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Business Process Re-Design Based on Human Resources Cost Analysis

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Abstract: *Performance measurement and optimization in companies and organizations relies on techniques like process mining, focusing on the analysis of processes using event data. Process re-engineering is the process mining type that aims at improving existing processes. Here we conduct a case study in the medical management domain to discover process optimization and resource reallocation opportunities. We focus on human resource-related costs in different activity decomposition levels. Our findings reveal discrepancies between the actual activity costs and their equivalents. Our study underscores the critical role of process mining and performance analysis in improving operational performance. This paper highlights process mining's potential techniques in driving organizational excellence by creating insights from event log analysis.*

1. INTRODUCTION

Over the last two decades, process mining emerged as a new research field that focuses on the analysis of processes using event data (Aalst, 2012). Process mining combines elements of both process science and data science. Process science focuses on understanding, modeling, and optimizing business processes (Laguna & Marklund, 2018). Data science involves the extraction of meaningful insights and knowledge from large sets of data.

The idea of process mining is to discover, monitor and improve real processes by extracting knowledge from event logs readily available in today's information systems (Aalst, 2011). Process mining establishes links between actual processes (and their data) and process models. Today's information systems log enormous amounts of events in what we call event logs.

The starting point for process mining is an event log (Aalst, 2011). The minimum requirements for an event log to be eligible for applying process mining algorithms are the following three elements: case id, activity and timestamp. Organizations can use event logs to discover, monitor, and improve processes based on facts rather than fiction.

Process mining may be used for different objectives (Ghasemi & Amyot, 2020) and can be grouped into three types (Aalst & Dustdar, 2012). The first type is process discovery, which extracts the blueprint of a business process. In other words, process discovery uses an event log and produces a model, referred to as de facto model (Aalst, 2014), without using any other a priori information. Dozens of techniques

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exist for extracting a process model from raw event data (Aalst et al., 2004). The second type of process mining is process conformance, which assesses the extent to which the de facto model conforms to a reference process, referred to as the de jure model (Munoz-Gama, 2016). The reference process describes how the business process should be carried out. This comparison shows where the real process deviates from the reference. Moreover, process mining techniques can quantify the level of conformance and diagnose differences. The third type of process mining is process re-engineering (or process enhancement, or process redesign) which aims at improving existing processes (Leoni, 2022). This means that, based on additional information, the de facto model is extended, altered or improved to match the de jure model. This is done by dealing with process bottlenecks, deadlocks, or frequencies of specific activities.

It is evident that process mining has emerged as a pivotal field bridging process science and data science, offering a comprehensive approach to analyzing business processes using event data. By establishing a connection between actual processes and process models, process mining extracts valuable insights from event logs, enabling organizations to discover, monitor, and enhance their processes based on empirical evidence. Furthermore, process mining's domain-specific, functional, and managerial perspectives provide a tailored approach to different industry sectors and organizational priorities. As organizations increasingly embrace data-driven decision-making, the integration of process mining methodologies offers a powerful tool for optimizing efficiency, identifying bottlenecks, and enhancing overall performance across various domains and managerial levels.

This paper aims to create insights based on metrics that improve the operational performance of organizations. In order to do that, and based on the literature review we formed four research questions (RQ), summarized in Table 1.

Table 1. Research Questions

#	Research Question
RQ1	What human resources meta-data can we derive based on event-log data?
RQ2	Which metrics are critical in an business process re-design challenge?
RQ3	How can we obtain employees' interrelationships depending on their subdivision level?
RQ1	What human resources meta-data can we derive based on event-log data?

Source: Own research

After the introduction in section 1, section 2 presents a literature review, highlighting existing methodologies, challenges, and research gaps. In section 3 we perform a case study focusing on the healthcare domain. Then, section 4 offers a discussion of the findings from the literature review and the case study and their implications, while section 5 concludes the paper by summarizing key insights and providing recommendations for future research and implementation in process mining endeavors.

2. LITERATURE REVIEW

In this section we dive into the literature surrounding event log data and business process re-engineering, exploring existing methodologies, challenges, and areas for further investigation. By synthesizing insights from prior research, we identify gaps in current approaches and formulate research questions that drive the development of innovative solutions. Business process re-engineering is, today, the least used process mining type. There is a lack of scientific contributions exploring business process re-engineering and, thus, a need to further investigate this type.

