & resources *for burnout, boredom and work engagement*

The variables used in the study of Bakker et al. (2003) are either incorporated, selected, or not selected because they are unmeasurable or irrelevant, as a job demand or resource. The variable *social support* is selected, *supervisory coaching* is seen as part of *social support* because it is about the support of a supervisor (Mikkola et al., 2018). *Workload* is selected as job demand and the variable *time-control* is part of the job demand *time pressure*. The variable *changes in tasks* is part of the job demand *monotonous work*. The *emotional demands* cannot be measured based on human behaviour. The relation between *burnout* and *work engagement* was unclear for the remaining variables and were therefore not selected. The relevant variables for *burnout, boredom* and *work engagement* are described in table 10.

| Job Demand/ Resource | The job demands or resources | Description |
|---|---|---|
| Job demand | Workload | The amount of work that must be performed within a period. |
| Job demand | Time pressure | How difficult it is to finish work before a deadline. |
| Job demand | Monotonous work | The level of variety in performed tasks |
| Job demand | Emotional demands | The amount of emotional effort in someone's interactions. |
| Job resources | Social support | The amount of support an employee receives from their colleagues/environment. |
| Job resources | Autonomy | The degree to which an employee can finish his/her tasks without help. And the extent to which an employee has the right to make decisions. |

Table 10, selected job demands & resources. Green= selected job demand or resource, orange= job demand or resource that cannot be measured based on the digital process execution.

### *Characteristics of well-being types*

In table 11 the characteristics of the *well-being types* are described. The characteristics can be divided into four categories:

1. Characteristics that are related to *burnout, boredom* and *work engagement*. *Autonomy* is directly mentioned as job resource for *work engagement*, the characteristics *relatedness*, *positive relations, social coherence, social integration* and *social acceptance* are related to the job resource *social support* (Berkman et al., 2000).
2. Characteristics that concern the development of humans. These are not resources or demands (Demerouti et al., 2001b). The characteristics that belong in this category are *personal growth* and *purpose in life*.
3. Characteristics that are not work-related, these are: *eating patterns, working out, diseases* and *purpose in life*.
4. Characteristics that cannot be measured based on process execution. The characteristics *moods, self-esteem, self-acceptance, environmental mastery* and *social contribution* require information from the thoughts/opinions of employees.
5. Characteristic that cannot be measured based on digital events, this concerns the characteristic *heavy physical activities*.

The category 1 characteristics are measured with the selected job demands & resources. Category 2 and 3 characteristics are irrelevant for this study and category 4 and 5 characteristics cannot be measured based on digital process execution. The table shows that the selected variables are capable of measuring social well-being to a great extent and emotional & psychological well-being partly. Unfortunately, physical well-being cannot be measured based on attributes of human behaviour.

| Characteristics /Well-being types | | | |
|---|---|---|---|
| **Physical** | **Emotional** | **Physiological** | **Social** |
| Working out | Moods | Personal growth | Social contribution |
| Eating pattern | Self-esteem | Purpose in life | Social coherence |
| Diseases | Autonomy | Self-acceptance | Social actualization |
| Heavy physical activities | Relatedness | Environmental mastery | Social integration |
| | | Autonomy | Social acceptance |
| | | Positive relations | |

Table 11, characteristics of the *well-being types*. Green= selected or part of a job demand or resource, yellow= irrelevant characteristics for work-related job demands & resources, orange= characteristics that cannot be measured based on the digital process execution.

## 4.2 RQ2: What information can be obtained with process mining techniques?

In this section, the results of the structured literature review are discussed to formulate an answer to the second research question. The goal of the literature review is to identify the process mining techniques that focus on resources and the information they provide. The selection procedure yielded 63 relevant papers. The papers are divided based on the type of contributions they perform, as described in table 12.

| Kind of paper | Number of papers |
|---|---|
| The paper describes one or multiple new techniques | 26 |
| The paper describes an approach | 12 |
| The paper describes a framework that makes use of existing techniques | 10 |
| The paper gives an overview of existing techniques | 5 |
| The paper applies an existing technique in a new domain | 7 |

*Table 12, different kinds of papers.*

| Technique types | Number of papers |
|---|---|
| Social Network Analyses | 7 |
| Organisational Structures | 8 |
| Other | 11 |

*Table 13, The type of technique that is explained in the selected papers.*

### 4.2.1 Social network analyses

Two frequently recurring topics in the selected papers are social network analyses (SNA) and organisational structures (OS) (see table 13). Social networks/sociograms visualise interpersonal relations of humans in a graph or matrix (van der Aalst & Song, 2004). A sociogram contains nodes that represent resources and arcs which represent the relations between the resources. The distances between nodes show how closely related the resources are. Weighted sociograms give weights to all arcs, the weights are determined by the frequency of communication between the resources.

*Social network analysis* is defined as the collection of methods, techniques and tools that are used to gain information about interpersonal relationships (sociometry) (van der Aalst & Song, 2004). Process mining can be used to discover the sociogram of an organisation. Metrics are used to gain information about the characteristics of the social network (van der Aalst & Song, 2004).

Process mining techniques that apply social network analyses are primarily used to analyse two types of interpersonal relationships (van der Aalst & Song, 2004). Metrics based on causality and metrics based on causality with special event types (Matzner, 2014). The metrics monitor how work is moved along performers. The special event type metrics require additional information from the event log. One example is a technique that investigates the hierarchical structure based on an event log that contains the event type “delegation”.

### 4.2.2 Organisational structures

Organisational structures are clusters of employees that show how an organisation is organised. There are two types of process mining techniques that determine organisational structures, these being joint cases and joint tasks (Matzner, 2014). Joint tasks create clusters based on how often performers execute similar tasks. Joint cases create clusters based on how often performers work on the same case together. Social network analyses and organisational structures are part of organisational mining (van der Aalst & Song, 2004). The main difference is that the *social network analysis* metric provides information on the interaction between employees while the *organisational structure* metric creates clusters of similar employees.

### 4.2.3 Overview of social network analyses and organisational structure techniques

As aforementioned, the SNA and OS techniques are divided into four metrics (technique types): causality, special event types, joint activities, and joint cases. The number of techniques found for each of the metrics is described in table 14. There are more techniques than process mining papers because some papers proposed multiple techniques. In this paragraph, the techniques found in the selected papers are explained in detail.

| **Metric (Technique type)** | **The outcome of the technique** | **Number of different organisational mining techniques identified in the SLR** |
|---|---|---|
| Causality | Communication structure where in it is visible who communicates with who. | 8<br>(Abdelkafi & Bouzguenda, 2010; Aghabaghery et al., 2020; Ahn & Kim, 2020; Dustdar & Hoffmann, 2007; Hanachi et al., 2012; Park et al., 2016; Song & van der Aalst, 2008; van der Aalst & Song, 2004) |
| Causality with special events | They identify the hierarchy within an organisation. | 2<br>(Hanachi et al., 2012; van der Aalst & Song, 2004) |
| Joint task | Clusters of organisational units/ performers that perform similar tasks. | 7<br>(Amrou M’hand et al., 2021; Delcoucq et al., 2020; Song & van der Aalst, 2008; Utama et al., 2020; van der Aalst & Song, 2004; Yang et al., 2018) |
| Joint cases | Clusters of organisational units/performers that work on the same cases. | 5<br>(Ferreira & Alves, 2011; Slaninová et al., 2015; Song & van der Aalst, 2008; van der Aalst & Song, 2004) |
| Combination of clusters with causality | Shows how clusters of people communicate with each other. | 2<br>(Jianhong et al., 2018) |
| Other techniques | The outcomes differ per technique. | 12<br>(Abdelkafi & Bouzguenda, 2015; Appice & Malerba, 2016; Bose & van der Aalst, 2013; Cabanillas et al., 2020; Cho et al., 2021; de Leoni et al., 2012; Hanachi et |

| | | |
|---|---|---|
| | | al., 2012; Martin et al., 2017, 2020; Nakatumba & van der Aalst, 2010; Schönig, Cabanillas, et al., 2015; Sikal et al., 2019; Suriadi et al., 2017) |

*Table 14, number of techniques found.*

### *Causality techniques*

Causality is about the interaction between performers. One of the first process mining causality techniques was created by Van der Aalst & Song (2004). Their technique analyses if people perform tasks sequentially for the same case and visualises the communication process as a sociogram. With a sociogram handovers, subcontracting, and metrics such as density and cohesion can be analysed.

For our research, causality techniques are used to investigate who and how often performers communicate online during work time. The *basic requirement* for process mining causality techniques is an event log which includes a case Id, activities, timestamps, and resources. Eight distinct techniques have been found which calculate the causality. The goal and outcome of the techniques differ slightly from one another. Some causality techniques calculate the amount of work per employee in addition to visualising a communication process. The inputs of the techniques differ as well, most rely on event logs but there are causality techniques that take a workflow as input.

### *Causality with special events techniques*

Two techniques (Hanachi et al., 2012; van der Aalst & Song, 2004) have been found which require the special event “task delegation”. This event enables the techniques to identify the hierarchy of a company. These techniques require the same datatypes in an event log as is common for causality techniques, with the additional requirement that the targeted event type is included in the event log.

### *Joint task techniques*

The joint task techniques cluster employees based on the tasks that they perform. Song & Van der Aalst (2008) identify two different joint task techniques. The first approach clusters employees based on hierarchical clustering. It determines a distance (such as, Euclidean distance) between the employees based on how often the employees execute the same tasks. The second approach creates clusters for all employees that execute the same task based on a performer-task matrix. These techniques require the activities and resources to be included in the event log. Furthermore, some of them also require the time(stamp) and case identification.

Most of the joint task techniques create a performer-task matrix and use a distance metric to calculate the differences between the employees. An example of such a matrix is given in table 15.

| Performer | Event A | Event B | Event C |
|---|---|---|---|
| Alice | 3 | 0 | 2 |
| Ben | 1 | 2 | 2 |
| Joey | 0 | 3 | 2 |
| Elise | 3 | 0 | 1 |

*Table 15, performer-task matrix, the numbers indicate the frequency that a performer executed a task.*

Delcoucq et al. (2020), propose an extension of the technique developed by Song & Van der Aalst (2008). Their technique considers the sequence in which the tasks are performed. Yang et al. (2018) contribute to this topic by creating a technique that discovers employees with overlapping or multiple roles. These employees can perform more activities and are therefore more widely deployable.

### *Joint cases techniques*

The joint cases metric clusters employees based on how many cases they performed together. In the technique of Van der Aalst & Song (2004) the metric is calculated by investigating how frequently performers work on the same case. The joint case techniques deliver similar outcomes, with one exception. The technique of Slaninová et al. (2015) which visualises the clusters with behavioural graphs.

#### *Other types of techniques*

Three techniques can be categorised as role mining. Role mining aims to derive the required permissions for each role. It first allocates roles to people based on their tasks and then identifies the permissions they require to perform their tasks (Matzner, 2014). The technique of Sikal et al. (2019) discovers roles with their characteristics. Another technique investigates if there are people with double roles (Jianhong et al., 2018). The techniques that have not been categorised, are used to:

1. *Investigate the work speed of performers* (Bose & van der Aalst, 2013; Nakatumba & van der Aalst, 2010).
2. *Evaluate the outcome of a technique* (Abdelkafi & Bouzguenda, 2015).
3. *Discover a process with resource allocation* (Cabanillas et al., 2020; Schönig, Cabanillas, et al., 2015).

## 4.3 RQ3: Overview of the information that can be gathered with process mining

This section provides an overview of the process mining variables used for measuring the selected job demands & resources (see section 4.1). In the previous sections, the job demands & resour*ces* related to well-being are selected, and an overview is created of the relevant process mining techniques. This section investigates which process mining variables (outcomes of process mining techniques) can be used to measure the selected job demands & resources.

