A Window of Opportunity: Active Window Tracking for Mining Work Practices

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***Abstract*—The field of process mining has evolved from discovering single work processes towards providing broad insights into peoples' work practices. Existing techniques can be used to analyse such work practices, but this can be problematic if the available data is limited to the use of a single IT system or is not captured at the right level of granularity. We propose the use of a personal informatics technique, called Active Window Tracking (AWT), as a new way of gathering data for mining work practices. In this study, we identify the opportunities that this technique brings through a case study within our research group. In particular, we show how AWT helps to: capture previously-unrecorded work activities, expose the relations between work processes, and navigate between different levels of data granularity. The technique, which allows for generating new data as well as complementing existing data, is a valuable asset for the community when it comes to better understanding people's work practices across individual systems and processes.**

***Index Terms*—process mining, work practices, active window tracking, personal informatics, UI logs.**

I. Introduction

The process mining field has expanded beyond discovering standard Purchase-to-Pay processes [1] to being used for a variety of other objectives such as assessing the effect of COVID-19 quarantine strategies [2] and exploiting energy flexibility potential [3]. Where traditional process mining focused on discovering single processes executed in the context of single systems, emerging streams of research such as object-centric process mining transcend this narrow view of processes. However, most studies in process mining still focus on event data from single systems, focusing on single processes [4]. The techniques are available; now all we need is the data.

As a result of the COVID-19 pandemic [5], screen time of adults and children has increased dramatically, presenting both risks and benefits for individuals and society [6]. In the context of process mining, the time we spend "on-screen" might provide an opportunity for an improved recording of the behaviour that takes place within organisations and beyond. Individual computer users can use a host of so-called *personal informatics* tools to collect data about their behaviour "on-screen" or "off-screen" using sensors [7]. However, the potential of these individually-collected data for process discovery has not been sufficiently explored. In this study, we discuss the potential of one such personal informatics tool for discovering processes in a broad sense. We present the data collection technique of Active Window Tracking (AWT) and analyze its use through a case study within our research group, in which ten academics took part.

Our contributions are threefold. First, we derive three major opportunities for using AWT as a new or additional source of data for process mining, outlining nine sub-opportunities. Second, on the basis of our view on how the field of process mining has evolved, we discuss how AWT might serve as valuable data for many of its sub-streams. Third, we explore how AWT data can be used to provide detailed insights into the work of academics.

II. Theoretical Background

Originally, three purposes were envisioned for process mining: discovery, conformance, and enhancement [8]. From the start, the focus has been on the first of the three. Over time, the view on control flow was complemented by other perspectives such as time, resources, and data. Within a few decades, the scope of the discipline expanded greatly, adding new purposes and perspectives. New purposes include comparative process mining, predictive process mining, and action-oriented process mining [1]. New perspectives include costs, roles, and objects. In an effort to illustrate the expansion of process mining, we present several new streams of research taking place within the discipline in Figure 1. In the next paragraph, we position these research streams and discuss how the process is no longer always the focal point. While the overview is not complete, we aim to provide a broad overview of subfields that are introduced as extensions of process mining.

A. Traditional and New Forms of Mining

Traditional process mining focused on discovering the order of activities for a single process based on event data. From that, many supporting techniques and entirely new ideas were developed, with varying scopes. On the most fine-grained level, *task mining* is used to identify individual activities in a process [9]. Typically, such activities are abstracted from user-interface interactions such as pushing buttons or filling in forms [1]. Another very recent stream of research targeted at individual processes, is *causal process mining* [10]–[13]. Causal process mining identifies causal relations between responses (e.g., executing a particular activity) and the resulting outcome of this response (e.g., the occurrence of another activity).