Process mining has been used to notify future events. In their paper, Pravilovic et al. (2014) use predictive clustering to equip an execution scenario with a prediction model. This way, a forecasting ability can provide insights and support decision-making. In their work, Senderovich et al. (2016) target the analysis of resource-driven, scheduled processes based on event logs. Other authors like Park et al. (2015), investigated the characteristics of event logs in make-to-order production and proposed a method to analyze and improve manufacturing processes in construction, shipbuilding and aviation. To validate the proposed method, a case study with real data was conducted.

Existing business process performance mining tools are not designed to help analysts understand how bottlenecks form and dissolve over time. In their paper, Nguyen et al. (2016) present an approach to analyze the evolution of process performance via a notion of staged process flow and demonstrate the advantages of this approach over state-of-the-art process performance mining tools using a real-life event log of a bank. Using time series of petri net models, Solti et al. (2017) aim to explicitly capture seasonality in business processes. Their evaluation showed the merits of this model in terms of better accuracy in the presence of time series effects.

Since existing process mining techniques assume processes to be static, Hompes et al. (2017) present a novel comparative case clustering approach that is able to expose changes in behavior. Claiming that the existing process mining approaches for enriching process models cannot discover rules like separation of duties, Cabanillas et al. (2018) present an approach for mining resource-aware imperative process models that use an expressive resource assignment language.

To demonstrate that the discovered process models can be extended with information to predict the completion time of running instances, van der Aalst et al. (2011) provide a configurable approach to construct a process model, augment this model with time information learned from earlier instances, and used this to predict the completion time. In their work, Caldeira and Abreu (2016) aim to bring forward new insights into the software development process by analyzing how developers use their development platforms. A life-cycle model is presented by Aalst (2011), consisting of five phases and describing how to apply process mining techniques to analyze challenging spaghetti processes.

A case study using process enhancement in manufacturing is shown by Rinderle-Ma et al. (2023). They present that conformance checking during run-time can help detect deviations and errors in manufacturing processes when they happen. Process mining algorithms use event logs to learn and reason about processes by technically coupling event history data and process models. Aalst (2013) focuses on applying process mining techniques to services and highlights the challenges that specifically appear in service-orientated systems.

It is noticeable, based on our literature review, that business process re-engineering has not yet been explored to its full potential. More specifically, we could not retrieve studies that, based on event log data, are calculating human resources-related activity costs nor are computing critical performance indices (e.g., equivalent salary, concentration index, etc.) and can suggest process changes (based on subdivision levels) and reorganization scenarios. This paper answers these research questions, using a case study in the healthcare sector.

3. A CASE STUDY IN THE MEDICAL MANAGEMENT DOMAIN

For demonstrating our proposition we performed a case study. The clinic occupies 10 employees with 4 different roles; 2 consultants (monthly salary 8000€), 3 nurses (monthly salary 3000€), 3 residents (monthly salary 5000€), and 2 anesthesiologists (monthly salary 4000€). Employees are working from 08:00 to 16:00 (including breaks), Monday to Sunday. Data have been recorded for January 2024, containing around 2000 events. The dataset contains 5 columns; case id, resource, activity, start time, and end time. The activities that each employee can write their working hours on are: surgery preparations, laboratory examinations, other examinations, anesthesia, operation, post-operation checks, in-patients diagnostics, in-patients therapy, out-patients diagnostics, out-patients therapy, in-patients emergencies, out-patients registration, out-patients treatment, discharge notes, patient file.

Using the synthetic data from the gynecological clinic of a hospital, we calculate two performance indices; the equivalent salary per activity and the concentration index of each activity. Then, we use the process tree of the hospital clinic to perform a cost analysis based on activity decomposition level. Before computing the equivalent salary and the concentration index, we calculate the total cost of each activity and the full time equivalent (FTE) of each activity.

The ActCost refers to the total cost of each activity and is calculated as

$$\text{ActCost} = \sum(\text{EmpSal} \times \text{EffperAct}) \; [€] \tag{1}$$

where EmpSal is the employee salary and EffperAct is the employee effort for a specific activity.

