Explaining Change with Digital Trace Data: A Framework for Temporal Bracketing

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Abstract

Digital trace data, along with computational techniques to analyze them, provide novel means to study how organizational phenomena change over time. Yet, as digital traces typically lack context, it is challenging to explain why and how such changes take place. In this paper, we discuss temporal bracketing as an approach to integrate context into digital trace data-based research. We conceptualize a framework to apply temporal bracketing in the analysis of digital trace data. We showcase our framework on the grounds of data from an onboarding process of a financial institution in Central Europe. We point to several implications for computationally intensive theory development around change with digital trace data.

Keywords: digital trace data, context, change, process mining, temporal bracketing

1. Introduction

The growing abundance of digital trace data offers novel means to study organizational change (Lindberg, 2020; Miranda et al., 2022; Pentland et al., 2021). Digital trace data provide granular insights into actions carried out with digital technologies; they typically appear in large quantities, entail fine-granular information about these actions, and can be analyzed in a variety of ways (Grisold et al., 2020; Lazer et al., 2020). Several recent arguments suggest that digital trace data, along with computational techniques to analyze them, provide promising opportunities for empirical research in the information systems field (Miranda et al., 2022) and beyond (Lazer et al., 2020). This holds particularly true for process-driven research studying change; since digital trace data are typically associated with temporal information (i.e., when certain actions or events took place), they provide insights into the dynamics of (organizational) phenomena and how they take shape over time (Oliver et al., 2020).

One key challenge, however, is to explain why and how change takes place (Grisold et al., 2020; Pentland et al., 2020). While it is possible to obtain insights and identify patterns in digital trace data that might remain hidden in traditional manual-driven research approaches, what is often missing is contextual information to make sense of actors' reasons, motives, and decisions that drive change (Pentland et al., 2021). Recent studies indicate that one way to do so is to apply *temporal bracketing* (e.g., Pentland et al., 2020; Wurm et al., 2021). Grounded in traditional, manual-driven process research (Langley, 1999), temporal bracketing centers around the identification of stages, i.e., distinct temporal dynamics that are related to each other, as well as events that explain why and how these dynamics occurred. When applying temporal bracketing, "a shapeless mass of process data is transformed into a series of more discrete but connected blocks" (Langley 1999, p. 703). To this date, however, there has not been a systematic discussion of how and when temporal bracketing can be applied to digital trace data research that studies change.

In this paper, we discuss temporal bracketing as a strategy to add contextual information to findings obtained through digital trace data. Building on claims that computationally intensive theorizing requires human as well as computationally-driven sensemaking (Lindberg, 2020), we conceptualize a framework to use temporal bracketing as an approach to systematically integrate context to make sense of change. At the center of our framework are four recursively related steps – (1) data preparation, (2) identification of brackets, (3) analysis and sensemaking, and (4) evaluation and validation; each step, in turn, is enabled by human and computationally-driven sensemaking.

We illustrate our framework by analyzing a digital trace data set from an onboarding process of a financial institution in Central Europe. We apply process mining techniques (van der Aalst, 2016) to look at changes in the onboarding process from different angles (Grisold et al., 2021). We further integrate insights from one of the authors, who is working in the organization and has substantial insights about contextual information. Finally, we provide recommendations for using

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temporal bracketing in computationally intensive theorizing.

2. Conceptual Background

2.1 Studying Change with Digital Trace Data

A number of emerging claims stress that digital trace data provide novel means to investigate socio-technical phenomena (Berente et al., 2019; Miranda et al., 2022). Digital traces reflect activities and events that are left behind as users interact with digital technologies in private or work-related contexts. In light of the fact that the ways we communicate, collaborate, and connect are increasingly enabled by digital technologies, more and more of such data become available (Zuboff, 2019).

For empirical research, the availability of such data is appealing for several reasons. First, digital trace data typically appear in large quantities and over extended periods of time (Lazer et al., 2020). Thus, they provide fine-granular, yet far-reaching insights into various kinds of socio-technical phenomena (e.g., Hukal et al., 2019; Pentland et al., 2020; Rhue & Sundararajan, 2019). Second, from the viewpoint of research on change, digital trace data are typically equipped with temporal information that specify when an activity or event occurred (Pentland et al., 2020). Hence, they are particularly useful to visualize and analyze the dynamics that unfold around (organizational) phenomena (Grisold et al., 2020; Langley, 1999; Langley et al., 2013; Lazer et al., 2020). Third, the analysis of digital trace data often reveals patterns and dynamics that could not be obtained through traditional, manual-driven research strategies (e.g., Hukal et al., 2019). This is because digital trace data sets are extensive, and can be analyzed from different angles and through different techniques (Oliver et al., 2020), including machine learning (Lindberg, 2020) or process mining (Grisold et al., 2020), among many others.

