Mining for Well-Being: The Potential of Process Mining for Evaluating Employee Well-Being

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Abstract. Monitoring work-related well-being is crucial for organizational success and part of good employment practices. This paper explores how process mining can evaluate employee well-being by conceptualizing variables of various work characteristics using the Job Demands-Resources model (JD-R), which explains how work characteristics influence employee well-being. We explored how the process mining variables compare to validated survey measures. Data was collected in two ways: first, a survey was conducted to measure the work characteristics of monotonous work, time pressure, workload, social support, and autonomy and the well-being outcomes of burnout, boredom, and work engagement. Second, process mining was used to calculate scores for the same work characteristics so that the scores could be compared with the survey variables. No strong correlations were found between corresponding survey variables and process mining variables. However, results reveal strong correlations between process mining variables of workload, social support, and autonomy with the survey variable of work engagement. These findings suggest that process mining variables can be valuable for predicting work-related well-being, especially work engagement. The combination of process mining and survey research has the potential to increase our comprehension of work-related well-being, make data collection more efficient, and monitor work engagement continuously.

Keywords: Job demands-resources model · Work-related well-being · Work engagement · Process mining.

1 Introduction

In addition to the ethical responsibility of creating a healthy work environment, numerous studies have demonstrated that higher employee well-being leads to increased productivity and greater business profitability [37,17]. Therefore, organizations need to monitor employee well-being and its causes to create a healthy and supportive work environment. Traditional methods of assessing employee well-being often rely on subjective self-report surveys [22,8]. Self-report surveys are valuable in capturing employees' perceptions of various work characteristics that influence their well-being [22], such as work engagement, feelings of exhaustion, and boredom. However, they might not provide a complete comprehensive understanding of employee well-being as it misses the more objective as-is setting of the work environment [22]. Moreover, survey variables have some limitations [26]. For example, the format of the survey, including the formulation and ordering of questions, can influence how participants answer. Additionally, participants tend to follow their beliefs of social acceptability rather than answer true to their feelings and behavior [26].

Process mining can more objectively investigate work characteristics by analyzing data generated by employees' use of information systems. Although process mining has limitations of its own (e.g., possibility of incomplete data, scalability issues, lack of contextual understanding [2,1]), it could provide additional information and knowledge of the objective side of work-related well-being and its antecedents, which is an important factor of employee well-being [22]. Process mining can also help lessen the effects of survey biases, especially when survey variables are combined with process mining variables. Moreover, in the long term, process mining is more time-efficient and demands less active labor from employees.

This study will explore how process mining can be used in combination with survey variables to evaluate employee well-being by answering two questions:

1. *How do process mining variables compare to survey measures for predictors of employee well-being?*
2. *To what extent can process mining variables be used to evaluate employee well-being outcomes, such as work engagement, burnout (exhaustion), and boredom?*

To answer these questions, we performed a case study in which we formulated process mining variables that measure various work characteristics. We compared these results with those of their counterparts, as measured using a survey among the same employees. In addition, we explored how well process mining could explain work-related well-being *outcomes*, namely burnout, boredom, and work engagement. This study contributes to process mining research and work- and organizational psychology research by examining how work-related well-being and its antecedents can be measured using process mining. In the long term, this new way of evaluating work-related well-being can be used by organizations to monitor and improve their employees' well-being.

2 Related Work

In the next section, we will briefly discuss the related work on work-related well-being by explaining the Job Demands-Resources model and the resource perspective of process mining.