The FTEs per Activity are the FTEs devoted to each activity and are calculated as

$$\text{FTEs per Activity} = \frac{\sum(\text{EffperAct})}{100} \; [-] \tag{2}$$

where EffperAct is the employee effort for a specific activity.

These two variables (ActCost and FTEs per Activity) are used to compute the critical indices.

3.1. Equivalent Salary

The purpose of calculating the equivalent salary is to determine if work can be performed at a lower cost to the organization, either through internal re-allocation to less expensive employees or through outsourcing. The EqSal is the equivalent salary for each activity. It is calculated as

$$\text{EqSal} = \sum \frac{\text{ActCost}}{\text{FTEs per Activity}} \; [€] \tag{3}$$

where ActCost is the cost of each activity and FTEs per Activity are the FTEs devoted to each activity. This kind of analysis can be used to identify trivial activities that are performed by highly qualified employees.

We show the results of the equivalent salary analysis together with the activity cost in Figure 1. There are several very useful insights that can be drawn from this plot. First of all, we can spot two activities (surgery preparations and out-patients treatment) that have a higher cost than the equivalent salary. This, most likely, happens because a lot of different resources are involved in their execution. Therefore, it needs to be checked that having multiple employees from different sections of the clinic is needed and valuable to perform these activities, otherwise, a redesign shall be proposed.

Secondly, focusing only on the activity cost, we can identify a few activities like discharge notes and out-patients registration, having equal if not even greater costs with activities like out-patients diagnostics, laboratory examinations and in-patients therapy. This is interesting to know because some activities are not as important as others. Therefore, after deciding which are the most critical activities, we should ensure that they are performed by highly qualified employees, so the rest of the activities can be executed by other employees at a lower cost.

What is more, this analysis can be useful for calculating how expensive the idle time of our resources is. In our example, this costs around 4000€ per month. Compared with the salary distribution data, we can see which employees are having a lot of idle time and come up with a different working model to accommodate that.

Also, we can use the equivalent salary analysis to decide whether or not outsourcing some activities might be cost-effective. In this clinic, we can think of ways to outsource, for instance, all the trivial activities related to documentation (i.e., discharge notes and patient files). Such a choice could potentially reduce the monthly costs of the clinic by a great amount and at the same time, have the employees focusing on more vital activities.

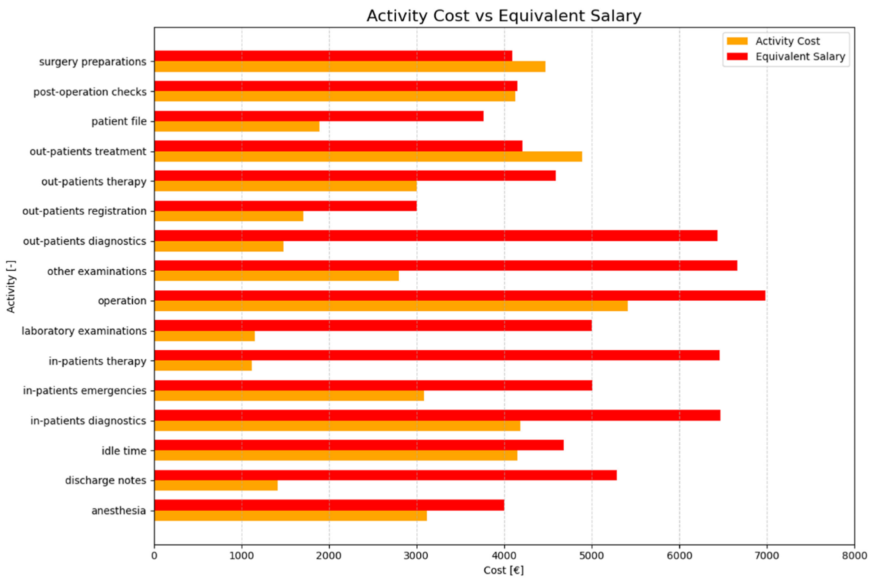

Figure 1. The equivalent salary compared to the activity cost

Source: Own research

Finally, it is important to note that the insights coming from this type of analysis cannot be our only source of judgment, for making robust decisions. Decision-making regarding the business process redesign of such an entity shall always be performed together with discussions with experts in the field.