What is important to note, however, is that digital trace data offer a limited view on a phenomenon (e.g., Østerlund et al., 2020) because they often lack contextual information (Grisold et al. 2020). Digital trace data may reveal *what* happened, but they do not necessarily explain *why* it happened. To make sense of and explain change, researchers need to collect and integrate additional information of various kinds. During the COVID pandemic, for example, governments around the world have leveraged digital traces in the form of mobile phone data to analyze mobility patterns at different stages of the pandemic. But importantly, they complemented these data with contextual information (such as information about policy interventions) to explain why and how people changed their behaviors over time (e.g., Oliver et al., 2020).

However, while several works emphasize the role of context in digital trace data research (Berente et al., 2019; Lindberg, 2020), and in process-driven research more specifically (e.g., Grisold et al., 2020; Pentland et al., 2020), we lack a systematic discussion of how such contextual information can be integrated. Considering the growing interest in guidelines, frameworks, and recommendations to conduct digital trace data-based research (Berente et al., 2019; Miranda et al., 2022; Østerlund et al., 2020; Shrestha et al., 2021) such a discussion seems promising and useful.

2.2 Temporal Bracketing

Several recent digital trace data-based studies indicate that change can be analyzed through temporal bracketing (Berente et al., 2019; Pentland et al., 2020; Wurm et al., 2021). Temporal bracketing was originally proposed as one of several strategies to study and make sense of temporal change in (qualitative) data (Langley, 1999). Generally speaking, temporal bracketing aims at structuring data along specific stages or phases in order to describe individual phases and make comparisons among them. More specifically, the idea behind temporal bracketing is that one decomposes the process of a given phenomenon into adjacent discrete stages whereby each stage represents data that are related to each other and evolve in "fairly stable or linearly evolving patterns" (Langley, 1999, p. 703). For each stage, then, one can identify how certain actions, events, and/or other variables of interest (such as contextual matters, actors' feelings, interpretations, etc.) influence what is happening within this stage (e.g., Barley, 1986).

Temporal bracketing has been established as a useful strategy to analyze change in the information systems field. In their recent case study on product platform development in a large manufacturing company, for example, Sandberg et al. (2020) used temporal bracketing to identify four major phases through which the platform evolved. These four phases were characterized by product continuity; discontinuity, in turn, referred to shifts in the platform and marked new temporal brackets. As another example, consider Nan and Lu's (2014) study of crisis response after a massive earthquake hit a student dormitory in China. Drawing from posts in the university-wide student forum, this study utilized temporal bracketing to identify different stages in crisis response.

While these examples drew from traditional qualitative research methods, they highlight two key points about the application of temporal bracketing. First, temporal brackets depend on the given research focus as well as the specific contingencies of the research case. Accordingly, such brackets can span across periods of years or decades (as in Sandberg et al., 2020), or a few weeks or months (as in Nan & Lu, 2014). Second, the definition of brackets requires extensive data that reveal differences across stages, but it also requires in-depth knowledge about the broader context to make sense of how and why these data were constructed. Nan and Lu (2014), for example, complement their analysis of student posts with contextual knowledge about regulations that affected posting behavior (e.g., that the forum was shut down at night and could not be used). These points are crucial to consider when using temporal bracketing to analyze digital trace data. In the following, we discuss the implications of temporal bracketing in the context of digital trace data research.

3. Bracketing Context to Study Change with Digital Trace Data

3.1 Human and Computationally-Driven Sensemaking for Temporal Bracketing

Following recent works around computationally intensive theorizing (Berente et al., 2019; Lindberg, 2020; Miranda et al., 2022), research with digital trace data implies human as well as machine pattern recognition. This sets it apart from traditional, manual-driven theorizing because it involves human as well as computationally-driven sensemaking (Lindberg, 2020).

Broadly speaking, sensemaking aims to construct the unknown in order to be able to act in it and give it a purpose, meaning or direction (Weick, 1995). Sensemaking is a procedure of interpretation and the construction of mental schemas and cognitive frameworks in light of new stimuli (Sandberg & Tsoukas, 2020; Weick, 1995). While human sensemaking relies on the capabilities of the human mind to identify and make sense of patterns, computationally-driven sensemaking uses a variety of computational techniques to identify regularities or irregularities in digital trace data (Lindberg, 2020). While computationally-driven sensemaking is becoming more prevalent in research (Lazer et al., 2020), it is crucial to stress that it still involves human sensemaking (e.g., choosing a certain algorithm or interpreting its results). To this end, temporal bracketing provides a means to combine human and computationally-driven sensemaking to contextualize digital trace data to understand and explain change.