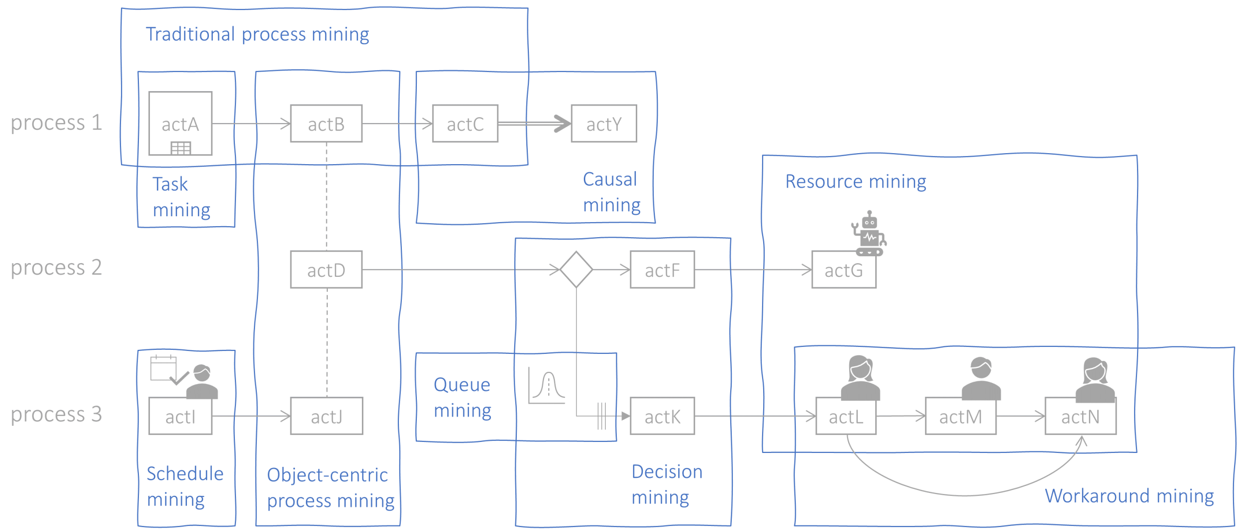

Fig. 1. An Overview of Traditional Process Mining and its Extensions.

Where causal process mining focuses on the relationship between responses and effects, *decision mining* identifies the influence of data attributes on the choices made in a process [14]. As such, decision mining represents the data perspective in a process [1]. *Queue mining*, on the other hand, focuses on the time perspective [15]. By building on past execution data, it can help predict future execution times. This forward-looking, time-aware perspective, is also adopted in *schedule mining*, which aims to predict the feasibility of schedules [16].

Schedule mining is one of those research streams that uses event data to provide insight into how people work, but that diverges from the traditional idea behind process mining: that of mining the order of activities for a single process. This is all the more evident in the paradigm shift that is currently taking place in the process mining discipline, namely from traditional process mining to *object-centric process mining*. Object-centric process mining was developed out of the idea that events do not all refer to one (type of) case [17]. Events may be related to different case notions, or object types. One of these object types can be resources. The field of *resource mining*, sometimes referred to as organisational mining [18], explicitly looks at the resource perspective and has long been under development. Research in that area provided methods and techniques for social network analysis (e.g., [19]) and resource allocation (e.g., [20]). Here, resources are typically studied across processes, which is also true for the field of *workaround mining*. Workaround mining refers to the use of event data to detect how resources deviate from the prescribed procedure to deal with obstacles in their work [21]–[23]. To do so, different process perspectives need to be taken into account, a well as the interaction with other processes.

In sum, for traditional process mining, the focus was evidently on the process. However, various techniques have been introduced that are able to use event data for other purposes, providing solutions for discovering more than the execution of single processes. These techniques can give insight into much broader aspects of work as performed by people within organisations, which we from here on refer to as *work practices*.

B. Cross-system Recording and User Interaction Logs

To provide insight into the execution of processes and general work practices, data on these work practices need to be recorded. However, one of the biggest problems in today's Business Process Management field is related to the recording of work outside of BPM tools [24]. Current BPM tools fail to capture the dynamic and frequently ad-hoc work that takes place within organisations. This is reflected in research. In a recent literature review of empirical process mining studies, 129 out of a total of 142 studies were found to be single-system studies [4]. Cross-system process mining is scarce, and cross-organisational mining even more so [4], [25]. This has implications for the completeness of behaviour that can be analysed with process mining. One of the major factors with regard to process mining adoption as identified by process managers is the lack of information because parts of the process are missing in the data [26]. As a result, the data does not contain the email that was sent or the spreadsheet that was edited, and this affects the value of the process analysis.