3.2. Concentration Index

Concentration shows the average amount of time employees spend on a particular activity. It is calculated as

$$\text{Concentration} = \frac{\text{FTEs per Activity}}{\text{Number of Employees that declared effort to the Activity}} [-] \quad (4)$$

where the FTEs per Activity are the FTEs devoted to each activity. The lower this index, the lower the concentration.

This analysis calculates the concentration values of all activities and is useful to understand how fragmented an entity is. The concentration values for all the activities of the gynecology clinic are shown in Figure 2.

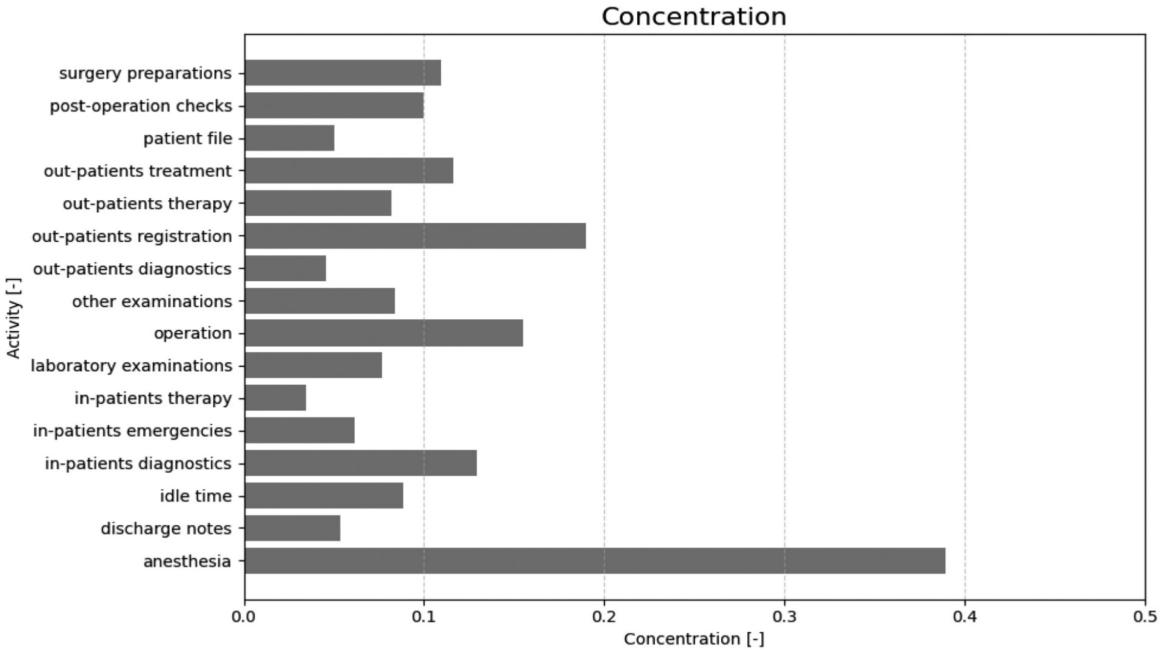

Figure 2. Concentration index in the gynecology clinic for all activities
Source: Own research

By using these results, we can outline multiple valuable insights. To begin with, we can observe that for most of the activities of this clinic, the concentration index is relatively low. This is, most likely, because a lot of employees are occupied with a very large number of different activities on a daily basis. Anesthesia is the only exemption, having a high score (around 0.39) on the concentration index. The explanation for this lies in the fact that only anesthesiologists are responsible for this activity. What is more, anesthesiologists are rarely busy with more than 6 activities in total daily.

Having a relatively low score for most of the activities on the concentration index does not necessarily imply that one shall intervene and redesign the entire organization. For making such a decision it is important to combine this analysis with information regarding the criticality of the activities performed. For instance, having a low score (around 0.05) on the concentration index for writing discharge notes, will probably not require any organization chance, since it might be a low risk activity. On the other hand, having a low score (around 0.16) on the concentration index for performing surgical operations is presumably a red flag, because this activity can be labeled as high risk, requiring to be performed by employees whose daily work is not as fragmented.