Figure 1 summarizes the key idea of temporal bracketing in computationally intensive theorizing. Digital trace data constitute a process through which a given phenomenon evolves and changes over time (bottom gray bar). How this process –and hence the data points– changes, depends on contextual factors that affect how these data are produced (top gray bar). For example, a business process in a company may change across a period of time as old employees leave and new employees start to work at the company. Temporal brackets denote phases where the process evolves in a stable manner and expresses some continuity; for example, intensive training for employees shows that the execution of the process is aligning with regulations. Discontinuities in the data, in turn, mark brackets (vertical black lines); for example, managers encourage employees at one point to organize in more agile ways and interpret regulations more loosely.

Throughout the entire process, both human and computationally-driven sensemaking are applied to identify brackets, analyze the data and evaluate the results. Hence, in the following section, we outline the particular steps of the temporal bracketing approach to study change with digital trace data.

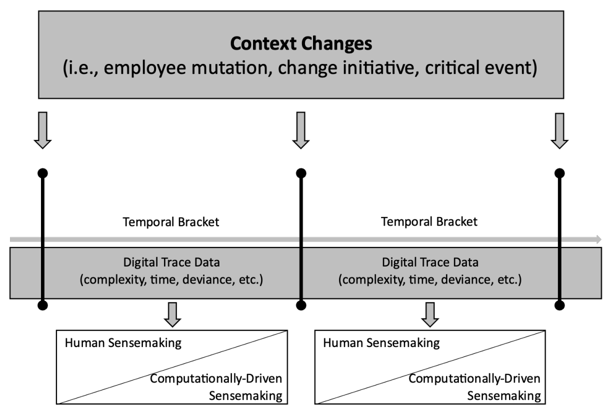

Figure 1. Temporal bracketing in digital trace data research

3.2 A Framework for Temporal Bracketing in Digital Trace Data Research

The proposed framework outlined below reflects the general discourse on computationally intensive theorizing. Our framework to inform temporal bracketing in computationally intensive theorizing is depicted in Figure 2. Integrating insights from traditional manual-driven theorizing and computationally intensive theorizing, the model comprises four steps; (1) data preparation, (2) identification of brackets, (3) analysis and sensemaking, and (4) validation and evaluation. We discuss them in the following.

The first step of our model is *data preparation*. Data preparation establishes the groundwork for further analyses. It is based on two observations. On the one hand, one needs to understand what a given set of digital trace data actually represents. The data structure of digital traces has been defined a priori (Alaimo & Kallinikos, 2016). Hence, understanding what these data may potentially show, and if appropriate, selecting subsets of the dataset is essential. On the other hand, data preparation implies that data quality is checked and, if needed, adjusted. It is crucial to prepare the dataset accordingly before engaging in human or computationally-driven sensemaking.

The second step in our framework revolves around the *identification of brackets.* This implies the analysis of contextual changes, recognition of patterns in the data, and sensemaking. Identifying meaningful temporal brackets is important since these brackets build the foundation for the subsequent analysis. This step involves human and/or computationally-driven sensemaking. Human sensemaking includes traditional, qualitative, and immersive procedures such as interviews, observations, ethnographic fieldwork, or insider reports that explain the organizational context (Barley, 1986). This helps to identify points of change and temporal brackets in the process (e.g., Sandberg et al., 2020). Such data is often hard to obtain and the analysis is time-intensive, however, it provides researchers with a rich understanding of the organizational context. Computationally-driven sensemaking draws from algorithmic procedures such as process mining (Pentland et al., 2021) or visual drift detection (Yeshchenko et al., 2021) to uncover critical events that indicate discontinuities in the data (Langley, 1999). Both approaches have their merits and it is beneficial to triangulate and combine them. For example, after computational approaches are applied to identify patterns in the data, human sensemaking can surface their meaning in "a deliberate, selective, and generative human act" (Miranda et al., 2022, p. vi) to identify temporal brackets.