2.1 Work-Related Well-Being

Monitoring and evaluating employee well-being is part of good and ethical employment practices. In fact, in many countries (notably all countries in the European Union), organizations are obliged by law to protect employee well-being [29]. Apart from being a legal responsibility, it is also crucial to uphold employee well-being because it is related to higher performance [36]. One of the most used work- and organizational psychology models is the Job Demands-Resources model (JD-R model) [7,29]. The JD-R model categorizes work characterizes into job demands and job resources within the work environment. Job demands are those aspects of one's job that come with physical, psychological and physiological costs [15,30], for example, workload and time pressure. Job resources are those aspects of one's job that provide support to achieve one's goals and help cope with the existing job demands [15,30], for example, autonomy and support of colleagues. Both job demands and job resources considerably impact employee well-being [9]. First, the health impairment process explains that job demands are the most important antecedents for a decrease in well-being, such as sickness and burnout. Second, the motivational process explains that job resources are antecedents for organizational commitment and work engagement. The health impairment process decreases the motivational process and increases work performance [9].

2.2 The Resource Perspective of Process Mining

Employee well-being is crucial for organizations but it has not received much attention in the process mining literature. The majority of process mining studies are focused on the order of activities in a process, i.e., the control-flow perspective [6]. A different perspective that is sometimes taken, referred to as the resource or organizational perspective, is geared towards providing insights regarding the involvement of employees and their collaboration patterns [1]. Studies taking this perspective typically provide techniques for social network identification [4,25] or resource allocation [18,5]. However, some recent works are moving towards the direction of measuring well-being and work characteristics. For example, Tang and Matzner [35] and Burden et al [13] discuss the potential use of process mining for analyzing aspects such as job satisfaction and workload. Other studies put some of these ideas into practice, for example, by analyzing the work-related preferences from event logs [12] or workloads and processing speeds of employees [24]. Although these studies provide interesting new methods and techniques that provide insight into aspects of employee well-being, they are typically (1) not applied to real-world data, (2) applied to isolated and individual well-being aspects such as workload, and (3) not compared to perceived well-being of employees. In this study, we explore the use of process mining to measure various job demands and resources and analyze their correlations with employee-perceived well-being. The ability to evaluate work-related well-being with process mining can help diminish survey bias and add an objective, real-life view of well-being and its predictors, creating a more complete view of the work context.

3 Conceptualization

This section discusses how work characteristics that influence work-related well-being may be measured using process mining and what attributes are needed to do so. We explore five work characteristics commonly discussed in the JD-R model [11]: monotonous work, time pressure, workload, social support, and autonomy.

`Monotonous work` refers to a work situation offering little variability in tasks. It typically involves repetitive and mundane activities that can lead to boredom [14]. Monotonous work can be found in numerous job positions. Examples are working at an assembly line, manual sorting in a postal distribution centre, or giving the same exact presentation five times a day. Process mining can investigate the monotony of employees' work by exploring the repetitiveness of activities that employees perform. The more similar the activities an employee performs, the more monotonous their work is. An attribute *activity type* is then needed in the event log to investigate monotonous work. There are two ways of measuring the repetitiveness based on the activity type attribute: (1) measuring the total number of tasks of the same activity type performed in succession and (2) measuring the average variance found in activity type per employee.

`Time pressure` refers to work done with limited time available to complete it [34]. This can be either in the form of a deadline on a fixed date or time or in the form of the available timeslot where work must be done in a specific amount of time after a trigger event. An attribute *deadline* or *due date* is needed in the event log to investigate if a deadline is connected to a particular activity and how far the deadline is in the future.

`Workload` can be described as the amount and difficulty of work. It can be measured using the number of tasks, hours of work, mental demands, or energy required to complete work [31]. A start and end timestamp are needed to examine the duration of tasks. The duration worked on tasks could be compared to the mean of the department or team to investigate what tasks are more complex or take longer than others. Another way of looking at workload could be to analyze the begin and end times of a workday per employee, assuming that employees with high workload are more likely to work longer hours.