In order to extract cross-system event data, we might need to look beyond traditionally targeted systems, like an ERP system or Hospital Information System, for other sources of data. UI logs are one type of data that is independent of the system in which users work, where 'UI' stands for User Interaction or User Interface. These UI logs are increasingly being used in process mining research, in particular in relation to *robotic process mining* [27], [28]. This fine-grained, low-level data is often also referred to as 'click data' [29] because it records user behaviour on the level of clicks and other detailed actions. Its high level of detail is both an advantage and a disadvantage. One disadvantage is that the data is so detailed that it is difficult to recognise process activities and cases [28]–[30].

Another is that the data is so detailed that it records privacy-sensitive information, sometimes even through screen captures [31].

To conclude, it is evident that single-system, single-process analyses provide an incomplete picture of the complex behaviour that takes place within organisations. This motivates the search for data that enables cross-system recording and that is suitable for process analysis in terms of granularity and sensitivity. In this study, we explore the use of a type of data that sits in between UI logs and traditional single-system event data, namely AWT data. Several personal time-tracking tools record the apps that a person uses and the title of the screen that is active. Recording behaviour on this level of granularity could allow for the analysis of work practices across systems, on a level that is possibly more feasible than click data, and less sensitive to personal information.

III. Research Methods

In order to identify the opportunities of using AWT for mining work practices, we adopted a case study approach. Specifically, we performed an exploratory case study within our own research group, with ten academics participating in this endeavour. In this section, we describe our data collection and analysis procedure.

A. Data Collection

First, a time-tracking tool was selected. After an exploratory search of time-tracking tools, the lead researcher selected three tools for a pilot test: Timely (timelyapp.com/), traqq (traqq.com/), and Tockler (tockler.io/). By using the tools in parallel over the course of two weeks, this researcher analysed the advantages and disadvantages of each and discussed these among the research team in a meeting on December 16, 2022. Tockler was selected for three main reasons: (I) it reliably logs application title, window title, start time and end time (see Fig. 2), (II) it does not require manual activation of recording, and (III) logs can be exported locally in a suitable format.

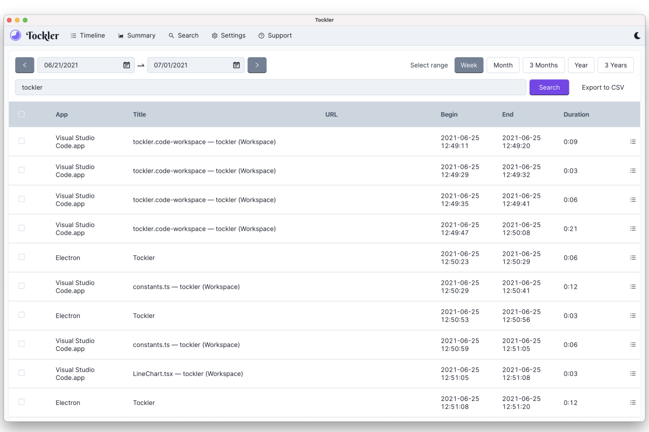

Fig. 2. Illustration of log information (source: tockler.io).

Then, teams were formed to tackle the different aspects of the project. A *technical team* of two researchers was formed to provide instructions for using the tool and processing the data. An *ethical team* of three researchers was made responsible for developing an informed consent form and reflecting on ethical considerations of using the tool. A *theoretical team* of two researchers formed to consider possible implications of using the tool in the broader field of research. Last, a *categorisation team* was formed to manually label data into higher-level categories of work practices.

When the prescribed procedure for configuring the tool and the informed consent was completed by the technical and ethical teams, respectively, the recording commenced. Ten researchers recorded their work behaviour for four weeks, from March 6 to April 2. Two members of the categorisation team continued the recording until the time of writing.

B. Data Analysis

Analysis of the recorded data took place in three stages. First, two members of the categorisation team manually labelled their data of the first four weeks. The labelling took place locally in Excel, by exporting the data from Tockler and adding two columns to the log, one for the corresponding activity and one for the case. The activities were deductively selected from the University Job Classification system used by Dutch universities (https://tinyurl.com/msbef7bx). Examples of such activities are ‘Assessing exams and giving marks’, and ‘Conducting research’. When the labelers could not fit the behaviour within the existing activities, a new activity was created. Examples of added activities include ‘Communicating about events’, ‘Planning teaching activities’, and ‘Reviewing journal and conference papers’. The cases were inductively selected after identifying possible case notions among the labelers. Case notions included courses that were taught, students that were supervised, research papers that the person worked on, events that the person organised, etc.