3.3. Activity Decomposition Levels

Activity based costing for calculating process costs has been used extensively to attribute costs to all cost drivers related to process resource consumption. We concentrate only on the human resource related costs. For this reason, we focus on employee effort devoted to activities. Based on the effort of each employee per activity we calculate the full-time equivalents per activity. In this way, and based on the process tree of the organization, we can compute the costs related to each decomposition level. The process tree for the gynecology clinic is shown in Figure 3.

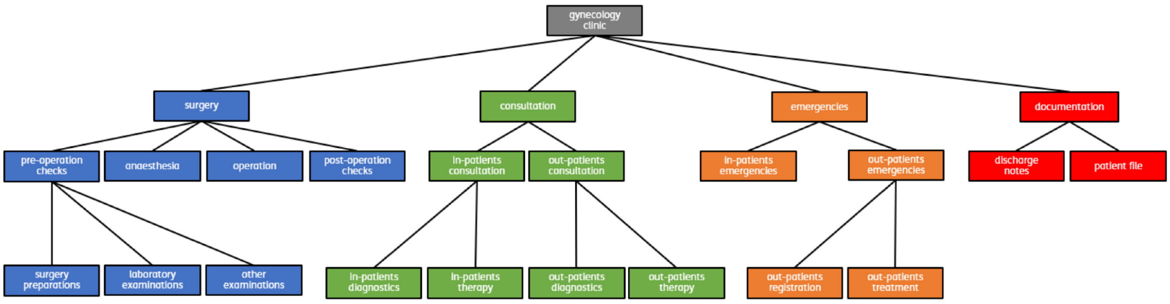

Figure 3. The organizational process tree of the gynecology clinic

Source: Own research

We can see that there are four activities in the first decomposition level, namely, surgery, consultation, emergencies and documentation. In the second decomposition level, we find pre-operation checks, anesthesia, operation, post-operation checks, in- patients consultation, out-patients consultation, in-patients emergencies, out-patients emergencies, discharge notes and patient files. In the third and final decomposition level, we find surgery preparations, laboratory examinations, other examinations, in-patients diagnostics, in-patients therapy, out-patients diagnostics, out-patients therapy, out- patients registration and out-patients treatment.

In our example, employees are writing hours on every activity that is either on the third (and last) decomposition level or is at the second decomposition level, but it does not include any activities on the third level. For example, an employee can write hours on in-patients emergencies (second decomposition level but without any activities on the third level) but not on out-patient emergencies (because this activity has two other activities on the third level).

For the activities that are in higher decomposition levels than the ones that an employee can write hours on, we compute the total costs steaming from the sum of the effort of the respective activities. In Figure 4 we can see the sum of the activities on the first decomposition level. It can be clearly depicted that documentation is the cheapest activity (around 3000€ per month) and surgery the most expensive one (around 22000€ per month). Emergencies and consultations are lying in the middle of this range costing around 10000€ per month each.

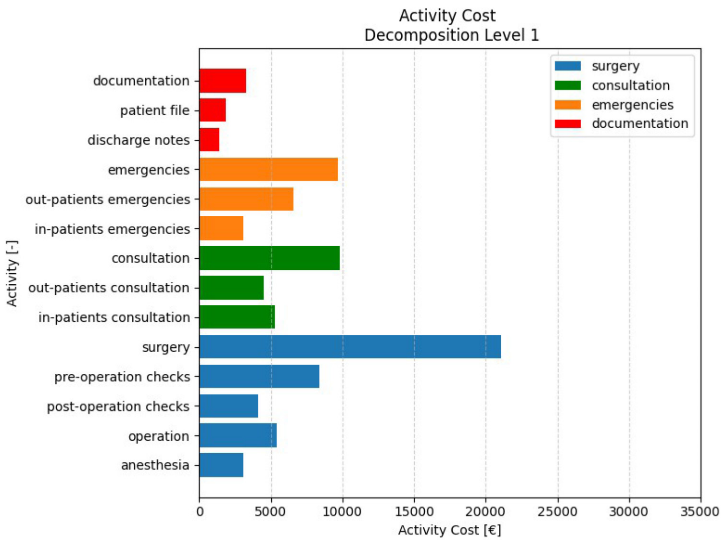

Figure 4. Activity cost for activities in the first decomposition level

Source: Own research

This type of analysis, instead of focusing on process performance, focuses on the organizational structure of entities and organizations. The aim is the evaluation of structural efficiency. This way, by having clear metrics and insights about the cost of each sub-group or department of an organization, we can leverage our human resources in a way to creates maximum performance.