#### *Domain independent attributes in event logs*

The techniques used to determine job demands & resources should be applicable to every domain. As a consequence, the event log may solely consist of attributes which can be acquired for all domains. We focus on processes where clients/patients are served.

According to Van der Aalst (2016), the attributes case id, activity and timestamp (start time) are required attributes for an event log. Furthermore, domain independent process mining techniques that focus on resources require the attribute “resources” and techniques that investigate performers require the attribute timestamp at the end of an activity. These five attributes are domain-independent.

According to Lantow et al. (2019), the well-being of employees cannot be determined with only these attributes. For that reason, we include additional attributes to determine well-being. No literature reported an overview of all domain-independent attributes that commonly occur in an event log. The research group discussed what attributes are commonly found in all domains. The derived attributes are:

- Clients/customers
- Priorities/urgency
- Prescribed goals, about the number/duration of activities & cases
- Categories about the case
    - The subject of the case
    - Entry of the case

In addition, event logs can contain extra (domain-dependent) information, which could be beneficial for measuring job demands or resources. However, the attributes that contain this type of information are not used in this study.

### 4.3.1 Links between process mining variables and job demands & resources

The process mining variables are divided into two groups:

- Process mining variables related to the job resources *social support* and *autonomy*.
- Process mining variables related to the job demands *workload, time pressure* and *monotonous work*.

#### *Correlated to the job resources social support and autonomy*

The process mining variables connected to *social support* and *autonomy* are presented in table 16 and table 17 respectively.

| Variable number | Variable | Organisational mining technique | Descriptive statistics |
|---|---|---|---|
| 1 | The frequency that a performer interacts with people. | Causality | Mean frequency of handovers |
| 2 | The number of people that perform similar tasks. | Joint cases | Mean |
| 3 | The number of people that work on the same case as the performer | Joint tasks | Mean |

*Table 16, variables for the process mining techniques related to social support, the main sources for the variables are (Song & van der Aalst, 2008; van der Aalst & Song, 2004). The variables correspond with metrics in table 14. The sources supporting those metrics also support these variables.*

Our research is focused on employee well-being, therefore only the *social support* of colleagues and managers is measured. *Social support* has two dimensions, structural and functional (Ozbay et al., 2007). The structural dimension is the quantitative side of *social support*, it measures elements such as the network size and frequency of social interactions. The functional side is the qualitative side of *social support*, it determines how important a social connection is. The functional side is about how much physical, psychological, or financial support a social connection gives. However, as the functional side is not measurable with process mining this research only focuses on the structural side of *social support*.

The variables selected for *social support* give an indication of the social network size and frequency of interactions. This can be done with social network analyses and organisational structure process mining techniques. The variables that measure the job resource *social support* are:

(1) The frequency that a performer interacts with people.
(2) The number of people that perform similar tasks.
(3) The number of people that work on the same case as the performer.

Gerard Dworkin (1988) states that there are multiple definitions for *autonomy*. The definitions are about the freedom to make certain actions and decisions in a specific domain. *Autonomy in this research is measured with the variables:*

(1) The number of times that a person finishes a case alone.
(2) The number of activity sequences that a employee can perform alone.
(3) How often a performer deviates from the process model.

| Variable number | Variables | Based on the papers | Descriptive statistics |
|---|---|---|---|
| 1 | The number of times that a person finishes a case alone. | (Cabanillas et al., 2020; Schönig, Cabanillas, et al., 2015) | Percentage |
| 2 | Number of activity sequences a employee performs alone. | (Cho et al., 2021) | Number/ percentage |
| 3 | Number of deviations. | (de Leoni et al., 2012) | Number |

*Table 17, Variables for process mining techniques related to autonomy.*

### *Variables related to Job demands*

The papers reviewed in the structured literature review also contained process mining techniques that discover resource-aware process models with their characteristics. The discovered process model allows us to use variables based on the process flow. These techniques deliver process mining variables that are related to the selected job demands and are described in table 18.

| **process mining techniques based on process flow** | | | |
|---|---|---|---|
| **Variable number** | **Job demand** | **Variables** | **Descriptive statistic** |
| 1 | Workload (Amount of work) | **Activity duration * number of activities.** | Total duration |
| 2 | Workload (Difficulty of work) | Cases with a case duration larger than 2 SD. | Number/ frequency |
| 3 | Workload (Difficulty of work) | Work time per difficult case category. | Duration |
| 4 | Workload (Difficulty of work) | Cases reopened. | Number/ frequency |
| 5 | Time pressure | The number of contracts kept that are about the **number** of activities/ cases. | percentage |
| 6 | Time pressure | The number of contracts kept that are about the **duration** of activities/ cases. | Percentage |
| 7 | Time pressure | Median case & activity **duration compared to** required case activity duration according to the prescribed duration of cases/ activities. | Number |
| 8 | Time pressure | Number of urgent cases. | Number/ frequency/ percentage |
| 9 | Monotonous work | workload per channel per incident category. | Standard deviation |

*Table 18, variables that can be created by discovering and enhancing the control flow.*

The job demand *workload* is determined by the amount and the difficulty of the work (Jex, 1998). However, there are also studies that view *workload* only as the amount of work (van Veldhoven et al., 2002). *To calculate the amount of work* the mean activity duration per performer is combined with the number of activities an employee has performed (variable 1). This results in the total work duration per employee. To calculate the *amount of workload* we require both a begin and an end timestamp. *Workload* is the only selected job demand that can entirely be measured with *existing* organisational mining techniques (Nakatumba et al., 2012; Park et al., 2016). These techniques view *workload* as the amount of work performed per resource. The measurement of the *amount of workload* only takes activities that are performed on a computer into consideration.

The aspects that make a job difficult differ per project and domain (Ivancevich & Smith, 2007), making it hard to measure *job difficulty*. Excessive workload is one of the main causes of increased job difficulty. Furthermore, conflicts and supervising others are also mentioned as *job difficulties* for the projects investigated by Ivancevich and Smith. Event logs generally do not contain an attribute that describes the difficulty of the activities and cases. However, there are attributes that give an indication of the *workload difficulty*. One of these attributes is the duration of a case. Sandry et al. (2014) have shown that activities with a long duration increase the fatigue of the subject. Furthermore, some cases may also be more difficult based on the type of the case. For example, it is known that the employees of ITS of UU find working at the channels telephone and counter harder because it involves direct contact with the clients (employee ITS, personal communication, 2021). *To determine workload difficulty we utilise the following variables* per employee:

(2) Number of cases with a duration > 2 standard deviations from the Z score.
(3) Work time in difficult case categories (such as category telephone and counter).
(4) The number of cases that were reopened.

The job demand *time pressure* indicates the amount of work that must be done within a certain timeframe (Rose et al., 2011). The *time pressure* increases when people feel like they have insufficient time to finish their work. The variables related to the job demand *time pressure* rely on contracts that specify what a performer must achieve within the timeframe. An example of such a contract is the Service Level Agreement which specifies a timeframe wherein the cases must be solved. *The variables used to measure time pressure are:*

(5) The number of contracts kept that are about the **number** of activities/ cases.
(6) The number of contracts kept that are about the **duration** of activities/ cases.
(7) The average (median) case duration compared to the timeframes wherein cases must be solved according to specified contracts.
(8) Number of cases that urgently need to be solved.

The job demand *monotonous work* indicates how varying the work is (McBain, 1961). With process mining, it is possible to check how often performers execute different tasks. Furthermore, provided that the event log contains an attribute that explains what kind of case is handled (such as subject category and entry), it is possible to investigate the variation in the types of cases that are handled. *The variable used for monotonous work is* the standard deviation of a performer's workload per activity type and per possible case category (variable number 9).

The job demands & resources can be calculated for different timeframes. This makes it possible to investigate whether a certain period was extra demanding for the employees.

### 4.3.2 To what degree can the selected job demands & resources be measured?

We conclude that the selected job demands & resources can be connected to process mining variables. Social support is the only job resource that cannot be fully measured. Whilst the quantitative side, the number of relations, can be measured with the current process mining techniques the meaning of these relations cannot. The other job demands & resources can be fully measured.

# 5 RQ4: Case study results

The job demand & resource are objectively measured with the process mining variables for the employees of the departments Support and User Collaboration Services. The survey measured the perceived/subjective values for the job demands, job resources, strains, motivation and outcomes. The correlation between the objective job demands & resources and the subjective job demands, job resources, strains and motivation are measured. Research question 3 explains how the job demands & resources influencing well-being are determined with process mining. In this chapter we describe:

1. The procedure of calculating the process mining variables.
2. The job demands & resources scores for ITS.
3. The correlation between the objective and subjective results.

## 5.1 The procedure of calculating the process mining variables

In this section, we describe how the process mining variables of the job demands & resources have been calculated. The calculated job demands are *workload, time pressure* and *monotonous work.* The job resources that are determined are *autonomy* and *social support.* Each job demand & resource is determined by one or multiple process mining variables. These process mining variables are calculated with the use of ProM plugins, Disco and Python code. The results of ProM and Disco are imported in Python, making it possible to calculate and visualise the job demands & resources scores in one code file. The outcome of each process mining variable is transformed into a Z-score, to guarantee that the scores are standardised. Another benefit of the Z-score is that it can be used as a baseline, as it shows how much something or someone deviates from the mean.

The calculations of the process mining variables are coded as functions. This way the job demands & resources can be determined for different datasets and timeframes. We developed two general functions to support the calculation of the process mining variables. The first general function creates a case perspective instead of the original activity perspective. Each row in the case perspective corresponds to a unique case for a performer. The second general function filters the dataset based on a pre-specified timeframe. The filtered dataset can be applied to other functions to calculate the process mining variables for a specific timeframe. There are 15 functions that calculate a process mining variable. The purpose and inner workings of the functions are explained in appendix 9.4 "Calculation of the variables".

The functions are used to calculate the process mining variables and job demands & resources for IT Support Utrecht University. The values are calculated with an anonymised dataset for the periods 01-09-2020 to 31-01-2022 and 01-01-2022 to 18-04-2022.

## 5.2 The job demand & resource scores

In this section, the scores for the job demands & resources are described. The scores are obtained from the dataset of the first period (2020-2022).

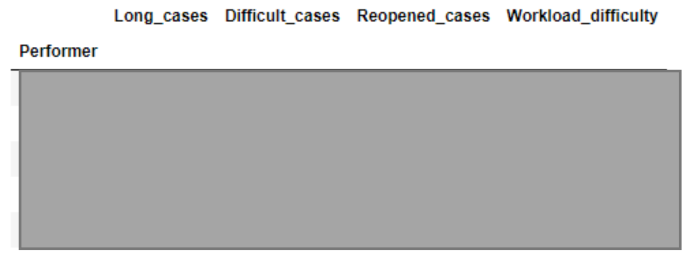
We started by examining the discovered process model. One of the things that stood out was that the discovered process model contained 5067 unique variants, of which only 9% occurred in multiple cases. For a detailed process model this is an indication that the process is either very complex or that the specified process is not followed (Schrepfer et al., 2015).