`Social support` refers to the extent to which employees work together in a supportive work environment where employees are considerate and attentive to each other and resolve possible conflicts in a constructive manner [20]. Social support can be between coworkers, between supervisor and employee, and between organization and employees. The experienced support varies per employee and can even vary per contact moment. Analyzing the experienced social support using data collected from information systems is difficult because of its subjective nature. The closest thing to support that can be investigated is the amount of contact at work. An attribute *resource* is needed to analyze which employees work together on the same task. Moreover, tasks such as meetings could be labelled as contact moments within the attribute *activity type*. It should be noted that contact is different from support. Every measured contact moment could also be experienced as negative.

`Autonomy` refers to the degree to which employees have the freedom and capability to execute tasks independently [16]. This could be investigated in event logs by looking at deviations from the standard procedures, as autonomous people have the freedom to deviate. Additionally, the attribute *resource* could inform how many tasks are completed by a single employee. Although working alone is not the same as autonomy, it could indicate employees' experience that they can complete tasks independently without first passing the task on to a colleague or supervisor.

4 Research Methods

For the case study, we focused on two IT service departments at a large university in the Netherlands which work closely together. Both departments primarily deal with gathering and resolving IT-related incidents encountered by university employees and students. Data was collected using two methods. For process mining, one year worth of data was collected from the dominant information system to measure the five work characteristics mentioned in the previous section. A one-time survey was used to measure the same work characteristics as well as the employee well-being outcomes: burnout, boredom, and work engagement.

4.1 Data Collection: Survey

The survey was conducted in April 2022 and was filled in by 15 employees. It consisted of different scales to measure various job demands, job resources and well-being outcomes. To measure burnout the exhaustion scale of the Maslach Burnout Inventory was used [28,32], containing items such as 'I feel mentally exhausted by my work'. The Dutch Boredom Scale was used to measure boredom with items such as 'At work, times goes by very slowly' and 'I feel bored at my job' [27]. Work engagement was measured with the 3-item Utrecht Work Engagement Scale. One sample item is 'At work, I feel bursting with energy'. Both the job demands and job resources were measured using items from the Job-Content Questionnaire [19], outlined in Table 1.

4.2 Data Collection: Process Mining

Event data was collected from the records of TopDesk for a time period of one year. The employees were asked for consent to share their data. The TopDesk dataset consists of 105 attributes, of which 22 were domain independent and relevant for determining job demands and resources. We found that 20 attributes contained missing values, with 15 attributes sharing identical missing values across cases. Due to their minimal representation in the dataset and negligible impact on overall observations, these instances were omitted. Notably, the attribute `Activity End Date` exhibited missing values in over 50% of observations, rendering it impractical for analysis. Consequently, this lead to its exclusion from further consideration. Due to missing end dates, activity duration was calculated based on the difference between start times of activities within the same case, potentially incorporating waiting time.

The resulting cleaned dataset contains 17 attributes and 739,436 activities, filtered to include only employees from the selected departments that have worked at least 40 hours between January 2020 and December 2022. Those not meeting these criteria were labeled as "unknown" to prevent incomplete case records. We created process mining variables for the work characteristics monotonous work, time pressure, workload, social support, and autonomy. Each variable is calculated as a weighted sum of its components. The process mining variables for the job demands and job resources can be found in Table 1.

4.3 Data Analysis

To explore the survey and process mining variables, bivariate correlational analyses were conducted to determine the correlations between the process mining and survey variables of the job demands and resources. Additionally, the correlations between the survey and PM variables and the well-being outcomes measured by the survey were compared. However, due to the small sample size the conclusions cannot be generalized to a larger population.

5 Results

5.1 Process Mining and Survey Variables

The correlations between the process mining variables and survey variables of the job demands and job resources can be found in Table 2. The results show that the survey variables with the corresponding process mining variables do not always strongly correlate. This indicates that the process mining variables did not measure the same concept as the survey variables. For example, the two time pressure variables had a small negative correlation (r = -.11), which might indicate that *perceived* time pressure (survey variable) is conceptually different from the time pressure measured with process mining.