The third step of our framework comprises *analysis and sensemaking*. It aims to create insights by mapping and understanding the contextual changes, analyzing them, and surfacing patterns (Miranda et al. 2022). This can be achieved, again, by applying a combination of human and computationally-driven sensemaking. Depending on the research focus and the features of the digital trace data set, computationally-driven sensemaking can capitalize on a variety of analytical techniques such as cluster analysis, process mining, deep learning, or social network analysis (Miranda et al., 2022). However, even when computational techniques are applied, human sensemaking plays a vital role as well, for example, in choosing appropriate techniques or interpreting the results of the analysis. Therefore, human and computationally-driven sensemaking are in a constant interplay in research that involves digital trace data (Lindberg, 2020).

The last step of our framework involves the *validation and evaluation* of findings. This step concerns the robustness of the results. Scholars can engage in both human and computationally-driven sensemaking to achieve this objective. On the one hand, human sensemaking can include conducting expert interviews to gather (additional) qualitative insights into the context of the analysis to corroborate the results. On the other hand, computationally-driven sensemaking can use computational techniques to test findings deductively (Abbott, 1995; Grisold et al., 2020). A combination of human and computationally-driven sensemaking strategies can provide a comprehensive validation and evaluation of the results because it allows for considering different perspectives and thus strengthens the theoretical insights. Figure 2 summarizes our proposed approach.

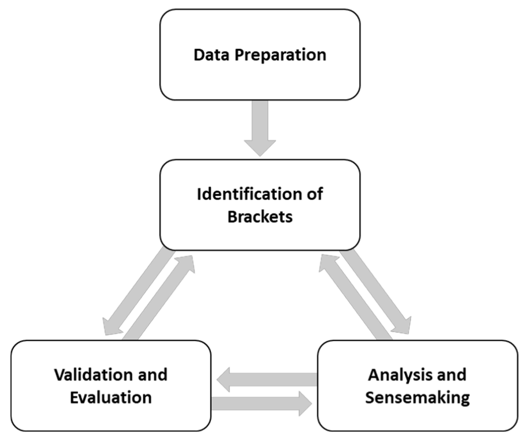

Figure 2. Framework for bracketing context with digital trace data

It is important to stress that Figure 2 shows a recursive relation between the three steps *identification of brackets, analysis and sensemaking,* and *validation and evaluation*. Hence, these three steps are not necessarily sequential but rather unfold in an iterative, overlapping, and recurrent way over the course of the research project. By that, we mean that it is possible to evaluate and validate the identified brackets to substantiate their significance and make sure that they are meaningful. This can be accomplished, for example, by using interviews to corroborate brackets that were identified through computational techniques. Similarly, there should be a reciprocal exchange between identifying brackets and analyzing them. For instance, the analysis and sensemaking phase could show that the initially identified brackets need to be modified. Lastly, throughout the analysis and sensemaking step, the evaluation and validation of the insights obtained should be recursively integrated. For example, the findings from computational analyses can be validated with qualitative data. Furthermore, the insights created in this step can be used to inform the identification of brackets in a second iteration.

Taken together, our framework combines guidelines from traditional manual-driven research (Langley, 1999) with basic tenets of computationally intensive theorizing (Berente et al., 2019; Miranda et al., 2022). It presents concrete steps and recommendations to apply temporal bracketing in digital trace data research to explain change by integrating context. In the following, we illustrate the use of our framework.

4. Illustrative Case

4.1 Case Description

To illustrate our framework, we analyzed a customer onboarding process of a financial institution in Central Europe. The process starts with a customer request for opening an account and ends when the account is opened. Besides the customer, there are up to four additional stakeholders included, depending on the risk level associated with the customer. The financial institution addresses different kinds of customers, such as private clients, institutional clients, and funds. The process, as depicted in Figure 3, is roughly the same for all customer groups. The illustrated process shows the current structure in the workflow tool with the respective roles. Prior to the organizational change, which is examined in 4.2, the role of the current relationship manager was divided between two people, a relationship manager and an assistant. With a change in the organizational structure, the responsibility was reduced to one person.

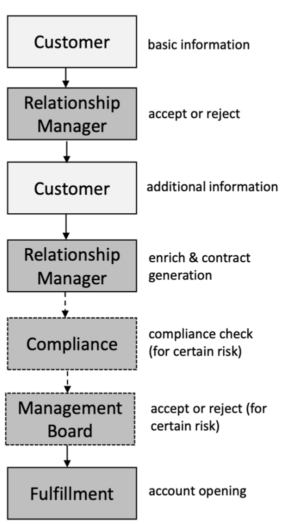

Figure 3. Customer onboarding process

With respect to the digital trace data set, we make the following observations. One case refers to one onboarding request and covers the whole process. One case consists of several activities, which represent the individual events within a process. There is a unique case number for each process that was triggered through the tool. The captured and analyzed data includes all onboarded cases from the introduction of the workflow tool until the last captured case. To showcase our framework and apply temporal bracketing, our analysis focused in particular on time-based variables (e.g., the time required for certain process activities, throughput times, or event frequencies) to study the effects of change.