The *amount of workload* (in hours) is the first job demand we calculated. Table 19 and figure 7 give an overview of the results. The high standard deviation and the difference between the lowest and highest *workload* are notable. The investigated departments employ both student employees with zero-hour contracts and traditional employees with fixed contracts. This could explain the large deviation in working hours. Furthermore, a line plot (removed because of personal information) indicates that there is a small percentage of employees that work more than 50000 hours. The work duration contains both the activity duration and waiting time, which results in unrealistic high work durations.

| Mean | Standard deviation | Max | Min |
|---|---|---|---|
| 24979 | 45515 | 257146 | 2434 |

*Table 19, amount of workload, descriptive statistics.*

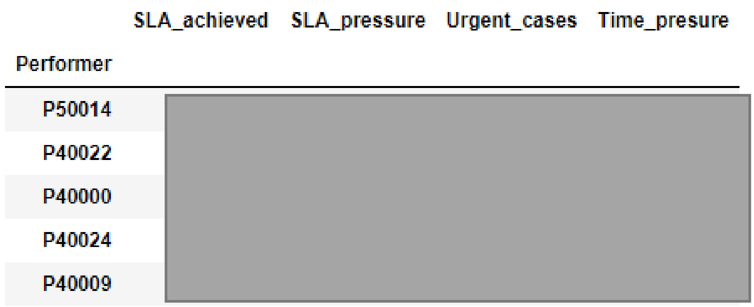
The second job demand we calculate is the *workload difficulty.* Similar to the *amount of work*, *workload difficulty* has a high standard deviation. It should be noted that the highest performer is not the same individual as the highest performer of “amount of workload”. The highest performer gained its score because of the variables “Difficult cases” and “reopened cases”. The other employees have significantly lower values than this performer. The variance in the distributions is interesting because it indicates which employees have a high or low *workload*.



| Performer | Long_cases | Difficult_cases | Reopened_cases | Workload_difficulty |
|---|---|---|---|---|
| [redacted] | | | | |

*Figure 7, The 5 employees with the highest score on workload difficulty (personal information removed).*

Utrecht University IT Service have a Service Level Agreement that specifies the maximum case duration per priority level. However, there are no contracts that specify how many cases must be executed per performer within a period. We can observe, from figure 10, that employee P50014 has a high *time pressure* because he/she must handle a lot of urgent cases. The employee has no trouble with finishing cases on time, which reduces his/her *time pressure* slightly. The second, third and fourth employees with the highest *time pressure*, experience high time pressure because they have trouble finishing their cases in the allotted time.



| Performer | SLA_achieved | SLA_pressure | Urgent_cases | Time_presure |
|---|---|---|---|---|
| P50014 | [redacted] | | | |
| P40022 | | | | |
| P40000 | | | | |
| P40024 | | | | |
| P40009 | | | | |

*Figure 8, the 5 employees with the highest score on time pressure (personal information removed).*

In the line plot of monotonous work, we observe two big outliers and two smaller outliers (higher is less variety in work). The rest of the distribution has little to no variance between the points. The interesting thing is that the employees with a low variety of work also have a high amount of *workload*.

This phenomenon is displayed in table 20, where the top 5 employees in *monotonous work* and *amount of workload* are compared with each other. It appears that these employees handle a lot of similar cases on the same channels.

| Employee monotonous work | Normalised monotonous work score | Employee (amount of) workload | Normalised (amount of) workload score |
|---|---|---|---|
| [redacted] | | | |

*Table 20, comparison of the 5 employees with the highest scores for monotonous work and amount of workload. Scores are rounded to 1 decimal (personal information removed).*

The process cannot be checked on deviations because the designed and discovered process are too different from each other. *Autonomy* is calculated based on the two other process mining variables, the results are visualised in figure 12. Employee P50048 has the highest score for the number of cases and variants performed.

| | Solo_cases | Solo_variants | Autonomy |
|---|---|---|---|
| Performer | | | |
| [redacted] | | | |

*Figure 9, results of autonomy (personal information removed).*

The descriptive statistics for the normalised *social support* scores are visualised in table 21. We observe that the mean of all values is centred around 0, which is in line with what the Z-score is supposed to do. The Z-score creates a baseline at the mean, and the scores below the mean get a negative value and scores above the mean get a positive value. An interesting insight into the *social support* scores is that the process mining variable *joint_tasks* has very low minimum and maximum values, while *joint cases* has very high minimum and maximum values. This is because of the variance in the distributions of the variables. Furthermore, there are many employees that score slightly above the mean for *joint_tasks* while there are but a few employees that score far below the mean. The variable *joint cases* experiences the inverse situation. This phenomenon becomes clearer when we investigate the boxplot visualised in figure 13.  The boxplot displays the outliers that influence the final score of *social support* (and other job demands & resources*)* the most.

| Desciptive statistics | Joint_tasks | Joint_cases | Handovers | Social support |
|---|---|---|---|---|
| Mean | 0.021 | -0.005 | -0.078 | -0.062 |
| Std | 0.98 | 1.00 | 0.67 | 1.81 |
| Min | -5.49 | -0.18 | -0.71 | -5.39 |
| Max | 0.86 | 8.47 | 3.98 | 12.67 |

*Table 21, scores of social support described.*

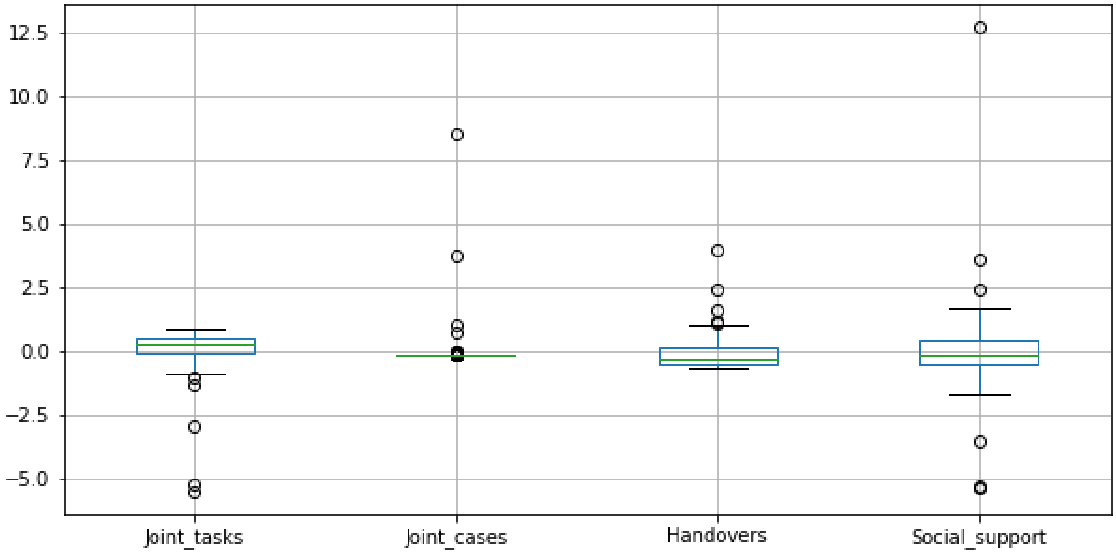



*Figure 10, boxplot of social support and its related process mining variables.*

The final values of 11 performers are visualised in figures 14 and 15. The values that indicate if an employee is in good shape are coloured green and those that indicate the opposite are coloured red. The term "in good shape" means values that indicate that employees *are unlikely* to get a *burnout* or *boredom* and that *they are likely* the be engaged in work. According to the JD-R model, the strains and motivation can be determined based on the combination of the job demands & resources. Even though we do not specifically calculate the strains and motivation, we can infer when an employee is likely to have a high score for a strain or motivation.

The most informational metric is the variance, this shows which employees have a higher job demand or resource than others. An outlier indicates one of two things:

1. The outlier has a very high job demand or resource.
2. The other employees have a very low job demand or resource.

However, we do not know whether the observations around the mean have a low or high job demand or resource. It could be the case that a group of employees are all overworked but clock a similar amount of hours. In this scenario all the employees will have a score around the mean and an intervention would be useful but the scores do not indicate that an intervention is required.