5.2 Job Demands-Resources and Well-Being Outcomes

The correlations between the work characteristics and the employee well-being outcomes can be found in Table 3. A strong correlation was found between the process mining variable of monotonous work and boredom (r = .55). A similar strong correlation was found between the survey variable of monotonous work and boredom (r = .57). Together with the moderate correlation between the process mining and survey variable (r = .31), this could indicate that these two corresponding monotonous work variables relate to the same concept. For the survey variables, other strong correlations were between workload and boredom (r = -.66) and between boredom and work engagement (r = -.52).

When comparing the correlations of the PM variables and the survey variables, most correlations were found to have a relation in the same direction

	Measurement	Weight
Monotonous work		
1.	Variation coefficient of work type duration	1
Survey items		
(i)	My work includes some repetitive tasks [19]	
(ii)	My work includes many activities (reversed) [19]	
Time pressure		
1.	Completion rate	1/4
2.	Overdue rate	1/4
3.	Median versus prescribed duration	1/4
4.	Number of urgent cases	1/4
Survey items		
(i)	My job requires me to work very quickly [19]	
Workload (work amount)		
1.	Sum of average duration times frequency per activity type	1/2
Workload (work difficulty)		
2.	Number of cases with a duration larger than 2 standard deviations	1/8
3.	Number of activities with a duration larger than 2 standard deviations	1/8
4.	Time worked via difficult channels	1/8
5.	Number of cases that have been reopened	1/8
Survey items		
(i)	I am required to do excessive work [19]	
Social support		
1.	Number of handovers	1/4
2.	Number of subcontracts	1/4
3.	Number of people on the same case	1/4
4.	Number of people doing the same activities	1/4
Survey items		
(i)	If I want, I can get help from one or more colleagues [19]	
Autonomy		
1.	Percentage of cases that the performer solves alone	1/3
2.	Number of variants that a performer can solve alone	1/3
3.	Number of deviations	1/3
Survey items		
(i)	I can interrupt my work as I wish [19]	
(ii)	I can determine my own work pace	
(iii)	My job allows me to make many decisions	
(iv)	I have much to say about what happens in my work	
(v)	I can determine the order in which I perform my tasks	

Table 1: Job Demands and Resources measurements

Variable	Monotonous work	Time pressure	Workload	Social support	Autonomy
Monotonous work	.31	−.31	−.54	.84*	−.72*
Time pressure	−.28	−.11	.25	−.19	.77*
Workload	−.13	−.10	.28	−.44	.24
Social support	−.08	−.08	.08	−.33	.29
Autonomy	−.04	.01	.06	−.05	−.12

Note. Vertically, the process mining variables are represented. Horizontally, the job demands and job resources measured using the survey are represented. N ranges between 10 and 13. $^*p < .05$

Table 2: Correlations between process mining variables and survey job demands and resources

(either positive or negative), however, there were quite some variations between the two types of measuring methods. For example, the PM variable of time pressure was negatively correlated with burnout (r = -.24) as expected from previous literature [15] but the survey variable of time pressure was positively correlated with burnout ($r = .36$). Either the different methods variable different concepts, or the objective work characteristic (PM variable) has a different effect on employee well-being than the subjective work characteristic (survey variable).

Variable	Burnout	Boredom	Work engagement
Monotonous work - PM	.13	.55	−.33
Monotonous work - Survey	.07	.57*	−.50
Time pressure - PM	−.24	−.30	.21
Time pressure - Survey	.36	−.49	−.10
Workload - PM	−.27	−.22	.61*
Workload - Survey	.06	−.66*	.15
Social support - PM	−.22	−.41	.61*
Social support - Survey	.26	.44	.11
Autonomy - PM	.26	−.07	.56*
Autonomy - Survey	−.28	−.41	.32

Note. N ranged between 10 and 13. For all survey variables the response options ranged from 1 to 5, except for work engagement which ranged between 1 and 7. $^*p < .05$

Table 3: Correlations between process mining and survey variables (vertical) and well-being outcomes (horizontal)