In the following, the framework for bracketing context with digital trace data (see section 3.2) is applied to the case described.

4.2 Bracketing Context at a Financial Institution

Data preparation. Our first decision in the data preparation stage was to select a subset of the whole data set. To investigate change in the process, we decided to select only cases that were completed successfully, that is, they depict a complete set of activities from the point where the customer requests opening up an account to the point where the account has been opened. In total, we analyzed 901 cases covering 32780 activities over a timespan of more than two years (March 2020 - April 2022). The event log data was exported from the workflow tool in a CSV file and contained all relevant information. To ensure that the digital trace data were complete, correct, and of high quality, we cleaned and preprocessed the data. This included the modification of the timestamp format and renaming of specific process activities, which were labeled identical on the customer side and within the internal workflow tool. Hence, we ensured that the names of the activities were unambiguous. To perform a temporal analysis, we assured that all data were associated with a unique case identifier (i.e., belonged to a specific process) and every activity had a timestamp (van der Aalst, 2016). Table 1 is an excerpt from the event log data and illustrates the cleaned trace data.

Table 1. Example of the cleaned event log data

case_id	timestamp	activity
O-10464	2021-09-16 05:53:00	Enter Service Area
O-10464	2021-09-16 05:54:00	Choose Bundle
O-10464	2021-09-16 05:54:00	Enter Sub Service Area
O-10464	2021-09-16 06:00:00	Insert Bundle Information
…	…	…
O-10489	2021-09-17 03:18:00	Enter Service Area
O-10489	2021-09-17 03:19:00	Choose Bundle
…	…	…

Identification of brackets. Next, we identified brackets. First, we engaged in computationally-driven sensemaking to identify patterns that potentially reveal temporal brackets. For this purpose, we used process mining, a family of computational techniques from the field of business process management to analyze digital trace data from business processes (van der Aalst, 2016). Recent arguments suggest that process mining can be used for theorizing about organizational change (Grisold et al., 2020; Pentland et al., 2021). We applied process mining to visualize and analyze the data from multiple angles and based on different variables, such as the number of activities processed per day, the processing time, or the duration of certain activities. Computationally-driven sensemaking alone, however, was insufficient to identify meaningful temporal brackets for our case process. Consequently, we engaged in human sensemaking to support the process of identifying brackets.

In this stage, we drew from the insights of one of the authors, who has been working for the financial institution. To this end, we reviewed the major initiatives during the observed period as well as documentations on workshops that were held in that time. The insights from workshops helped to determine which changes were perceived as impactful (Barley, 1986). The author pointed to a series of critical events, including various dynamics within the organization (e.g., employee mutations), and the incident and service request tickets created related to the customer onboarding. This contextual knowledge was then mapped against a timeline (Langley, 1999) as well as the patterns found in the digital trace data (Pentland et al., 2021). By combining computationally-driven and human sensemaking, we identified two major changes in the organization, which we further analyzed by using the temporal bracketing approach.

The first change period, which we refer to as 'reorganization', resulted in extensive changes regarding roles and employees. The reorganization was a consequence of the rapid growth of the financial institution and was aimed at improving the customer experience. At the core of this change was a newly established department responsible for customer contact. This was accompanied by a change in the organizational structure. Previously, the activities of the relationship manager were carried out by a relationship manager and an assistant, which was now passed on to one person alone (see Figure 3); the new relationship manager.

Within this first change initiative, we identified three temporal brackets. The first bracket represents the time until the reorganization was officially announced. The second bracket includes a time frame of about two months, between the official announcement and the actual implementation of the new organizational structure in the workflow tool. This bracket was characterized by tensions because teams were already formed but the tool worked according to the old organizational structure. The third bracket starts at the time when the changes in the workflow tool were implemented and ranges to the last activity considered in the analysis.

The second change that we uncovered through a combination of computationally-driven and human sensemaking is the restructuring of a team. Here, a new team leader was assigned to a team that previously worked without a team lead for a few months. Since it only concerned one team, we examined the cases that were handled by this team; this included 181 of the 901 onboarded cases. Within this change initiative, we identified two brackets. The first bracket covered the time from the day when the team had no leader (which coincides with the announcement of the reorganization) until the appointment of a new team lead. The second bracket ranged from the entry of the new team leader until the last recorded activity.