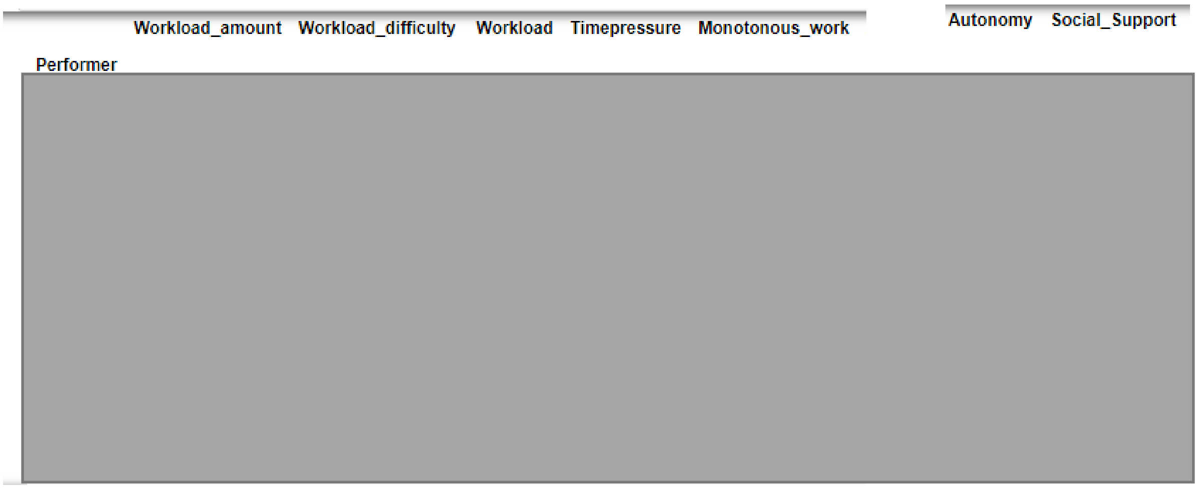


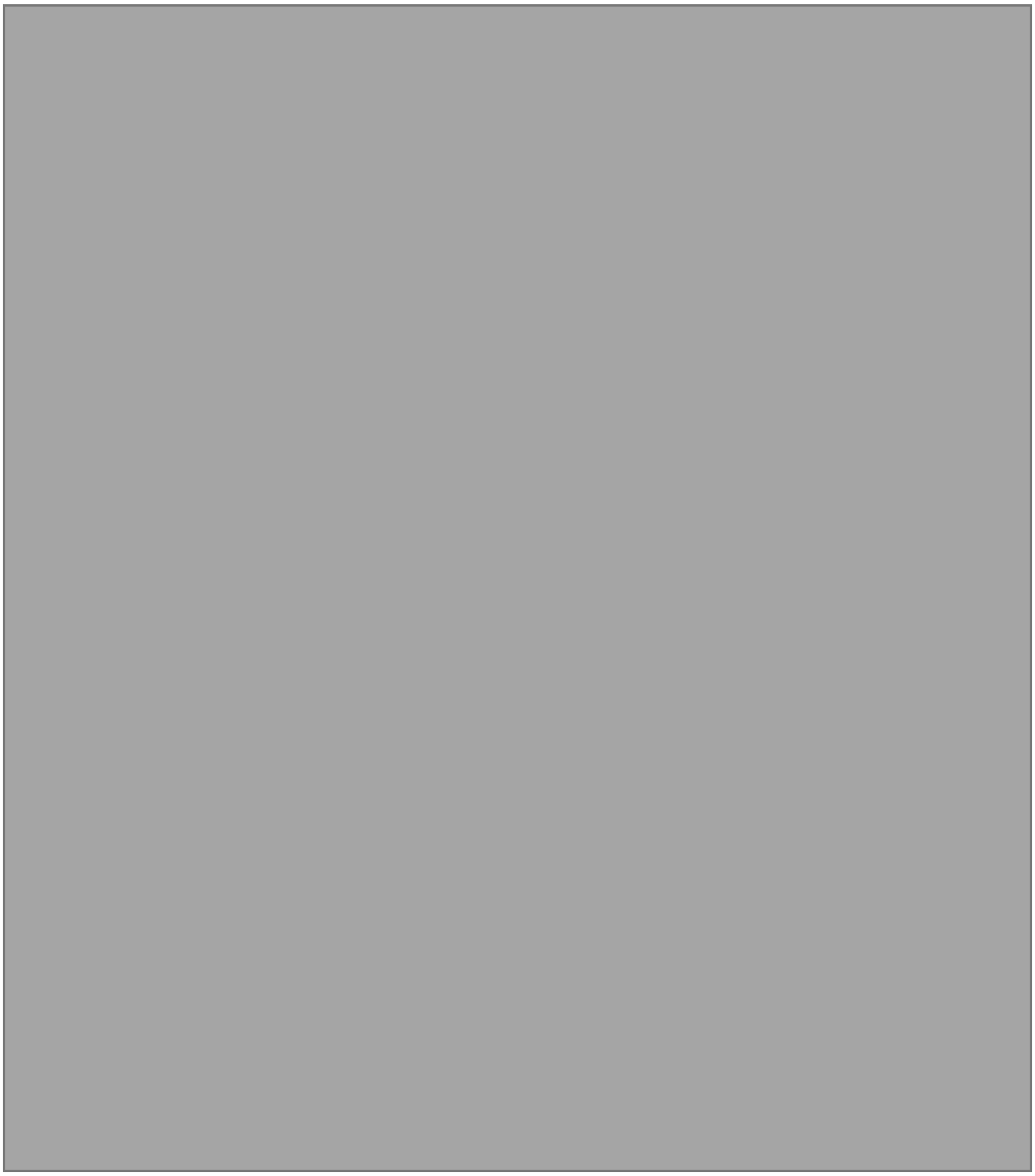

*Figure 11, the job demands (personal information removed).*

*Figure 12, the job resources.*

## 5.3 The correlation between the objective and subjective results

In this section we investigate if there is a correlation between the job demands & resources that are measured with process mining and the job demands & resources that are measured with a survey. This study investigates the correlation between the two methods by comparing the results from the survey that is held on 7 April 2022 at UU IT Service with the dataset from TopDesk that contains data from 01-01-2022 to 18-04-2022. Process mining determines the results based on digital data which is observed by information systems. Therefore, we call the job demands & resources which are measured by process mining *observed or objective* results. Surveys measure variables based on the opinions and feelings of people. We refer to the job demands & resources which are measured with a survey as *subjective* results.

The survey was filled in by 16 respondents, two of the respondents answered less than 10% of the questions and two respondent was not included in the dataset of TopDesk of the period 01-01-2022 to 18-04-2022. The survey and the dataset were filtered on the remaining 12 respondents[redacted] (Personal information).



The heatmap for the 12 performers is visualised in figure 18. The correlation between the subjective (survey) and the objective (process mining) job demands & resources is low. The job demand & resources *workload, monotonous work* and *autonomy* have a positive correlation and the job demands *time pressure* and *social support* have a negative correlation. The sample size is a lot smaller than ideal, and it would be preferable if the correlation between the observed and objective results would be rechecked on a larger sample size in future research.

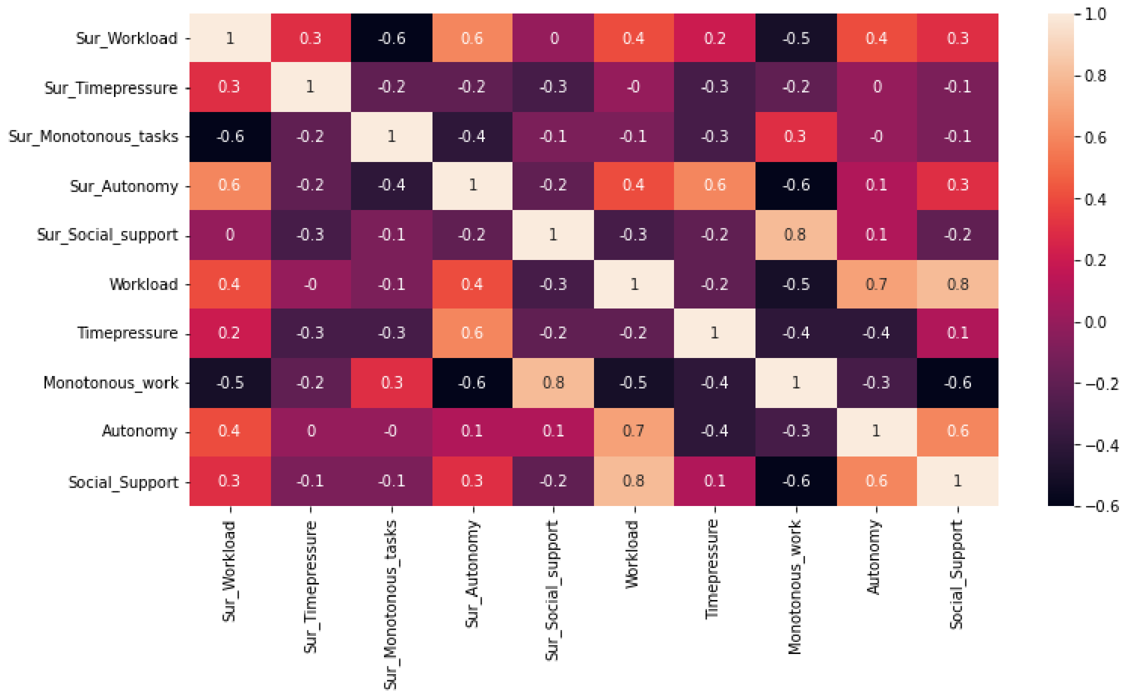



*Figure 15, correlation (Pearson) heatmap, rounded on 1 decimal. The variables that are measured with the survey have the prefix "Sur_", the ones that are measured with process mining have no additional prefix.*

A correlation of 1 (positive) means that the slope of the two variables is identical (they increase and decrease with the same percentage). A correlation of zero indicates that there is no relation between the two variables and when the correlation is -1 (negative) the slopes of the two variables are inverse of one another. The correlations can be interpreted with the Pearson criteria for effect size, the results are described in table 22.

| **Job demands & resources** | **Correlation between the objective & subjective job demand & resource** | **Pearson's r *** |
|---|---|---|
| Workload | 0.4 | Medium |
| Time pressure | -0.3 | Negative (small) |
| Monotonous work | 0.3 | Small |
| Autonomy | 0.1 | Small |
| Social Support | -0.2 | Negative (small) |

*Table 22, the effect size of the correlations with Pearson's r. *Pearson's r criteria: small: 0.1 to 0.3 or -0.1 to -0.3, medium: 0.3 to 0.6 or -0.3 to 0.6, large: higher than 0.7 or lower than -0.7.*

The survey questions can be found in appendix 9.5, the focus of the survey questions for each job demand & resource are:

- Workload: the amount of work.
- Time pressure: the amount of work that must be done within a certain timeframe.
- Monotonous tasks: the variety in tasks.
- Autonomy: The freedom/authority to make decisions and decide the sequence of work.
- Social support: the atmosphere at work and if colleges are willing to assist.

The job demand *workload* and the job resource *social support have a* slightly different focus in the survey compared to how they are measured with process mining. The survey measures *workload* just by the amount of work, while process mining measures *workload* by both the amount of work and the difficulty of work. The structural side of *social support* is measured with process mining (the size of the social network) and the functional side of *social support* is measured with the survey (how much each connection means). This could be a reason that the subjective and objective values for *social support* have a negative correlation.

The strains, motivation and outcomes measured with the survey are presented in table 23. We observe that, in general, the employees are highly motivated and perform both the required and additional tasks.

| Strains/motivation/outcomes | Average score |
|---|---|
| Burnout | |
| Boredom | |
| Work engagement | |
| Performance in roll | |
| Auxiliary role achievements | |

*Table 23, survey results. Scale of 1 to 5 for all variables except work engagement, where 5 is the highest score. Work engagement has a score of 1 to 7, where 7 is the highest score (personal information removed).*

### *Comparing the objective job demands & resources with the subjective strains and motivation*

The correlation between the objective job demands & resources and the subjective strains & motivation is visualised in figure 19. Medium and high correlations indicate that a job demand & resource is related to a strain or motivation. We expected that *workload* and *time pressure* had a positive correlation with *burnout* and a negative correlation with *work engagement*. *Monotonous work* should be correlated to *boredom*. *social support* and *autonomy* were expected to have a positive correlation with *work engagement* and a negative correlation with *burnout*. We can observe four expected correlations:

1. Workload has a medium correlation with burnout
2. Monotonous work has a medium correlation with boredom.
3. Autonomy has a medium correlation with work engagement.
4. Social support has a medium correlation with work engagement.

An unexpected result is that *workload* has a positive correlation with *work engagements*, which indicates that a higher *workload* is beneficial for *work engagement*. *Time pressure* has a low correlation with the strains, which indicates that it is wrongly measured or that it is not related to the specified strains. Additionally, the job resources have a low correlation with burnout.

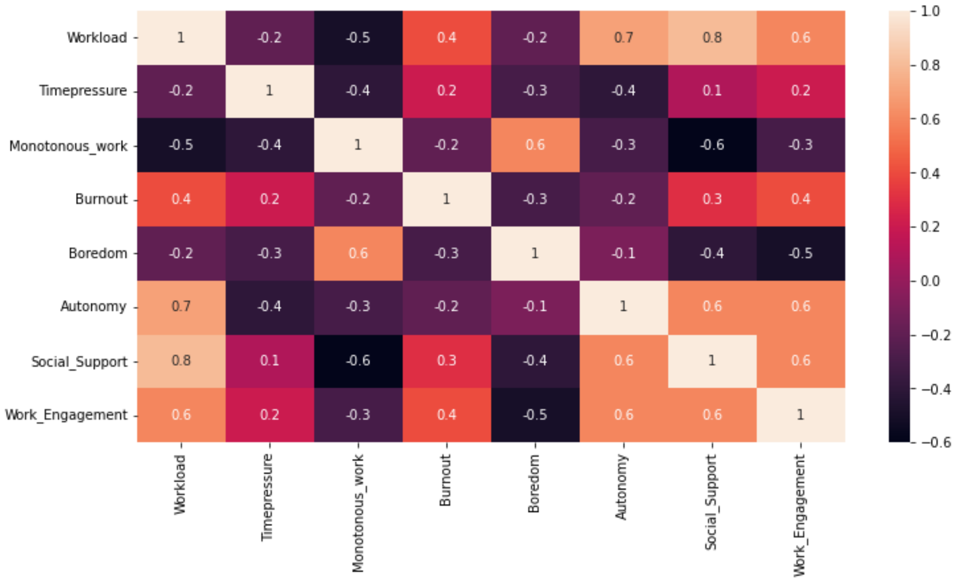



*Figure 16, the heatmap visualises the correlation between the job demands & resources and the strains and motivation*

## 5.4 Conclusion: is it possible to measure the job demands & resources with process mining?

The case study showed that it is possible to measure the job demands & resources with process mining. Python functions were created for all the process mining variables encountered in this case study. The functions are able to calculate the process mining variables as specified in section 4.3 and by combining the process mining variables the job demands & resources were measured in Python. The functions can calculate the job demands & resources for different datasets and timeframes.

The results of the job demands & resources showed a wide variety in values. All the job demands & resources contained some outliers, referring to the employees that have a far higher or lower score than the rest of the population. These outliers can indicate that employees have a too high or low value and should be acted upon with an intervention.