6 Discussion

In this study, we formulated process mining variables measuring work characteristics that predict work-related well-being. We compared the process mining and survey variables in a case study. Although we did not find strong correlations between the process mining variables and their corresponding survey variables, our results suggest that process mining could provide valuable insights into employee well-being. The different correlations of the PM and survey variables to the well-being outcomes could indicate two things. First, the PM and survey variables measure two different concepts that both, to various extents, relate to employee well-being. Second, the process mining variables measure a different side of the same concept (objective rather than subjective), which shows that the perception of a work characteristic can have a different effect on well-being than the objective presence of the work characteristic. Both confirm our belief that the combination of process mining and survey variables provides a more comprehensive view of the effects of work characteristics on employee well-being.

Specifically, we found that the process mining variable of workload, social support, and autonomy were significantly positively correlated with work engagement. This finding supports previous research that suggests job resources such as social support and autonomy are important predictors of employee well-being [10], and that job demands such as workload can have a positive effect on work engagement when perceived as a challenge or if the workload is balanced [21,23]. Additionally, we found the process mining variable of monotonous work to have a moderate positive correlation with the survey variable of monotonous work, indicating a possible relation or similarity in construct for these two measurements. Further support for the potential similarity between the two variables can be found in the finding that both the process mining variable and survey variable are strongly correlated with the well-being outcome boredom.

Our study contributes to the broader discussion on survey bias, as process mining variables could diminish some of the limitations associated with self-report surveys. Process mining variables provide an objective and real-time assessment of job resources and job demands, reducing the potential for bias and improving accuracy. However, it is important to note that process mining variables have their own limitations. For instance, process mining assumes the researcher captures the complete data from the system, which may not always be the case [2]. This was also seen in our dataset, where the end time of activities was not always saved in the system. Moreover, the process mining approach does not consider the subjective aspects of job resources and demands, which is important for understanding the overall employee well-being [22]. For example, one employee might find a certain workload quite manageable and engaging, while another might find it too much. Therefore, it is essential to consider objective and subjective variables in conjunction when evaluating employee well-being. To accomplish this without overwhelming employees with frequent surveys, analysts can design a monitoring plan where surveys are administered at extended intervals, for example, annually. Process mining can then be used to monitor employee well-being in between these intervals and identify problems bottlenecks or possible risks for employee well-being. Additionally, process mining data can be collected from all employees, whereas surveys are more likely to have a smaller sample size due to response rate limitations [26]. The results of this study further support the argument for the use of both survey variables and process mining variables to evaluate employee well-being comprehensively (both the objective and perceived work characteristics) and more accurately (collecting real-time data from a larger sample).

This exploratory study is subject to a couple of limitations that should be considered. First, only a small group of participants filled in the survey. This decreases the generalizability of the findings. Future research should gather data from a more extensive and diverse sample to ensure more representative results, for example, by conducting similar research in other sectors. Second, some data, such as part of the activity's end times, were missing from the event data. Missing timestamps can impact the quality of the used data [3,33] and, thus, the accuracy of the process mining variables. Additionally, the data was collected from one system, which caused missing data from other systems used in the department. Accuracy can be improved in future studies by collecting data from all systems used within the sample. The process mining variables were formulated specifically for this context but could be calculated differently. Further research should consider what calculates scores would work best in the sample used.

7 Conclusion

The case study conducted in this research explored how process mining variables can be used to evaluate employee well-being. The results indicate that perceptions of job demands and job resources, such as time pressure, and autonomy do not strongly match the corresponding data extracted from information systems. However, interesting relations were found between the process mining variables of workload, social support, and autonomy and the well-being outcome of work engagement. This suggests that process mining may be a valuable tool for continuously monitoring the work-related well-being of employees, especially work engagement. Combining this with questionnaires that measure the corresponding employee perceptions will provide a more complete picture of work-related well-being.

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