Analysis and sensemaking. After we identified these two broader change contexts and defined temporal brackets for both, we moved to *analysis and sensemaking*.

In the onboarding process, we identified two activities that were strongly affected by the reorganization. The reorganization entailed merging the role of the former assistant and that of the relationship manager; this changed the responsibilities for the respective process activities. The first process activity that was affected by this change was 'approve and prioritize request', which represents the first touchpoint with the customer. There, the relationship manager decided whether a request should be accepted or rejected. Driven by computational sensemaking, we observed that the process had an average duration of 66 hours from the customer sending the request to the termination of the process in the first bracket. In the second bracket, the time increased to 105 hours. In the third bracket, it decreased again to 71 hours. We made a similar observation with regards to the second process activity 'answer client advisor questions'. This activity included the last questionnaire filled out by the front department before the case was either passed on to the compliance department or closed. Prior to the reorganization, this activity was carried out after the assistant answered the questionnaires and the case was assigned to another person. After the reorganization, the case was handled by one person and the activity 'answer client advisor questions' followed directly after the previous questions. In the first bracket, this activity took on average 146 hours. It increased to 338 hours in the second bracket. After the realization of the organizational change in the workflow tool according to the new organizational structure, the average time decreased to 124 hours.

The same applies not only to the time taken for the individual process steps, but also to the violations of conformance in this process step of ‘answer client questions’. Conformance checking allows us to compare the event log with the process model in order to identify differences and commonalities (Grisold et al., 2020). Whereas 33% of the cases in the first bracket showed a deviation in this process step, 43% of the cases in the second bracket did. The violations then dropped considerably in the third bracket to 9% of the cases. Similar observations can also be made when looking at the general conformance with the process model per bracket. An optimal onboarding process has 27 process steps per case, whereas now, however, deviations could be identified. In the first bracket, the process entailed 34.7 executed process steps on average; this increased in the following bracket to an average of 38 executed process steps per case. Conformance therefore dropped considerably. In contrast, a strong reduction to 33.3 steps was achieved in the last bracket.

We also observed a similar development with regard to the average throughput time of a whole case. In the first bracket, a case needed, on average, 57 days from request to closing. In the second bracket, there was a considerable increase to an average of 93 days. In the third bracket, the throughput time decreased to an average of 71 days.

Taken together, we concluded that the announcement of the reorganization, thus, first had an immediate (negative) effect on the process, which resulted in an increase of the throughput time and the processing time of the respective activities. After the workflow tool was adapted according to the changes that accompanied the organizational change, the performance indicators leveled off and were similar to the process before the reorganization.

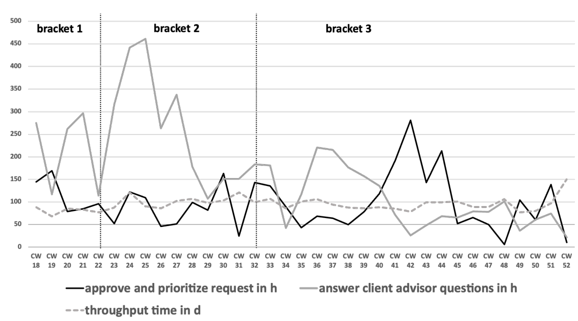

Figure 4. Change 1 - reorganization

As shown in Figure 4, all three considered aspects– the throughput time and the time spent for the process activities ‘approve and prioritize request’ and ‘answer client advisor questions’–had a similar development from their average time throughout the three brackets. The general trend is most visible in the tremendous increase of the ‘answer client advisor questions’ in the second bracket. The other two variables were also at a higher level on average in the second bracket, indicating a general trend in the process following the announcement of the reorganization.

With the combination of computationally-driven and human sensemaking, we were able to make several observations regarding the change process. First, the announcement of the reorganization resulted in an increased need for communication between the various employees and a change in working methods. Second, the announcement of the change without a corresponding system adjustment led to confusion and tensions.

Applying temporal bracketing and decomposing the process into brackets allowed us to assess these dynamics on a more granular level as well as from a temporal perspective. For instance, temporal bracketing revealed a drastic increase in time during the second bracket that later leveled off in the third bracket. One plausible explanation for this is t the change caused confusion. On the one hand, there were new responsibilities and tasks, which led to a greater need for communication. On the other hand, however, it also became apparent that the process changes were already enacted by the employees, even though the changes were yet to be formally adopted in the system. The latency between the announcement and the implementation caused an increase in all considered time-related variables. To ensure that the process ran smoothly, it was therefore recommended to keep the latency as low as possible. Furthermore, in this phase, it was important to strengthen internal communication, explain the changes in concrete terms and guide employees along the way. Within the organization under consideration, this was carried out rather gradually in the second bracket, which may also explain the latency that we observed through computationally-driven sensemaking.