In the second stage, we elaborated on one activity in detail: reviewing journal and conference papers. Reviewing is a major component of academic work[1]. In order to provide insight into the process of reviewing, the two labellers went through another round of labelling, this time for the period from March 23 to May 17. In this second round, another layer of detail was added for the reviewing activity, specifically for reviews in relation to the BPM 2023 conference. Within the main activity of reviewing, we distinguished the subactivities of bidding, preparing, assigning a subreviewer, assessing, and discussing.

Finally, another meeting was organised on May 30, to identify interesting opportunities for mining work practices with AWT, using the two labelled datasets as inspiration. In preparation, the lead researcher imported the data into Fluxicon Disco and Power BI in order to export visualisations of the insights that could be drawn from the data. The visualisations were presented to the rest of the team, starting a discussion on the opportunities that AWT brings for mining work practices. Consensus was reached on three major opportunities, which are outlined in the next section.

[1]Although interestingly, it is not in the original classification system.

IV. Results

We start by describing the results from our analysis of two AWT datasets: (1) the two researchers' labelled data for the specific process of reviewing for the 2023 BPM conference, and (2) the labelled data from four full weeks for all activities. Then, we reflect on this analysis by discussing three major opportunities that we identify for using AWT, connecting them to the mining types outlined in Fig. 1.

A. Analysis of the AWT Data

We start with a typical discovery use case, discovering the reviewing process for the ten individual papers for the two researchers. We take the subactivities of bidding, preparing, assessing, and discussing papers as activities, and the individual papers as case notion. This results in the discovered process model presented in Fig. 3. It shows how most papers go through some kind of preparation, assessment, and discussion. A subreviewer was assigned to one paper.

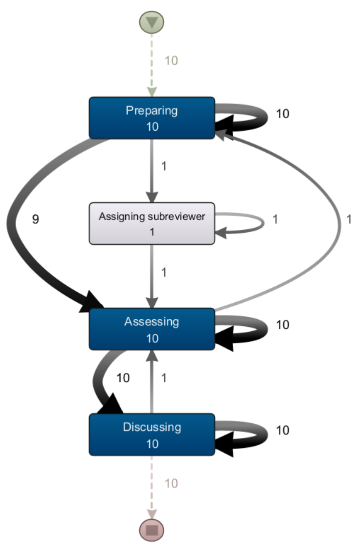

Fig. 3. Reviewing individual papers (case notion = individual papers).

What is not reflected in this model, is the paper bidding subprocess. Paper bidding cannot be recorded on an individual paper level, as this is done for the full set of papers, including the ones that are not assigned to the researcher in question. In order to discover the full process of reviewing for the BPM conference, we therefore selected the conference as the case notion as well. As activities, we selected a combination of the subactivities and the paper numbers. The results are shown in Fig. 5, with time details projected on the model. It shows how Researcher 1 has a very linear way of working: preparing the papers one after another before starting the assessment and only starting the discussion phase after all papers were assessed. The process for Researcher 2, on the other hand, is much more spaghetti-like. This researcher prepared the assessment just before assessing and assigned a subreviewer for one paper. The paper reviews were completed shortly before the deadline, when other reviewers already had submitted their reviews. This meant that as soon as Researcher 2 submitted a review, the other reviews of that paper would be revealed. Researcher 2 could read these reviews and even start the discussion, before reviewing the other papers.

AWT also allows us to analyse the different apps in which the two researchers worked while reviewing, illustrated in Fig. 4. Researcher 1 wrote the reviews in Microsoft Word and used Google Chrome as the main browser for accessing the reviews and for studying related literature, while Researcher 2 wrote the reviews in Evernote and used Microsoft Edge as the main browser. Both researchers continuously switched between the writing app, the browser, and Adobe Acrobat, where the paper was opened.