Three of the five job demands & resources have a positive correlation between their calculation with process mining and with the survey. Two of them have a small effect size with the last having a medium effect size. The correlation between the objective job demands & resources and the subjective strains and motivation were also measured. This identified that four job demands & resources were correlated, with a medium or high effect size, to the expected strain and motivation. The expected relation between the job demand *time pressure* and burnout was not found. The job demand *workload* also had an unexpected high positive correlation with work engagement.

The small number of respondents makes the results from the survey less reliable. However, we can still get an idea of the relation between the objective job demands & resources and subjective job demands, job resources, strains and motivation.

# 6 Discussion

This paper sets the first steps in determining well-being with process mining on which other researchers can expand. In this section, we discuss and interpret our findings.

## 6.1 Discussing the literature results

The literature results prove that job demands & resources related to well-being can be measured to a great extent with process mining. The parts that cannot be measured are those which require access to physical activities and human thoughts. Those information pools can be accessed by other technologies such as sensor devices that measure physical activities & text mining which determines people's opinions. Therefore, measuring well-being can be enhanced by combining process mining with these technologies. Process mining can be applied continuously but is limited to investigating activities which are recorded by (process-aware) information systems. Well-being can be measured with process mining exclusively during work.

According to Knoop et al. (2013), there are three main challenges for measuring well-being: "(a) what to measure, (b) how to measure, and (c) the need for time- and cost-efficient measures" (Knoop et al., 2013, p. 31). Our study addresses the third challenge by providing a publicly available Python file with functions that calculate the specified job demands & resources. However, organisations need to collect and prepare the event log for the processes they want to investigate. Furthermore, a limitation of the python file is that our code is only capable of measuring well-being to a certain degree.

## 6.2 Discussing the accuracy of the relations between the job demands & resource and process mining variables

There were no sources found which explain how the process mining variables can be connected to the job demands & resources. Therefore, we decided to select the most logical process mining variables based on what the job demands & resources entail. Furthermore, we discussed our selection of process mining variables with the research group. This leaves room for interpretation, for example, *autonomy* is about the freedom to make decisions but there are no process mining variables that directly measure *autonomy*. Instead, we gathered multiple process mining variables that measure a part of *autonomy*. For each variable we determined if and to what degree it is related to the corresponding job demand or resource.

The fit between the process mining variables and the job demands & resources differs per job demand & resource and is discussed below:

- The *amount of workload* is the only job demand that can be entirely measured by existing techniques. These techniques combine the work duration and the number of tasks. Therefore, we think that the *amount of workload* has a great fit with its process mining variable.
- *Workload difficulty* had a lesser fit because what makes a job difficult differs per domain. This makes it impossible to determine all aspects that make a job difficult as we use domain-independent variables. Based on the literature, three domain-independent variables were selected for *workload difficulty* which are related to the difficulty of work. Therefore, we think that *workload difficulty* has a decent fit with the process mining variables.
- *Time pressure* is about the shortage of time and the feeling of being rushed (Szollos, 2009). Goals that need to be achieved within a certain period can be indicators for time shortage (Šamalíková et al., 2009). The progress in achieving these goals is measurable with process

mining. This would indicate a decent fit between time pressure and its process mining variables. However, time pressure has a negative correlation with its subjective results and the strain *burnout,* which is an indication that related variables do not measure *time pressure* correctly. Therefore, we think that *time pressure* has a poor fit with its process mining variables.

- We think that *monotonous work* has a great fit with its process mining variables. Because they can measure the variety of tasks and cases, which is what monotonous work entails.
- *Autonomy* is a broad subject, there are many ways that *the freedom to make decisions* can be analysed. We think that the three selected variables have a good fit with *autonomy*. However, we cannot rule out that there might be other process mining variables which also are related to *autonomy*.

*The calculations of the process mining variables*

Process discovery has been applied to examine the process model and the process characteristics. The job demands are mostly measured with process mining variables that are based on the process characteristics. The process mining techniques that determine these process mining variables were not found in the literature and have been developed in this study (see appendix 9.4 for more information). We assume that these techniques do not exist because they served no clear purpose on their own. For example, it is only interesting to find out how many urgent cases an employee performs when we connect it to a higher-level variable such as the job demand *time pressure*. This is in line with Lantow et al. (2019) who states that there are currently not enough process mining techniques to measure well-being. The techniques that were found and applied measure the *number of handovers, number of subcontracts, joint tasks, joint cases* and *amount of work*. Van der Aalst & Song (2004) proposed techniques for the first four technique types. There were new techniques published with similar goals but none of them are supported by the tools ProM or Disco. This aligns with the findings of Van der Aalst (2020), who state that process mining tools do not update to the state of the art. Therefore, the techniques of Song & Van der Aalst have been applied in this study.

A way to transform the results of process mining techniques into information about job demands & resources has not been published in the literature. Therefore, a procedure was created to transform the outcomes of process mining techniques into scores for job demands & resources. The purpose of this procedure is to examine whether the job demands & resources can be determined with process mining. The accuracy with which the procedure determines the correct values for the job demands & resources is less important for this study. We think that the procedure satisfies this goal, it should however not be seen as a method that determines *how* well-being can be measured. The creation of such a method requires a study on its own.

## 6.3 Discussing the case study

Activity duration has been calculated for illustration in this case study. However, in case an event log does not contain the attribute "Activity end time" we advise using the number of activities instead of activity duration where possible and skip the other process mining variables that involve activity duration.

*Interpretation of the objective job demands & resources scores*

The process mining variables and the determined job demands & resources have no fixed scale. We can investigate how far above or below the mean a performer scores, but we do not know what the score means. For example, if a performer scores *+3* on the job demand *workload* (measured with process mining), then we know that he is far above the mean but we do not know if he has an extremely high *workload* or if the average employee has a very low *workload*. In contrast, surveys have a fixed scale, a survey with a Likert scale can have scores between 1 and 5, where 5 is very high and 1 is very low.

*Interpretation of the relations that the objective job demands & resources have*

The relation between the objective and subjective job demands & resources is unclear. While some job demands & resources have the same objective and subjective trend others do not. The subjective results measured with the survey are less reliable because of the low number of respondents (12 respondents). Two possible reasons for a positive correlation, between the objective and subjective values of a job demand or resource, are:

- Survey questions measure similar elements as the specified process mining variables.
- The observed results are similar to how people perceive them.

A negative relationship can imply the opposite. It could be that the process mining variables investigate different things than the survey questions or it could mean that the employees perceive this job demand and job resource differently from what is observed. There is also a chance that an employee has other work-related participations than the incident process or that his/her scores are similar or different because of coincidence. These reasons could lead to erroneous results.

The correlations between the job demands & resources and the strains & motivation were investigated. The identified correlations indicate that the objectively measured *workload, monotonous work, autonomy* and *social support* are related to the expected strains & motivation. This indicates that these job demands & resources were measured correctly. Two kinds of expected correlations were not found:

1. Time pressure has no correlation with a strain or motivation, which indicates that the job demand is measured incorrectly.
2. The job demands do not negatively influence the motivation and the job resources do not positively influence the strains.

Additionally, we observe a positive correlation between the job demand *workload* and *work engagement*. This indicates that an increase in workload could also increase work engagement. This is the opposite of what the study of M. Tomic & E. Tomic (2010) indicates. We think that a very high workload would lower the work engagement, as indicated by multiple studies (Freeney & Tiernan, 2009; Tomic & Tomic, 2010). The identified correlation could be coincidental, there is also a chance that workload has an inverted U-shaped pattern with work engagement, which would indicate that work engagement is the highest when workload is moderate. This pattern has previously been identified between workload and innovative work (Montani et al., 2019).

## 6.4 Discussing data quality & data preparation

Data quality is very important for the calculation of the job demands & resources with process mining. The most important part of the data quality is that everything is registered correctly. For example, when a person doesn't administer the activities that he/she performs then the *workload* score can wrongly state that the person has a low *workload*. The following quality assumptions were made:

1. The data is correct (no values were incorrectly entered).
2. The required attributes are present and have (nearly) no missing values.

3. Most of the activities that the investigated employees perform are captured in the event log, i.e., all the processes that a performer operates in should be registered.

Data preparation was performed carefully, because simply deleting activities could result in incomplete cases. The calculation of the process mining variables assumes that all cases are complete. If not, the process mining variables will give erroneous results. For example, the variable *number of handovers* will not be able to count the handovers between departments, when employees of different departments with their activities are removed from the event log.

# 7 Conclusion

The main research question is: To what degree can the work-related job demands & resources be determined for employees with the use of process mining?

We conclude that process mining can be used to objectively measure some job demands & resources which are related to well-being. Well-being is decomposed from two perspectives, which are visualised in figure 20. The first perspective states that well-being can be measured with certain strains and motivation. In this study the strains *burnout & boredom* and the motivation *work engagement* are selected. The second perspective investigates how well-being types (physical, emotional, physiological and social) can be measured. An overview of the job demand, job resources & well-being characteristics related to well-being is visualised in figure 20. The limitation of process mining is that it can only gather information that can be observed in a digital environment. The job demand, job resources & well-being characteristics that cannot be measured with process mining require information from physical activities and human thoughts (these are coloured orange in figure 20). Psychological, emotional and social well-being can be partially measured with the selected job demands & resources, while physical well-being cannot be measured with process mining.

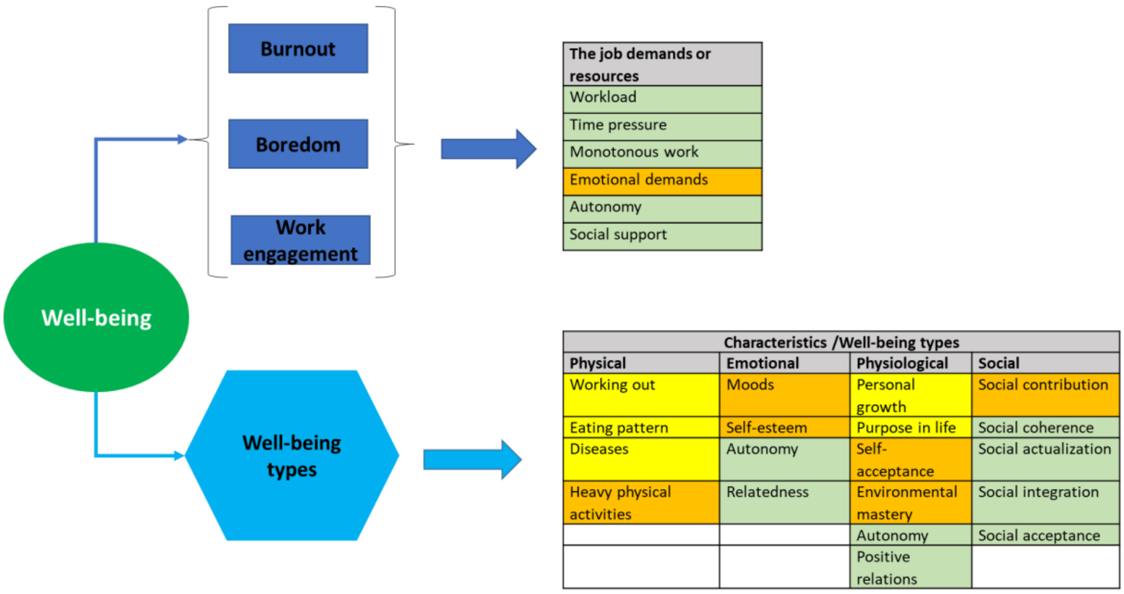



*Figure 17, decomposer of well-being.* Green= selected job demand or resource, yellow= irrelevant characteristics for work-related job demands & resources, orange= characteristics or job demands & resources that cannot be measured based on the digital process execution.