We also analyzed a second change, that is, the restructuring of one team. Concerning this change, the most notable effect was the sharp decline in the number of onboarded cases. Computationally-driven sensemaking revealed that in the first bracket, there was an average of 20.5 accounts opened per month, whereas only 14.5 new account openings could be registered in the second bracket. We made a similar observation regarding the activities processed per day, which were, on average, 22 per day in the first bracket, and 16 per day in the second bracket. This is shown in Figure 5. Looking at the conformance of the considered cases to the desired process model, an increase in conformance can be observed. An optimal process consists of 27 steps, whereas in the first section the cases averaged 28.8 steps. In the second bracket, however, this number fell to 27.8, which constitutes a higher conformance. Similarly, the throughput time also decreased from an average of 57 days in the first bracket to 42 days in the second bracket, which corresponds to a reduction of more than 25 percent. We illustrate this by means of the 'approve and prioritize request' activity, since it showcases how long it took until a new case could be processed. Even though the average time for the process activity 'approve and prioritize request' hardly varied (80h in the first bracket, 83h in the second bracket), through temporal bracketing we recognized large variations after the entry of the new team leader, which are visualized in Figure 5.

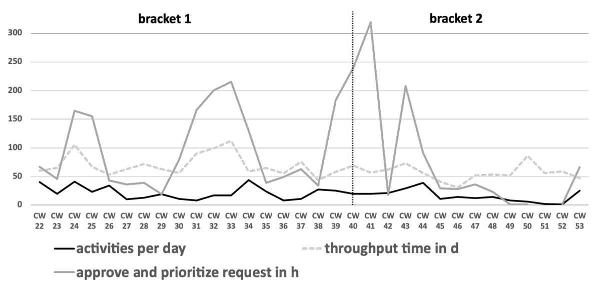

Figure 5. Change 2 - employee mutation

This allows us to make some statements about the impact of the restructuring of the team. First, adding the team leader provided additional human resources, which could speed up the processing. Second, the team leader was able to give the team better guidance which reduced the number of onboardings as well as the throughput time. Third, as Figure 5 shows, it takes time to accept this mutation and to implement and accept the accompanying changes. The effect of the change is therefore not immediate; rather, it evolves incrementally. Importantly, the temporal perspective we provide here was enabled by applying the bracketing approach in combination with human and computationally-driven sensemaking.

Validation and evaluation. In the last step – validating and evaluating– we ensured the rigor and robustness of our findings. In our illustrative case, this was mainly done through human sensemaking with the help of qualitative insights. The evaluation allowed us to reflect on the findings and, if necessary, make adaptations within the previous two steps of the proposed framework. As indicated in section 3.2, this step can also lead to adjustments with respect to the identified brackets, or analysis and sensemaking.

As the analysis has shown, the effects of change 1 (reorganization) and change 2 (employee mutation) mainly became visible as we applied temporal bracketing. For the reorganization, we identified an adoption period after the announcement of the reorganization (second bracket), where almost all time-based performance indicators of the process aggravated. To validate the plausible explanations presented in the previous section, we engaged in human sensemaking by integrating qualitative, contextual insights from the organization. Our evaluation corroborated our initial explanations. We found that the lack of communication within the organization about the impending change was the main driver for the increase in time-related variables during the second bracket.

With regards to the restructuring of the team, we reasoned that the newly gained structure along with better guidance by the new team head led to a better acceptance on the side of the team, which resulted in fewer onboardings and, in turn, more resources for the cases to be processed. Our evaluation further showed that the expertise and experience of the new team leader also played an important role in explaining the effects of the change initiative. We found that the team changed how they approached customers. Instead of deciding on the 'approve and prioritize request' activity based on the information provided in the workflow tool, they sought direct contact with a potential customer outside of the tool to gain a better impression in an initial dialog. This may explain why the number of cases decreased; as the team obtained better impressions of prospective customers, they were more likely to reject requests. Furthermore, our evaluation identified stricter requirements in the 'approve and prioritize request' activity as a major contributor to the decrease in overall cases. Following the instructions of the new team leader, the employees selected customers according to certain predefined criteria in the second bracket, which increased the likelihood of rejections.