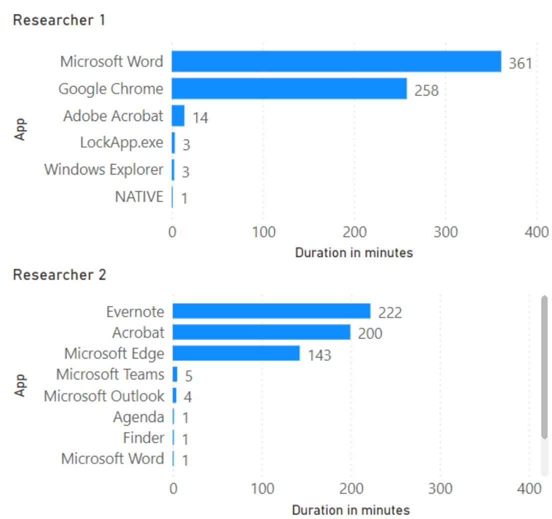

Fig. 4. Illustration of the minutes spent in different apps whilst reviewing.

Other than focusing on the reviewing activity, and in particular, the subactivities in that process, AWT allows for analysing the higher-level activities as a process by itself. That is, taking reviewing as one activity within the larger process of a researcher performing work during the day. In Fig. 6, we illustrate such a working day, namely that of Researcher 1. The day started with writing part of a conference paper, followed by performing work on a paper revision. A significant amount of time was spent on preparing an event that the researcher was organising, alternated with some explorations of the need for research in society and organising international travelling. The day ended with time spent communicating about events, alternated with reviewing a paper.

B. Opportunities of Using AWT

Generalising from our analysis of the two datasets, we distinguish three main opportunities of AWT for mining work practices. In the following subsections, we discuss these opportunities in the context of the different streams of research presented in Fig. 1, outlining nine sub-opportunities that address different aspects of these streams. An overview of these opportunities and associated mining types is given in Table I.