Process mining variables are connected to five selected job demands & resources. Four of these can be entirely measured with process mining variables while the job resource *social support* can be measured partially. The case study proved that all the process mining variables could be calculated. The case study also investigated two kinds of relations:

1. The correlation between the objective and subjective job demands & resources.
2. The correlation between the objective job demands & resources and the subjectively measured strains and motivation

We identified a positive correlation between the objective and subjective job demands & resources for three of the five job demands & resources (see figure 21, the green arrows on the left side). The expected relations between the job demands & resources and strains & motivation were found for four of the job demands & resources (green arrows on the right side of figure 21). Time pressure had no correlation with neither the subjective time pressure or burnout. According to JD-R model the job demands should also negatively influence the motivation and the job resources should positively influence the strains. However, these relations were not observed.

To conclude, three job demands & resources can entirely be measured with process mining and one partly.

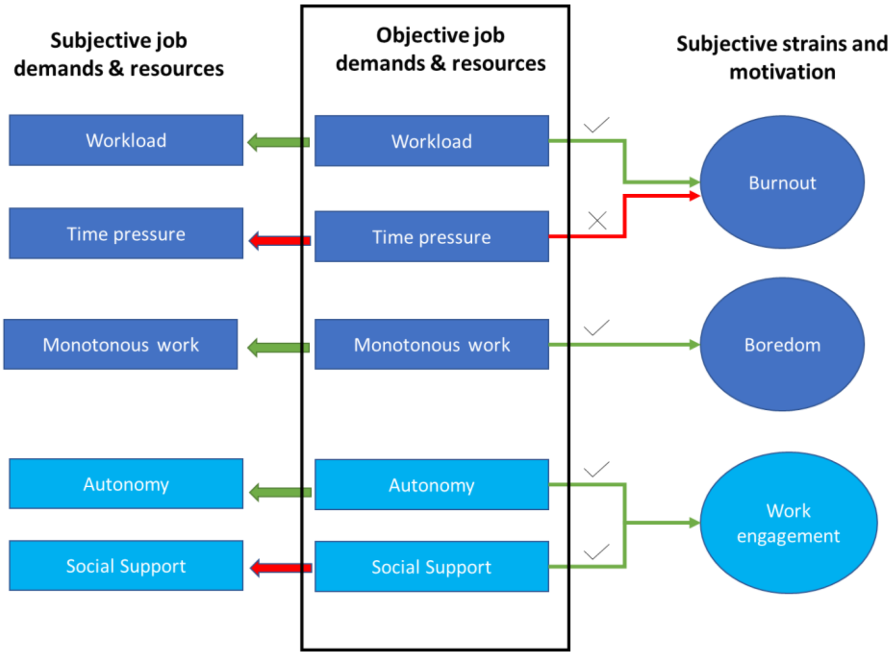



*Figure 18, the found relations of the objective job demands and resources. Green= the expected correlation is found, red= the expected correlation is not found.*

## 7.1 Future work

Our research sets the first steps in determining well-being with process mining. It proved that certain parts of well-being can be measured with process mining. However, there are still many elements that need to be further explored before well-being can be accurately measured with process mining. We identified five possible avenues for future research:

1) At the moment it is difficult to validate how accurate and reliable the results of the with process mining measured job demands & resources are. The creation and application of a validation test is therefore a necessary step.
2) Currently, the process mining variables related to one job demand or resource have equal weights. A possibility for future research is to investigate if all process mining variables are equally important, if that is not the case weights can be assigned.
3) The third option for future research is to develop and validate a method that describes how (aspects of) well-being can be measured with process mining.
4) The study measured job demands & resources related to strains and motivation. The calculation of the strains and motivation itself was out of scope and is an interesting research possibility for future research.
5) Another interesting possibility is to extend the investigation of what job demands & resources influence well-being.

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# 9 Appendix

## 9.1 Structured literature review

All selected sources in the structured literature review are described in table 24.

| index | Author(s) | Title | Reference (first author, year) |
|---|---|---|---|
| 1 | Deokar, AV; Tao, J | “OrgMiner: A Framework for Discovering User-Related Process Intelligence from Event Logs “ | (Deokar & Tao, 2021)(Deokar & Tao, 2021) |
| 2 | Bose, RPJC; Van der Aalst, WMP | “Process Mining Applied to the BPI Challenge 2012: Divide and Conquer While Discerning Resources” | (Bose & van der Aalst, 2013)(Bose & van der Aalst, 2013) |
| 3 | Delcoucq, L; Lecron, F; Fortemps, P; Van der Aalst, WMP | “Resource-Centric Process Mining: Clustering Using Local Process Models “ | (Delcoucq et al., 2020)(Delcoucq et al., 2020) |
| 4 | Schonig, S; Cabanillas, C; Jablonski, S; Mendling, J | “A framework for efficiently mining the organisational perspective of business processes “ | (Schönig et al., 2016)(Schönig et al., 2016) |
| 5 | Abdelkafi, Mahdi; Bouzguenda, Lotfi | “Discovering organizational perspective in workflow using agent approach: an illustrative case study “ | (Abdelkafi & Bouzguenda, 2010)(Abdelkafi & Bouzguenda, 2010) |
| 6 | Schönig, Stefan; Cabanillas, Cristina; Jablonski, Stefan; Mendling, Jan | “Mining the organisational perspective in agile business processes “ | (Schönig, Cabanillas, et al., 2015)(Schönig, Cabanillas, et al., 2015) |
| 7 | Zhao, WD; Zhao, XD | “Process Mining from the Organizational Perspective “ | (W. Zhao & Zhao, 2014)(W. Zhao & Zhao, 2014) |
| 8 | Song, M; Van der Aalst, WMP | “Towards comprehensive support for organizational mining “ | (Song & van der Aalst, 2008)(Song & van der Aalst, 2008) |
| 9 | Appice, Annalisa; Malerba, Donato | “A co-training strategy for multiple view clustering in process mining “ | (Appice & Malerba, 2016)(Appice & Malerba, 2016) |
| 10 | Hanachi, C; Gaaloul, W; Mondi, R | “Performative-Based Mining of Workflow Organizational Structures “ | (Hanachi et al., 2012)(Hanachi et al., 2012) |

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|---|---|---|---|
| 11 | Appice, A | "Towards mining the organizational structure of a dynamic event scenario " | (Appice, 2018)(Appice, 2018) |
| 12 | Pika, A; Wynn, MT; Fidge, CJ; ter Hofstede, AHM; Leyer, M; Van der Aalst, AMP | "An Extensible Framework for Analysing Resource Behaviour Using Event Logs " | (Pika et al., 2014)(Pika et al., 2014) |
| 13 | Swennen, Marijke; Martin, Niels; Janssenswillen, Gert; Jans, Mieke; Depaire, Benoît; Caris, An; Vanhoof, Koen | "Capturing Resource Behaviour From Event Logs. " | (Swennen et al., n.d.)(Swennen et al., n.d.) |
| 14 | Nakatumba, J; Westergaard, M; Van der Aalst, WMP | "Generating Event Logs with Workload-Dependent Speeds from Simulation Models" | (Nakatumba et al., 2012)(Nakatumba et al., 2012) |
| 15 | Cabanillas, Cristina; Schönig, Stefan; Sturm, Christian; Mendling, Jan | "Mining expressive and executable resource-aware imperative process models" | (Cabanillas et al., 2018)(Cabanillas et al., 2018) |
| 16 | Tang, Willi; Matzner, Martin | "Creating Humanistic Value with Process Mining for Improving Work Conditions-A Sociotechnical Perspective." | (Tang & Matzner, 2020)(Tang & Matzner, 2020) |
| 17 | Ogunbiyi, N; Basukoski, A; Chaussalet, T | "Investigating the Diffusion of Workload-Induced Stress-A Simulation Approach" | (Ogunbiyi et al., 2020)(Ogunbiyi et al., 2020) |
| 18 | Utama, NI; Sutrisnowati, RA; Kamal, IM; Bae, H; Park, YJ | "Mining Shift Work Operation from Event Logs" | (Utama et al., 2020)(Utama et al., 2020) |
| 19 | Sikal, R; Sbai, H; Kjiri, L | "Promoting resource discovery in business process variability" | (Sikal et al., 2019)(Sikal et al., 2019) |
| 20 | Cho, M; Park, G; Song, M; Lee, J; Kum, E | "Quality-Aware Resource Model Discovery" | (Cho et al., 2021)(Cho et al., 2021) |
| 21 | Arndt, Brian G.; Beasley, John W.; Watkinson, Michelle D.; Temte, Jonathan L.; Tuan, Wen-Jan; Sinsky, Christine A.; Gilchrist, Valerie J. | "Tethered to the EHR: primary care physician workload assessment using EHR event log data and time-motion observations" | (Arndt et al., 2017)(Arndt et al., 2017) |
| 23 | Slaninova, K; Vymetal, D; Martinovic, J | "Analysis of Event Logs: Behavioral Graphs" | (Slaninová et al., 2015)(Slaninová et al., 2015) |
| 24 | Alvarez, C; Rojas, E; Arias, M; Munoz-Gama, J; Sepulveda, M; Herskovic, V; Capurro, D | "Discovering role interaction models in the Emergency Room using Process Mining" | (Alvarez et al., 2018)(Alvarez et al., 2018) |
| 25 | Dustdar, Schahram; Hoffmann, Thomas | "Interaction pattern detection in process oriented information systems" | (Dustdar & Hoffmann, 2007)(Dustdar & Hoffmann, 2007) |

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|---|---|---|---|
| 26 | Ye, JH; Li, ZW; Yi, K; Al-Ahmari, A | "Mining Resource Community and Resource Role Network From Event Logs" | (Jianhong et al., 2018)(Jianhong et al., 2018) |
| 27 | Van der Aalst, WMP; Song, M | "Mining social networks: Uncovering interaction patterns in business processes" | (van der Aalst & Song, 2004)(van der Aalst & Song, 2004) |
| 28 | Schwade, Florian | "Social Collaboration Analytics Framework: A framework for providing business intelligence on collaboration in the digital workplace" | (Schwade, 2021)(Schwade, 2021) |
| 29 | Jafari, P; Mohamed, E; Lee, S; Abourizk, S | "Social network analysis of change management processes for communication assessment" | (Jafari et al., 2020)(Jafari et al., 2020) |
| 30 | Park, Minjae; Ahn, Hyun; Kim, Kwanghoon Pio | "Workflow-supported social networks: Discovery, analyses, and system" | (Park et al., 2016)(Park et al., 2016) |
| 31 | Ferreira, DR; Alves, C | "Discovering User Communities in Large Event Logs" | (Ferreira & Alves, 2011)(Ferreira & Alves, 2011) |
| 32 | M'hand, MA; Boulmakoul, A; Badir, H | "FuSTM: ProM plugin for fuzzy similar tasks mining based on entropy measure" | (Amrou M'hand et al., 2021)(Amrou M'hand et al., 2021) |
| 33 | Djedovic, A; Karabegovic, A; Avdagic, Z; Omanovic, S | "Innovative Approach in Modeling Business Processes with a Focus on Improving the Allocation of Human Resources" | (Djedovic et al., 2018)(Djedovic et al., 2018) |
| 34 | Pinto, PL; Mendes, C; da Silva, MM; Caetano, A | "Using Event Logs and the psi-theory to Analyse Business Processes" | (Linares Pinto et al., 2015)(Linares Pinto et al., 2015) |
| 35 | Cabanillas, C; Ackermann, L; Schonig, S; Sturm, C; Mendling, J | "The RALph miner for automated discovery and verification of resource-aware process models" | (Cabanillas et al., 2020)(Cabanillas et al., 2020) |
| 36 | Zhao, JJ; Wang, Y; Yu, LA | "Applying process mining techniques to improve emergency response planning for chemical spills" | (J. Zhao et al., 2019)(J. Zhao et al., 2019) |
| 37 | Gupta, Monika; Sureka, Ashish; Padmanabhuni, Srinivas | "Process mining multiple repositories for software defect resolution from control and organizational perspective" | (Gupta et al., 2014)(Gupta et al., 2014) |
| 38 | Lee, D; Park, J; Pulshashi, IR; Bae, H | "Clustering and Operation Analysis for Assembly Blocks Using Process Mining in Shipbuilding Industry" | (Lee et al., 2013)(Lee et al., 2013) |
| 39 | Aghabaghery, R; Golpayegani, AH; Esmaeili, L | "A new method for organizational process model discovery through the analysis of workflows and data exchange networks" | (Aghabaghery et al., 2020)(Aghabaghery et al., 2020) |