Taken together, applying the framework to the case, we could evaluate the changes made and their impact on the organization. Based on these findings, further temporal brackets can be analyzed or additional analysis can be done.

5.Implications

5.1 Theoretical Implications

We proposed a framework for explaining change with digital trace data through temporal bracketing. In doing so, we contribute to the recent research interest in computationally intensive theory development (Berente et al., 2019; Miranda et al., 2022), especially around process-driven theorizing to explain change (Grisold et al., 2020; Langley, 1999). By applying new approaches and data sources, computationally intensive theory building pledges to reinvigorate scientific knowledge

(Miranda et al., 2022). At the core of our framework is the integration of human and computationally-driven sensemaking. Thus, our framework aligns with approaches to study change with traditional qualitative methods (e.g., Langley 1999; Barley 1986), but it is tailored to research with digital trace data.

By creating temporal brackets to study digital trace data, we facilitate the assessment of the effect of changes on a process and enable the comparability between the different stages. In light of the increasing interest in temporal research with digital trace data (Grisold et al., 2020; Oliver et al., 2020; Pentland et al., 2021), and considering the increasing interest in recommendations, frameworks and methods to guide research with digital trace data (Lindberg, 2020; Miranda et al., 2022; Shrestha et al., 2021), we believe that our proposal makes a valuable contribution to the discourse around computationally intensive theorizing.

Furthermore, our proposed framework presents the systematic integration of computationally-driven sensemaking and human sensemaking (Lindberg, 2020) when studying change. We suggest to leverage computationally-driven sensemaking and human sensemaking throughout all steps of the proposed framework: in the identification of brackets, the analysis and sensemaking, and also in the evaluation and validation. By combining manual-driven qualitative insights, gained through observations or interviews, with computational approaches, we can obtain a thorough understanding of contextual phenomena in a complex organizational setting. While we drew on process mining as a means for computationally intensive theorizing (Grisold et al., 2020; van der Aalst, 2016), our framework is compatible with a range of other computational techniques (Miranda et al., 2022).

5.2 Practical Implications

Our research also has practical implications, in particular for business process improvement (Grisold et al., 2021). With our framework, we facilitate the explanation of process mining-based findings by systematically integrating contextual factors through temporal bracketing. Our framework allows for evaluating the effects of contextual change on a process and therefore making more comprehensive statements about process changes as well as possibilities for improvements (Grisold et al., 2021). This opens up the possibility for organizations to not only understand their processes, but also directly assess the effects of changes in the process landscape and explain them (vom Brocke et al., 2021). These findings, in turn, can also provide valuable input for redesign initiatives in organizations.

5.3 Limitations and Future Work

For the illustration of our framework, we used process mining as a computational technique to analyze digital trace data. While it opens up promising opportunities to study processual phenomena (Grisold et al., 2020), it is not the only computational method that can be used for temporal bracketing. Future work could include other techniques, such as social network analysis to study different phenomena and patterns (e.g., patterns of association or complex social dynamics) (Miranda et al., 2022).

In our work, we applied a specific combination of human and computationally-driven sensemaking in each of the steps in our framework. As mentioned in sections 3.1 and 3.2, all steps can be performed in a variety of ways using different degrees of human and computationally-driven sensemaking. Hence, future work can utilize our framework and experiment with a stronger focus on either computationally-driven or human sensemaking. For example, future research could take a more computational approach and apply algorithmic procedures such as diachronic analysis of process dynamics (Pentland et al., 2021) or visual drift detection (Yeshchenko et al., 2021). However, regardless of the selected focus, we stress the importance of combining human and computationally-driven sensemaking to increase the robustness of the findings.

Finally, while the illustrative case served to showcase our framework, it is important to note that we analyzed a limited set of dependent variables. Using our framework provides an opportunity for future research to investigate and theorize about different variables such as process structure, order variation, drift (Pentland et al., 2021) or complexity (Hærem et al., 2015; Pentland et al., 2020) to create novel and interesting contributions.

It is challenging to generalize from insights obtained through digital trace data to the whole organization (Lazer et al., 2020). However, the inclusion of human sensemaking was an attempt to circumvent this to a large extent. By applying the framework to the case, it was possible to assess the changes made and their effect on the organization. Nonetheless, further analyses or evaluations can be performed, as shown in Figure 2. For this reason, we motivate researchers to evaluate this framework and to challenge its completeness and efficiency.

In spite of these limitations, we believe that this paper offers useful guidance to study change through digital traces by integrating human and computationally-driven sensemaking.

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