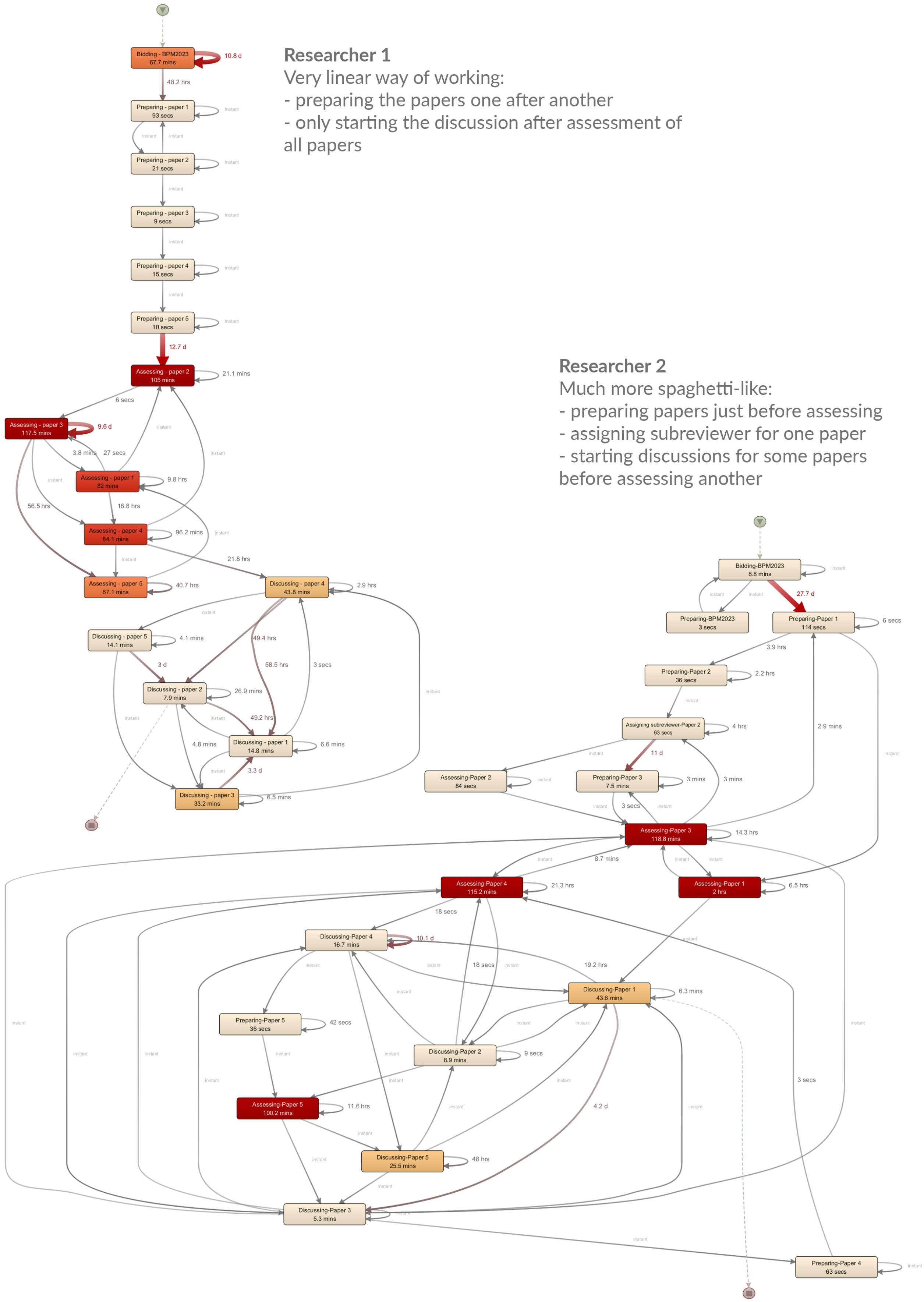

Fig. 5. Illustration of the review process for BPM 2023 (case notion = the conference for which the researcher is reviewing; all activities and paths shown).

TABLE I
OVERVIEW OF OPPORTUNITIES OF ACTIVE WINDOW TRACKING

Main opportunity	Sub-opportunity	Associated mining type
Recording of previously-unrecorded work practices	Recording across systems	Workaround mining
	Recording data attributes	Decision mining
	Recording precise timestamps	Queue mining
Exposing the relations between processes	Exposing the evolution of cases	Object-centric process mining
	Exposing switches between processes	Resource mining
	Exposing preferences and prioritisation patterns	Resource mining
	Exposing differences between scheduled work and actual work	Schedule mining
Navigating across levels of granularity	Interpreting low-level data	Task mining
	Differentiating high-level data	Causal mining

1) Recording of previously-unrecorded work practices: The first opportunity that we identify is the possibility of recording previously-unrecorded work practices. AWT provides additional behaviour in at least three ways: (a) in recording work across systems, (b) in recording data attributes through its titles, and (c) precisely recording timestamps of windows that are active.

Recording across systems. AWT can provide traces that are not recorded in any system as well as enable insights about switches between different systems. As Fig. 4 shows, the two researchers worked in different apps while reviewing. Extracting event data from only one of these systems provides a limited perspective on the actual work practices. AWT allows for a detailed analysis of these switches between systems, as well as the parallelism in paper reading and review writing.

Using AWT data in this way is ideally suited for *workaround mining*. A typical example of a workaround is the use of a shadow IT system to perform a task rather than doing so in the prescribed system. The prescribed system, in the context of our analysis, would be the conference management system EasyChair (easychair.org). However, most of the behaviour takes place in - what one could describe as - shadow systems such as Microsoft Word and Evernote. The current standard for mining shadow IT behaviour is to search for batching behaviour in the event data of the prescribed system [21], [23]. AWT allows for observing exactly where the behaviour takes place, how much time is spent there, and what the order of activities is.

Recording data attributes. AWT also provides information from the data perspective. The recorded window titles allow for the derivation of data attributes that may be used for *decision mining*. For example, when working on a conference or journal paper, we researchers typically apply version control, albeit low-key. We append a Word-document or online document with 0.1 when it is the first version, with 0.2 when it is the second, etc. Similarly, when we supervise a student