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| 40 | Yang, Jing; Ouyang, Chun; Pan, Maolin; Yu, Yang; ter Hofstede, Arthur HM | "Finding the "Liberos": discover organizational models with overlaps" | (Yang et al., 2018)(Yang et al., 2018) |
| 41 | Abdelkafi, M; Bouzguenda, L | "Evaluating Organizational Structures for Supporting Business Processes Reengineering: An Agent Based Approach" | (Abdelkafi & Bouzguenda, 2015)(Abdelkafi & Bouzguenda, 2015) |
| 43 | Matzner, Martin; Scholta, Hendrik | "Process mining approaches to detect organizational properties in cyber-physical systems" | (Matzner, 2014)(Matzner, 2014) |
| 44 | Appice, A; Di Pietro, M; Greco, C; Malerba, D | "Discovering and Tracking Organizational Structures in Event Logs" | (Appice et al., 2015)(Appice et al., 2015) |
| 45 | Nakatumba, J; Van der Aalst, WMP | "Analyzing Resource Behavior Using Process Mining" | (Nakatumba & van der Aalst, 2010)(Nakatumba & van der Aalst, 2010) |
| 46 | Huang, ZX; Lu, XD; Duan, HL | "Resource behavior measure and application in business process management" | (Huang et al., 2012)(Huang et al., 2012) |
| 48 | Martin, N; Swennen, M; Depaire, B; Jans, M; Caris, A; Vanhoof, K | "Retrieving batch organisation of work insights from event logs" | (Martin et al., 2017)(Martin et al., 2017) |
| 49 | Leitner, M; Baumgrass, A; Schefer-Wenzl, S; Rinderle-Ma, S; Strembeck, M | "A Case Study on the Suitability of Process Mining to Produce Current-State RBAC Models" | (Leitner et al., 2012)(Leitner et al., 2012) |
| 50 | Li, M; Liu, L; Yin, L; Zhu, YQ | "A process mining based approach to knowledge maintenance" | (Li et al., 2011)(Li et al., 2011) |
| 51 | Pika, A; Leyer, M; Wynn, MT; Fidge, CJ; Ter Hofstede, AHM; Van der Aalst, WMP | "Mining Resource Profiles from Event Logs" | (Pika et al., 2017)(Pika et al., 2017) |
| 52 | Martinez-Millana, A; Lizondo, A; Gatta, R; Vera, S; Salcedo, VT; Fernandez-Llatas, C | "Process Mining Dashboard in Operating Rooms: Analysis of Staff Expectations with Analytic Hierarchy Process" | (Martinez-Millana et al., 2019)(Martinez-Millana et al., 2019) |
| 53 | Schonig, S; Gillitzer, F; Zeising, M; Jablonski, S | "Supporting Rule-Based Process Mining by User-Guided Discovery of Resource-Aware Frequent Patterns" | (Schönig, Gillitzer, et al., 2015)(Schönig, Gillitzer, et al., 2015) |
| 54 | Ahn, H; Kim, KP | "Formal approach for discovering work transference networks from workflow logs" | (Ahn & Kim, 2020)(Ahn & Kim, 2020) |
| 55 | Aloini, D; Benevento, E; Stefanini, A; Zerbino, P | "Process fragmentation and port performance: Merging SNA and text mining" | (Aloini et al., 2020)(Aloini et al., 2020) |
| 56 | Ebrahim, M; Golpayegani, SAH | "Anomaly detection in business processes logs using social network analysis" | (Ebrahim & Golpayegani, |

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|---|---|---|---|
| | | | 2021)(Ebrahim & Golpayegani, 2021) |
| 57 | Hiraishi, Kunihiko; Kobayashi, Koichi | “Detection of Unusual Human Activities Based on Behavior Modeling“ | (Hiraishi & Kobayashi, 2014)(Hiraishi & Kobayashi, 2014) |
| 59 | Boulmakoul, A.; Besri, Z. | “Scoping enterprise organizational structure through topology foundation and social network analysis“ | (Boulmakoul et al., 2013)(Boulmakoul et al., 2013) |
| 60 | Bouzguenda, L; Abdelkafi, M | “An agent-based approach for organizational structures and interaction protocols mining in workflow“ | (Bouzguenda & Abdelkafi, 2015)(Bouzguenda & Abdelkafi, 2015) |
| 61 | Sophia, Gabriel; Sarno, Riyanarto | “AHP-TOPSIS for analyzing job performance with factor evaluation system and process mining“ | (Sophia & Sarno, 2019)(Sophia & Sarno, 2019) |
| 62 | Suriadi, S; Wynn, MT; Xu, JX; Van der Aalst, WMP; ter Hofstede, AHM | “Discovering work prioritisation patterns from event logs“ | (Suriadi et al., 2017)(Suriadi et al., 2017) |
| 63 | Martin, N; Depaire, B; Caris, A; Schepers, D | “Retrieving the resource availability calendars of a process from an event log“ | (Martin et al., 2020)(Martin et al., 2020) |
| 65 | de Leoni, M; Van der Aalst, WMP; Van Dongen, BF | “Data- and Resource-Aware Conformance Checking of Business Processes” | (de Leoni et al., 2012)(de Leoni et al., 2012) |

*Table 24, selected sources for the structured literature review.*

## 9.2 Data types TopDesk

The variables that are included in the TopDesk dataset are described with explanation in table 25.

| TopDesk variable | Meaning |
|---|---|
| generatedIndex | random index value |
| CallNumber(naam) | Unique Call number of the incident |
| Activity | Action name |
| ActivityStartDate | Action start timestamp |
| ActivityEndDate | Action end timestamp |
| Incident_BudgetHolder_Reporting(aaanmelderbudgethouder) | BudgetHolder info of the incident reporter |
| Incident_Department_Reporting(aanmelderafdeling) | Department info of the incident reporter |
| Incident_Name_Reporting(aanmeldernaam) | Name of the incident reporter |
| Incident_Phone_Reporting(aanmeldertelefoon) | Phone info of the incident reporter |
| PersonGroupOfReporter | Person group info of the incident reporter |
| Incident_OperatorGroup_BudgetHolder | BudgetHolder info of the incident operator group |
| Incident_OperatorGroup_Department | Department info of the incident operator group |
| Incident_OperatorGroup | Operator group (solution group) of the incident |
| Incident_Operator | Operator of the incident |
| Closed(afgemeld) | Whether the incident is closed |
| Completed(gereed) | Whether the incident is completed |
| ismajorincident | Whether the incident is a major incident |
| PartialCall | Whether the incident is a partial call |
| IsArchived | Whether the incident is archived |
| Line(1st\|2nd) | Line-level of the incident |
| Priority | Priority of the incident |
| Entry(soortbinnenkomst) | Entry source of the incident |
| CallType(soortmelding) | Call type of the incident |
| Category(incident_domein) | Category of the incident |
| Subcategory(incident_spec) | Subcategory of the incident |
| SolvedWithinSLADuration | Whether the incident is solved within SLA |
| ActivityPerformerResource_Department | Department info of the resource who performed the current action |
| CurrentOperatorGroup_Department | Department info of the operator group at the moment of the current action |
| ActivityPerformerResource_BudgetHolder | BudgetHolder info of the resource who performed the current action |
| CurrentOperatorGroup_BudgetHolder | BudgetHolder info of the operator group at the moment of the current action |

| | |
|---|---|
| CurrentOperator | Operator of the incident at the moment of the current action |
| CurrentOperatorGroup | Operator group of the incident at the moment of the current action |
| ActivityPerformerResource_Name | Name of the resource who performed the current action |
| CurrentStatusName | Status info of the incident at the moment of the current action |
| CurrentCallType | Call type info of the incident at the moment of the current action |
| CurrentPriorityText | Priority info of the incident at the moment of the current action |
| CurrentTotalDuration_InMinutes | TotalDuration info of the incident at the moment of the current action |
| AdjustedDuration | Adjusted duration of the incident in minutes |
| AdjustedDuration_Hour | Adjusted duration of the incident in hours |
| AdjustedDuration_Day | Adjusted duration of the incident in days |
| AdjustedDuration_Day_Range | Adjusted duration of the incident in day-range |
| OnHoldDuration | Onhold duration of the incident in minutes |
| OnHoldDuration_Hour | Onhold duration of the incident in hours |
| OnHoldDuration_Day | Onhold duration of the incident in days |
| CreationDate(dataanmk) | Creation (recording into the database) timestamp of the incident |
| CallDate(datumaangemeld) | Received timestamp of the incident |
| CallDate(datumaangemeld)_nameOfMonth | Received month of the incident |
| CallDate(datumaangemeld)_year | Received year of the incident |
| ClosureDate(datumafgemeld) | Closed timestamp of the incident |
| ClosureDate(datumafgemeld)_nameOfMonth | Closed month of the incident |
| ClosureDate(datumafgemeld)_year | Closed year of the incident |
| ClosureDate(datumafgemeld)_week | Closed weeknumber of the incident |
| ActivityStartDate_hourOfDay | Hour of day info of the performed action |
| ActivityStartDate_daynameOfWeek | Day name of week info of the performed action |
| ActivityStartDate_dayNumberOfWeek | Day number of week info of the performed action |
| ActivityStartDate_dayNumberOfMonth | Day number of month info of the performed action |
| ActivityStartDate_weekOfYear | Week number info of the performed action |
| ActivityStartDate_quarterOfYear | Quarter of year info of the performed action |

| | |
|---|---|
| Total_UniqueActivityPerformerResource_Departments | Total number of unique departments involved in the incident |
| Total_UniqueActivityPerformerResource_BudgetHolders | Total number of unique budget holders involved in the incident |
| Total_Reopens | How many times the incident is reopened |
| Total_Escalations | How many times the incident is escalated |
| Total_DeEscalations | How many times the incident is deescalated |
| Total_HoldOns | How many times the incident is heldon |
| Total_HoldOffsCaller | How many times the incident is held of by the caller |
| Total_HoldOffsOperator | How many times the incident is held of by operators |
| Total_OperatorGroupChanges | How many times the operator group of the incident is changes |
| Total_OperatorChanges | How many times the operator of the incident changed |
| Total_SupplierChanges | How many times the supplier of the incident changed |
| Total_PriorityChanges | How many times the priority of the incident changed |
| Total_TargetDateChanges | How many times the target date of the incident changed |
| Total_CallTypeChanges | How many times the call type of the incident changed |
| Total_AddedActions_ACTIE_Operator | How many times ACTIE type action added on the incident by operators |
| Total_AddedActions_VERZOEK_Operator | How many times VERZOEK type action added on the incident by operators |
| Total_AddedActions_ACTIE_CALLER | How many times ACTIE type action added on the incident by the caller |
| Total_AddedActions_VERZOEK_CALLER | How many times ACTIE type action added on the incident by the caller |
| numberOfCommentsInConversation | Total number of comments on the incident |
| SLAtargetdate(datumafspraaksla) | SLA target date of the incident |
| CallDate(datumaangemeld)_daynameOfWeek | Day name of week of the Received timestamp of the incident |
| CallDate(datumaangemeld)_month | Month of the Received timestamp of the incident |
| ClosureDate(datumafgemeld)_daynameOfWeek | Day name of week of the Closed timestamp of the incident |
| ClosureDate(datumafgemeld)_month | Month of the Closed timestamp of the incident |
| CompletionDate(datumgereed) | Completed timestamp of the incident |