4. DISCUSSION

Our study dives into the multifaceted domain of process mining, with a specific focus on business process re-engineering. Through a literature review coupled with a practical case study, we unravel the complexities of event log analysis and its impact on organizational processes.

In our literature review, we surveyed the utilization of process mining techniques in the realm of business process re-engineering. We discovered that while event logs serve as the bedrock for process mining endeavors, their inherent quality variations present significant obstacles, hindering accurate analysis and decision-making. This is where we answered RQ1, depicting that important human resources meta-data such as the specific activities per working day for all employees can be derived in a straightforward way from event logs.

Moreover, our exploration revealed a notable gap in the use of metrics, regarding business process re-design challenges. Computing the equivalent salary and the concentration index responded to RQ2.

In order to obtain employees' interrelationships depending on their subdivision level, we used the organization process tree. This is how we answered RQ3, by computing the human resources-related costs based on different activity decomposition levels.

In tandem with our literature review, our case study provided reorganization ideas in the operational dynamics of a healthcare setting. By using event logs and computing critical performance indices, our study uncovered opportunities for process optimization and resource reallocation, answering RQ4. The analysis brought to light discrepancies between activity costs and perceived value. Additionally, the examination of the concentration index revealed the organizational structure shedding light on areas that might need optimization.

Finally, our work shows the important role of process mining and performance analysis in driving organizational excellence. Through the utilization of event log data, organizations can unlock hidden insights, improve operational efficiency and create a competitive advantage.

5. CONCLUSION

This paper focuses on business process re-engineering and organizational performance analysis through a literature review and a practical case study. The literature review provided valuable insights into existing methodologies, challenges and gaps. The case study demonstrated the practical application in organizational settings. The integration of data-driven insights with domain knowledge facilitated evidence-based decision-making and informed process improvement initiatives.

We reached our aim to create insights based on metrics that improve the operational performance of organizations by answering the four identified research questions. We showed that human resources meta-data for all employees can be derived in a straightforward way from event logs. In our effort to use metrics, we used the equivalent salary and the concentration index. Also, we used the organization process tree to compute the human resources-related costs based on different activity decomposition levels. Finally, we uncovered opportunities for process optimization and resource reallocation.

Before going forward, there are certain limitations to be addressed. First of all, most research works do not validate their findings using real-world data. Without leveraging datasets spanning various domains, researchers cannot ensure the generalizability and robustness of performance analysis across a spectrum of organizational settings.

Moreover, current studies are not prioritizing user-centric design principles and are not incorporating feedback from stakeholders to streamline tool interfaces and workflows. By not optimizing usability and user experience, researchers cannot empower organizations to leverage performance analysis tools effectively, driving informed decision-making and process improvement initiatives.

In trying to complement this work, some future steps can be defined. Firstly, future research should explore the incorporation of additional performance metrics to offer a more comprehensive analysis of organizational processes. Metrics such as process efficiency, cycle time, and resource utilization play a pivotal role in understanding process dynamics and identifying areas for improvement. By enriching performance analysis tools with a broader array of metrics, researchers can provide deeper insights into process performance and empower organizations to make data-driven decisions that drive operational excellence. Furthermore, seamless integration with existing organizational workflows is essential for maximizing the impact of performance analysis tools within organizations. Future research should focus on developing interoperability features and compatibility with common software platforms used in business process management. In conclusion, continued research and development efforts in the field of performance analysis tools are crucial for empowering organizations to unlock hidden insights, optimize processes, and achieve sustainable competitive advantage in today's dynamic business environment. By addressing current limitations and embracing emerging technologies and methodologies, researchers can pave the way for the next generation of performance analysis tools that drive organizational excellence and innovation.

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