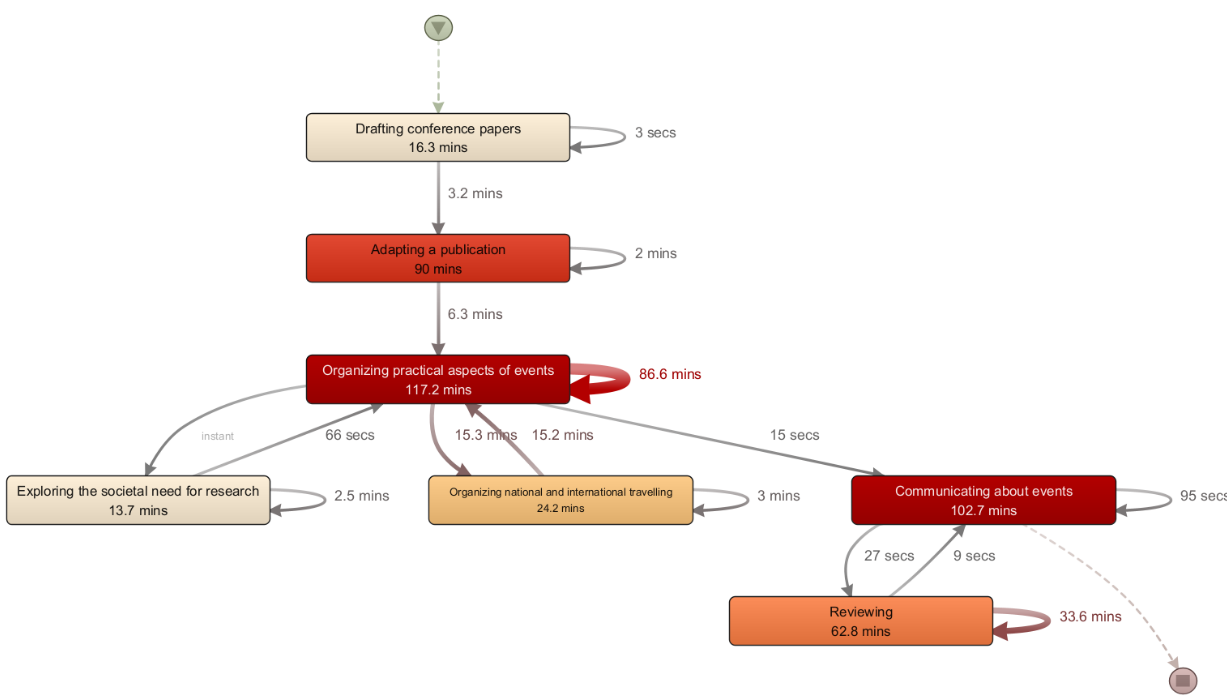

Fig. 6. A day in the life of a researcher (case notion = one day of Researcher 1; all activities and paths shown).

writing their master thesis, the document name often shows whether the researcher is providing feedback on a proposal or a final thesis. Such attributes are recorded in our AWT log and can be taken into account to understand the data dependencies that affect the routing of a case.

Recording precise timestamps. Next to the system and data perspective, AWT provides additional time information through its detailed timestamps. We therefore see new possibilities for using AWT to improve the prediction of future execution times, i.e., for *queue mining*. A notorious problem for queue mining is the determination of start times of activities. Due to the more fine-granular recording of underlying activities, it is more likely that good estimates of start times for higher-level activities can be established.

2) Exposing the relations between processes: A second opportunity that AWT brings is in exposing the relations between processes. In particular, we see four aspects that AWT can expose: (a) exposing the evolution of cases, (b) exposing switching between processes, (c) exposing preferences and prioritisation patterns, and (d) exposing differences between scheduled work and actual work.

Exposing the evolution of cases. AWT allows one to define a hierarchy of case notions and follow these cases across processes as well as their evolution within processes. This brings interesting opportunities for *object-centric process mining*. In the example in Fig. 5, we selected a particular conference as a case notion and discovered the reviewing process for that conference. As opposed to using the individual papers as a case notion, selecting the conference as case notion shows us the evolution of cases: from the bidding on the full set of papers to the preparation, assessment and discussions of the separate papers. Together, the different case notions provide a more complete picture of what is happening and allows one to zoom in on particular aspects.

Exposing switches between processes. The analysis above relates to the selection of different perspectives on the process but is still limited to studying one higher-level process. As described in relation to the first opportunity, AWT allows for the detailed analysis of the switches between systems within the same process. However, it also allows for the analysis of switches between different processes. This is particularly interesting from the perspective of individual resources, i.e., in *resource mining*. Fig. 6 presents the working day for an individual resource, exposing the different processes in which the resource is involved.