| | |
|---|---|
| LinkedToAny_KnowledgeBaseItems | Whether the incident is linked to any knowledgebase items |
| LinkedToAny_Problems | Whether the incident is linked to any problems |
| LinkedToAny_KnownErrors | Whether the incident is linked to any known errors |
| LinkedToAny_ChangesWithCausedBy | Whether the incident is linked to any changes via caused by relation |
| LinkedToAny_ChangesWithResolvedBy | Whether the incident is linked to any changes via resolved by relation |
| LinkedTo_StandardSolution | Whether the incident is linked to any standard solution |
| ObjectAssetType | Type of the related object to the incident |
| ObjectAgeYears | Age of the related object to the incident in years |
| ObjectAgeMonths | Age of the related object to the incident in months |
| ActualDuration | Actual duration of the incident in minutes |
| ActualDuration_Hour | Actual duration of the incident in hours |
| ActualDuration_Day | Actual duration of the incident in days |
| ResolvedDuration | Resolved duration of the incident in minutes |
| ResolvedDuration_Hour | Resolved duration of the incident in hours |
| ResolvedDuration_Day | Resolved duration of the incident in days |
| InProgressDuration | InProgess duration of the incident in minutes |
| InProgressDuration_Hour | InProgress duration of the incident in hours |
| InProgressDuration_Day | InProgress duration of the incident in days |
| Site(vestiging) | Site related to the incident |
| Service(dno) | Service related to the incident |
| ShortDescription(korteomschrijving) | Short description of the incident |

*Table 25, variables of TopDesk.*

## 9.3 Discovered and designed process model

The discovered process model is visualised in figure 22 and the designed process model is visualised in figure 23.

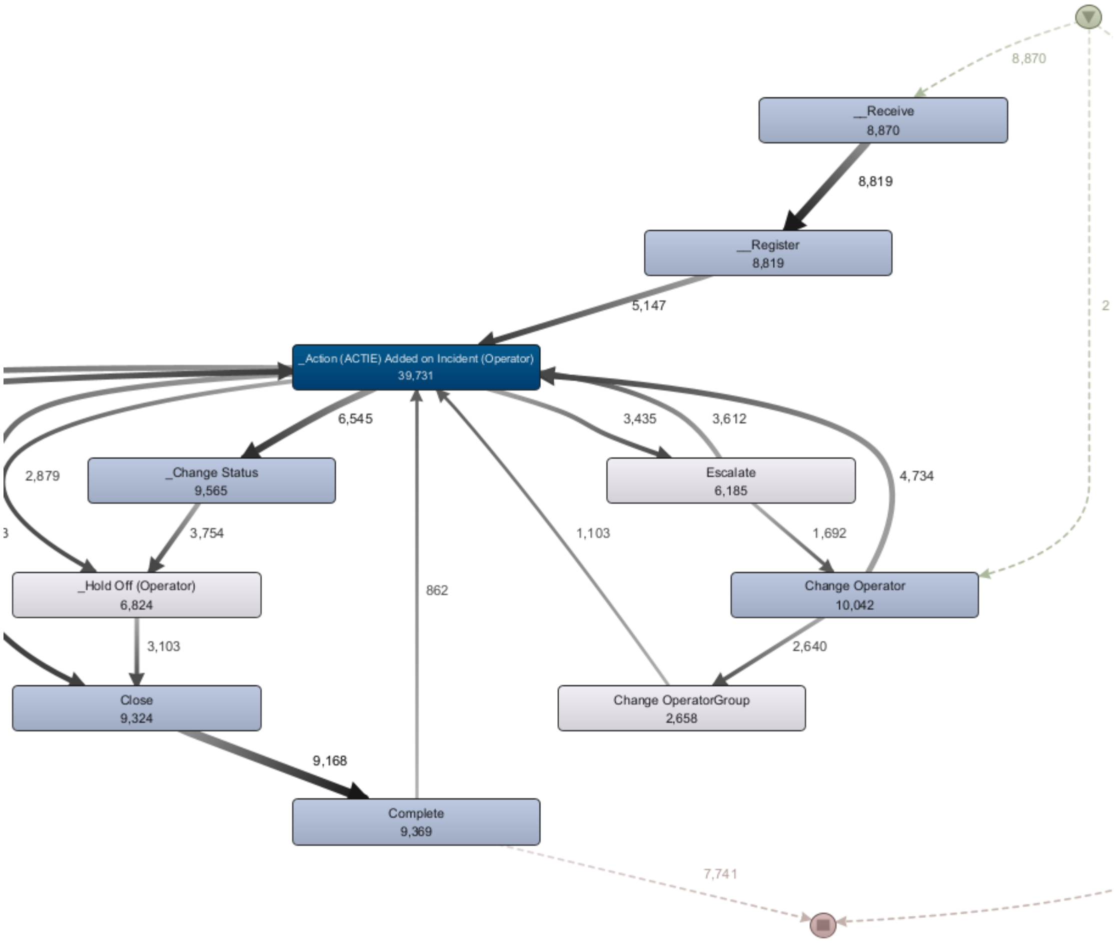


*Figure 19, part of the discovered incident management process.*

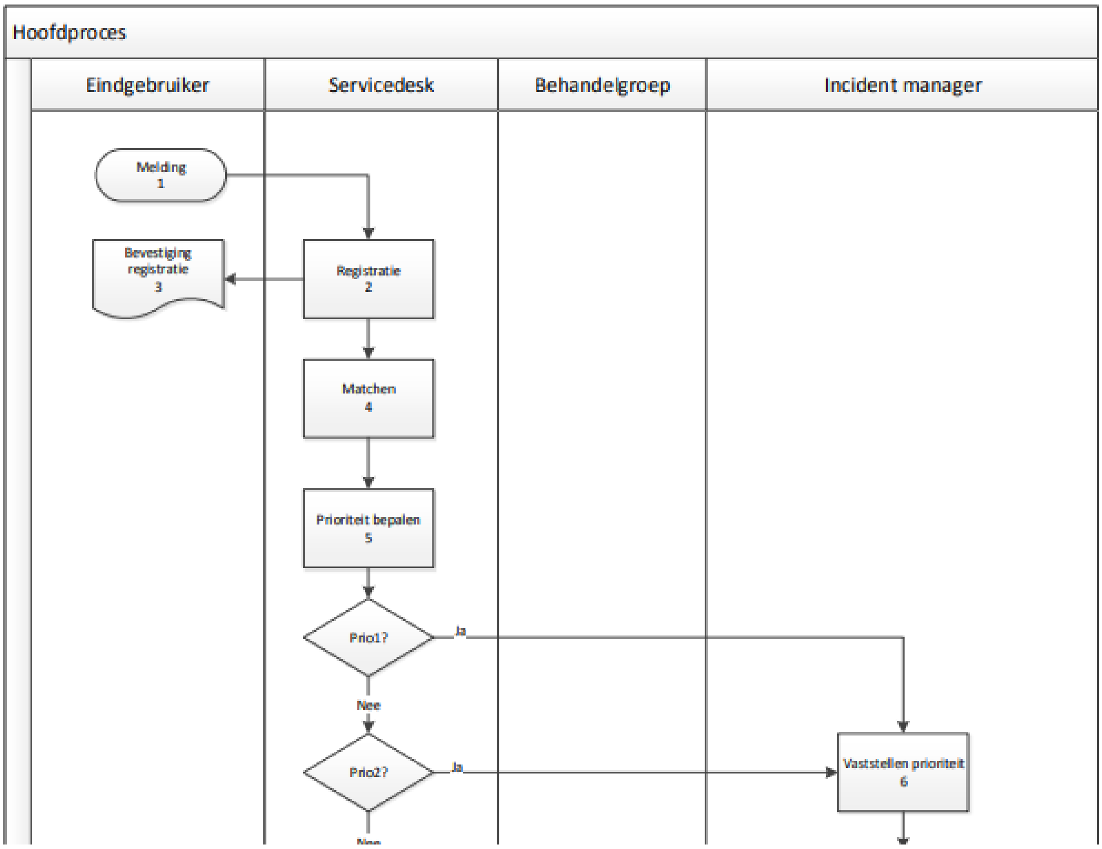


*Figure 20, part of the designed incident process model.*

## 9.4 Calculation of the variables

This information is not available in the anonymized version, for more information contact the author.

## 9.5 Survey questions

In this section, the survey questions with their answer options are described. The survey questions were asked in Dutch.

*Job demands*

The answer options were: 1= never, 2= rarely, 3= sometimes, 4= often, 5= always.

- I'm required to do excessive work
- I can interrupt my work as I wish 6
- My work involves a high level of qualification 11

Time pressure

- My job requires me to work very quickly 2
- I can determine my own work pace 8

Monotonous work

- My work includes some repetitive tasks 3
- My work includes many activities 7

*Job resources*

The answer options were: 1= never, 2= rarely, 3= sometimes, 4= often, 5= always.

Social support

- If I want, I can get help from one or more colleagues 4
- The atmosphere in the workplace is good 9

Autonomy

- My job allows me to make many decisions 5
- I have much to say about what happens in my work 10
- I can determine the order in which I perform my tasks 12

*Burn-out*

The answer options were: 1= never, 2= rarely, 3= sometimes, 4= often, 5= always.

1. At the end of a working day I feel empty.
2. I feel mentally exhausted from my work.
3. Working all day is a heavy burden for me.
4. I feel burned out by my work.
5. I feel tired when I get up in the morning and have another working day ahead of me.

*Boredom*

The answer options were: 1= never, 2= rarely, 3= sometimes, 4= often, 5= always.

1. At work, time goes by very slowly
2. I feel bored at my job
3. During work time I daydream
4. I tend to do other things during my work
5. At my work, there is not so much to do

### *Work engagement*

The answer options were: 0= never, 1= sporadically (few times a year or less), 2= sometimes (once a month or less), 3= on a regular bases (few times a month), 4= often (once a week), 5= very often (few times a week), 6= always (daily).

1) At work I am brimming with energy. (VIT01)*
2) When I work I feel fit and strong. (VIT02)*
3) I am enthusiastic about my job. (TOE02)*
4) My work inspires me. (TOE03)*
5) When I get up in the morning I feel like going to work (VIT03)*
6) When I am working very intensively, I feel happy. (ABS03)*
7) I am proud of the work I do. (TOE04)*
8) I am completely absorbed in my work. (ABS04)*
9) My work thrills me. (ABS05)*

### *Job satisfaction*

The answer options were: 1= very dissatisfied, 2= dissatisfied, 3= not dissatisfied, 4= satisfied, 5= very satisfied.

Overall, how satisfied are you with your work?

### *Intention to leave*

The answer options were: yes, no, I did rather not say.

- Are you currently looking for another job within the university?
- Are you currently looking for another job outside of university?

### *In-role and extra-role behaviour*

The answer options were: 1= strongly disagree, 2= mostly disagree, 3= do not disagree, not agree, 4= mostly agree, 5= strongly agree.

1) I meet the formal performance requirements of my job.
2) I perform the tasks that are expected of me.
3) I perform my duties as described in the job description.
4) I help colleagues who have a high workload.
5) I help new colleagues, even when it is not expected of me.
6) I pass on information to my colleagues.