Exposing preferences and prioritisation patterns. A second area in which AWT brings opportunities for *resource mining*, is in analysing preferences and prioritisation patterns. Where the focus in resource mining has predominantly been on social network analysis and resource allocation, new research streams are emerging that take into account individual preferences and prioritisation patterns of employees [32], [33]. AWT can show how Researcher 1 prefers to start the day with concentrated writing, namely drafting a conference paper and working on a revision, before tackling other tasks (see Fig. 6).

Exposing differences between scheduled work and actual work. Checking the AWT data against the employee's calendar also allows for studying the differences between scheduled activities and actual activities as performed in practice. This could serve as valuable input for *schedule mining*. Consider once more the example in Fig. 6. According to the calendar in Microsoft Outlook, Researcher 1 planned to work on the paper revision for the entire morning and on organising practical aspects of a particular event in the afternoon. In reality, drafting the conference paper was unplanned but prioritised over the other activities, and adapting the publication was finished earlier than planned. Therefore, the researcher already started the third activity around 11AM and found time to do unscheduled activities in the afternoon.

3) Navigating across levels of granularity: The third and final opportunity of AWT that we will describe here is that of supporting the navigation between different levels of data granularity. AWT offers an intermediate granularity level that sits between traditional event logs and UI logs. This allows for achieving two objectives: (a) interpreting low-level data, and (b) differentiating high-level data.

Interpreting low-level data. When using UI logs for discovering processes, it is difficult to abstract from the clicks of buttons to higher-level tasks and activities [34]. AWT can be used next to UI logs to quickly define what people are working on. As such, AWT can help interpret the data to support *task mining*. For example, one might extract UI data from the EasyChair conference system to study Researcher 2's behaviour in that system. With an accompanying AWT log, one quickly sees which paper the researcher was reviewing, as well as the behaviour surrounding the use of EasyChair.

Deconstructing high-level data. AWT might also be used the other way around, to interpret and deconstruct high-level data. For example, when meeting with a master student in a Teams meeting, Researcher 1 typically opens Microsoft Teams on one screen and the thesis proposal of the student on the other. When extracting data from Microsoft Teams to analyse the meetings that the researcher took part in, the log would only show the time at which that person entered and left the meeting. AWT can be used next to such logs to study this parallel behaviour. This will reveal the windows that the person has active at the same time, such as note-taking tools, personal chats with colleagues or emails they are answering. In this way, it provides a more detailed level that brings new possibilities for analysis.

Getting a better understanding of what is happening, the context in which it is happening, and the possible consequences of certain behaviour offers many possibilities, also in the emerging field of *causal mining*. For example, we know from the analysis shown in Fig. 5 that Researcher 2 finished the reviews near the deadline. This meant that as soon as Researcher 2 submitted a review, the other reviews of that particular paper were already available. Researcher 2 could enter the discussion phase immediately, even before reviewing the other papers. Collecting and analysing more data around such behaviour could point out whether reading the reviews of peers of other papers influences a reviewer's assessment.

V. Conclusion and Future Work

In this work, we discussed the opportunities that AWT brings in mining different aspects of processes and general work practices. We conducted an exploratory case study within our own research group, studying the data for four full weeks as well as the specific process of reviewing papers for the BPM conference. We identify three major opportunities for this type of data: (1) recording of previously-unrecorded work practices, (2) exposing relations between processes, and (3) enhancing the navigation across different levels of granularity. We provide examples of how AWT data can create data that presents new information about work practices, as well as complement existing data, such as UI logs and calendar data. For those who would like to try out AWT themselves, we provide practical guidelines for how to get started and how to prepare the data for process mining analysis[2].

As the data collected in this study were manually labelled by the researchers, a major challenge for scaling up the use of AWT is to develop (semi-)automatic labelling techniques. For UI logs, techniques are currently being developed for automatically determining activities (e.g., [30]) and cases (e.g., [29]). Future work might prove whether these techniques can also be used to automatically label the window titles from AWT data. If so, AWT presents a valuable source of data for analysing diverse work practices: at a more detailed and comprehensive level than traditional event logs, but with a higher abstraction level than UI logs.

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[2]Find the document here: https://tinyurl.com/ActiveWindowTracking